A Study on Provider Support with Value Inference in Service Design

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Chapter 1

Introduction

1.1 Background

With the development of the information society, various services are provided through systems, and large numbers of data are accumulated, mainly by companies. Vargo and Lusch [VL04] defined service as "the application of specialized competences (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself." Following Vargo and Lusch's proposal, IBM took the lead in establishing the field of service science, which attempts to treat services with a scientific methodology [MSKS06]. A service can be viewed as the creation of value by two or more entities. A service system enables the actual operation of a service. Several definitions of service systems have been proposed [WWZ+14], and no consensus has been reached in the field. In recent years, the scale of service systems has been increasing. This thesis treats a service system as a system allowing a service provider to provide acceptable results to both the provider itself and to the receiver, considering the receiver's value as the service results. While the definition of value is open to much consideration [Ama21], value in services can be categorized into three types [UTF08, TNU08]: provided value, which can be specified in advance; adaptive value, in which value fluctuates due to environmental influences; and co-creation value, in which the values of the provider and the recipient are correlated. Among these, this thesis deals with the service of adaptive value. The value of the service outcome in this thesis can be expressed as utility, which is a numerical expression of satisfaction for providers and receivers.

In Japan, service engineering has been proposed as one of the service science fields, which considers services scientifically from a broad perspective, and examines engineering approaches to services. Service engineering deals with engineering approaches to understanding, designing, producing, and developing services [SHW+05]. Unlike the management approach in service science, the main focus is on implementing or improving services that work in reality. This thesis deals with improving real-world services, which is the research objective of service engineering, especially with the solution of problems in the elemental technologies used to design existing service systems.

Well-known elemental technologies for service system design are based on mechanism design theory, such as auctions, and mathematical optimization, such as scheduling. These technologies are based on the assumption that service receivers understand the value of the results obtained and act rationally. However, owing to the bounded rationality [Sim47] caused by the restriction of human cognitive ability and the limitation of service design in terms of convenience, it is difficult to grasp the value of the results achieved by the service. Owing to this difficulty, it is currently difficult for service providers to provide the desired results guaranteed by the elemental technologies of the service system.

Providers are one of the important entities involved in the service system. Providers ask the service receivers directly about the values and summarize them, or they set up a place for value exchange and promote smooth negotiations among service receivers. In this thesis, we call the former case a top-down model and the latter case a bottom-up model. Either model is used depending on various assumptions of the service system. The top-down model is preferred when there is a solid need to satisfy constraints such as scheduling. The bottom-up model is preferred when the receivers participating in service systems cannot be specified in advance. In either case, the provider can observe the entire process in service systems. Therefore, the way in which the provider interacts with the receiver is important for a smooth service system.

In recent years, with the popularity of *big data*, data has been accumulated under all types of situations. Data on service systems is also accumulated. In such a situation in which data is continuously generated, a data-driven approach is essential. Although data-driven approaches have received more attention, elemental technologies for service systems have not fully exploited data. As one of the reasons for this, data on service systems is inefficient. In service systems, only information regarding the expressed evaluation values can be obtained. In addition, it is problematic that receivers rarely know their accurate values. In this thesis, we propose a new method that can be used to estimate the value of the service results.

1.2 Research Objective

This research aims to solve the difficulty for providers and receivers to grasp the value of service results in service design using conventional service system elemental technologies. The value of service outcome in this research refers to how the service has improved the benefits of the provider and receiver. There are various instances of value, such as price and preference order. The difficulty in grasping the value is mainly due to the receiver's cognitive ability in the bottom-up case and the provider's high cost of grasping the value in the top-down case. By eliminating the difficulty of understanding the value, both the service provider and the receiver will obtain a higher service value than before.

In this study, we emphasize the provider, which has not been considered in conventional service system elemental technologies, to organize the structure of the problem. Providers are essential because they can interact with all entities involved in the service. Based on the role of the provider in the service and the theoretical and empirical perspectives of the research objectives, this thesis organizes the elemental technologies of the service system into four areas. Among these areas, this thesis focuses on top-down and bottom-up empirical techniques. This thesis shows that the value-grasping problem in the service can be solved by presenting the value information estimated by the provider.

For value estimation, the challenges are data inefficiency and value variation in service systems. In the service system, only the value data expressed by the receiver can be obtained, so it is impossible to obtain the value information of all the entities involved in the service. In addition, even if all the conditions are the same, changes in the values of service receivers are inevitable, so from the provider's point of view, values appear to be changing stochastically. In order to deal with these two difficulties, this thesis uses a hierarchical Bayesian model for value estimation. This thesis shows that the hierarchical model can deal with a small amount of data in the service. The Bayesian estimation can be used to understand the value in the service, which is a quantity with variability.

For information presentation, this thesis deals with the timing of the presentation and efficient presentation methods. Considering the application in actual services, the provider needs to present the information to increase the value the most. This thesis develops a method to analyze at what point in the auction period the presentation of information increases the end price. Auction is a suitable service system for analyzing presentation timing because of its relatively long session. In addition, an efficient presentation method is essential when there is a time constraint. Since the constraint on due dates is relatively strict in work scheduling, we develop an efficient presentation method for work scheduling. In this case, it is necessary not to broadcast the information. Broadcast is not suitable for this studies' purpose, which reduces the burden of understanding value because it presents the information even to the targets who do not need it.

1.3 Outline of the Thesis

The structure of this thesis is as follows. Chapter 2 categorizes the elemental technologies of conventional service systems in terms of top-down/bottom-up and theoretical/empirical axes and clarifies the position of this thesis. Chapter 3 describes a value estimation algorithm for provider support in service systems, using B2B luxury brand item auction as a real-world example. Chapter 4 analyzes the timing of information presentation using estimated values in online B2B luxury brand item auctions. Chapter 5 describes a simulation of alternative attendance request as an information presentation environment and develops the information presentation method on the simulation. Chapter 6 summarizes this thesis. Chapter 3 is based on study [HYYK21b], chapter 4 is based on study [HYYK21a], and chapter 5 is based on study [HYYK19].

Chapter 2

Literature Review

2.1 Elemental Technologies for Service System

The service systems targeted in this research are mainly systems that coordinate people's interests in situations where resources are limited. In the design of service systems, techniques such as mechanism design, game theory, and mathematical optimization are used. The elemental technologies in such a system can be classified into two models based on the transfer of the value information between the service provider and the receiver. Figure 2.1 shows the conceptual diagram of these models.

A bottom-up model is a technology in which there is a flow of the value information from the receiver to the provider. Service receivers exchange the value information with each other, and the provider receives the results of the coordination of the value information among the receivers. In bottom-up technologies, the provider sets the rules the receivers exchange value information. Receivers exchange value information according to rules. Such technologies include mechanism design and the sharing economy.

A group of technologies with a flow of value information from the provider to the receiver, in which the service provider obtains the receiver's value information through direct exchange and determines the service result, is called a top-down model. In top-down technology, there are various ways in which the providers interact with the receivers, including dynamic pricing, which is indirectly through prices, and work scheduling, which is directly ascertaining and optimizing.

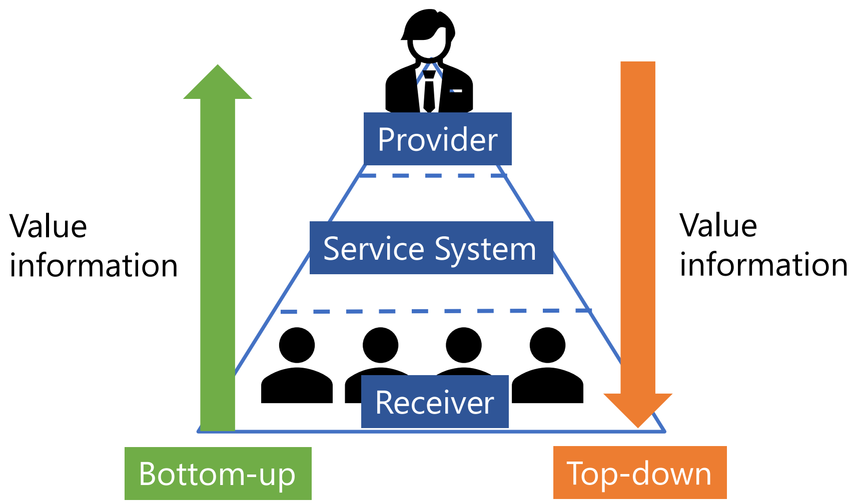


Figure 2.1: Overview of the classification of service system technologies

These two groups of technologies can also be classified according to whether their research objectives are theoretical or empirical. In theoretical studies, equilibrium and optimal solutions are analyzed under the assumption that the provider and the receiver are rational and thoroughly understand the value of the service outcome. In the aforementioned elemental technologies of the service systems, mechanism design and mathematical programming are theoretical research areas. Empirical research examines how to apply the results of these theoretical studies to reality. Empirical techniques include the design of mechanisms for real-world auctions and matching systems and the formulation of real-world problems, such as work scheduling, to be solved by mathematical programming. This research addresses the difficulty of understanding the value in the service systems using empirical technologies.

The structure of this chapter is as follows. Section 2.2 outlines the state of research on elemental technologies for bottom-up models, focusing on mechanism design and automated negotiation. Section 2.3 focuses on the elemental technologies of the top-down model, namely, work scheduling and dynamic pricing. Section 2.4 summarizes the problems of the elemental technologies of service systems and specifies the areas to be addressed in this research.

2.2 Bottom-up Model

2.2.1 Mechanism Design

The bottom-up service system technologies are based mainly on the theoretical background of a mechanism design. A mechanism design is an academic discipline in which mechanisms are developed to maximize social utility when various people act according to their values. The main application areas are auctions and matching. With auctions, the auctioneer asks participants to declare the valuation of their goods and determine the allocation and price of goods to maximize the social surplus. By contrast, with matching, the participants are asked to express their preferences for possible options while ignoring price, and the combination of participants and options is sought without a price consideration. In the mechanism design theory, separate theories have been developed for each application area, such as auctions and matching, although they share the same background. In the following, we outline the theoretical research conducted on auctions, matching, and other representative research areas, followed by an overview of applied research.

Auction

An important theoretical result regarding auctions is the revenue equivalence principle presented by Vickery [Vic61]. This principle shows that four forms of single-commodity auctions, i.e., English auction, Dutch auction, first-price sealed-bid auction, and second-price sealed-bid auction, are equivalent in terms of total revenue under the assumptions of independence and private value. In the English auction, bidders bid on items, and the participant with the highest bid wins the auction. In the Dutch auction, the auctioneer decreases the price, and the first bidder to declare a bid wins the auction. The other two auction mechanisms are auctions where the bidding price is not disclosed, and the highest bidder wins both auctions. In the first-price auction, the successful bidder pays the highest bid price, and in the second-price auction, the second-highest bid price. This revenue equivalence principle was shown by Riley and Samuelson [RS81], and Myerson [Mye81] to hold more for general auctions. The historical background of these is detailed in the textbook [Ste07]. However, such property often does not occur in reality.

In reality, most auctioneers want to conduct auctions for multiple items, not just a single item. There have been many theoretical studies on auctions for multiple items. One important example is the VCG auction, which is an acronym for Vickery [Vic61], Clarke [Cla71], and Groves [Gro73]. VCG auction is a combinatorial auction in which bids are placed on bundles of items and are the only ones in which honest bidding is the dominant strategy. Although this auction has excellent theoretical properties, it is not used in practice. There are several reasons for this, the most common being the complex payment rules in VCG, which are challenging to understand. Simultaneous multiple-round auctions are applied in spectrum auctions [Cra97], and a generalized second-price auction (GSP) is used in advertising auctions [EOS07] for practicality. Various other theoretical properties of auctions have also been identified, and textbooks [Kri09, Mil04] describe these properties in detail.

The recent development of the Internet has led to the emergence of online auctions. In particular, eBay is one of the largest auction sites, and owing to the increased availability of data, various empirical studies have been conducted from the early 2000s to the present. In the following, we will discuss some of the representative examples.

Most auction data used in the previous study was collected from eBay because of their ease of use. Bidding strategies specific to online auctions have been studied. According to a survey [HS10], there are three distinctive strategies in eBay auctions. Roth and Ockenfels [RO02] described a sniping strategy, which is bidding just before the end of an auction to avoid a bidding war or informing other bidders, as a well-known bidding strategy characteristic of online auctions. Other bidding strategies include proxy bidding and incremental bidding [Wil00, OR06]. In proxy bidding, bidders use eBay's automatic bidding system, and in incremental bidding, bids are placed within a minimum incremental range. Bidding a large amount at the beginning of the auction and then using a proxy bid is called squatting [EH09]. These bidding strategies are not unique to eBay and have also been observed in other auction sites as well as in Taobao, an auction site in China [CL13].

In recent years, one of the most popular research areas using auction data has been automated mechanism design. Conitzer and Sandholm [CS02] proposed an automated mechanism design. Auction mechanisms using deep learning have been designed [DFN$^+$19, FNP18]. Research [LYZ$^+$21] showed that a data-driven automated mechanism design is effective when the number of auctions conducted is extremely large, such as in advertising auctions. It is difficult to collect sufficient data for automated mechanism design for commodity auctions such as luxury brand item auctions, which are the subjects of this research.

Many studies have focused on the strategies of the sellers, with the most popular research area being the setting of the reserve price (starting price). Various studies have analyzed the effect of reserve prices [LBPR07, CNR16] on the optimal reserve price [YWD06]. The research [CpLY18] analyzed the listing strategies of sellers on eBay.

The bidding process, one of the critical features related to auction results, has also been studied. Studies have shown that a functional data analysis can capture the bidding process [ZGL11], as well as the proposed features for this process [BGGJ04]. Clustering was conducted using bidder paths, which are a bid time series composed of bid point data [BGGJ04].

Some research has focused on decision support in auctions for general consumers. In [GW06], a system is proposed that collects the winning bids of products from multiple Internet auction sites and suggests recommended bids and starting prices based on statistics such as median prices. In [vPv08], a study is conducted on developing the recommended price within this system using a price prediction. In this study, a decision tree-based method based on product descriptions for four products listed on eBay achieved better accuracy than predictions based on averages.

In addition, one of the ways to deal with a large number of items in B2B auctions, which we deal with in this research, is item recommendation. Because auctions are different from everyday purchases, it has been challenging to apply recommendation algorithms to them; however, recent research has addressed recommendation in auction [RJSH20].

There are also ongoing efforts focusing on price estimation. In one of the earliest studies [BH03], the authors conducted a Bayesian estimation of the bid distribution for auctions of U.S. coins that are frequently traded on eBay. Subsequent studies have focused on the end price. Studies on the estimation of end prices in auctions can be divided into two categories: static estimation, which uses information only before the start of the auction, and dynamic estimation, which uses bid information during the auction. In static estimation of end prices, the study [GS04] showed that estimation problem is formulated as regression and classification problem. However, this study was limited to a single item listed on eBay. In addition, [Gha05] showed that the results could be applied to auction price insurance.

By contrast, the studies [DJS10, WJS08] described methods for dynamically forecasting the end price that also uses information during the auction. Other studies included an estimation using K-nearest-neighbors [ZJS10], and a study focusing on changes in bidding trends during auctions [CL17] was conducted. Unlike eBay, where we deal with real products, in domains where large amounts of data are collected, such as advertising auctions, a deep learning approach [WYC18] was applied.

Matching

One of the most important results on matching theory is the deferred acceptance (DA) algorithm [GS62]. The DA algorithm is for finding matches in which no one would prefer any other combination for a one-to-one assignment with mutual preferences. The DA algorithm has been applied to resident assignments. See the paper by Roth [Rot08] for the historical background. At present, the DA algorithm has not been applied at a large scale in comparison to auctions.

The TTC algorithm [SS74] is also a well-known theoretical achievement. The TTC algorithm was developed for dealing with more realistic situations in which some people already hold certain goods, and others do not [AS99]. One such application is the matching for a kidney transplant.

In recent years, research on online matching has been conducted as a more applied field. Online matching deals with allocation methods when the matching entity appears dynamically. This type of problem is widespread in real-world systems. An example of an application is ridesharing. In ridesharing, people who want to travel in a car appear dynamically. Research was conducted on the modeling of matching environments based on the reusability of drivers as offline entities in ridesharing services [DSSX21]. In taxi dispatch platforms, which are similar to ridesharing services, an allocation method that considers the preferences of both drivers and users was proposed [ZXS$^+$19]. Crowdsourcing is another typical application area. In spatial crowdsourcing, where a user with a mobile device physically moves to the task execution location and executes the task in the real world, an allocation method that considers the user's preferences was developed [ZXL$^+$19]. In addition, in crowdsourcing, not only users but also tasks may appear dynamically. An allocation method that considers the dynamic appearance of both has also been proposed [DSSX18].

2.2.2 Automated Negotiation

The technology of automatic negotiation, in which agents negotiate on behalf of humans and automatically find a compromise point based on the values of the agents involved in the negotiation, has also been actively developed. In studies on game theory, negotiation strategies and equilibrium behavior were analyzed under somewhat simplified circumstances [JFL+01]. In this field, a competition called ANAC [BHJ+12] has been held to test the performance of automated negotiation agents in a simulation environment. It is expected to be applied to traffic management systems as a social system, and various studies in this area have been conducted. At present, the main focus is on studying future social systems, and few technologies have been put to practical use.

2.3 Top-down Model

Scheduling and dynamic pricing are typical top-down service system technologies, with mathematical optimization and supply-demand theory as the theoretical background. In mathematical optimization, optimization algorithms, such as combinatorial optimization and linear programming, are the focus of theoretical research. Against the background of theoretical research on an optimization methodology, applied research has been conducted to formulate and solve real-world problems as optimization problems. The operations research field overlaps with this application area to a large extent and includes technologies other than those supporting service systems, such as route planning. The main application of operations research for service systems is in the area of work scheduling. Because work scheduling is the core of supporting business in all situations, such as airplane personnel, hospitals, and part-time work, it is of high social importance in service systems. Dynamic pricing is a method for finding the optimal price that balances supply and demand, based on the theory of supply and demand in economics. The seller acts as a provider. Dynamic pricing is well suited to the recent development of e-commerce and has been applied in various ways. In the following, we explain the related technologies, focusing on the scheduling technology treated in this thesis.

2.3.1 Staff Scheduling

Research on personnel scheduling has been conducted for several decades [VBD$^+$13, EJKS04]. The target area of scheduling research is a wide variety of industrial applications, such as the scheduling of transportation crews and the allocation of employees in call centers and retail stores [EJKS04]. Nurse scheduling, which determines the shifts of nurses in hospitals, is a typical application of staff scheduling, and many studies have been conducted in this area [BDBV04]. Nurse scheduling involves creating a shift schedule that satisfies many conditions, such as the work preferences of nurses and the number of nurses required in a ward.

Personnel scheduling is often formulated as an integer programming problem. The research on the method can be divided into two categories: those that seek an exact solution and those that seek a fast approximate solution. In the past, it was difficult to obtain exact solutions for problems of realistic scale, but recent advances in computers and algorithms have made it possible to use general-purpose solvers such as CPLEX and Gurobi to obtain exact solutions in the time required by the application. For complex cases with many constraints, such as nurse scheduling, many studies have been conducted using metaheuristics to solve the problem in real-time [AD04, Dow98]. The issue of shift assignment to part-time workers requires consideration of employee preferences, and several studies have been conducted recently [XLSTF18].

Personnel scheduling includes rescheduling, which deals with sudden changes from absenteeism after shifts have been decided. In rescheduling, a shift schedule that has become unworkable owing to absenteeism is revised into a feasible shift schedule while maintaining as much as possible the previously determined employee allocation. In a real workplace, the sudden absence of an employee owing to a sudden illness or family reason is a common occurrence. Rescheduling to cope with such situations has been dealt with in scheduling studies and has attracted significant attention in recent years [CMTS13]. The rescheduling problem is relatively new and was formulated by Moz and Pato [MP03]. There are various rescheduling methods, such as rescheduling when there is no spare personnel [MP07] or reassigning available personnel in response to absenteeism [BP05]. Even in recent years, many papers have been published to solve the problem [WSB19, BDcH16, MK14].

2.3.2 Dynamic Pricing

Dynamic pricing, in which a seller discovers the price at which profits are maximized by changing the price of a product to match demand, is an application area that has recently received increasing attention. One area where dynamic pricing is already widely used is selling airline tickets and hotel rooms. In recent years, dynamic pricing has been used in the context of accommodation pricing in Airbnb [YQC+18], and ancillary pricing in the airline industry [SKO+19], where features vary from product to product, using deep learning approaches to estimate demand functions.

2.4 Discussion

All of the theoretical studies mentioned in the previous sections assume that the service provider or service receiver understands the value of the results and tries to obtain results that take into account the value of each user. For example, in an auction, participants, who are the receivers in the service, bid on a product after recognizing its value to them. In scheduling, the provider, i.e., the planner, aggregates the values of the receivers to create a schedule. Empirical studies have inherited the assumptions of such theories. For the desired behavior of each method, the receiver in the bottom-up case and the provider in the top-down case must understand the value of the outcome.

In reality, there are many cases in which receivers and providers do not or cannot grasp the value of the results. There are two possible causes for difficulties in grasping a value: one is caused by the receivers, and the other is owing to service system constraints. The receivers cannot grasp the value of the result because the receiver's cognitive ability is limited. In economics, this cognitive limit is called bounded rationality [Sim47]. A specific cause of bounded rationality is the time constraint of having to make a decision within a limited period of time. Even if the ideal result is obtained, the time cost for the provider to inquire about the value when there are many users is high. In such a case, the results obtained in reality are considered to be Pareto dominated by the ideal results of each method.

In this thesis, the difficulty in understanding the value that occurs regardless of the top-down or bottom-up model described above is resolved through a value estimation and the presentation of information. The desired results required by the service system can be obtained more easily. The main contribution of this thesis is supporting a more realistic operation of existing methods rather than developing new mechanisms or scheduling methods. This study treats providers, who have not been explicitly shown thus far in elemental technologies, as the subjects of real-world services and provides support for them, which has yet to be applied.

Chapter 3

Value Estimation Using Hierarchical Bayes Model

3.1 Introduction

Auction is one of the most powerful service systems for trading items. The auction is an effective service system for determining the prices and allocations of items when their values are unknown. Auction is well known for its use in trading art and used automobiles. As represented by the Internet auction platforms, eBay and Yahoo!, auction is also actively used for transactions between individuals.

In recent years, the scale of auctions has expanded, and there are many cases in which different auctions are held simultaneously for large numbers of items. Notable examples of such auctions include wholesale business-to-business (B2B) auctions. In wholesale auctions, the host company is the only seller and trades items with participating companies. The participating companies in the wholesale auction select the items to be handled as their own items from the items on display and place bids. In a wholesale environment, there are many items on display, and the participating companies have to decide which items to bid on from a large number of items. When deciding on whether to place a bid, or when choosing the bidding price, it is necessary to consider multiple factors such as the market price, the valuation of other companies, and the sales channels of the company itself. For this reason, the burden on participating companies is likely to increase as the number of items increases.

The time required to make bidding decisions for all items handled in a single auction is considered to be proportional to the number of items. Therefore, it is difficult for bidders to make bidding decisions for all items.

Decision-making regarding the bidding becomes problematic when there is no uniformity in the attribute information of the items handled. An example of such an auction is a B2B luxury brand item auction, which is a wholesale auction of used luxury brand items. Used items come in a wide variety of types, and identical items are rarely sold in large quantities. Even if an item is identical in terms of the model number, it is unlikely to be completely identical when attribute information such as dirt, scratches, and the presence or absence of accessories are considered. In general, in B2B luxury brand item auctions, skilled staff with expert knowledge of luxury brand items make bidding decisions. Thus auction-based price determination works effectively at present. However, it is difficult for newcomer companies to participate in the auctions because it is difficult for them to evaluate the items without experts. In the case of existing participants, the number of staff members is limited, and thus they may not be able to respond to an increase in the number of auctioned items and make appropriate bidding decisions. Such a situation leads to a decrease in the number of companies participating in the auction and a halt in the expansion of the auction scale, which is undesirable from a sales standpoint.

An increase in decision-making costs owing to the increase in the number of auctioned items also occurs for the organizers of B2B luxury brand item auctions. As the only auctioneer, the organizer needs to set the reserve price, i.e., the minimum bid price, after understanding the value of many different items. The end price is currently estimated manually, and the time cost of accurately estimating the end price for all items increases in proportion to the number of items. As the number of items increases, the accuracy of the estimations decreases, and there may be cases in which auctioneers do not realize that some items have lost the opportunity to be sold at a higher price.

These problems occur regardless of the auction mechanism employed and hinder a stable auction operation. Both problems are caused by the fact that the values of the auctioned items are known only implicitly by skilled experts. It is therefore necessary to inform participants of the values of auctioned items to support the auction operations and allow participating companies and organizers to understand the values. In most conventional studies on such understanding, the value is estimated as a point. However, given the characteristics of an auction, which often deals with items whose values are not uniquely determined owing to differences among buyers, point estimates alone are insufficient to provide information for auctions-related decision-making, such as determining the reserve prices.

This chapter estimates the distribution of the end price, which is considered to reflect the value. Estimation of the value is an elemental technology used in supporting auction decisions. The subject of this chapter is a B2B luxury brand item auction, which is a wholesale auction of used luxury brand items. The items handled in this auction are brand-name watches, brand-name bags, and jewelry. These items have characteristics making it difficult to collect data for completely identical items. Compared to the items handled in other B2B auctions, used brand-name goods have less attribute information that can be used as the source of features for a value estimation. For example, in the case of used automobiles, functions such as the presence or absence of a car navigation system and the drive system can be used as features, whereas for used luxury brand items, only a comprehensive evaluation index of scratches and stains can be obtained. Therefore, it is challenging to estimate the end price for used luxury brand items.

This chapter addresses the problem by modeling the distribution of end prices using a hierarchical Bayesian model. Although hierarchical Bayesian models have rarely been applied to the estimation of auction prices, they are among the most powerful methods for handling uncertain prices. This chapter describes the effectiveness of the hierarchical Bayesian model in estimating the distribution of end prices.

In addition, this chapter demonstrates that the end price distribution model proposed in this study can be used to provide bidding support to participants, which is often the target of previous studies, as well as decision support to auctioneers, which has few precedents. A conventional distribution estimation was applied in an auction for a structural analysis. There are few examples in which a price distribution estimation has been evaluated in terms of applications such as a decision support. In a practical auction mechanism, it is important to consider the fact that multiple items are handled. In such a mechanism, the basic first-price auction and the second-price auction, which do not consider the handling of multiple items, are used. It is therefore important to mitigate the high decision-making costs when the number of items increases by providing bidding support and operational support. In decision support, it is significant to treat the end price as a distribution because the items handled in auctions have uncertainty regarding the value considered by buyers.

The structure of this chapter is as follows. Section 3.2 gives an overview of the B2B luxury brand item auction covered in this chapter and the data to be used. Section 3.3 discusses the comparison of features of data from B2B luxury brand item auctions and data from other domains where price estimation is performed. Section 3.4 describes a probabilistic model for estimating the end price. Section 3.5 describes the analysis of the effectiveness of the proposed model and the comparison experiments with conventional machine learning methods, and Section 3.6 summarizes this chapter.

3.2 B2B Luxury Brand Item Auction

This section provides an overview of the B2B luxury brand item auctions covered by the research described in this chapter. In addition, this section explains the data to which the end price estimation is applied.

3.2.1 Overview of the Auction

In this chapter, B2B luxury brand item auctions are auctions for wholesale used luxury brand items. The auctioneer companies list items they have purchased from consumers, and most of the items in the auction are listed by the auctioneer companies. By contrast, all participating firms are bidders. The participants are mainly companies that organize similar auctions, and antique dealers that sell brand-name items to consumers. They are believed to decide the bidding items and prices by considering their inventories and sales channels, and sometimes listing the items they buy to other auctions. Figure 3.1 shows the structure of the B2B luxury brand item auction described above. The value of the listed items depends on the mutual relationship among consumers, participating antique dealers, and the auctioneer company. In addition, it is difficult for non-experts with limited knowledge of commodities to make bidding decisions owing to the nature of this auction, which rarely includes completely identical items.

The auctioneer decides the items to be sold each month and notifies the participating

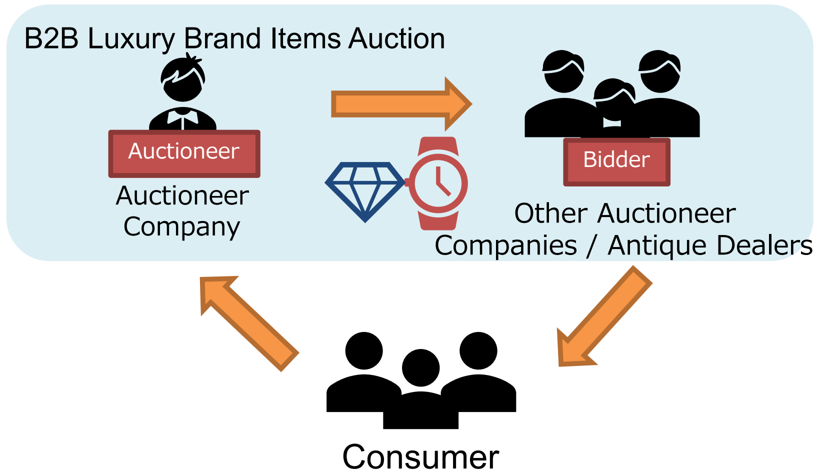


Figure 3.1: Structure of the B2B luxury brand item auction

companies of these items several days before the auction starts. The auctioneer in this chapter uses English auctions, in which bidders declare the bidding price for each item. The auction is conducted face-to-face, and the bidder's information, including the company name and the bidding price, is open to all participating companies. Because the auctioneer conducts the auction sequentially for each item, bidders cannot bid on multiple items simultaneously. Although some auctions are conducted through the Internet, this chapter treats them the same as face-to-face auctions owing to their small volume.

3.2.2 Auction Data

This chapter describes the development and evaluation of a method for estimating the distribution of end prices based on historical data of successful auctions of B2B luxury brand items. This study uses auction history data, which contains information regarding the attributes and prices of items sold in auctions held from August 2018 to July 2019. The items have three main categories, i.e., watches, brand bags, and jewelry. This chapter estimates the end price distribution of Rolex watches, which have relatively high transaction volumes.

The distribution of end prices in B2B luxury brand item auctions has two characteristics. One is the stability of the distribution. In general, the distribution of end prices varies greatly depending on the number of participating firms and changes in the breakdown of participating firms. However, in the B2B luxury brand item auctions that are the subject of this study, there is little change in the breakdown of participating firms each month, and thus, the fluctuations in the distribution are small. This slight change makes it possible to estimate the distribution of end prices from historical data.

Another characteristic is the difference in the evaluation of items among companies. Items handled in B2B luxury brand item auctions are sold to consumers by the winning bidders after being sold to them. The end price will vary due to the uncertainty of the market value, such as the value fluctuating over time and differences in sales channels, transportation, and storage costs among the participating companies. Both uncertainties vary from the average price. The end price distribution can be modeled as a normal distribution.

The item information contained in the data includes various information, such as the material and the serial number assigned to each item. This chapter uses the model number, guarantee status, and item rank as variables in model building, which are generally available for watches including Rolex watches. The model number identifies the watch. Because the model number determines the price range of the watch, it has the most significant impact on the end price among the other variables. There are three types of guarantee status: non-existent, domestic authorized, and parallel import. The presence or absence of a warranty card has a substantial effect on the price. By contrast, the difference between genuine items sold in Japan and parallel imports is considered small, and thus this chapter treats it collectively as the presence or absence of a guarantee. The item rank is a value that indicates the quality of the item according to the degree of damage and use and is determined by a specialized appraiser before the item is put up for auction. The lowest rank is C, and the highest is N. There are eight ranks shown in Table 3.1. The higher the rank, the higher the end price tends to be.

The price information available in the auction data is the end price and the estimated end price determined by a professional appraiser. The auction data do not include the bidding prices of each participating company. The estimated end price is set at the time of inspection before the auction by the appraisers. The estimated end price is determined by considering the rank of the item and the existence of a warranty, as well as differences in engraving depending on the time of manufacture, the condition, and past end prices. Consequently, it is unlikely that the estimated end price will differ significantly from the end price. In the

Table 3.1: Types of item ranks and their definitions

Item rank	Definition
N	Items that appear to be unused and in perfect condition with price tags and protective stickers attached
S	Items in excellent condition with no signs of wear or use.
SA	Items that show signs of having been used a few times but are in good condition, comparable to new items.
A	Items in good condition with some signs of use
AB	Items with inconspicuous stains or minor scratches
B	Items that show scratches or stains from use.
BC	Items whose appearance is affected by scratches or stains.
C	Items that cannot be used as designed

estimation methods described in the following sections, the deviation between the estimated end price and the end price itself is used as a criterion for evaluating the estimation accuracy.

3.3 Comparison with Other Domain Data

Item price estimation is an issue that is not limited to B2B luxury brand item auctions. This section compares the target data with data from other domains in which a price estimation

Table 3.2: Metadata on data related to price estimation

Data	Term	Sold items	Users	User features	Item features
B2B luxury brand items	a year	thousands	hundreds	1	3
eBay	—	626	3,388	2	4
Used cars	five years	269,104	3,220	7,750	572

is conducted to clarify the characteristics of B2B luxury brand item auctions.

Conventional auction studies have dealt with general consumer online auctions such as eBay and used car auctions. A study on recommending bid items on eBay and in used car auctions [RJSH20] estimates the end price, and eBay and used cars are domains in which price estimation has been applied. Table 3.2 shows the metadata of the B2B luxury brand item auctions discussed in this chapter and the eBay and used-car auctions addressed in the previous study [RJSH20]. The table includes the numbers of items and features, which are the main comparison targets and the number of users, indicating the scale of the auction. The eBay items in the target data are identified as Cartier wristwatches, Palm Pilot M515 PDAs, and Xbox game consoles, and there are more than 100 items in each category. However, to exclude the effect of price fluctuations in B2B luxury items in auction data, we were forced to use only data on the most recent few months for estimation. As a result, the number of data used to estimate a single watch model was smaller than 100. This lack of data indicates that it is necessary to use the data more efficiently than in the case of eBay when items handled in B2B luxury brand item auctions are the subject of an end price estimation.

Although the number of items handled in used car auctions is more significant than that of B2B luxury brand items, many features such as mileage, which are standardized regardless of the vehicle model, are available for cars. In B2B luxury brand item auctions, it is challenging to prepare features that can be used for a price estimation because the attribute information for each model number is different. Price estimation using machine learning methods with a large number of features is unrealistic.

In summary, B2B luxury brand item auctions are characterized by the need to estimate prices for a large number of items with small numbers of available features and data per model number.

Table 3.3: Price estimation domains other than auctions

Domain	Term	Items	Item features
Airbnb	a month	15,716	16
Used fashion e-commerce	a year	36,923	10

Examples of price estimation in domains other than auctions include real estate [GGG$^+$18] and used fashion e-commerce [NMG19]. Table 3.3 compares the properties of the data covered in these studies and the auction data covered in this chapter. The real estate data are the price information data of Airbnb in Canada, which was the subject of [GGG$^+$18]. Real estate is a highly unique domain in the sense that no two houses are identical. However, there are many similar features available for all houses, such as area and location, which can explain the prices in a hedonic price model. In this chapter, the distribution is estimated instead of applying a point estimation under a situation in which fewer features are available.

3.4 End Price Model

This section describes the design of a probabilistic model for the end price and calculates the predictive distribution of the end price based on a Bayesian inference. In the following, outlines of the probability model and the inference method are described.

3.4.1 Probabilistic Model

The value of a Rolex watch fluctuates depending on exchange rates, quantity in the market, and popularity. Although the price fluctuation is continuous in most cases, a significant price increase may occur when there is an external influence, such as the suspension of watch production. In light of these characteristics, limiting the data used to estimate the near term rather than the entire past history is appropriate. In this study, based on the policy of using the most recent period for a parameter estimation, four models with different numbers of parameters were designed as the end price distribution model: a linear model, a reference number hierarchical model, an individual standard deviation model, and an item rank coefficient model. The linear model is the basic model, and the other models were improved in the following order: stratification of coefficients by model number, introduction of standard deviation by model number, and introduction of the item rank. Therefore, the item rank coefficient model is a full model. The following subsections describe each model in detail.

Linear Model

First, this thesis explains the linear model, which is the basis of the proposed model. This research assumes that the end price is normally distributed based on the properties of the end price described in Section 3.2.2. In addition, the preliminary data analysis confirmed the effect of the presence of a warranty on the end price. The end price s_i of a Rolex watch with model number i, when taking these factors into account, is expressed through the following equation.

$$s_i \sim N(base_i + eg, \sigma_s) \tag{3.1}$$

where $base_i$ is the coefficient representing the underlying price of model number i in the linear model, e is the coefficient of the effect of the warranty on the end price, g is a binary variable representing the presence or absence of the warranty, and σ_s is the standard deviation common to all watches. In addition, $base_i$ and e are all uniformly distributed as uninformative prior distributions.

Reference Number Hierarchical Model

The model described in the previous section does not consider the relationship among reference numbers, making it difficult to estimate the distribution of end prices for watch models with a small number of data. To solve this problem, we add prior distributions of reference numbers. The following equation expresses the model.

$$s_i \sim N(\alpha_i + \beta_i g, \sigma_s) \tag{3.2}$$

Here, α_i is the coefficient that expresses the basic price for each watch model, and β_i is the coefficient of influence of the warranty on the end price.

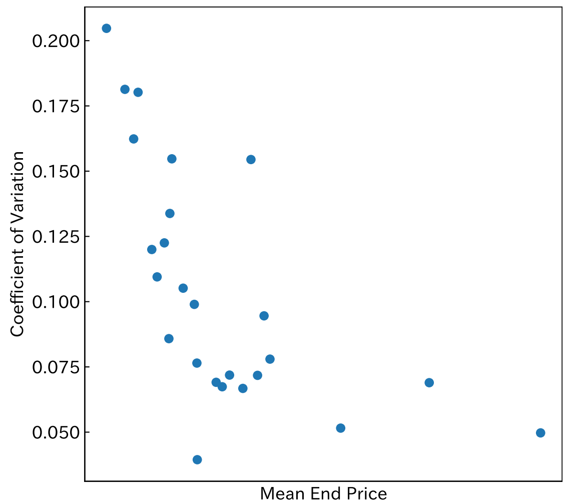


Figure 3.2: Coefficient of variations for each Rolex watch model

Because α_i and β_i are similar among the reference numbers, we construct a hierarchical model as a random variable according to the following equations:

$$\alpha_i \sim N(\mu_\alpha, \sigma_\alpha), \tag{3.3}$$

$$\beta_i \sim N(\mu_\beta, \sigma_\beta). \tag{3.4}$$

A uniform distribution is used as the uninformative prior for μ_α, σ_α, μ_β, and σ_β.

Individual Standard Deviation Model

The model in equation 3.2 assumes that the distribution of end prices has the same standard deviation for all model numbers. Figure 3.2 shows the coefficient of variation of the end price of Rolex watches for a 3-month period for each model number. For confidentiality, the average end price is not shown. The figure does not include items that are judged to deviate significantly from the average bid price owing to their rarity. The value of the coefficient of variation varies according to the average end price. It is therefore appropriate to set the standard deviation σ_s in equation 3.2 for each watch model number. This setting adjusts the distribution variance for each watch model, resulting in a better fit of the data. In this case, the following equation expresses the model:

$$s_i \sim N(\alpha_i + \beta_i g, \sigma_{s_i}) \tag{3.5}$$

For the prior distribution of σ_{s_i}, this research sets a half-t distribution with 4 degrees of freedom as the weak information prior distribution. The scale parameter of the half-t distribution was determined to be 100,000, which is the most significant standard deviation estimated from Figure 3.2.

Item Rank Coefficient Model

The model described in the previous section incorporates information on the item rank. The item rank is an indicator of the degree of use of an item, and the higher the rank and the closer the item is to a new item, the higher the end price will be. However, the effect is not necessarily equally distributed among the various ranks. Therefore, the effect on the price of each rank is modeled as a separate parameter. For a more straightforward interpretation, the effect is expressed as a product of equation 3.5 prices. Unlike the reference number, the parameter is the same for all items because it is considered an indicator commonly recognized among antique dealers. The following equation represents the final model.

$$s_i \sim N\left((1+\gamma_k)(\alpha_i + \beta_i g), \sigma_{s_i}\right) \tag{3.6}$$

Because γ_k is a variable that serves as a coefficient changing the price of an item of rank k, a uniform distribution of [0, 5] is set as the prior distribution. In this chapter, rank C and BC items are treated as the same rank because of their low frequency of occurrence. The value of the coefficient for the lowest rank is fixed at zero such that the parameters are uniquely determined.

3.4.2 Parameter Inference

The parameter distribution of the model is obtained through a Bayesian estimation using historical bidding data. Because it is difficult to compute the posterior distribution of the final model analytically, this study uses Markov chain Monte Carlo (MCMC) methods, a general term for algorithms that generate random numbers according to a specific probability distribution. The value of the random output number is determined by a Markov chain transition from an appropriate initial value to a random number according to a given probability distribution. When applying this method to a Bayesian estimation, this research uses the fact that the posterior distribution is proportional to the product of the likelihood and the prior distribution. Random numbers with a higher value of the product are output with higher frequency. This study uses the MCMC sampler Stan, which employs NUTS [HG14] as its sampling algorithm. Bayesian estimation using an MCMC method has been used extensively in fields that often include uncertainty in observations, such as item response theory in psychology [PJ99], which estimates the abilities from the test results, and an estimation of biological populations in ecology [Wik03].

As mentioned earlier, the end price is a quantity that can fluctuate slowly over time. To cope with this, when estimating the end price for decision support in an auction, we apply a parameter estimation based on the data of the last few months prior to the estimation and estimate the end price distribution based on the parameters obtained.

3.5 Experiments

This section describes an experiment conducted to check the validity of the probability model proposed in this chapter and the appropriate data period for an estimation.

3.5.1 Experiment Settings

To verify the effectiveness of the item rank coefficient model as a probabilistic model representing the end price in B2B luxury brand item auctions, we evaluate the model accuracy through a cross-validation along with a time series. Because items with many listings are highly important for decision support in B2B auctions, we will focus on Rolex watches with more than 100 listings per year. Using such data, we can confirm whether the proposed model is effective when the number of items is sufficient for a parameter estimation.

The accuracy of the estimation by the appraiser is used for comparison with the accuracy of the human estimate. The mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) are used as the accuracy evaluation indices. The equations defining each of these factors are shown below.

$$MAE = \frac{1}{n} \sum_{j} |s_j - s_j^{pred}|, \tag{3.7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{j}(s_j - s_j^{pred})^2}, \tag{3.8}$$

$$MAPE = \frac{100}{n}\sum_{j}\frac{|s_j - s_j^{pred}|}{s_j}, \tag{3.9}$$

where s_j is the end price for the jth watch in the data, s_j^{pred} is the predicted end price for that watch, and n is the number of samples. For the MAE and RMSE, where the unit is Japanese Yen, the absolute value of the error can be evaluated, and the error is likely to be more significant in watches from among higher-priced watch models. The RMSE is more sensitive to outliers than the MAE and tends to have more significant errors when outliers occur. Comparing this error between models will reveal whether there is a difference in the estimation accuracy depending on the price of the reference number. By contrast, MAPE calculates the error as the percentage of deviations from the actual value, which allows us to evaluate the accuracy independent of the price. We use MAPE to evaluate the effect of different prices for different models of Rolex watches.

When estimating the end price for new data using a probability model, the expected value of the estimated distribution of end prices is regarded as the representative value of the distribution. The mean of the MCMC samples is used as an approximation of the expected value. Stan is used in the Python interface, Pystan.

In addition, to confirm the superiority of the stochastic model over the baseline machine learning methods, we employ random forests and multilayer perceptrons as the baseline machine learning methods and compare the expected values of end prices obtained through these methods with the results obtained by the proposed stochastic model. This chapter reports the average accuracy of the random forest and the multilayer perceptron, which were trained by changing the random seed ten times, using a grid search and Optuna [ASY$^+$19], respectively.

Because estimated distributions are used for decision support in B2B luxury brand item auctions, we evaluate the accuracy of the distribution estimation. There is no human-estimated reference value for the end price distribution, and it is not output by the baseline machine learning method. The results are compared only among the proposed models. The log posterior predictive density of the data to be estimated, expressed through the following equation, is calculated for each model, and the model with the more significant value is considered to have a higher estimation accuracy.

$$\log p(s^{test}|input^{test}, input^{train}, s^{train}) \tag{3.10}$$

This value is calculated according to the method shown in Chapter 27.1 of the Stan User's Guide [Sta19].

A cross-validation is used as the evaluation method, and maintains a time-series relationship for all data. The specific procedure is to divide the B2B auction data into monthly parts and repeat the parameter estimation and accuracy evaluation using all monthly data as the target of the accuracy evaluation. The data period used for the accuracy evaluation was 1 month, and the data used for the parameter estimation was the past several months. In the experiment conducted to confirm the effectiveness of the probability model, the period used for the parameter estimation was fixed at 3 months.

In the parameter estimation used in Stan, the number of iterations reached 3000, and 4 chains were applied. The default values were set for the other parameters.

The period of data used for parameter estimation varies from 1 to 7 months in 1-month units, and the difference in estimation accuracy when the same month data are used for evaluation is discussed.

3.5.2 Experiments Results

Probablistic Models

Tables 3.4, 3.5, 3.6, and 3.7 show the values of the evaluation indices for each probability model. Bold values in each table indicate the best value for each model, excluding the estimation of the appraiser. The Rhat criterion, which is an index used to judge the convergence of the parameters in an MCMC method, is less than 1.1 for all models. Under this criterion, all models converged.

Comparing the linear model with the reference number hierarchical model, the MAE and RMSE for all months except March, when the number of data is small, are lower than those of the linear model, as shown in Tables 3.4 and 3.5, indicating that the introduction of the hierarchical model improves the estimation accuracy. This improvement shows that the assumption of the hierarchical model indicating that the price of a product is approximately determined for each reference number and that they are normally distributed is valid.

In the case of the individual standard deviation model, when the standard deviation for each reference number is introduced, the RMSE and MAE tend not to change significantly from the reference number hierarchical model. By contrast, the logarithmic probability densities shown in Table 3.6 are more significant, indicating an improvement in the fit of the distribution to the data.

Furthermore, in the item rank coefficient model that introduced the item ranks, the MAE and RMSE values improved during many months in comparison to the individual standard deviation model. Although there were some cases of larger errors, the degree was small. This indicates that the introduction of the product rank contributes to an improved estimation accuracy throughout the year.

Table 3.4: MAE of each model

Estimation term	Linear model	Reference number hierarchical model	Individual standard deviation model	Item rank coefficient model	Random forest	MLP	Specialist
2018/11	42,356.0	40,813.6	41,132.8	**38,419.1**	41,948.7	40,306.1	31,090.9
2018/12	46,017.3	44,100.4	43,900.4	**42,753.9**	43,529.9	45,422.8	34,115.9
2019/01	48,578.0	45,821.7	47,094.5	46,009.1	**44,807.9**	49,303.0	36,598.4
2019/02	42,323.4	39,552.5	40,140.1	36,528.1	**36,013.8**	38,091.3	29,753.4
2019/03	40,148.9	39,691.5	**39,451.7**	39,916.9	46,977.1	40,043.0	41,588.2
2019/04	71,881.0	70,325.1	70,553.9	70,143.2	69,678.8	**69,046.7**	59,408.3
2019/05	70,387.8	68,867.9	68,766.0	**67,619.9**	69,036.3	68,311.1	55,538.6
2019/06	53,514.4	49,216.0	50,474.5	**48,973.5**	49,623.2	52,186.6	39,036.1
2019/07	50,089.5	47,268.5	**47,202.4**	48,263.4	49,256.9	49,828.4	40,259.4

Table 3.5: RMSE of each model

Estimation term	Linear model	Reference number hierarchical model	Individual standard deviation model	Item rank coefficient model	Random forest	MLP	Specialist
2018/11	63,781.6	61,650.6	62,935.2	**56,040.0**	75,260.2	59,434.2	42,680.1
2018/12	96,815.7	95,626.0	95,230.9	**93,751.4**	96,067.1	95,548.8	50,797.4
2019/01	66,931.5	62,924.4	64,399.3	62,899.2	**62,335.2**	67,227.3	50,420.8
2019/02	57,013.1	52,530.3	53,059.7	50,553.9	**48,842.4**	52,783.4	40,092.7
2019/03	55,413.1	56,184.2	56,318.4	**54,698.9**	81,780.9	56,654.1	55,541.5
2019/04	121,091.4	119,026.5	119,596.8	119,480.9	119,357.7	**118,819.8**	88,684.2
2019/05	127,172.0	123,536.3	124,339.5	**121,241.7**	125,688.5	122,548.6	85,035.8
2019/06	96,821.2	**92,817.4**	94,732.1	94,018.8	94,757.2	95,935.8	64,355.1
2019/07	71,197.4	69,380.4	**68,524.0**	70,048.5	75,066.0	72,256.8	58,011.5

Table 3.6: Log posterior predictive density of each model

Estimation term	Linear model	Reference number hierarchical model	Individual standard deviation model	Item rank coefficient model
2018/11	-4,009.9	-4,001.6	-3,812.3	**-3,794.3**
2018/12	-4,072.9	-4,049.6	-3,925.1	**-3,900.1**
2019/01	-4,800.4	-4,781.2	-4,594.5	**-4,573.4**
2019/02	-5,567.0	-5,544.3	-5,397.1	**-5,356.8**
2019/03	-1,054.5	-1,050.6	-1,031.8	**-1,025.6**
2019/04	-6,206.4	-6,161.7	-6,024.0	**-5,994.4**
2019/05	-5,214.4	-5,196.0	-5,034.3	**-5,017.4**
2019/06	-5,636.3	-5,624.6	-5,393.8	**-5,346.6**
2019/07	-4,069.2	-4,045.2	-3,888.0	**-3,860.8**

Table 3.7: MAPE of each model

Estimation term	Linear model	Reference number hierarchical model	Individual standard deviation model	Item rank coefficient model	Random forest	MLP	Specialist
2018/11	9.00	8.54	8.56	**8.22**	8.50	8.54	6.56
2018/12	8.27	7.86	7.80	**7.59**	7.85	8.20	6.91
2019/01	9.31	8.71	8.88	**8.70**	**8.70**	9.39	7.05
2019/02	9.15	8.50	8.64	8.02	**7.89**	8.28	6.44
2019/03	**6.91**	7.12	6.99	6.96	8.64	7.17	7.17
2019/04	10.52	10.05	10.04	**9.82**	9.90	9.83	9.44
2019/05	9.42	8.89	8.79	**8.43**	8.86	8.91	7.89
2019/06	8.98	8.06	8.15	**7.71**	8.05	8.57	7.05
2019/07	10.25	9.34	9.38	**9.30**	9.39	9.84	7.46

In comparison with the MAE and RMSE indices, which tend to show significant errors for high-priced watches, the MAPE index has a more negligible effect of scale on the error. Table 3.7 shows that the item rank coefficient model achieves the highest accuracy for the MAPE indicator, except for the case in which the data for March are used for the evaluation. This indicates that the item rank coefficient model may have more minor errors for items with small end prices, and more significant errors for products with large end prices, than the reference number hierarchical model and individual standard deviation model. When using the estimation results, it is more important to achieve a good accuracy within the price range where the frequency of occurrence is high than to have a high accuracy for a few expensive watch models. Therefore, it is desirable to use the item rank coefficient model that has been confirmed to achieve the highest accuracy for MAPE. In addition, the item rank coefficient model has a more stable performance than the other proposed models regardless of the month.

The item rank coefficient model has the same or better accuracy when compared with the baseline machine learning method. Unlike the baseline model, the proposed model is a probabilistic model and does not require a parameter search. It also has an advantage in that it can output a probability distribution that represents the uncertainty of the value in the auctions.

Comparing the expected value of the distribution of end prices estimated by the probabilistic model with the accuracy of the end prices estimated by the appraiser, the appraiser's estimated end prices have smaller MAE, RMSE, and MAPE values in most cases. This is because the detailed information used by the appraiser to estimate the price of an item is not used in the probabilistic model. For example, it is known that a small number of wristwatches with a particular pattern on the dial are sold at a much higher price than the ordinary same watch model. Because such information is described uniquely for each watch model and appears infrequently, it is not easy to express it using the same variables for all products.

The difference in accuracy between the results estimated using the item rank coefficient model and the price estimated by the appraiser is at most 1.84%. This percentage indicates that the end prices estimated by the proposed probability model for the products within a price range of several hundred thousand yen to several million yen are several thousand yen to several tens of thousands of yen different from the prices estimated by the appraiser. In B2B luxury brand item auctions, it is empirically known that a reserve price discounted from the price at which the product is expected to be sold makes the bidders bid on the item, and some price differences are within the acceptable range during the current operation. Although not the subject of this study, in B2B online luxury brand item auctions, the minimum bid price is set at approximately 5% of the current bid price for items ranging from several hundred thousand yen to several million yen. Here, 1.84% is a smaller price difference than this value. Auction practitioners have commented that the accuracy of the item rank coefficient model in estimating the end price of a product is sufficient in this regard. Therefore, the proposed probability model is sufficiently effective. In summary, the proposed method achieves a good performance in supporting the organizing and participating companies by applying a value estimation in B2B luxury brand item auctions.

Term for Parameter Estimation

Table 3.8 shows the MAPE of the item rank coefficient model, which performed well in a previous experiment when the data used for the parameter estimation varied from 1 month to 7 months. An N/A listed the table indicates that there is no data to be used for the parameter estimation. When the period applied for the parameter estimation is 1 month and April 2019 is the period to be estimated, the parameters with an Rhat of greater than 1.1 exist owing to the small number of data in March 2019, and thus MCMC were considered to not have converged.

Table 3.8 shows that minimum errors often occur when using the 4 or 5 months immediately preceding the period to be evaluated for the parameter estimation or when using only data from the most recent month. This result suggests that it is necessary to change the period used for a parameter estimation according to the change in time-series regarding the value of a Rolex. Specifically, if there is little change in the average price of a Rolex, it is sufficient to use data for the most recent 5 months, whereas if there is a sharp change, it is appropriate to use only the data for the most recent 1-month period. However, when data from only the most recent month are used, the estimation accuracy is unstable because the results may not converge owing to insufficient data, or the error may be higher than 10%. Based on the above discussion, a period of approximately 4 to 5 months, which provides a stable estimation accuracy, is suitable for applying this estimation method to real-world problems.

Table 3.8: MAPE for each period used for parameter estimation

		Data periods for parameter estimation						
		1 month	2 months	3 months	4 months	5 months	6 months	7 months
	2018/10	**7.31**	7.38	N/A	N/A	N/A	N/A	N/A
	2018/11	8.11	**7.71**	8.22	N/A	N/A	N/A	N/A
	2018/12	**7.24**	7.38	7.59	8.04	N/A	N/A	N/A
	2019/01	10.10	9.16	8.70	7.77	**7.51**	N/A	N/A
	2019/02	**6.73**	8.18	8.02	7.87	7.45	7.54	N/A
Target Period	2019/03	7.03	7.26	6.96	6.63	**6.47**	6.56	7.03
	2019/04	Not Converged	9.57	9.82	9.03	**8.79**	8.90	9.15
	2019/05	**7.30**	7.31	8.43	9.30	9.20	9.22	9.44
	2019/06	8.23	7.78	7.71	**6.95**	7.11	7.29	7.48
	2019/07	8.88	9.67	9.30	9.09	7.86	**7.37**	7.51

Comparison of estimated and actual distributions

To check whether the estimated distribution captures the actual data distribution, in this section, the histogram of the actual data is compared with the end price distribution of the item rank coefficient model that was judged to fit the data best from the log probability density. Because the distribution is determined by the item rank, guarantee status, and reference number, the histogram shows the data where these attributes are entirely consistent. For spatial reasons, it is impossible to show all of the data, and thus only two cases are shown: one with a large number of data and one with a small number of data.

First, Figure 3.3 shows a histogram comparing data on a watch with a particular reference number in February 2019 with the actual data having the highest relevance. The estimated distribution of the parameters was estimated using data from November 2018 to January 2019. The graph of the estimated distribution shows the kernel density estimation for the MCMC samples obtained. To facilitate a comparison with the shape of the distribution, the height of the vertical axis is the class with the most significant frequency. The class range is 16,571 yen, which is the value obtained by dividing the difference between the maximum and minimum values of the MCMC sample by 20. Figure 3.3 shows that an estimated distribution similar to the actual data distribution has been obtained. In many cases, the data are located within the range of high probability distribution, which means that the estimated bid price distribution is appropriate for the actual data.

Next, Figure 3.4 shows a histogram of the end prices for June 2019, for which we have a small number of data, and the distribution of end prices estimated using data for the 3 months from March to May 2019. The class range of the histogram is 43,814 yen. Even in this case, the data are often located near the mean of the distribution. In addition, for one data, the price is much higher than the average. There are a few cases in which the prices deviate significantly from the average for a particular reason.

3.6 Conclusion

This chapter estimated the value of service results in a service system. We used a hierarchical Bayesian model to estimate the distribution of end prices for Rolex watches in B2B luxury

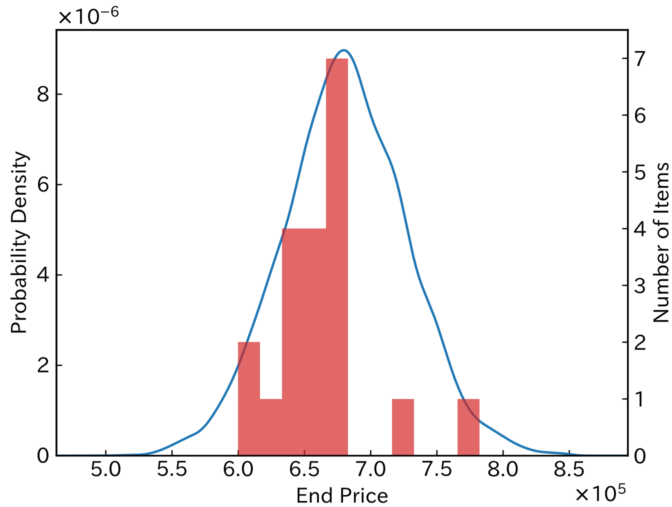


Figure 3.3: Estimated end prices distribution and actual data histogram when the number of data is large

brand item auctions. The accuracy of the proposed model is comparable to that of expert estimates, and the distribution of the prices fits the real data. The accuracy achieved is sufficient to support various types of auctions. Although the number of available features was limited in this chapter, it is expected that a more accurate estimation than that of experts can be achieved by improving the data infrastructure. The features used to estimate the distribution of end prices can be used for watches other than Rolex models and brand bags that can be identified based on their reference numbers, and thus the proposed method can be applied to these cases as well. The proposed method can be applied to watches, bags, and jewelry, which are two of the three main categories in B2B luxury brand item auctions. This method cannot be applied to jewelry because it is difficult to identify jewelry based on its reference number.

In this chapter, we made it possible to automatically indicate the range of possible prices for items without human intervention. This will ease the problem of difficulty in grasping the value of large auctions and lead to a smoother operation.

The framework for value estimation in auctions proposed in this chapter can be applied to service systems other than auctions. The techniques in this chapter enable the estimation of the value of outcomes in service systems of adaptive value characterized by scarce data and variable values.

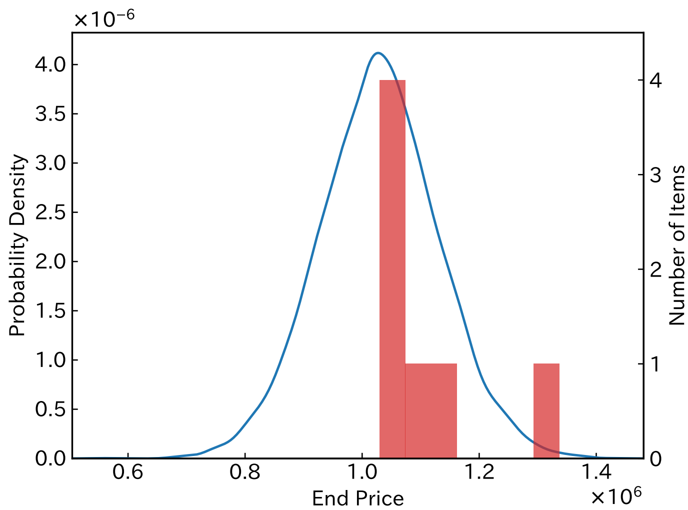


Figure 3.4: Estimated end prices distribution and actual data histogram when the number of data is small

Chapter 4

Analysis of Information Presentation Timing

4.1 Introduction

The auction service system described in the previous chapter is now held online as well. Over the past two decades, eBay has grown into an enormous platform for online C2C transactions; however, in recent years, B2B auctions, traditionally held face-to-face, have also been held online. Because of which an increasing number of people can participate in auctions.

Many studies have tried to understand the process and outcome of auctions. The results of many outstanding theoretical studies clarified the nature of single item auctions, such as the revenue equivalence principle [Vic61, RS81, Mye81] under the assumption of individual rationality. There have also been a considerable number of analyzes on real-world online auctions. Due to the dramatic development of eBay since 1995, many researchers have used eBay, which primarily deals with C2C transactions data, to study real-world auctions [HS10]. In eBay, bidders can bid on one or a few items at the same time; therefore, the change in the bidding price of one auction has little impact on other auctions. Furthermore, statistical analysis is straightforward when the data to be analyzed are for the same items. For these reasons, most conventional auction analyzes have been conducted on the same item auctions.

However, in B2B online auctions, bidders often bid on more than fifty items. In many B2B online auctions, items to be listed are categorized, for example, as used cars and brand-name products. Bidders in the auctions select items based on their budgets and the number of items to buy. Excessive bids often lead to budget overruns, and insufficient bids lead to stock shortages; therefore, bidders bid in consideration of expected auction results. Another characteristic is that the number of sellers is small compared with the number of bidders. In B2B auctions, the host company may be the largest seller. In this case, changing the listings of the item set may significantly change the results of the entire auction. Therefore, it is necessary to understand the relationship between the listings and auction results for a smooth operation. To understand the characteristics of B2B auctions, an analysis of the listings and their bidding processes, which are price transitions during the auctions, is required. Although there are differences between B2B and C2C auctions, research on B2B auctions is few due to the inaccessibility of data.

Because of the differences in the behavior described above, the current method of holding online auctions, which uses the same auction rules for C2C as for B2B, is not likely to achieve effective allocation. This chapter assumes that this is because bidders only recognize part of the products' value and bidding status. Presenting item information for bidders can mitigate this problem. Therefore, the main focus of this chapter is to confirm whether the hypothesis is valid and when the information presentation timing should be.

This chapter analyzes the bidding behavior and end price of B2B luxury brand item auctions handling such as luxury watches or jewelry using real-world data. In general, it is difficult to measure high and low bidding prices because the value of the items handled in the auctions varies among bidders. This chapter proposes a high-low bid price metric based on the bid prices expected by experts and uses this index to clarify the relationship between the number of bidders and the end price. The same analysis was performed for two product categories with different characteristics, namely watches and jewelry. The characteristics of the number of bidders and the increase in the end price were compared between the categories.

This chapter also analyzed the bidding process, which has been the focus of previous studies. In B2B auctions, the number of bidders and prices for each product vary significantly owing to the many products listed. This paper proposes a clustering method for the bidding process, which can handle B2B auctions with an extensive price range and clarify the types of bidder behaviors in B2B auctions. Our clustering method combines existing methods but is generally applicable when the data points are disjoint and the vast difference in values per process. This chapter also clarifies the relationship between the bidding process of the extracted clusters and the degree of increase in the end price. This chapter compared the clustering results of the two categories mentioned above and propose a guideline for B2B auction management with less opportunity loss, as suggested by the analysis results.

The rest of this chapter is organized as follows: Section 4.2 explains the rules and characteristics of B2B auctions, which are the focus of this chapter, and Section 4.3 describes the analysis methods, such as the metrics that show high- or low- end prices and the clustering method of the bidding process. Section 4.4 discusses the analysis results, and Section 4.5 discusses ways to improve auction management. Section 4.6 concludes this chapter.

4.2 Auction Data

This study used the bidding history data of B2B luxury brand item auctions held by Valuence Japan Inc. from October 2020 to June 2021. Auctions are held online once or twice a month, with the main items auctioned being luxury brand goods, such as watches, jewelry, and brand bags. The duration of each auction term is 6 or 7 days, depending on the item category. The auction is conducted in the form of a second-price auction with proxy bidding, similar to eBay, and bidders bid on thousands of items in the same term. Bids are displayed as the second-highest bid plus the minimum bid range. Proxy bidding is a bidding system that automatically increases the bid when the highest bid is updated, provided that the bid does not exceed the amount entered. The end price is equal to the second-highest price displayed on the website in addition to the minimum bid. The bidding history data used in this study include changes in the displayed bids, including proxy bids. The participants in the auction are antique dealers, who retail and reauction the purchased items. Since each participant has a different sales channel and customer type, the same item may be valued differently by different participants. By contrast, since there is a market price for the product, the value is not entirely private, as in auctions selling antiques and art. This paper analyzes the items listed by Valuence Japan Inc., which accounts for most of the data. Data that appear to have been recorded in error, such as anomalous bidding process, were excluded.

In C2C auctions, bidders select a specific product to bid on and rarely bid on multiple products simultaneously. Due to the wholesale nature of B2B auctions, bidders select and

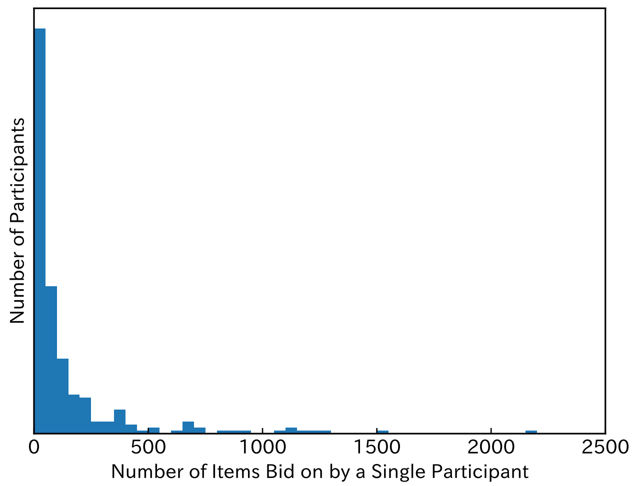


Figure 4.1: Distribution of the number of products bid on by participants

bid on multiple products from a large number of products within their budget. Figure 4.1 shows the distribution of the number of items bid on by bidders for a group of products in an auction held in the same term. There are not only bidders that bid on one or a few items but also those that bid on many items. The percentages of bidders who bid on more than 50 items are shown in Table 4.1. Although the number of products on display affects the percentage, approximately 40% of the bidders bid on more than 50 products. These results indicate that many products can be targeted in B2B auctions.

Another feature of B2B auctions is the wide range of item prices for a bidder. In C2C auctions, bidders search for the items they want and bid on a few selected items; therefore, the need to deal with products in different price ranges does not arise during the analysis. By contrast, in B2B auctions, bidders can bid on all products, implying that it is necessary to analyze items with different prices. Figure 4.2 shows the end price histogram of a B2B luxury brand item auction , with a class width of 500,000 Japanese yen. The prices of items range from 500,000 Japanese yen to over 5 million Japanese yen.

4.3 Analysis Method

In this section, we discuss a method for calculating the high and low metrics for bid prices and a clustering method for the bidding process, to analyze B2B auction data.

Table 4.1: Percentage of bidders who bid on over 50 items

Term	Percentage
2020/10 term 1	50.7
2020/10 term 2	39.4
2020/11 term 1	40.8
2020/11 term 2	41.9
2020/12 term 1	42.9
2020/12 term 2	34.7
2021/01	51.2
2021/02 term 1	30.0
2021/02 term 2	35.2
2021/03	41.1
2021/04 term 1	41.1
2021/04 term 2	40.7
2021/05 term 1	32.0
2021/05 term 2	32.1
2021/06	33.9

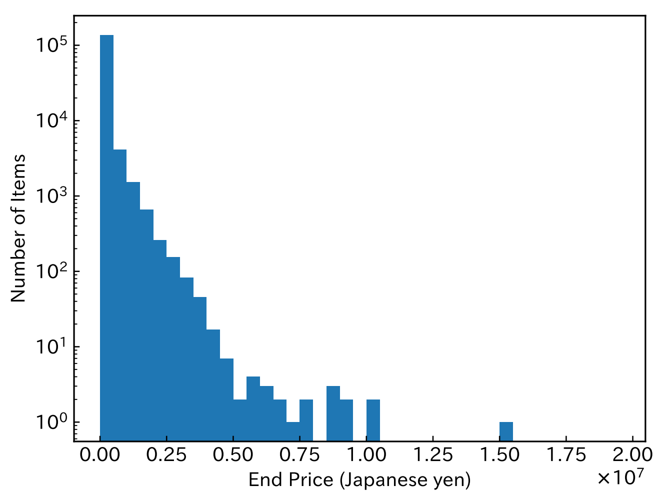
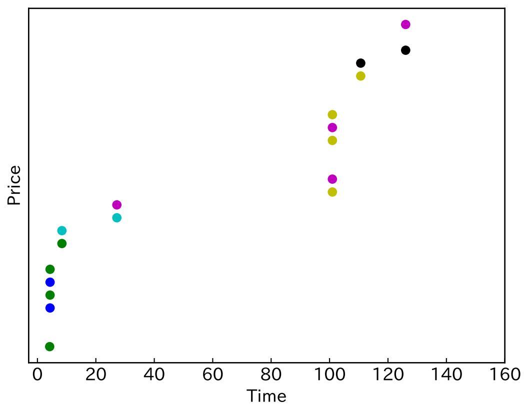
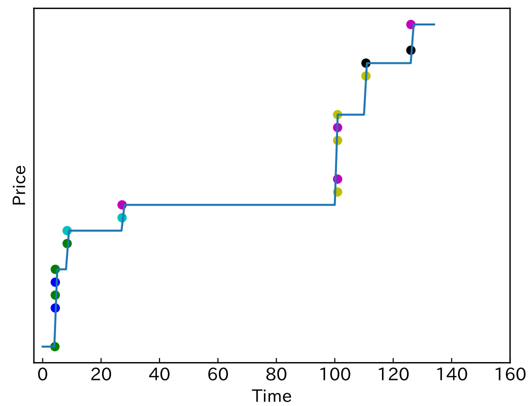


Figure 4.2: End price histogram in B2B luxury items auction



(a) Original data



(b) Time-series data

Figure 4.3: Convert bidding process into a time-series

4.3.1 End Price Metrics

The auction has a role in determining the price. When selling items with a market price, such as luxury brand items, sellers expect the end price $Price_{\text{ex}}$ in the auction to rise above the market price. Therefore, to manage auctions more efficiently, it may be helpful to analyze the extent to which the end prices of the auctioned items are compared to the market price. In general, it is not easy to measure the degree of price increase in auctions. In this study, we used a professional appraiser's estimated end price as a criterion for high and low end prices. This price is assigned to a product by the auctioneer of the target auction, which sets the expected end price. The appraiser estimates the end price by considering the market price, past sales history, and the item's condition. This value was also used to set the starting price. The degree of increase in the end price R_{increase} using $Price_{\text{ex}}$ is defined as follows:

$$R_{\text{increase}} = \frac{Price_{\text{end}}}{Price_{\text{ex}}} - 1, \tag{4.1}$$

where, $Price_{\text{end}}$ is the end price as a result of the auction. If this indicator is negative, it means that the bidder won at a price lower than the expected price, and if it is positive, it means that the bidder won at a price higher than the expected price.

4.3.2 Bidding Process Clustering

Clustering was used to analyze the bidding process. Since the price range of items handled in B2B luxury brand item auctions is extensive, it is necessary to consider the difference in price scales. We considered the bidding process as a time series, and performed clustering using a k-shape [PG15], which is a shape-based time series clustering method.

To convert the bidding process into time-series data, we adopted the bidder path [HBW10]; however, bidding data are sparse because they are recorded only when someone bids on an item and the price changes. In the original bidder path [HBW10], the bid price of a bidder is used, while in this study, the bid price of all bidders was used to create the time-series data. For example, given the data points shown in Figure 4.3a, we assumed that the prices remained constant between the data points, and the bidding process was converted into step-wise time-series data(Figure 4.3b). The time unit was set to one hour because the auction continues for several days. With this encoding method, sniping, can be represented as a rapid increase in price in the last hour. Next, we explain the necessity of using a clustering method coping with the wide price range of B2B auctions. We can obtain the desirable bidding process classification results in eBay data by applying ordinary clustering methods such as k-means. Owing to the wide range of price bands in B2B auctions, simply running k-means on the auction time series will result in clusters divided by price.

This study adopted a time-series clustering method, k-shape [PG15], that z-normalizes the time series and uses a shape-based distance measure for clustering. The main effect of z-normalization is to absorb the differences in the price scales. The distance measure based on the normalized cross-correlation makes it possible to classify the time series with similar shapes. The number of clusters k was determined using the Elbow method, where the sum of the squares of the intra-cluster errors (SSE) is calculated, and the number of clusters is the point at which the decrease is slight.

4.4 Relationship Between End Price and Bidding Process

This section uses the analysis method presented in the previous section to clarify whether the number of bidders and the bidding process affect the end price. The two hypotheses to be tested are as follows:

- Do prices tend to increase when the number of bidders is large in B2B auctions? What is the degree of increase?
- Is there a bidding process pattern that tends to result in a high end price?

By testing these hypotheses, we provide guidelines for improving B2B auctions.

4.4.1 Number of Bidders and End Price

In general, the higher the number of bidders in an auction, the higher the end price. To confirm that this property also exists in B2B auctions, we compared the values of price metrics presented in Section 4.3 according to the number of bidders. Figure 4.4, 4.5 shows the value of the price metrics for each number of bidders for watches and jewelry, which were the major product categories in B2B luxury item auctions. Outliers are defined as points which value is 1.5 times the interquartile range away from the first or the third quartile, and they are not shown in the graph for visibility. The prices of all categories tended to increase as the number of bidders increased. This indicates that in B2B auctions, end prices tend to increase as the number of bidders increases. Due to the small number of data, the range of $R_{increase}$ becomes wide when the number of bidders becomes large.

By contrast, when we compared the price metrics for watches and jewelry, the increase in the end price of jewelry was more significant according to the number of bidders. This was attributed to the difference in the degree to which the market price is shared among bidders. It is easy to identify the item by its model number or other information; therefore, it is easy to investigate the market price in brand watches. However, it is often difficult for experts to determine the market price for jewelry because no two jewelry pieces are the same. Under

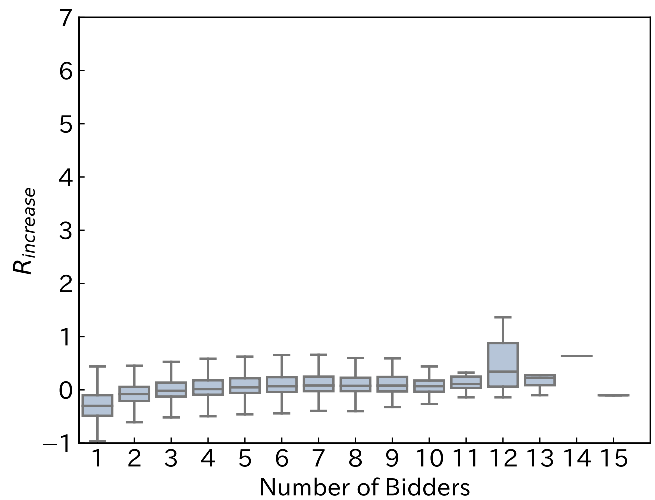


Figure 4.4: Price metric and number of bidders in watch category

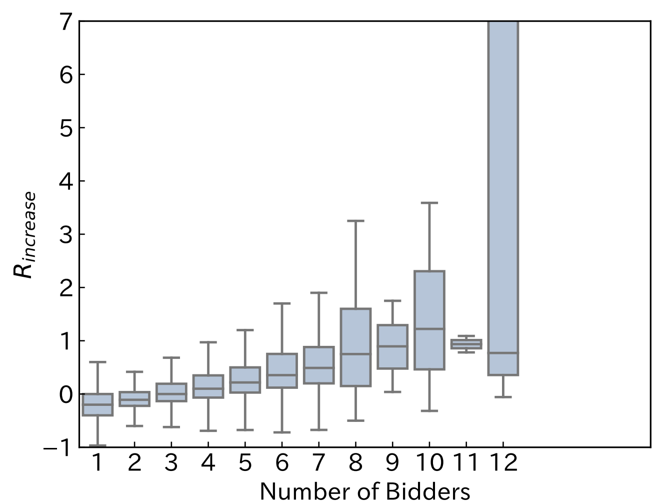


Figure 4.5: Price metric and number of bidders in jewelry category

Table 4.2: Number of items classified according to the number of bidders

	Number of Bidders														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Watch	1,282	5,245	8,858	7,700	4,802	2,362	990	405	146	54	17	10	5	1	1
Jewelry	1,089	6,323	8,876	6,077	2,550	983	342	101	32	15	2	3	0	0	0

these circumstances, a product whose price rises during an auction is a signal that it has a high value, and the signal may further increase the price.

Table 4.2 shows the number of products for each number of bidders. From this table, it can be seen that there are many products with fewer than two bidders in B2B auctions. Considering the correlation between the number of bidders and the degree of price increase mentioned earlier, it can be assumed that it is essential to increase the number of bidders in B2B auctions for higher revenue.

4.4.2 Bidding Process and End Price

Clustering was performed for each category, considering the differences in the properties of watches and jewelry. We assumed the watches to have shared market price and jewelry a less shared market price. The best values of SSE for five clustering trials with different initial values are shown in Figure 4.6 and the number of clusters k was determined to be five, with a slight decrease in the SSE.

The clustering results are shown in Figure 4.7, 4.8. The orange line represents the cluster centroids, and the blue lines represent the z-standardized bidding process time series. The clusters obtained were separated according to the time when the price increased for both watches and jewelry. Among the bidding processes in the watch category, the proportion of clusters with a significant price increase at the end of the auction was the large (Table 4.3). This is because sniping is more likely to occur for watches whose market information is shared among the bidders. In the jewelry category, bidding processes in which the price increased in the middle of the auction comprised the largest cluster. The large cluster in the watch category was the small in the jewelry category. In the case of jewelry, the evaluation value of other participants acts as a signal of the value of the product itself. Those bidding

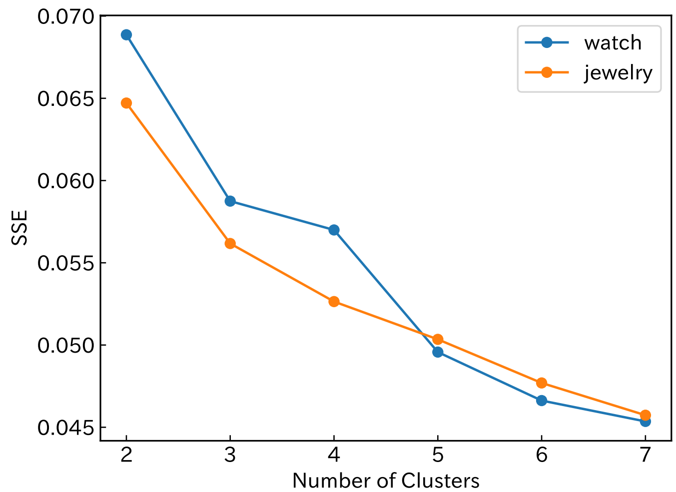
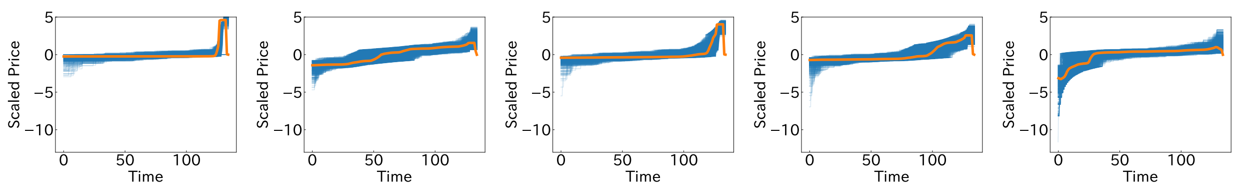


Figure 4.6: SSE for k-shape in watch category



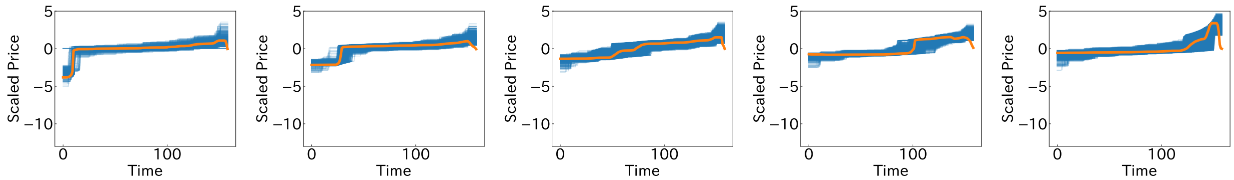
(a) Cluster 1 (b) Cluster 2 (c) Cluster 3 (d) Cluster 4 (e) Cluster 5

Figure 4.7: k-shape results for watch category

on jewelry tend to bid on an already bid product in the middle of the auction.

Table 4.4 shows the degree of price increase R_{increase} for each cluster is almost no difference. The results show that there change in the end bid price for each cluster is not significant, which indicates that the bidding process does not significantly impact the end price of an item in the entire category. The roughly equal occurrence of low-and high-price bids eliminates price increases and decreases on average.

The clustering method used in this study focuses only on the shape of the bidding process and does not consider information such as the time of day when bids are more frequent. By considering more detailed information, it may be possible to determine factors other than the number of people that determine the high and low prices of successful bids.



(a) Cluster 1 (b) Cluster 2 (c) Cluster 3 (d) Cluster 4 (e) Cluster 5

Figure 4.8: k-shape results for jewelry category

Table 4.3: Number of items belonging to each cluster

	Watch	Jewelry
Cluster1	6,324	1,841
Cluster2	7,117	3,271
Cluster3	5,831	9,499
Cluster4	8,143	5,250
Cluster5	4,463	6,531

4.5 Discussion

This chapter identified that many participants bid on a large number of items in B2B auctions, and there are many products for which the number of bidders is small. The actual data showed that the higher the number of bidders, the higher the price. It was also found that the time of price increase in the auction did not significantly affect the end price. These results imply that helping participants decide which items to bid on is effective in B2B auctions because opportunity losses occur when products that should be bid on are not found.

In B2B auctions, many items can be used as substitutes. Therefore, it is effective to have a system that encourages bidders with low chances of winning to bid on other products. Because the time of price increase does not significantly impact the end price, it is not necessary to consider the time at which the system promotes bidding. There are many cases in which bids are placed at the end of the auction, and the price rises, which implies that bidders monitor items at the end of the auction and place bids according to their strategies. If auction organizers want to promote bidding, they should increase the number of participants

Table 4.4: Median degree of increase in the end price R_{increase} where the number of bidder is 3

	Watch	Jewelry
Cluster1	-0.05	0.00
Cluster2	0.00	0.04
Cluster3	-0.05	0.00
Cluster4	-0.01	-0.03
Cluster5	-0.02	0.00

at the end of the auction. As mentioned in section 4.1, one possible method is to recommend bidding items. Because many items do not receive bids, methods, such as recommending similar products by collaborative filtering or a recommendation algorithm specialized for auctions, can be effective. These measures will ensure that bidders do not lose bidding opportunities and that prices will increase sufficiently for the auctioneer.

4.6 Conclusion

This chapter demonstrated that the end price increases with the number of bidders, using real-world auction data. Moreover, we proposed a clustering method for the bidding process, which can be applied to B2B auctions with an extensive price range and clarified that the bidding process does not significantly impact the end price. This chapter is significant because it shows that there exists a theoretically predicted relationship between the number of bidders and the end price. This relationship made it clear that to increase profits, the auctioneer company should take measures to encourage more companies to participate in the B2B auction.

In this chapter, we established an analytical method to check whether there is an appropriate information presentation timing in an auction, a bottom-up service system. It is essential to investigate whether there is an appropriate information presentation timing when there is a relatively large margin of time allowed for getting outcomes of service systems. The technology developed in this chapter enables us to investigate whether the timing of information presentation in service systems affects the outcome of service systems.

Chapter 5

Development of Efficient Information Presentation Method

5.1 Introduction

There is a set deadline for getting the outcome in a service system. When the time required to get an outcome is long, as in the case of auctions dealt with in the previous chapter, the effective timing of a notification is essential. By contrast, the efficient presentation of information is necessary when the time required to get an outcome is short, such as scheduling when absenteeism occurs.

In this chapter, as a domain requiring an efficient information presentation, we deal with a case in which scheduling for absenteeism is solved by alternative attendance request. As shown in Figure 5.1, there are two main types of work related to scheduling: scheduling itself, which is applied before the shift table is finalized, and rescheduling, which is conducted after the shift table is finalized. During the scheduling process, a shift table is created that considers the work preferences of the workers and the various work conditions of each job category. By contrast, during a rescheduling, when the number of workers to be assigned to a particular time slot cannot be met owing to worker absenteeism, the shift table is redesigned to meet the work requirements as much as possible.

There are two ways to revise the shift schedule: rerostering, which involves reassembling the shifts of all workers in the event of an absence, and an alternative attendance request,

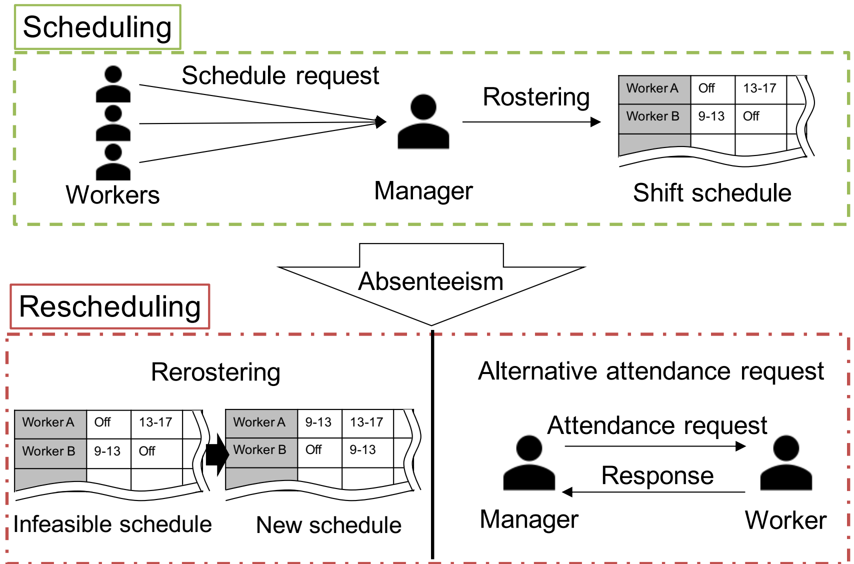


Figure 5.1: Work regarding a shift schedule

which involves selecting a worker to take the place of the absent worker and requesting attendance. Previous studies have focused on the rescheduling of shifts for all workers. The basis for this is personnel scheduling technology. In staff scheduling, the total working hours and the work hour preferences of the workers are considered to create a shift schedule that minimizes the costs (the total labor costs and discrepancies between preferences and assignments) as much as possible. Rerostering, which is the re-creation of shifts when absences occur, modifies the shift schedule such that this cost is small while satisfying the constraints. These modifications effectively automate the shift adjustment process for nurses and other workers whose work schedule strictly determines the attendance.

However, in business firms that manage many part-time workers, such as call centers and retailers, alternative attendance requests are often used because it is unlikely that everyone will accept the modified shift. In the alternative attendance request, a worker who is not scheduled to work on the target date and has the skills to handle the shift vacated by the absence is selected as a candidate for the alternative attendance request. Then the selected candidates are asked to work. In practice, managers who supervise their employees often conduct alternative attendance requests. The problems in alternative attendance request are as follows.

- It is difficult to select candidates for alternative work from a large number of workers.
- Requests for alternative work are frequently made by telephone; however, workers sometimes do not answer the phone when the manager calls, and it takes a long time to complete the request.
- Managers might feel mentally burdened if they cannot fill their shifts because they cannot find replacement workers.

The economic loss to the company becomes significant because the managers are deprived of time that could be used for work that utilizes their abilities.

In recent years, there has been a movement to introduce a system that uses messaging apps such as e-mail and LINE to request alternative work schedules to reduce the heavy workload of telephone requests for managers. Through the use of a messaging app, it is expected that managers will avoid calling back workers who did not answer their call to request an alternative attendance, and workers will not have to respond to calls from managers. However, most of the uses of messaging apps toward alternative attendance requests have been for replies to messages from users, and we have not obtained any knowledge regarding the order of contact when actively contacting users.

For these reasons, this study examines an efficient method for requesting alternative attendance using messaging applications, which are expected to become popular in the future. The messaging application envisioned in this study combines the ability to send and receive text messages asynchronously with quickly posting and selecting options. The asynchronous nature of messaging applications eliminates the need to consider the request time, which is a problem with phone calls. It is also expected to shorten the time required for requests, taking advantage of the ease of parallelization of delivery compared to telephone calls. To improve the efficiency, it is crucial to find workers who are willing to accept alternative work requests and fill their shifts with the minimum number of requests. Therefore, it may be possible to reduce the number of requests by estimating who is likely to accept a request and determining the order of the requests. There is also a possibility of reducing the number of requests by requesting more workers than the required number to work as substitutes. However, there is a concern in that securing an excessive number of substitute workers will incur labor costs and the company will not be able to receive requests for substitute workers in the future if it does not assign work to the secured workers. Therefore, in this chapter, a method is proposed for requesting many workers to work in place of one another while suppressing excess availability. In this study, a simulation environment was developed using a worker model based on actual shift data, and the effect of an alternative attendance request method using a messaging application was analyzed.

As a simulation method, this study employed a multi-agent simulation, which can quickly reflect the tendency of each worker to have different desired shifts and accept alternative work requests. For those elements applied during a simulation whose parameters are expected to differ significantly between e-mail and chat-based messaging applications, parameter settings that assume the use of chat-based messaging applications, considering the recent spread of social media among young people, were adopted.

The structure of this chapter is as follows. Section 5.2 describes the simulation model that serves as the verification environment for the request method. In Section 5.3, the request method for requesting an alternative attendance is described. Section 5.4 describes the experiments and results for verifying the request method described in Section 5.3. Section 5.5 summarizes this chapter.

5.2 Simulation Model

This section describes a simulation environment using a worker model to examine the effectiveness of the alternative attendance request method.

To simulate the revision of the shift schedule and the associated request for alternative work, this thesis describes the modeling of the behavior of the manager agent who creates the shift schedule and requests substitute work, and the worker agent who is the target of the request of the manager agent. To obtain proper validation results for the alternative attendance request method, we need a shift roster and a set of worker agents that reflect the actual work status. However, when using only actual data, the number of available shift rosters and worker data is limited, making it difficult to secure a sufficient number of shift roster and worker data to demonstrate the effectiveness of the substitute fulfillment method. This research uses real-world data to create behavior models of the manager agent, such as the creation of shift schedules and alternative attendance requests, and models that represent

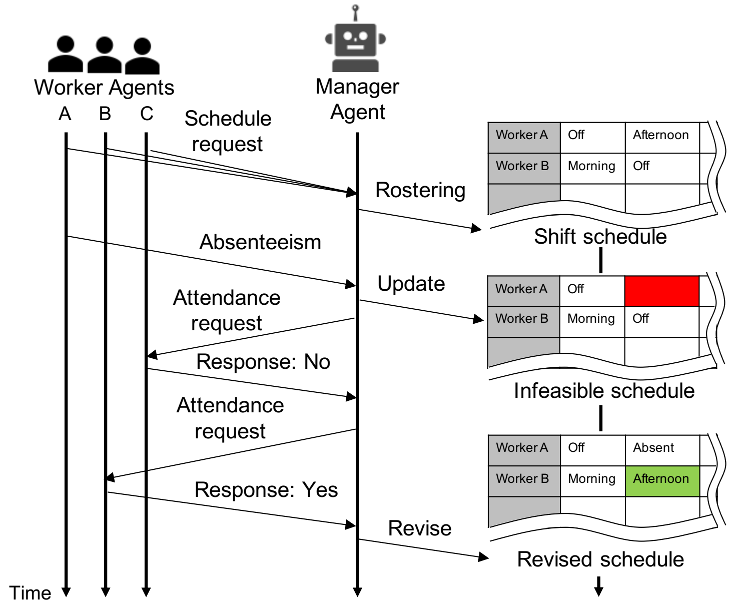


Figure 5.2: Flow of rostering and substitute fulfillment in simulation environment

the behavior of the worker agents associated with these activities. This thesis will compare alternative attendance request methods in a simulation environment using such models.

Figure 5.2 shows an overview of the attendance request in the simulation environment. The simulation environment consists of two main components: the creation of a shift schedule by the manager agent and the attendance request. During the shift table creation process, the manager agent receives the work hour requests of the worker agents and creates a shift table based on the information regarding how many people need to be assigned to which time slots for each day within a predetermined period.

In the alternative attendance request, the manager agent receives a notice of absence from the worker agent and enters it into the shift schedule. Based on the number of absences, the manager agent selects the worker agents to be requested and sends alternative attendance requests to the chosen worker agents. A worker agent who receives an alternative attendance request decides whether to accept or decline it based on the worker's schedule and preferences and replies to the manager agent. When the number of substitute workers required to make up for the number of absences is secured, the request for substitute work by the manager agent is completed. The following describes the behavioral models of the worker agent and the manager agent necessary for creating shift schedules and requesting substitute attendance.

Table 5.1: Example description of shift schedule

Worker	Day 1	Day 2
Worker1	9:00-12:00	
Worker2		12:00-18:00

Each model was realistically adjusted using the actual shifts of TMJ Inc., a large-scale call center operator company.

5.2.1 Rostering

This section describes the format of the shift table, which represents the working dates and times of the worker agents, as well as the working time preferences of the worker agents needed to create the shift table, followed by the conditions used to create the shift table and the method applied to create it.

Shift Roster

The working date and time are information indicating when a worker agent should work. The working dates and times are represented in a shift table for each worker agent, as shown in Table 5.1. Table 5.1 shows a portion of the shift schedule for two workers, where worker 1 works from 9:00 to 12:00 on day 1, and worker 2 works from 12:00 to 18:00 on day 2. The overall shift table is a compilation of these shifts in time units, such as a 1 month period. In an actual business, there are multiple shift schedules for each business case. To be assigned to a project, workers must have complementary business skills, and workers who do not have these skills will not be assigned to the project. In addition, a certain number of workers have several work skills, and such workers may be engaged in multiple tasks. In this model, we consider multiple cases to reflect this.

To simplify the shift table in this simulation, several hours are grouped and treated as one work period based on the actual minimum work hours. As shown in Table 5.1, shift schedules are in reality often set in 1-h increments; however, excessively fine increments increase the computational cost of creating a shift schedule. Although assigning a preference for each

Table 5.2: Symbols for each time period

Time period	Symbol
9:00-12:00	M
12:00-15:00	A
15:00-18:00	E
18:00-21:00	N

Table 5.3: Example description of shift schedule with symbols for each time period

Worker agent	Day 1	Day 2
Worker1	M	
Worker2		A-E

period to a worker's work hour preferences is necessary, it is sufficient to divide the day into several parts and assign preferences to compare the request methods.

The minimum working time obtained from the actual data was approximately 3 h, and the majority of the workers worked between 9:00 and 21:00. Based on the results of this analysis, the shift schedule is divided into four 3-h periods from 9:00 to 21:00. For each time zone, the symbols M (Morning), A (Afternoon), E (Evening), and N (Night) are assigned, as shown in Table 5.2. If we use these symbols to represent consecutive work periods, we can write the 9:00-18:00 work period as M-A-E. The shifts in Table 5.1 can be represented as indicated in Table 5.3 by using such an expression of the working hours.

Schedule preference model for worker agent

The shift schedule is created considering the work hour preferences of the worker agents. Table 5.4 shows the work hour preferences corresponding to the shift table defined in the previous section. In the table, Off indicates that no shift has been assigned.

A shift schedule is created based on the work hour requests submitted by the worker agents to the manager agent. The information needed to make the table is the number of days and hours the worker wants to work.

Table 5.4: Example of schedule request

Worker agent	Request for day 1	Request for day 2
Worker1	M	Off
Worker2	Off	A-E

The analysis of the actual shift schedule showed that each worker often came to work at a specific time and day. Based on this fact, we developed a model in which all workers have their own pattern of workdays and work hours, and the workdays and work hours for each day are determined based on this pattern. The method for requesting work hours is the same as in the real world: workers request to work for a certain period regardless of the project.

The following sections describe each pattern. Table 5.5 shows the seven different attendance time period patterns. The clusters obtained through the k-means clustering of the actual working hours are the basis of each pattern. The ratio of each pattern and the desired work hours are also based on the clustering results. The same method is used to create patterns for the days of the week. For both patterns, when clustering, the number of clusters is gradually increased such that there are a few clusters that can be interpreted with fewer other patterns. This method of determining the number of clusters is intended to represent the diversity of worker tendencies in reality while reducing the complexity of the model. Tables 5.6 and 5.7 show the parameters. Table 5.6 shows the pattern of the number of working days for each day of the week within a 4-week period. Because the patterns shown in Table 5.7 are not independent of the parameters in Table 5.6, they reflect the actual shift schedule by changing the percentage of attendance day patterns based on each attendance time period pattern.

The developed simulator calculates the work hour preferences of the worker agents based on these patterns. Specifically, the worker agents request to work as many days as defined by their attendance day pattern for each day of the week. Then, for each day, the worker agents decide which time to request based on the attendance time period pattern.

Table 5.5: Pattern of time period when workers request for attendance

Pattern	Ratio (%)	Ratio of attendance request time period(%)									
		M-A-E-N	M-A-E	A-E-N	M-A	A-E	E-N	M	A	E	N
MAE	22.2	0	87	3	3	1	0	5	0	0	1
AEN	14.8	1	4	86	0	0	3	0	1	0	5
MA	11.1	0	4	0	86	0	0	10	0	0	0
EN	5.6	1	4	5	3	0	76	2	0	0	9
Only A	9.3	0	7	0	7	0	0	85	0	0	1
Only N	27.8	0	4	0	0	0	0	2	0	0	94
Other	9.3	2	16	19	4	8	10	6	9	6	20

Table 5.6: Pattern of attendance days

Pattern	MON	TUE	WED	THU	FRI	SAT	SUN
SUNOFF	2	3	3	3	3	4	0
LITTLE	1	1	1	1	1	1	1
SUNSAT	2	2	2	2	2	4	4
AVERAGE	3	2	2	2	2	2	1
WEEKDAY	2	3	3	3	3	0	0

Rostering

Shifts in the real world are created to fulfill shift requests and meet the required number of people for each day during the period. To create a shift that satisfies these conditions, we describe the use of mathematical optimization in this section. Because some employees can work on more than one case, the shifts for each project are related and are created simultaneously. For a mathematical optimization, the constraints in this study are as follows.

1. Do not assign workers to workdays that they do not wish to work.

2. Minimize the shortage or excess in the number of persons assigned to each time slot for each day.

Table 5.7: Rate of patten of attendance days in pattern of time period

Pattern	MAE	AEN	MA	EN	Only M	Only N	Other
SUNOFF	22	15	12	19	12	13	8
LITTLE	12	26	28	35	42	50	36
SUNSAT	10	28	3	14	6	17	26
AVERAGE	13	16	2	21	3	10	20
WEEKDAY	43	15	55	11	37	10	10

3. Do not work more than seven consecutive shifts.

4. The worker possesses the necessary skills to handle a particular case.

5. Do not work more than one type of period per day.

The constraint conditions set in this study are not specific to any particular type of business, and the minimum conditions are considered so as to maintain the generality. For constraints 1 and 2, if the number of desired workers is less than the required number, and it is impossible to create a shift that satisfies the requirement, a violation of the condition is acceptable. Because it is necessary to create a shift schedule even when the number of workers is less than the required number, such a violation is tolerated in a real business. In this study, the above conditions are formulated based on [MSW$^+$16], and the solution is obtained using a general-purpose solver. The details of the formulation are as follows.

$$
\begin{aligned}
&\text{minimize} \\
&\quad 1000 \sum_{d \in D} \sum_{w \in W} \sum_{p \in P} \sum_{t \in T} r_{dwt} x_{dwpt} + 10 \sum_{d \in D} \sum_{p \in P} \sum_{t \in T} l_{dpt} \\
&\text{subject to} \\
&\quad x_{dwpt} = \{1, 0\} \quad d \in D, w \in W, p \in P, t \in T \\
&\quad y_{dw} = \{1, 0\} \quad d \in D\, w \in W \\
&\quad r_{dwt} = \{1, 0\} \quad d \in D, w \in W, p \in P \\
&\quad E_{dpt} \in \mathbb{N} \quad d \in D, p \in P, t \in T \\
&\quad l_{dpt} \leq \sum_{w \in W} x_{dwpt} - E_{dpt} \quad d \in D, p \in P, t \in T \\
&\quad l_{dpt} \leq -(\sum_{w \in W} x_{dwpt} - E_{dpt}) \quad d \in D, p \in P, t \in T \\
&\quad \sum_{p \in P} x_{dwpt} \leq 1 \quad d \in D, w \in W, t \in T \\
&\quad \sum_{t \in T} \sum_{p \in P} x_{dwpt} \leq 1 \quad d \in D, w \in W \\
&\quad y_{dw} = \sum_{t \in T} \sum_{p \in P} x_{dwpt} \quad d \in D, w \in W \\
&\quad \sum_{d \in S} y_{dw} \leq 6 \quad w \in W, S \in D_7
\end{aligned}
$$

In these equations, P is the set of cases, T is the set of periods, W is the set of workers, D is the set of working days, and D_7 is the family of sets of seven consecutive working days. The variable x_{dwpt} is a binary variable indicating whether worker w is assigned to a d-day shift in the period t of case p, and y_{dw} is a binary variable indicating whether worker w is assigned to a d-day shift. In addition, r_{dwt} is a binary variable that expresses whether worker w has requested to work during period t on day d, E_{dpt} represents the required number of people for case p on day d and time t, and l_{dpt} represents the difference between the required and desired numbers of people for case p on day d and time t. There are many general-purpose solvers available for solving planning problems. In this study, we adopted Coin-or branch and cut (Cbc) [For15], a solver that can be used commercially and free of charge.

5.2.2 Alternative Attendance Request

This section defines the terms absenteeism and requests and describes a model of the response and response time of a worker agent.

Absenteeism

Absenteeism is defined as the inability of a worker agent to work a period within in the shift schedule. When there is a shortage of workers owing to absenteeism, the manager agent needs to request substitute workers to fill in for the lack of workers. The number of deficiencies owing to absenteeism is set for each period. For example, if a worker agent who is scheduled to work in time slots M (morning), A (afternoon), and E (evening) is absent, the shortage will be one agent in M, one agent in A, and one agent in E. The manager agent requests an alternative attendance to meet the required number of workers for each period.

Alternative Attendance Request Format

Because absenteeism causes a shortage of workers in each time slot, the manager agent asks worker agents to substitute for the worker agent in the time slot where there is a shortage of workers. There are two ways to request alternative attendance. In one method, the manager agent can present all the time slots for which there is a shortage of workers to the worker agent. The worker agent can then choose from among the time slots available for alternative work. In the other method, the manager agent can decide in advance the time slots to be assigned to each worker and ask the worker agent if the agent is willing to work during those time slots. In this study, the latter method is adopted based on the messaging application that is expected to be used by TMJ, Inc. As an advantage of this method, it is easy for workers to answer because they only have to choose Yes or No. Section 5.3 describes the detailed setup of alternative attendance requests.

Response Model for Worker Agent

In the form of the alternative attendance request adopted in this study, the response can be either an acceptance or rejection. We modeled the response to the request by determining the method to determine the probability of accepting the request for each worker agent. When

Table 5.8: Variation width in acceptance probability

Number of attendance	variation v
0	-0.2
1	-0.1
2	0
3	0.1
4	0.2

creating a model of a request response of a worker, a problem can occur in which a request method that is effective during the simulation does not produce the expected results when applied in reality. To create an accurate model, it is necessary to conduct modeling based on data related to actual request responses. However, because no relevant data were available, we modeled the responses using the information on work shifts, which to some extent reflects the tendency of each worker to respond to a request.

To reflect the fact that the ease of accepting a request differs for each worker, we set a probability $P_{personal}$ that represents the ease of accepting a request for each worker agent. Here, $P_{personal}$ is a uniform random number of [0, 1] for all worker agents. The model assumes that the acceptance probability of a worker differs for each day of the week and for each workday. Based on this assumption, the probability $P_{personal}$ varies based on the work shift information. To reflect the fact that some days of the week are more accessible for workers to attend work than others, we vary the probability $P_{personal}$ according to the number of days attended within a 4-week period. Table 5.8 shows the range of variation v for each number of attendances. In the actual shift data, the majority of workers always worked the same hours. We assume that this fact is also reflected in the desired attendance pattern, as described in Section 5.2.2 and apply a weight h such that the ratio of a specific period in the desired attendance pattern is 1 if it is above the median, 0.5 if it is below, and 0 if the ratio is 0. The final model of the probability of acceptance follows a Bernoulli distribution, in which the probability of acceptance is $h(P_{personal} + v)$.

Response Time

The simulations conducted in this study assume the use of a chat-based messaging application. When using a messaging application, a variation occurs within the time required for each worker agent to reply. Therefore, if a response depends on the time, the administrator agent can wait for a reply. Because of this time dependency, messaging applications need a response time model of how long it will take to reply.

To model the response time and understand the distribution of response times in actual messaging applications, we surveyed the response data of an alternative attendance request system using a messaging application that had been operated on a trial basis. The alternative attendance request system uses the LINE system to ask workers whether they can selectively work during a specific period. From these data, we used approximately 140 cases that had information on the response time. Although most workers replied to the manager's messages in approximately 1 min, some took several hours to send a reply. From these results, we developed a model in which the response time of each worker follows an exponential distribution with a mean of 5 (minutes) at a 90% probability and with a uniform distribution of [30, 120] at a 10% probability.

5.2.3 Model Validation

This section examines the simulation model to see if it is consistent with real-world data for the shifts, response times, and request responses. Because we do not have complete real-world data, we are trying to verify the model only to the extent possible with the data at hand.

The shifts were designed to match the reality of the desired working hours and the conditions of the mathematical optimization. As the number of people required for each period in the case of a shift preparation, we used the aggregated value of the actual number of people assigned. In addition, the constraints used in the mathematical optimization were limited to those most commonly used to avoid unnatural shifts. For the shifts generated with the parameters described below, the objective function after optimization was at most approximately 1,500. It was confirmed that there was almost no assignment of workers to undesired the time slots and that the shifts were created giving priority to the wishes of the workers, just as in reality.

The response times were modeled based on the distribution of response times in reality, and the response time distributions of the constructed models were roughly the same. From these results, it can be said that there is no significant deviation from reality in terms of the shift and response time.

For the responses to the requests, it is not easy to see how they match with the actual data because the purpose of this study was to conduct preliminary verification for the collection of actual data. To verify the model, we interviewed people who are engaged in administrative work at call centers, and they answered that the model is not inappropriate in this regard.

5.3 Substitute Fulfillment Method

As described in Section 5.2.2, this simulation adopts the alternative attendance request format of asking workers if they can come to work during a specified time. In the following, we describe the request method used in this study.

Owing to the asynchronous nature of messaging applications, the request timing does not need to be considered. In addition, because it is easier to parallelize requests than phone calls, requests can be completed quickly by making them in parallel when multiple people need to be secured. Therefore, the request method proposed in this study divides the working hours into time slots that can be requested to a single worker, given the number of people required for each slot. This method makes parallel requests by changing the order of requests and the number of people requested. To ask workers if they can come to work during a specific period, it is necessary to divide the required number of workers per period received as input into a number of periods that can be assigned to individuals. Each method divides the allocatable period into bundles such that each bundle has as long a period as possible. The dividing is achieved by repeatedly checking whether one person can take charge of the necessary number of people in M-A-E, A-E-N, M-A, A-E, E-N, M, A, E, and N.

For example, the required number of workers for each period is [M, A, E, N] = [2, 2, 2, 2]. First, remove [1, 1, 1, 0] from the required number of workers because one person can handle M-A-E. Then, the remaining number of required persons will be [1, 1, 1, 2]. Furthermore, because [1, 1, 1, 0], which represents M-A-E, can be removed from the remaining required number of persons again, the assignment M-A-E is applied once more. The remaining required number of people is then [0, 0, 0, 2]. For this remaining number of people, we can only assign period N to two people. Therefore, the division of periods is as follows: 2 persons for morning, noon, and evening, 2 persons at night. In addition to the above, it is necessary to determine which workers are to be requested for the required number of workers for each assignment. After deciding on the workers to be requested, the system uses the easily parallelizable nature of messaging applications to send requests to all workers. The request timing is not considered in this study because it is not as important as a phone call for the success or failure of the request owing to the asynchronous nature of messaging applications.

In this study, we consider two ways for deciding the number of workers to be requested for each period: One is to allow for an excess number of workers, and the other is to not allow for such an excess. These two ways of determining the number of workers to be requested are based on the following two real situations. It is better to not over-secure workers from the viewpoint of increasing labor costs and the undesirability of refusing to work for an accepted worker. By contrast, there are cases in which it is desirable to recruit workers as quickly as possible, even with some over-allocation. In cases in which a worker is found to be absent on the morning of the workday, and a replacement must be secured by noon, it is desirable to use a method that can secure the replacement as quickly as possible. The following section describes the possible methods used for selecting workers in each case.

5.3.1 When Over-Securing is Not Allowed

Random Method

With this request method, the manager agent randomly decides which worker agent to assign to each time slot. The manager agent only considers the satisfaction of the minimum constraints for the work shift assignment. As a specific example of a constraint, a worker is not scheduled to work on the day the worker is asked to work, or a new shift assignment will not result in seven consecutive shifts.

Probability Estimation Method

With this method, workers are selected in descending order of the probability of acceptance using the estimated probability of acceptance of each worker during the assigned period. This method can reduce the number of requests compared to the random method with no information regarding worker acceptance. Still, the range in which the method can reduce the number of requests depends significantly on how accurate the estimated probability is. In the experiments described below, this study examines the effect of changing the accuracy of the acceptance probability estimation on reducing the number of requests.

5.3.2 When Over-Securing is Allowed

Fixed Number Selection

This method allows for over-securing and requests multiple people in anticipation that a candidate worker will not accept a request. With this method, a fixed number of people are requested for each type of time slot. For example, suppose the required number of workers is 3 in the morning, afternoon, and evening, and 1 in the morning and afternoon. In this case, the administrator agent requests $3 + a$ and $1 + a$ for the morning, afternoon, evening, and for the morning and afternoon, respectively. Here, a is the fixed number of people, and this study compares the excess number of people and the number of requests when a is changed during the experiment.

Adaptive Number Selection

Suppose the probability of acceptance can be estimated to a certain extent. In this case, the expected number of workers who will accept the request can be obtained when the request is made to several people. A request method by which the expected number of accepting workers is close to the required number of workers can be used to select a more appropriate number of workers than a fixed number selection. In this chapter, this method is called adaptive number selection. With this method, the number of workers to be requested is set as the expected number of workers who will accept $+b$, and requests are made to multiple people for a specific period. This study compares the excess number of people and the number of requests when b is changed during the experiment.

5.4 Simulation Experiment

This section compares the effectiveness of the alternative attendance request methods using the constructed simulation environment described in the previous section.

5.4.1 Experiments

Experiment Settings

This section describes an experiment comparing the effectiveness of each request method for absenteeism of a particular project and under which situations it is functional. During the experiments, a shift table was created using the rostering module, and then the manager asked workers who were not assigned to work in the shift table to cover for a particular absence. The parameters needed to create a shift table are the term represented by the shift table, the number of projects, the number of workers required for each project, the number of workers, the number of workers available for each project, and the worker preferences. The worker preferences are generated for each worker as described in Section 5.2.1. The other parameters are shown in Table 5.9. The period was set to 1 month, which is a standard unit for shift tables. For ease of use, we used 4 weeks for which all days of the week occur equally often. The number of projects is 2, which is the minimum number representing a situation in which a worker is assigned to multiple cases. Each project is denoted as project 1 or project 2. The number of workers required for each project is based on the actual shift tables, which have many workers involved and are adjusted to the four slots applied in this study. The number of workers was determined by referring to the number of people who can take charge of the projects in the actual shift tables. The sum of the number of workers who can work on each project in the table exceeds the total number of workers. This excess is caused by the fact that 60 of the workers are counted as duplicates because they are set to work on any of the projects. Based on these parameters, this study created 20 worker sets and a shift table.

In this chapter, the request method is examined for absenteeism when [morning, noon,

Table 5.9: Patameters for rostering

Parameter	Value
Term	4 weeks (28 days)
Number of projects	2
Number of workers	540
Number of workers who can be assigned for project 1	400
Number of workers who can be assigned for project 2	200

evening, night] = [i, i, i, i], where i varies from 1 to 10, and the required number of workers is equal for each period in project 1. This absenteeism pattern is one of the most frequently observed periods in the collected data of past absenteeism periods. This pattern was chosen because it is easy to change the scale of absenteeism, and the number of substitute workers exceeds the required number of workers even when the required number of workers i is increased. During the experiment, absenteeism occurs on all 28 days per shift schedule, and the mean scores are compared. The wait time for a response is set to 10 minutes, and if the response time is longer, it is considered unacceptable regardless of the answer.

Experiment when over-securing is not allowed

This experiment compares the number of requests in two cases: one in which workers are selected at random, and the other in which workers are selected in order of the estimated value of the acceptance probability. The series of processes described in Section 5.3, i.e., dividing the required number of people for each period into allocations for one person, determining the allocation, and making the request, is counted as a single request. For an estimation of the probability of acceptance, this chapter varies the deviation from the actual probability of acceptance and examines the effect of the accuracy of the probability estimation on the request. Estimating the probability of acceptance is represented by sampling from a normal distribution with the true acceptance probability as the mean. The accuracy is controlled by varying the variance σ. When sampling from a normal distribution, the probability may be less than zero or greater than 1, and thus this study used a truncated normal distribution of [0, 1]. When using a truncated normal distribution, the final variance will vary depending on the mean value. Still, it is only necessary to control the degree of accuracy, and the variances do not have to be the same for different mean values.

Experiments when allowing over-securing

In the case of allowing an excess number of people to be secured, it is essential to reduce the number of requests while controlling the excess number of people. The number of requests is the same as that defined in the previous section. The excess number of people is defined as the sum of the number of people secured greater than the required number for each period. For example, if the required number of people is [M, A, E, N] = [2, 2, 2, 2] and the number of people secured is [3, 3, 3, 2], the excess number of people is 3.

The accuracy of the probability estimation and the parameters in each method are varied to compare the proposal request methods. In the case of a fixed number of people, we change the value of a, which indicates how many more people are requested than the required number, and then examine the relationship between the value of each indicator. Using the acceptance probability, we change the value of b, which indicates how many more people are requested than the expected number of acceptors, and examine the relationship between the value and each indicator. The accuracy of the estimated probability of acceptance is varied as in the previous section, and the effect on the number of requests is examined.

5.4.2 Results and Discussion

The average number of requests, the maximum number of requests, and the minimum number of requests for each method when excess staffing is not allowed are shown in Figures 5.3, 5.4 and 5.5, respectively. Figure 5.3 shows that a smaller σ, i.e., the parameter indicating the accuracy of the estimation, results in a smaller average number of requests. Figures 5.4 and 5.5 show the same trend for the maximum and the minimum numbers of requests. In addition, the average number of requests for each method increased as the scale of absenteeism increased. When the scale of absenteeism is small, requests can be made mainly to workers

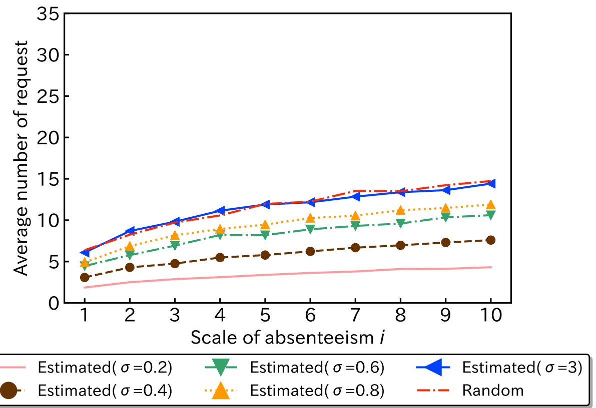


Figure 5.3: Average number of requests disallowing excess staffing

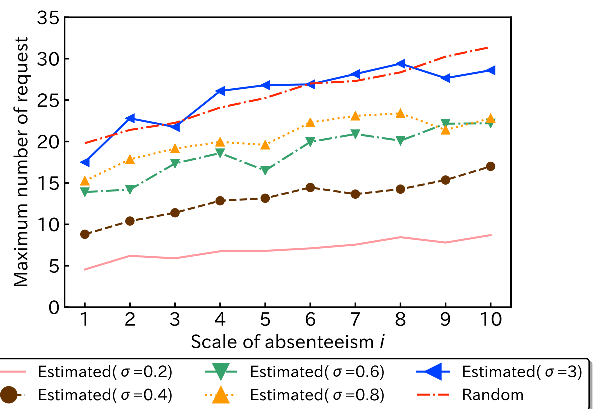


Figure 5.4: Maximum number of requests disallowing excess staffing

with a high probability of acceptance. By contrast, when the scale of absenteeism is large, the number of requests increases because it is difficult for all workers to have a high probability of accepting a request. With the probability estimation method, the phenomenon mentioned above is less likely to occur when σ is small, and thus the average number of requests is almost constant regardless of the scale of the absenteeism. As the deviation in the estimated value increases, the number of requests gradually approaches the value in a random case. In each figure, the probability estimation method for the case of $\sigma = 3$, where the estimation is not nearly correct, shows the same behavior as a random situation.

In summary, the probability estimation method can reduce the average number of requests more than the random method if it can estimate the acceptance probability even with low accuracy. When the scale of absenteeism is large, the difference in the average number of

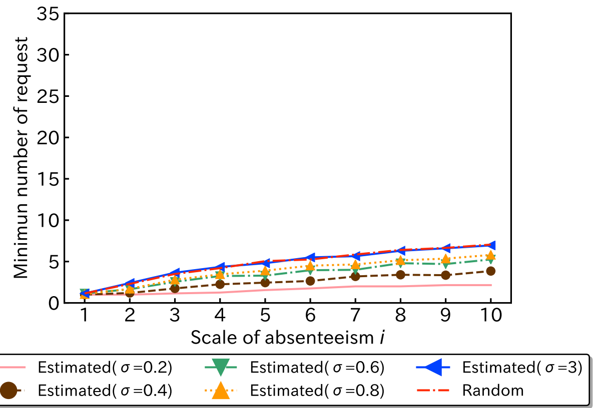


Figure 5.5: Minimum number of requests disallowing excess staffing

requests is significant, and thus the probability estimation method is an effective method for large scales.

Figures 5.6 and 5.7 show the average numbers of requests and the average number of people in excess for each method when excess is allowed. Figure 5.6 shows that the average excess number of people increases linearly with the number of fixed people in the fixed number selection. Figure 5.7 shows that the average number of requests decreases as the number of fixed workers increases. By contrast, the average excess staffing decreases as the accuracy of the probability estimation decreases for adaptive number selection. This decrease occurs because when the probability estimation is accurate, the requests are made in order of those with the highest probability, which tends to cause an over-allocation. By contrast, when it is inaccurate, the requests are closer to random, preventing an over-allocation. The average number of requests in adaptive number selection increases as the accuracy of the probability estimation deteriorates.

Figure 5.8 shows the relationship between the average excess number of people and the average number of requests when changing the fixed number of additional people a in the fixed number selection and when changing the parameter b used to determine the threshold in the adaptive number selection. The numbers in the figure represent the value of b, which determines how many people should be added to the expected number of requests as a threshold in the case of adaptive number selection, and the value of a, which is a fixed number of additional people in the case of fixed number selection. This result indicates that

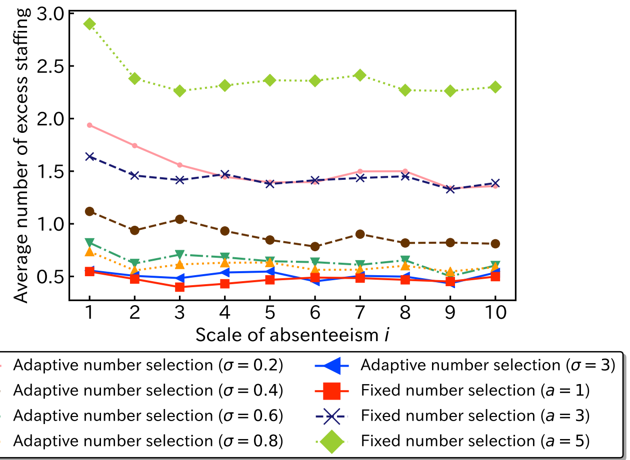


Figure 5.6: Average amount of excess staffing

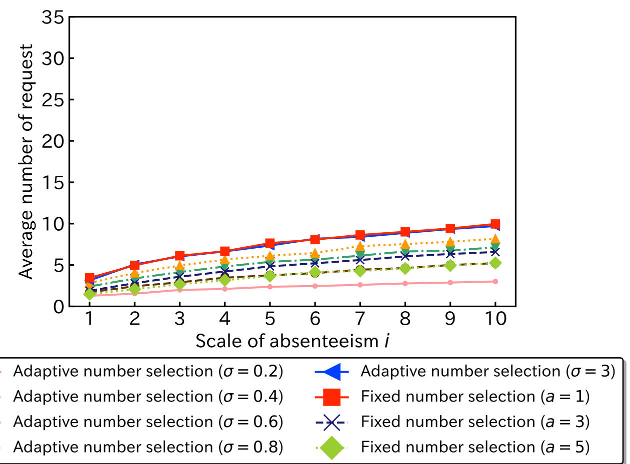


Figure 5.7: Average number of requests when allowing excess staffing

the probability estimation method is superior to the fixed number of selections. Considering a real-world application, the administrator should adopt the fixed number selection method because it is difficult to confirm the accuracy of the acceptance probability estimation in the initial stage when the data on the acceptance or rejection of requests have yet to be collected. This policy is used because in adaptive number selection, the excess number of people secured varies with the accuracy of the estimation, and it is difficult to control an excess number of people.

It is desirable to control the amount of excess staffing because the acceptable range of excess staffing is determined at each site. When the data collection has progressed to a

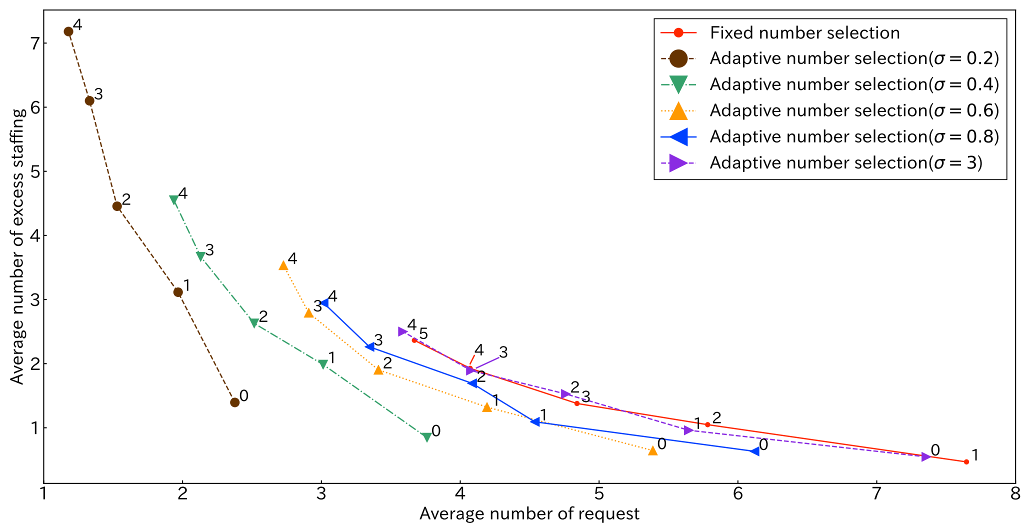


Figure 5.8: Relationship between average number of request and excess staffing ($i = 5$)

certain extent and the accuracy of the probability estimation has increased, the number of requests can be further reduced without increasing the number of excess people by applying the adaptive number selection method.

The various parameters used in this simulation are adjusted to cases in which a certain number of workers can accept a request when an alternative attendance request is made, such as during a usual work period. During busy periods, when the ratio of the number of available workers to the total number of workers is meager, it is necessary to use a request method that combines external approaches, such as varying wages.

5.5 Conclusion

In this chapter, we proposed a request method that can be executed on a messaging application for alternative attendance requests, which is a significant burden when revising a shift schedule. To verify the effectiveness of the proposed method, we created a simulation environment. We compared the methods applied in terms of the number of requests and an excess number of workers.

As a result, it was confirmed that estimating and requesting worker acceptance or rejection effectively reduces the number of requests even when the estimation accuracy of the worker agents' acceptance probability is low. We also showed that the number of requests could be further reduced when requests are made by allowing excess reserves. It was confirmed that the number of requests could be reduced while controlling excessive numbers of people if the two methods are used according to the data collection status for probability estimation.

This chapter showed the effectiveness of information presentation using value information in a top-down service system. The probability estimation in this chapter corresponds to the estimation of value information in a service system, and the request corresponds to the presentation of information. The proposed method of presenting information is generic and can be used regardless of the call center, as long as there is a structure for the approach from the service provider to the receiver.

Chapter 6

Conclusion

This thesis examined the possibility of developing a solution through information presentation by the provider to the difficulty in grasping the value of service results achieved during the execution of real-world service systems owing to bounded rationality and system constraints. When applying the underlying technology behind value-aware rational behavior in existing service systems, there have been times when the results given by providers have been undesirable. The contents of this thesis are summarized as follows.

In chapter 1, the background and purpose of the research are described. In recent years, service systems have become a research subject, and the academic field has been developed. There are various research approaches to services, such as service science and service engineering. The important entities in service systems are the provider and the receiver, and this thesis classifies service systems based on these relationships. This chapter has proposed that the difficulty in grasping value information should be solved by information presentation while data on service results are being accumulated.

Chapter 2 has clarified the problem of this research by organizing the elemental technologies used in a service system along the bottom-up to top-down and theoretical to empirical axes. This chapter has outlined previous research on mechanism design and automatic negotiation as techniques for bottom-up models with a structure of value information transfer from the service receiver to the provider. This chapter has also outlined work scheduling and dynamic pricing as techniques for a top-down model in which the service provider asks the receiver for value information. These technologies were shown to be predicated on the understanding of value information that would be impractical without assistance.

In chapter 3, a hierarchical Bayesian model developed to estimate the value of the service system results is described. In this chapter, we focused on auctions as a service system and used actual data from B2B luxury brand item auctions, where the above difficulty in grasping the value of the receivers owing to a large number of products is likely to occur. We designed a hierarchical Bayesian model for estimating the end price of a Rolex watch based on the results of data analysis and compared the difference in accuracy between the predictions made through machine learning models such as a multilayer perceptron and random forest and the end price estimated by a professional appraiser. As a result, the proposed model achieved performance comparable to that of the machine learning models with the advantage of being able to output the winning bid price distribution. Although the accuracy of the proposed model was lower than that of the professional appraiser, the information used by the appraiser could not be applied owing to limited available data. In summary, the value estimation method in this chapter has been shown to be effective in service systems where there is little data, and the value of the outcome varies with people and time.

In chapters 4 and 5, the method of presenting information based on the estimated value of the service result has been verified based on the data obtained from the support technologies corresponding to the bottom-up and top-down technologies, i.e., an auction and an alternative attendance request, respectively.

In chapter 4, we analyzed the data from B2B online luxury brand item auctions and showed that the timing of the information presentation does not affect the service system results obtained when it takes the bottom-up technology a relatively long time to get service results. This chapter also found that increasing the number of bidders in an auction increases the end price. This fact indicates that promoting participation through information presentation in bottom-up service systems is effective in obtaining better service results.

In chapter 5, we have described the design of a multi-agent simulation environment for alternative attendance request using the data on work shifts and evaluate an efficient information presentation method. The results of the simulation experiments have shown that the information presentation based on estimated value is more efficient than real-world methods such as random requests. The effectiveness of the information presentation in both top-down technologies is demonstrated in this chapter. The information presentation method in this chapter was tested only in the case of alternative attendance requests in a call center. Still, this method can be applied to other service systems where the provider approaches the receivers.

The above results have shown that the difficulty in understanding the values, which has been overlooked in elemental technologies used in service systems, can be solved through value estimation and information presentation based on the estimated value. A service system in which this thesis method works effectively is one in which interactions between service providers and receivers are possible, and values can be expressed numerically in terms of prices and probabilities. It is challenging to apply this method to a one-time service for an unspecified number of people where the set of receivers cannot be specified in advance. However, the scope of the service systems covered in this thesis is broad and is valid for many online service systems where it is easy to contact the receivers. Applying the framework of this research to the design of services with co-created value, in which the values of the provider and the receivers interact, may make it possible to realize effective services.

The distinctive feature of our contribution is the proposal of a data-driven framework for better service results. Although data accumulation has progressed in various fields, including service systems, there is still a lack of knowledge on improving systems using data and applying it to the real world. This research's approach of using data to improve social activities is very important.

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