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Small Queuing Restaurant Sustainable Revenue Management

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Abstract: When competitive small restaurants have queues in peak periods, they lack strategies to cope. However, few studies have examined small restaurants' revenue management strategies at peak times. This research examines how such small restaurants in South Korea can improve their profitability by adapting their price increases, table mix, and the equilibrium points of the utilization rates, and reports the following findings based on the analysis of two studies. In Study 1, improving profitability by increasing prices should carefully consider the magnitude and timing. In Study 2, when implementing the table mix strategy, seat occupancy and profit also increase, and we further find the equilibrium points of the utilization rates. Under a queuing system, the utilization rate and average waiting time are also identified as having a trade-off relationship. The results provide insights into how managers of small restaurants with queues can develop efficient revenue management strategies to manage peak hours.

Keywords: queuing system model; sustainable revenue management; small restaurant; utilization rate

1. Introduction

Customers often wait in line during peak hours in various places, such as restaurants, shops, and sports venues [1]. This notion is similar to "the bandwagon effect" in economics, when the increasing demand for goods or services encourages more people to "get on the bandwagon," which thereby increases demand [2]. In this study, we focus on queuing because it is not only a driver that we should manage to enhance profit, but also a tool that promotes sales. In particular, we focus on small restaurants, because 85% of the restaurants in South Korea are small [3], but few have a revenue management strategy. Hereafter, these small restaurants characterized by queueing during peak hours are called SQRs.

Demand-based pricing to achieve demand dispersion [4–6] and managing and redesigning service processes (i.e., duration control) are the most representative revenue management strategies for restaurants during peak hours. However, given that these strategies are typically applied by small restaurants, they are no longer perceived as providing competitive advantage. SQRs could raise prices and expand restaurant space to accommodate more customers in order to improve profitability during peak hours. However, Becker [7] argued that these strategies do not enhance profitability in the long run because customer behavior tends to be fickle. Since the social influence of queuing weakens and the value perceived by customers diminishes after price increases or spatial expansion to the extent that the restaurant is no longer competitive, such strategies do not increase profitability in the long term.

Given that SQRs have limited resources (including financial resources), they use cost-efficient strategies to maximize profit. Based on the foregoing, this study aims to identify whether the effectiveness of price increases, spatial expansion implemented through a table mix strategy, and optimal server levels during peak hours can also be applied to SQRs in South Korea. Meanwhile, owing to the nature of lunchtime (peak hours), customers may be affected by time limitations as well as willing to be seated close to others; however, such a setting is typical and not limited to Korea.

If customers are willing to pay a much higher price than at a competitor restaurant, an SQR will enhance its profit by increasing prices. Moreover, if a restaurant could accommodate more customers, this would be a useful strategy to increase sales. Owing to the difficulty of spatial expansion in a short period, we focus on the table mix strategy because it can increase restaurant capacity by increasing the seat share [8,9]. Queuing management strategies related to customer demand management must also be considered [1,10–12]. When customers wait in queues outside a restaurant, this provides a positive evaluation of the food or service [13,14]. Thus, when demand exceeds capacity, restaurant managers should have strategies to handle waiting times without leading to customer dissatisfaction [15,16]. Studies have examined improving customer service by managing waiting times and implementing a queuing management strategy related to customer demand management [1,12,15]. From the perspective of improving profitability through efficient queuing management, reducing waiting times by providing an adequate number of tables and servers is also critical. However, a dearth of research has investigated the utilization rate, derived from the relationship between the waiting time and service rate (number of employees).

Although some studies have examined revenue management strategies such as capacity management, waiting time, table mix, and queuing analysis based on cost [1,8,15–17], integrated strategies for SQRs that include essential tools may be more suitable. Thus, to attain a profit, restaurant managers of the SQRs need to know what price increase can meet customers' willingness to pay. Managers also must determine how table mix should be used based on party size and derive the optimal utilization rate to match the relationship between customers' expectations of waiting time and the number of employees.

This study therefore suggests an efficient revenue management strategy for SQRs in two ways. First, it aims to identify the range of price increases within which the profitability of SQRs can be maximized through an exploratory study to suggest a revenue management strategy. Second, it aims to identify the effect of table mix based on Ittig's [17] formula and derive the equilibrium points of the utilization rates by considering the relationships between customers' acceptable waiting time and the cost of maintaining the optimal service rate of servers to increase profitability by improving customer service and the efficiency of servers at peak times. This study thus provides a new revenue management strategy for SQRs.

2. Theoretical Background

2.1. Restaurant Revenue Management

Kimes [18] defined restaurant revenue management as selling the right seat, price, and meal duration to the right customer. She also argued that the definition of "right" here is achieving the maximum possible revenue from the restaurant's perspective and receiving the greatest value and utility from the customer's perspective. The restaurant revenue management strategies that many prior studies have identified are demand-based pricing and the table mix approach [4,8,19–21]. Restaurant operators have traditionally used strategies to increase demand through price discounts. For example, some restaurants promote time-related promotions such as "early bird" and "night owl" through sales promotions, which is a strategy that focuses on the distribution of demand in restaurants [22]. The table mix is an especially important factor because of the difficulty of expanding space rapidly, while demand-based pricing can generate immediate results. Thus, adapting the table mix [8] and adopting demand-based pricing [6,23] are the two essential strategies focused on in this study that restaurant managers can use to manage revenue.

First, restaurant operators might avoid demand-based pricing because it is based on price discrimination and could lead to customer dissatisfaction [4]. Most consumers consider demand-based pricing to be unfair unless the increase in price is based on changes in market conditions or increases in production costs [24]. Customers believe that increases in price due to increases in original cost are fair, whereas price increases without increases in production costs are unfair [19,20]. From an economic standpoint, however, price and service levels should be determined by the different needs and price elasticities of customer segments [4]. Therefore, many restaurant operators use strategies related to price to expand or shift peak hour demand. Price change strategies include day-part pricing, day-of-week pricing, and price premiums or discounts based on party size, table, and customer type [18].

Second, the optimal table mix that matches the party size as closely as possible would increase the seat occupancy rate at peak times, thus allowing the restaurant to serve more customers without increasing the number of seats [25]. Kimes [18] argued that even when all tables are occupied, many restaurants still end up having empty seats because the table setting does not consider the types of party sizes visiting the restaurant. Kimes and Thompson [8] maintained that restaurant seat occupancy could be increased by over 30% by using the right table mix. Follow-up studies have also shown that seat share could be improved through efficient table mix strategies [8,26,27].

However, the causal relationships between the physical environment (i.e., table layout, crowding) and customer behavior differ. Noone and Mattila [28] argued that crowding may affect customer behavior by dissuading positive in-store behavior such as spending more time and money in the restaurant. Yildirim and Akalin-Baskaya [29] found that customers prefer a seating layout that is not congested. Robson et al. [21] maintained that consumers are reluctant to dine in a dense table layout. In particular, diners consistently express an uncomfortable, crowded, and generally negative feeling toward a restaurant when presented with the image of tables at six-inch intervals. In summary, the emotions perceived by customers in a highly crowded environment are generally negative.

Studies of the relationships between the environment of the restaurant and consumer behavior also differ according to consumers' perception. Paulus and Matthews [30] argued that rational information about the specific cause of arousal in crowded environments, regardless of the source, increases consumer tolerance to overcrowding. Punj and Stewart [31] suggested that consumer expectation is a crucial determinant of consumer satisfaction. Because consumers tend to make perceptions based on the individual's reference point before the task [32], post-purchase customer satisfaction is determined by the difference between expectation and performance [33]. Therefore, an increase in seat occupancy through the table mix means that even if the restaurant's internal environment is crowded, it does not harm consumer behavior.

2.2. Demand and Supply Curves for SQRs

As shown in Figure 1, the supply curve for an SQR is vertical, since its service is offered in a limited space because of the nature of the restaurant industry. The demand curve for an SQR, on the contrary, slopes downward ($\partial q/\partial p < 0$), but there exists an inflection point (point A in Figure 1). As a result, the curve temporarily slopes upward and then slopes downward again at a certain point (point B in Figure 1). For SQRs, the demand curve increases even if the price rises. Hence, because of the bandwagon effect, SQRs are generally more highly competitive than other restaurants. Becker [7] suggested that the curve temporarily slopes upward because of the factors affecting demand, namely price, quantity, taste, and social interaction (i.e., the bandwagon effect).

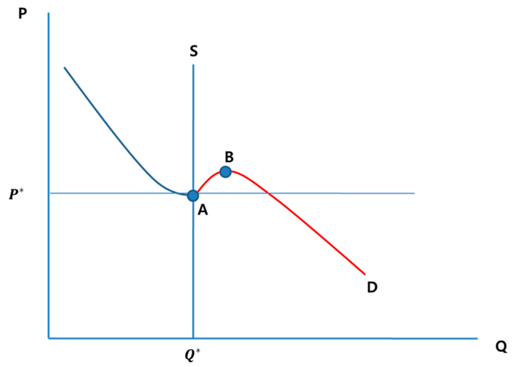

Figure 1. Demand and supply curves of an SQR.

2.3. Queuing Theory

Queuing theory is an analytical method that can monitor system quality using mathematical equations [1]. When more customers arrive than can be served by restaurants, they inevitably form a queue. If it is unavoidable to make customers wait in line, the organization has to decide what type of queuing system to use. Queue configuration refers to the number of queues, their locations, their spatial requirements, and their effects on customer behavior [34]. Queuing management strategies used in restaurants include implementing a "take a number" system, offering information (about the waiting and queuing time), and filling in a phone number on the board (notifying of the entrance time via text) [35]. The advantage of these strategies is that customers can anticipate the waiting time; however, the notification service by text message has a disadvantage in that the likelihood of customers entering the restaurant is low [36].

The waiting time that customers perceive is subjective and based on personal experience [16]. The theory of counterfactual thinking has been suggested to explain customers' psychological factors related to queuing management [37–39]. Counterfactual thinking is a likelihood comparison between the consequence of perceived events and alternative versions [39], for which variability has been argued to be the most important factor [40]. Zhou and Soman [41] showed that a customer has a higher probability of waiting when there are more people in the queue behind him or her. Previous studies explain that downward social comparison leads to relief, the feeling of being lucky, and, consequently, a better evaluation of the situation [42], which have a positive influence on an evaluator, minimizing the likelihood of him or her leaving the queue [43].

Demand management using queuing models is necessary for SQRs. Queuing models provide information that can help managers determine the best way to deploy the restaurant's resources (e.g., employees and physical capacities) to reduce the wait to be served to an acceptable time [1]. Previous studies have adopted queuing models. For example, in the simulation study of a queuing system in a fast food restaurant conducted by Chou and Liu [12], no significant difference is found in the waiting time between the three-line system and one-line system. However, the number of servers has a significant difference on the waiting time in the three-server and four-server systems. Hence, the highest net benefit is achieved by adding more servers during peak hours. Lambert and Cullen [1] analyzed three plans to improve customer service and reduce waiting times. They argued that such a queuing analysis can help decide the most efficient service level and number of servers based on the value of time perceived by customers and queuing management cost.

2.4. Research Propositions

Proposition 1. *To increase profitability during peak hours, if SQRs raise prices, what is the most appropriate range of price increases and how should this be introduced? Then, what is the effect of the price increase on profit?*

Proposition 2. *To manage SQRs using cost-efficient methods, does the table mix have a significant effect on profit? Further, which equilibrium points of the utilization rates can maximize profitability based on the table mix?*

3. Study 1: Exploratory Study of the Pricing Strategy of SQRs

3.1. Pilot Test

A pilot test was carried out as follows. Previous studies were reviewed, and pilot research was conducted on the attributes of SQRs. Survey questionnaires on loyalty (because queuing outside a particular restaurant can be judged to be more active purchase behavior by customers compared with other restaurants) and purchase intention (depending on the degree of the price increase by the SQR and degree of the price decrease by its competitors) were developed and refined to analyze the pricing strategy.

3.1.1. Scales

The independent variable, the attributes of SQRs, was adapted from Becker [7] and measured with four items: price, taste, food quantity, and brand name. We used two loyalty-based items as the dependent variables from McMullan [44]: "I would recommend a busy restaurant" and "I would want to purchase from a busy restaurant" (two items: Cronbach's $\alpha = 0.755$). Each question was scored on a seven-point Likert scale (1 = "strongly disagree" to 7 = "strongly agree").

We also used two open-ended questions adopted from Ashton et al. [45]; one was related to purchase intention following a price increase by an SQR ("If an SQR raised its prices, what percentage increase could you afford?") and another was related to purchase intention following a price decrease by its competitors ("If a competitor opened nearby, what percentage discount would entice you to purchase from its menu?").

The subjects of this study were 77 customers (74% women; 53.2% 20–30 years) arriving at an actual restaurant (pork cutlet specialty restaurant) open for business and waiting in line. As the number of restaurant visits varies for each customer, the criteria for evaluating food quality also differ between customers who have visited several times and those who have never visited. Thus, it is meaningful to analyze the differences between these two groups. However, this issue is not considered because it is beyond the focus of the present study. Hence, we controlled for an exogenous variable (i.e., a repeat vs. a first-time diner) using random sampling. We introduced the purpose of this study and they were willing to answer the survey.

3.1.2. Results

According to a regression analysis of how the attributes of an SQR influence loyalty, the regression equation was $\hat{y} = 1.222 - 0.268$ (price) + 0.557 (taste) + 0.107 (food quantity) + 0.076 (brand name) and the standardized coefficients were as follows: taste (0.525), price (−0.0217), food quantity (0.197), and brand name (0.95). The validation showed that taste ($t = 5.172$, $p = 0.000$) and price ($t = -2.333$, $p = 0.022$) were significant. The pricing analysis showed that customers maintained their intention to purchase at the SQR (price elasticity of demand = 0.79), up to a 12.7% price rise, while they switched their purchase intention to its competitors (price elasticity of demand = 1.75) when they gave customers a discount of 21.3% off the same product compared with the SQR.

3.2. Exploratory Discussions

The following conclusions about the pricing strategy of SQRs can be drawn from the analysis. As shown in Figure 2, the supply curves are presented as "S" based on restaurants' size. These curves are not upward-sloping but vertical because of the limited supply. A demand curve generally slopes downward, but the demand curve of an SQR is expected to be a "D" demand curve according to our analysis as well as Becker's findings [7].

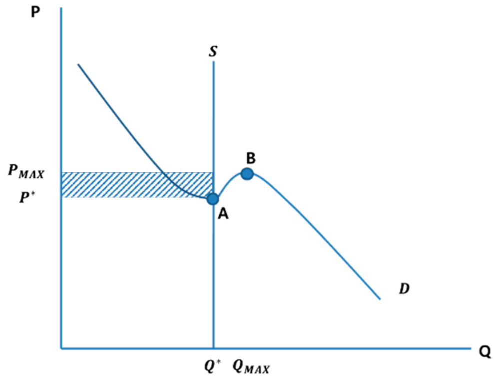

Figure 2. Changes in the prices and supply of an SQR.

Based on the "D" demand curve, point A is the inflection point at which the demand curve slopes upward and is an equilibrium point between demand (D) and supply (S) when customers start queuing in the restaurant. Point B is the peak queuing point and thus the maximum point at which customers can afford the price increase (up to 12.7%). Demand exceeds supply from Point A to Point B depending on the size of the restaurant, and thus queuing occurs. Point B is the maximum point to which SQRs can increase prices. As seen in Figure 2, total sales volume rises with increasing prices. However, as shown in the regression analysis, price negatively affects loyalty. Moreover, when competitors start a sales promotion through price discounts on a menu similar to that of the SQR, consumers can switch to rival restaurants. Thus, managers should carefully consider the magnitude and timing of price increases.

The following explanations of the strategy of an SQR based on the points above are offered. Point A to Point B comprises an interval within which demand increases despite an increase in prices. Within this interval, word of mouth among customers as well as sales promotion effects can arise, as customers are willing to queue. At the same time, supply increases and price competition start because the number of competitors increases. Therefore, it is recommended that restaurant managers or operators of SQRs manage revenue by queue management rather than make profits from price increases. Becker [7] argued that the demand curve slopes downward in a highly competitive market in which market supply exceeds market demand, and thereby customers can switch to competitors whenever they want.

In summary, this study found that the strategy used to maximize the profitability of an SQR by raising prices is an inefficient revenue management strategy from a long-term perspective considering that customers become more fickle as the competitive environment of the restaurant sector rapidly intensifies (e.g., the implementation of price decreases, coupons, and sales promotions strategies). Therefore, Study 2 focuses on an efficient revenue management strategy, namely queuing management.

4. Study 2: Service Rates of an SQR Using Queuing Analysis

4.1. Pilot Test

Pilot tests about size and business features were conducted by visiting a real restaurant (pork cutlet specialty restaurant) to analyze its queuing system. The SQR had 50 seats and customers' average meal duration was 30 minutes (including clearing tables, ordering, and dining). The observation of arrivals showed that an average of 68 customers (75% women; 50% 20–30 years) arrive during peak hours (between 12 p.m. and 1 p.m.), when people always form a queue. The service rate during peak hours was found to be about 19 customers per hour (interviews with managers and observations) for each server based on four employees (three cooks and one server).

We also conducted an online survey to determine SQR customers' acceptable waiting time. Following Hwang and Lambert [15], customers' acceptable waiting times were divided into three categories: satisfactory, unsatisfactory, and very unsatisfactory. The results of the survey showed that the satisfactory waiting time is 8.67 minutes, the unsatisfactory waiting time is 13.23 minutes, and the very unsatisfactory waiting time is 17.77 minutes, on average. These groups are significantly different (average satisfactory waiting time=8.67^a < average unsatisfactory waiting time=13.23^b < average very unsatisfactory waiting time = 17.77^c; $F(2, 87) = 150.344$, $p < 0.001$, $\eta = 0.776$).

As a precondition for simulating the queuing system, the seat occupancy rate depended on the table guidance method and table mix [46]. Table guidance means that customers are guided to a table by an employee. Otherwise, customers select their table without the help of an employee. We adopted table guidance to increase the seat share. To calculate the table mix, we first gathered data on party sizes through observations on different days of the week and times (party size of 1 = 0.216, party size of 2 = 0.613, party size of 3 = 0.106, party size of 4 or more = 0.065). Based on Thompson's [27] formulation, we derived the most suitable table mix (one-top = 5, two-tops = 15, three-tops = 3, four-tops = 2).

We derived the seat occupancy rate as follows. First, table placement was classified into two types: a real restaurant table layout and table placement through the table mix. Second, two-tops could be combined for party sizes of more than two, and service was first-come first-served. Third, each group was simulated 30 times (using an arrival order derived randomly) and then average seat occupancy was obtained (see Table 1).

Table 1. Seat occupancy per hour.

	Table Mix-Yes: My	**Table Mix-No: Mn**
Table guidance-yes: Gy	GyMy: 92 (seat occupancy)	GyMn: 72 (seat occupancy)
Table guidance-no: Gn	GnMy: 76 (seat occupancy)	GnMn: 68 (seat occupancy)

Note: For brevity, we use the following abbreviations in this table: My (table mix-yes), Mn (table mix-no), Gy (table guidance-yes), Gn (table guidance-no).

We found that seat occupancy had significantly different effects on the groups (GnMn = 67.67^a < GyMn = 71.77^b < GnMy = 76.33^c < GyMy = 92.03^d; $F(3, 116) = 730.124$, $p < 0.001$, $\eta = 0.950$). In summary, the seat occupancy rate is higher when applying the table mix. Moreover, compared with table guidance, the table mix is a more efficient strategy (GnMy = 76 vs. GyMn = 72). Hence, hereafter, we focus on the table mix to increase seat occupancy. The pilot test was conducted to manage the utilization rate of servers efficiently in peak hours by identifying the maximum seating capacity of a restaurant.

4.2. Preconditions for the Queuing Analysis

The queuing system in this study is a Markovian queuing system. Specifically, it is a M/M/1 queuing system in which the arrival procedure follows a Poisson distribution (discrete probability distribution that can be used when a certain event occurs randomly in a fixed unit time and unit space), the arrival interval follows an exponential distribution (continuous probability distribution frequently used to indicate the time it takes until a certain event occurs), and the service time also follows an exponential distribution. The number of servers was one in this study, because orders are made by a single-channel or single-line order count using one server in most small restaurants. In addition, Larson [47] argued that customers prefer single lines because it guarantees the first-come, first-served principle from a social justice perspective.

M/M/1 assumes that the arrival of customers is irrelevant to the number of customers in the system. $\rho = \lambda E(s) = \lambda/\mu < 1$ in this case. In other words, $\lambda E(s)$ (the average workload given to a server by customers that arrive in unit time) needs to be smaller than 1 (the maximum workload that a server can manage in unit time). Based on $P_0 = 1 - \rho$, $P_n = \rho^n (1 - \rho)$, the probability that the number of customers is n in the stationary M/M/1 system follows the geometric probability distribution with the parameter ρ (traffic intensity).

The terms used in this study are explained as follows: λ (customer arrival rate per hour), μ (service rate per hour: average number of customers who can be provided with service per hour), ρ (utilization rate: average workload given to a server by customers that arrive per hour), L_q (average number of customers in the queue), and W_q (average customer time in the queue).

The equations used in this analysis follow the laws of Little [48]:

Total average number of customers in the restaurant:

$$L = \lambda W \tag{1}$$

Average customer time in the queue:

$$W_q = L_q/\lambda = \lambda/(\mu(\mu - \lambda)) = \rho/(\mu(1 - \rho)) \tag{2}$$

Average number of customers in the queue:

$$L_q = \rho^2/(1 - \rho) = \lambda^2/(\mu(\mu - \lambda)) \tag{3}$$

4.3. Results of the Queuing Analysis

4.3.1. Results of the Queuing Statistics

To calculate the utilization rate, the average workload needed to first be identified. There were three ways to determine the average workload based on the pilot study. The first was the customer arrival rate per hour. The average workload (λ; same as the customer arrival rate) during peak time (from 12 to 13; people always form a queue) of small restaurants identified in the pilot study was 68 people. The second was the number of seats in the restaurant. There were 50 seats in the restaurant and this could be converted into an average workload of 100 people under the assumption that the average dining time is 30 minutes and thus two rounds of customers can sit per hour. The third was seat occupancy through the table mix and table guidance. Based on the seat occupancy deduced from the simulation, the average workload was 92, 72, 76, and 68 people for GyMy, GyMn, GnMy, and GnMn, respectively (see Table 2).

Table 2. Queuing statistics for the current restaurant and hypothetical restaurants.

	Current	**GyMn**	**GnMy (Option 1)**	**GnMy (Option 2)**	**GyMy**
Customer arrival rate per hour	68	72	76	76	92
Service rate per hour	76	76	82	95	95
Utilization rate	89.5%	94.7%	92.7%	80.0%	96.8%
Average number of customers in the system	8.5	18.0	12.7	4.0	30.7
Average number of customers in the queue	7.6	17.1	11.7	3.2	29.7
Average customer time in the system (minutes)	7.50	15.00	10.00	3.16	20.00
Average customer time in the queue (minutes)	6.71	14.21	9.27	2.53	19.37
Probability that all servers are idle	10.5%	5.3%	7.3%	20.0%	3.2%
Probability that an arriving customer will have to wait for service	89.5%	94.7%	92.7%	80.0%	96.8%

Next, the maximum workload was determined. From the perspective of restaurant operators (or managers), the maximum workload given to a server in the different time slots of business hours depends on which average workload is used as a criterion. However, the rule of ρ = λ/μ < 1 applies to calculate the maximum workload that a server can manage. Therefore, the maximum workload (the number of average customers per employee is 19) was selected based on the customer arrival rate per hour, the number of seats, seat occupancy through the table mix and table guidance, and in-depth interviews with restaurant managers.

When the utilization rate per hour during peak times was calculated, the current restaurant that did not implement either table mix or table guidance had the lowest seat occupancy (68 people per hour). Further, the real restaurant's utilization rate (89.5%) and waiting time (6.71 minutes) were lower than those of the hypothetical restaurants, whereas the probability that all servers are idle is higher than those of others, except for GnMy. For GnMy, there are two options for the service rate. Option 1 is that the restaurant keeps the same employees and employs experienced cooks to enhance productivity [15], resulting in a slight increase in the service rate from 76 to 82. Option 2 is that the restaurant uses an additional cook. However, adding a cook to enhance the service speed will not increase service efficiency because some cooks will inevitably be idle from time to time.

4.3.2. Results of the Contribution to Profit

According to Ittig's [17] formula (Maximize = M (the average margin per customer) $\times \lambda - C_1$ (the average cost of a server per hour) $\times$ N), when the real restaurant's average margin per customer is M = 1200 ₩ ($1.02), the average cost of a server per hour is about C = 8350 ₩ ($7.09), the customer arrival rate per hour (λ) is 68, the service rate per hour is 76 (four employees), and the contribution to profit per hour (GnMn) is 48,200 ₩ (Max = $1200 \times 68 - 8350 \times 4$). Using the same formula, each situation was calculated (see Table 3). [72 (λ) / 76 (GyMn; four employees) = 53,000 ₩, 76 (λ) / 82 (GnMy; four employees) = 55,260 ₩ (the cost of an experienced employee is about 10,855 ₩ per hour), and 76 (λ) / 95 (GnMy; five employees) = 49,450 ₩, 92 (λ) / 95 (GyMy; five employees) = 68,650 ₩; $1 = 1178.79 ₩]. However, considering the cost of waiting [49], the contribution to profit will slightly decrease.

Table 3. Results of the contribution to profit.

	Current	GyMn	GnMy (Option 1)	GnMy (Option 2)	GyMy
Service rate per hour	68	72	76	76	92
Employees	4	4	4	5	5
Average margin per customer (₩)	1200	1200	1200	1200	1200
Average cost of a serve per hour (₩)	8350	8350	10,855 *	8350	8350
Contribution to profit per hour (₩)	48,200	53,000	55,260	49,450	68,650

Note: $1 = 1178.79 ₩; *: the cost of an experienced employee is about 10,855 ₩ (30% higher than other employees' wages) per hour.

Therefore, we find that expanding space (i.e., increasing seat occupancy; see Figure 3) through the table mix strategy is efficient to maximize profit: 76 (λ) / 82 (GnMy; four employees) and 92 (λ) / 95 (GyMy; five employees). In addition, customers' waiting time is significant in the queuing model. Considering the average satisfactory waiting time is 8.7 minutes according to the pilot test, the most suitable queuing model is GnMy's Option 1. The queuing model that we propose in this study provides SQR managers with a utilization rate criterion that can be related to the restaurant's profits. Thus, it is crucial to find the equilibrium points of the utilization rates.

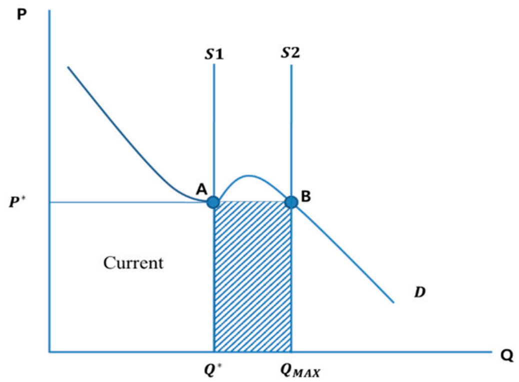

Figure 3. Changes in the seat share and supply of an SQR.

4.3.3. Equilibrium Points of the Utilization Rates

The revenue management strategy to maintain the optimal profitability during peak times would be to optimize the maximum workload of a server by identifying accurate seat occupancy (under the assumption that an average workload per hour occurs during peak times) and find the optimal utilization rate. Therefore, the utilization rate for the optimal profitability was found by calculating the utilization rate after changing the maximum workload of a server based on the seat occupancy deduced from the peak time simulation and identifying changes in the average number of customers in the queue (or the average customer time in the queue).

The results of the analysis based on the current restaurant and three hypothetical restaurants are as follows (see Figure 4 and Table 4). First, the relationship between the utilization rate and average waiting time showed a curvilinear upward slope. Second, the average waiting time of each customer's arrival rate (i.e., $\lambda = 68$; $\lambda = 72$; $\lambda = 76$; $\lambda = 92$) dramatically decreased at utilization rates between 0.989 and 0.944, whereas the degree of change was minimal at lower utilization rates (0.902~0.731). Third, the equilibrium points (we call these "elbow zones") between the utilization rates and average waiting time are about $\rho = 0.929$~0.907 (depending on each customer's arrival rate). These elbow zones are within the satisfactory waiting time (8.67 minutes) allowed by customers. Thus, we recommend these equilibrium points of the utilization rates ($\rho = 0.929$~0.907) during peak hours as a strategy to increase profit.

Table 4. Results of the relationship between the utilization rate and average waiting time.

$\lambda = 68$		$\lambda = 72$		$\lambda = 76$		$\lambda = 92$	
ρ	W_q	ρ	W_q	ρ	W_q	ρ	W_q
0.986	59.13	0.987	59.22	0.986	59.18	0.989	59.35
0.944	14.17	0.950	14.25	0.947	14.21	0.958	14.38
0.907	7.77	0.916	7.85	0.911	7.81	0.929	7.97
0.872	5.23	0.884	5.30	0.878	5.27	0.902	5.41
0.840	3.87	0.854	3.94	0.847	3.91	0.876	4.04
0.810	3.04	0.826	3.10	0.818	3.07	0.852	3.19
0.782	2.47	0.800	2.53	0.791	2.50	0.829	2.62
0.756	2.06	0.776	2.12	0.766	2.09	0.807	2.20
0.731	1.75	0.752	1.81	0.742	1.78	0.786	1.89

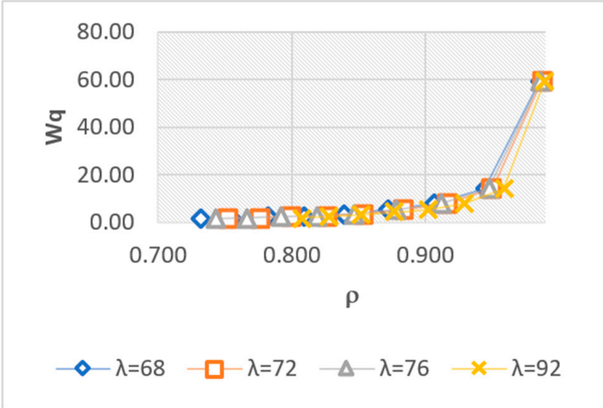

Figure 4. The relationships between the utilization rate and average waiting time.

5. Conclusions and Implications

This study has implications for strategies to enhance the profitability of SQRs from a revenue management perspective. The results of the study are as follows. An exploratory study of the pricing strategy of SQRs in Study 1 can be summarized in two parts. First, the regression analysis of the effect of an SQR's attributes on loyalty showed the positive influence of taste and negative influence of price. Second, customers maintain their purchase intention for SQRs up to a 12.7% price increase, while they start to demonstrate purchase intention toward competing restaurants upon a 21.3% decrease in the price of the same product. This finding indicates that SQRs have 12.7% competitive power in terms of price compared with their competitors, while such a competitive advantage can be removed by a 21.3% discount by their competitors.

The results of a study of the table mix using the queuing model in Study 2 are summarized as follows. First, when implementing the table mix (e.g., GyMy and GnMy), seat occupancy and total sales volume were higher than those of the real restaurant (GnMn) and a simulated restaurant (GyMn). This is because the table mix increases the seat share without a physical expansion of space. When implementing the table mix, the contribution to profit per hour is higher than that in the real restaurant (GnMn) and a simulated restaurant (GyMn). Thus, restaurant managers should continuously observe the party size and identify the seat share during peak hours. Second, for GyMy, the relationship between the utilization rate and average customer time in the queue shows a curvilinear pattern and heavy traffic that rises almost vertically regardless of the average workload when the utilization rate is close to one. These results suggest that an increase in the utilization rate increases the average customer waiting time. Therefore, maintaining the utilization rate that considers the properties of a real restaurant (average customer time in the queue that customers can accommodate, average number of customers in the line) and job performance of servers is the most efficient revenue management strategy.

This study provides a number of theoretical and practical implications. The theoretical implications are twofold. First, this study evaluated price competition and table mix/table guidance strategies based on a supply and demand curve through an exploratory study to enable follow-up studies of restaurant revenue management. Second, by studying the relationship between the utilization rate and average waiting time from the perspective of the queuing system, which has rarely been covered in previous work, this study extended our understanding of restaurant revenue management.

The practical implications are as follows. First, if SQRs have to increase prices, up to around 12.7% would be an appropriate level. However, since customers are expected to leave if a 12.7% increase is made in one adjustment, it would be preferable to increase prices gradually [7]. Moreover, restaurants that wish to compete with a local SQR using a similar concept would entice customers if they provide at least a 21.3% discount in prices and have a competitive advantage in terms of taste.

Second, we found that the table mix is a useful tool to increase the seat share and profit. Hence, an SQR manager consistently has to observe party sizes and relocate table types (i.e., two-top and four-top tables). Further, the layout design should include whether tables can be moved to accommodate a variety of party sizes [50].

Third, this study found that the equilibrium points of the utilization rates are about ρ = 0.929~0.907 during queuing at peak times, making it the most efficient revenue management strategy for SQRs. Therefore, to apply to this to business, restaurant managers should choose the most balanced utilization rate (ρ) in comparison to the cost of labor, enhance seat occupancy through the table mix and queuing analysis, identify the average waiting time that customers can tolerate, and place suitable servers based on their proficiency and the restaurant's marginal productivity. The waiting time of customers and work intensity of servers can be affected in restaurants where customers form queues during peak periods. For instance, an increased utilization rate can increase customers' waiting time, negatively affecting customer satisfaction, or increase the work intensity of servers, increasing their turnover intention [51,52]. Hence, revenue management strategies using the utilization rate not only develop revenue management models of SQRs but also apply to various fields in the food service industry.

6. Limitations and Future Research

The limitation of this study is that customers can always leave a queue whenever they want. Therefore, subsequent studies could examine the utilization rate by taking this into account. Further, the utilization rate presented in this study is specific to small restaurants. Thus, this study may not be generalized to different types of restaurant environments. Meanwhile, in this study, customer characteristics (e.g., a repeat diner vs. a first-time diner, waiting time tolerance, price sensitivity, food preference) and the restaurant environment (e.g., table arrangement) are not considered, again preventing us from generalizing the research results.

Because this study explains the results based on exploratory research and mathematical models, our study's sample size is smaller than those in other causal studies. However, the sample size in our study satisfies the guidelines set out by Hair et al. [53]. Thus, generalization should not be a problem. However, one weakness is that the data were taken from only one restaurant. Therefore, the generalizability of this study's research results is limited.

In addition, it has a limitation in explaining the causal relationships between the waiting time and customer behavior (i.e., customer satisfaction or revisit intention), as well as between employees' workload and turnover intention. These causal relationships need to be explored in future studies to provide restaurant managers with more in-depth insights. Meanwhile, a restaurant's internal stimuli would affect the evaluation of the customer's experiences of waiting in the queue. Therefore, it is essential to identify whether internal stimuli such as background music have positive effects on a waiting customer. In addition, these stimuli would affect the performance of employees. Finally, it is important to focus on psychological factors such as types of queues (e.g., single-line or multi-line). Because using psychological factors can often enhance the fairness of a service, reducing the dissatisfaction from waiting in line and decreasing the total operating cost.

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