Chapter 2
Analysis and Prediction of Customer Behaviors for Restaurant Management

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Abstract An important task for restaurant managers is the prediction of customer behaviors. A restaurant manager must predict the number of customers coming in several days in advance and prepare foods based on the estimated sales quantities of their products. Based on those estimations, the manager's most important job is purchasing foods and ingredients and preparing for the necessary staff members in advance. However, the job is not always easy for several reasons. An important task for restaurant managers is the prediction of customer behaviors. A restaurant manager must predict the number of customers coming in several days in advance and prepare foods based on the estimated sales quantities of their products. Based on those estimations, the manager's most important job is purchasing foods and ingredients and preparing for the necessary staff members in advance. However, the job is not always easy for several reasons. This chapter discusses the problem structure of restaurant management related to customer behaviors. Then it presents some research examples for demand forecasting and menu design through analysis of customer behaviors using big data. Moreover, it describes the customer satisfaction mechanism based on survey data and presents discussion of how service productivity can be enhanced based on customer behavior characteristics.

2.1 Restaurant Management Problem Structure Related to Customer Behavior

First, if a restaurant is always full of customers with reservations, and if there is only one menu determined by the restaurant, then it is expected to be quite easy for an experienced manager to estimate the necessary foods or adequate labor input in advance. In other words, a manager does not need so-called demand forecasting.

Nevertheless, most restaurants welcome non-reserved customers if they have sufficient seats and allow customers to choose products from a menu book to any degree

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the restaurant can accommodate such customers. Additionally, a restaurant cannot control when such non-reserved customers enter the restaurant. Accordingly, it becomes difficult for a restaurant manager to estimate the exact number of customers and product sales for each time period of a day.

Figure 2.1 illustrates the basic problem structure of the restaurant manager's decision-making and performance indicators appearing as results of the manager's decision and other factors. The first difficulty arises from uncertainty in the estimation of the number of customers for a day. In practice, restaurant managers usually predict the number of customers for a day based on past data considering the day of the week or season. Additionally, they must consider external factors such as weather, temperature or special events near the restaurant. However, the mode of demand forecasting is often based on the manager's experience and intuition rather than on a scientific methodology. Therefore, the authors have developed a demand forecasting method for service providers including SMEs based on service engineering, as introduced in Sect. 2.2.

On whatever way of demand forecasting, a restaurant manager must make decisions about food purchases and the necessary labor input of kitchen or hall staff to serve meals to customers adequately. Consequently, those decisions lead to direct or indirect managerial indicators. If a manager estimates the number of customers as much less than the actual number, then the manager might reduce the labor input of staff members. As a result, labor productivity, which is often expressed as the total sales per staff, per hour will be higher than usual. Although it is apparently

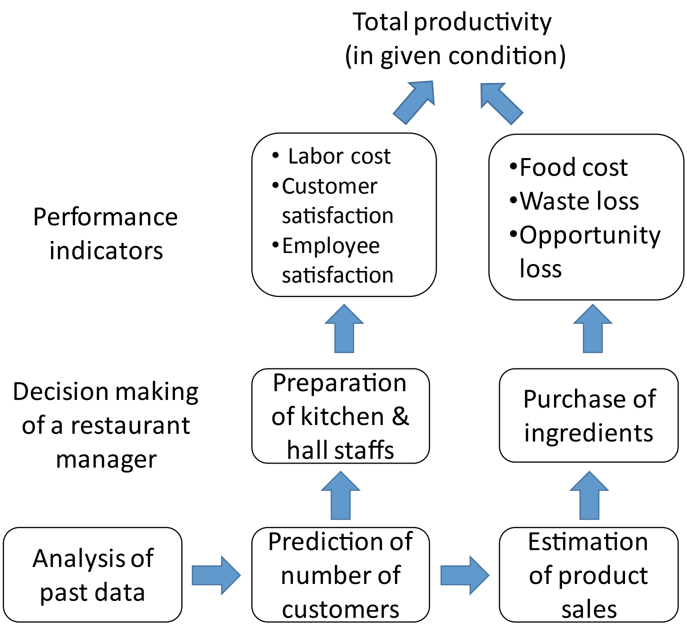

Fig. 2.1 Basic structure of a restaurant manager's decision making and performance indicators

good from the viewpoint of labor cost, it might also entail other negative results such as a decline of customer satisfaction because of increased waiting times or delay in serving dishes. Moreover, employees would be exhausted and complain about staff shortages. What is worse, overworked employees might not provide sufficient services or hospitality to customers. Poor services might result in losing repeat customers. However, oversupply of labor input based on overestimated customers can simply cause increased labor costs.

Estimation of product sales can be more difficult than that of the number of customers for restaurant managers because customers of various types choose from a menu on the table based on their preferences or health conditions. Accordingly, managers might try to prepare sufficient foods to satisfy various customer needs without a shortage of products. However, it can engender loss of foods because fresh foods spoil easily. Therefore, another difficulty derives from the constraints of food inventory control.

In fact, how can we predict various customers' choice of foods? A method often used in restaurant or retail industries is to calculate the share of customers who purchase a product among all customers. The figure is sometimes called the Purchase Index (PI) value in retail or restaurant service industries, especially in Japan. For instance, when 1000 customers out of all 10,000 customers who visit a restaurant in a certain period bought product A, the PI value of A is 10%. However, this method only considers the average probability of all customers and does not explain which types of customers purchase the product. Additionally, in the restaurant industry, because it is still not popular to introduce Customer Relationship Management (CRM) systems that can record the purchase history of all member customers, it is difficult to know the repeat rate of each product. Accordingly, the PI value cannot explain why 10% of all customers purchased the product. To elucidate the meaning behind the PI value, one should know a customer's decision-making processes and customer types who chose the product.

Figure 2.2 presents customer processes related to choosing products in a restaurant. Customers have various motivations to come to a restaurant related to their preferences for foods, experiences with a restaurant or similar type of other restaurant, or feeling of the day. Because repeat customers know the restaurant, they have expectations about products and services. Therefore, they sometimes do not need the menu book for choosing their favorite products. However, it is difficult to know first-time customers' expectations for the restaurant. Some customers might happen

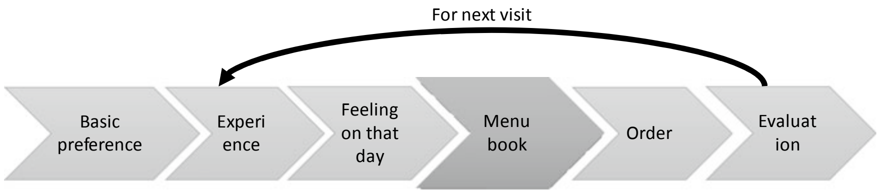

Fig. 2.2 Customer decision-making processes in a restaurant

to visit a restaurant with no expectations. Other customers might choose a restaurant based on information from the internet. In either case, a menu book might strongly influence first-time customers' choice of products.

Against that backdrop, a study example of how a menu might influence customers' decision making is introduced in Sect. 2.3. Moreover, a discussion of how one can ascertain various customers' needs and satisfaction at restaurants using technology is presented in Sect. 2.3.

2.2 Demand Forecasting

As discussed above, the number of the customers for a day is a fundamental measure for service industries, including restaurants, to infer customer demands. However, customer behaviors can be influenced by many environmental factors such as the calendar, the day of the week, weather, time, area, promotion or nearby events. Therefore, it is reasonable to understand customer arrival behaviors in terms of environmental factors.

The authors have developed a demand forecasting method using aggregate purchase data and environmental factors as "causal data" (Takenaka et al. 2011a, b). Using this method, one can specifically investigate common factors underlying customer behaviors as causal data. This method estimates the numbers of customers using more than 50 parameters with a multiple regression model including stepwise selection of parameters. Figure 2.3 presents an example of estimation results of the number of customers for a restaurant. In this case, the averaged accuracy of the model is 87.7%; 20 parameters are selected using stepwise selection of parameters,

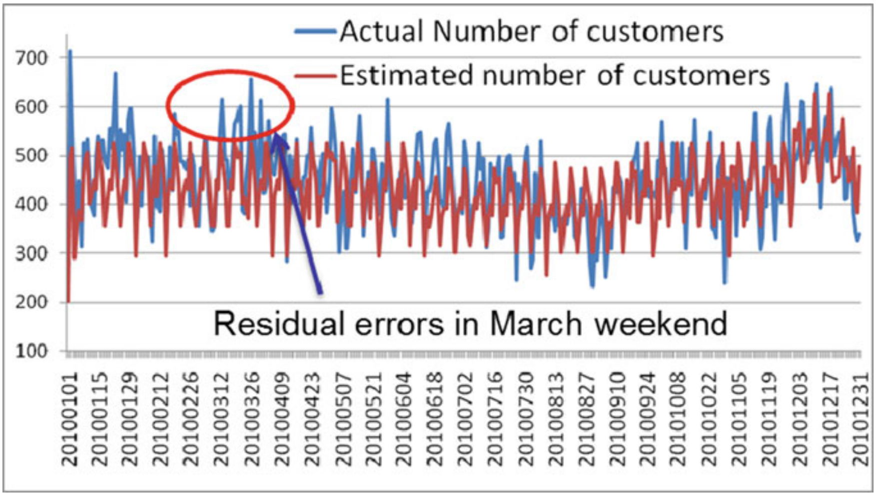

Fig. 2.3 Estimated number of customers for a restaurant

Table 2.1 Parameters and their respective multiple regression coefficients (n = 3500, Izakaya = 2500, Japanese restaurant = 700 and other type restaurants)

Constant term	353
Friday	172
Sunday during big holidays	154
Saturday	144
Jan. 3 (new year holiday)	143
Holiday during successive holidays	137
Weekday before holiday (except Fri.)	124
Holiday	121
End-year party season	103
Wednesday	98
Sunday	93
Thursday	76
Tuesday	60
Jan. 1 (new year holiday)	−289
Christmas Eve	−151
End of the year (3 days)	−150
Last day of holidays	−74
New year party season (Weekday of early Jan.)	−63
Rainfall exceeding 10 mm	−59
Max. Temp. over 32 °C	−52
Max. Temp. 27–31 °C	−39

as shown in Table 2.1. Using this table, they can readily estimate the numbers of customers according to environmental factors.

Using this method, one can construct a basic model for customer behaviors. The model includes some important measures that can be compared with other shops' models, as explained below.

(a) Accuracy of the model: The coefficient of determination (r^2) represents the model reliability using a prepared causal dataset. We can also calculate the model accuracy using a cross variation method.
(b) Selected parameters from the causal dataset: It is important information which parameters were selected using stepwise method because those factors have strong effects on customer behaviors. Moreover, the coefficient (number of customers according to each parameter) represents the size of the effect.
(c) Residual errors: Fig. 2.3 shows some residual errors, especially on some days. It is important to devote attention to which day such errors occur. We can sometimes find underlying factors except for causal data that are selected using the model.
(d) Variation of customer behaviors according to environmental factors: customer behaviors are not stable even on the same day of the week for instance. Variation

according to environmental factors can be an important measure, especially for comparison of stores of a chain or of an area.

Using demand forecasting models, one can compare standardized coefficients (coefficient divided by constant term) of constructed multiple regression models for many stores. Effects of factors can differ according to the characteristics of trade areas or customer needs. Especially, day-of-the-week effects vary according to the store location. Through those analyses, for example, area managers of a chain can realize differences of circumstances among restaurant stores.

Figure 2.4 presents a comparison of standardized coefficients (coefficient divided by constant term) of multiple regression models constructed for five restaurants. Effects of factors differ according to the trade area characteristics. Especially, day-of-the-week effects vary according to the restaurant location. Through those analyses, for example, area managers of a chain can realize differences of circumstances among restaurant stores.

As introduced above, the authors used a multiple regression model to predict customer numbers or sales because we think it is helpful for managers to know the causal factors in a quantitive manner. However, many other forecasting methods exist, such as the Box–Jenkins (ARIMA) model, Bayesian network model (Lasek et al. 2016) or other machine learning methods (Tanizaki et al. 2019). Recently many commercial software and cloud services using machine-learning methods for demand forecasting are also available. By those services, users can input many parameters related to day of the week, weather, events or other information without verification

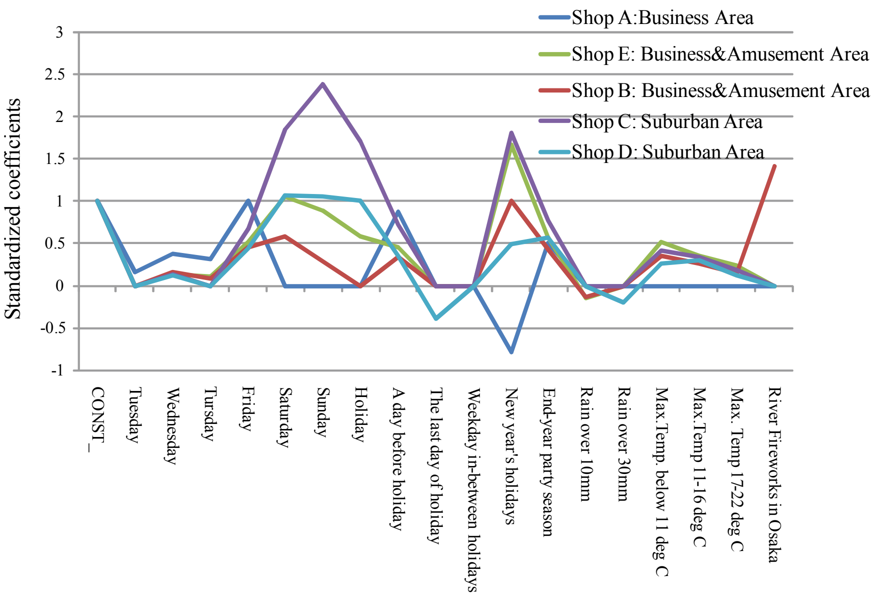

Fig. 2.4 Standardized coefficients of constructed multiple regression models for five restaurants

of each parameter. Although we actually confirmed that the accuracy of forecasting using machine learning with many unverified parameters is sometimes better than our method introduced above, it remains unclear how much each parameter affects the sales or number of customers because the constructed models are often too complicated for humans to understand. Acquired models using machine learning are sometimes a black box. When constructing a demand forecasting model, it is most important to choose adequate parameters considering that some parameters can have mutual multicollinearity. For example, because humidity and the amount of rainfall might have multicollinearity, we should verify those parameters carefully in advance. Moreover, effects of events on sales should be verified considering other factors. It is useful to check the degree to which sales have increased with a particular event using past data considering other factors such as the day of the week. Through those verifications, restaurant managers might have additional scientific hypotheses.

2.3 Customer Choice of Products and Menu Design

Customer choice of products in a restaurant is affected strongly by the menu book design. The menu book is an important touchpoint that provides various information about products and which gives messages from the restaurant to customers. Many variations exist in menu books, such as simple lists of dish names and prices, lists with pictures, or unprogrammed menus with recommendations or pop-up messages from restaurant.

Customers' choices of products are greatly affected by pictures of products, the position on the menu, recommendations, and prices. One major factor affecting customers' choice is expected to be the position of products on a menu book. Although a famous story of menu design is that the customer's eye movement often starts from the upper right to other positions on the menu, it might be not so simple in actual cases of restaurants (Bowen and Morris 1995; Yung 2012) because menu design varies according to countries and cuisine. Figure 2.5 shows a menu book of a Japanese cuisine restaurant chain. The number of the figure shows the sales rank of products included in each area of the menu book. Table 2.2 shows actual sales of products in each area in a certain period. Results show that product sales on the upper area of the menu book were greater than in the middle or lower areas.

However, many other factors such as the product name, picture, price, and pop-up recommendation can also affect customers' product choices. Therefore, the analysis above is insufficient to elucidate the effects of the menu book on the customer choice of product as an experiment. If one wants to verify factors in a scientific way, one must prepare some variety of menu books that use the same products with different layouts, although such experiments might not be easy for actual restaurant companies. A possible means of verifying various effects of the menu book on customer choice is the comparison of product sales made before and after changes of a menu book. Actually, many restaurant chains change their menu book seasonally.

Fig. 2.5 Product sales according to menu position. Number shows sales ranking of 6 areas

Table 2.2 Product sales by position

Upper left (9 items): 1816	Upper right (9 items): 2012
Middle left (14 items): 1110	Middle right (5 items): 544
Lower left (15 items): 1318	Lower right (11 items): 1280

Therefore, the authors conducted an experiment (Takenaka and Shimmura 2010). Figure 2.6 shows two lunch menus of a Japanese restaurant chain which mainly provides pork cutlets (Tonkatsu). This restaurant chain changed the lunch menu on the table during summer–autumn on September 21, 2009. We used purchase data of five restaurant shops that used the same menu, two months in all before and after the

Fig. 2.6 Two seasonal lunch menus of a Japanese pork cutlet restaurant

change in menu. We analyzed the effects of the change on product sales. The total sales on those menus during the two periods were almost equal (16034 vs. 16047). Therefore, the numbers of customers for both periods can also be regarded as almost equal. Based on those conditions, it might be reasonable to compare changes in all sales of some products that appeared on both menus while considering the change in menu design.

Product A on Fig. 2.6, for example, is the top-selling lunch set, which is also the least expensive product (680 Japanese yen) on both menus. This phenomenon coincides with the popular hypothesis that the upper left is the best position to catch the customer's eye. However, with the change in menu, the sales of product A went down 21%, although the product remained the top seller in the new lunch menu. However, product B (two products with different volumes) is a regular pork cutlet product. The position on the menu of B changed from the lower right to the upper left. Consequently, the sales of B increased by 12 and 15%. Those results in the change of sales of products A and B might be affected by the menu position. However, we also find a change in sales of products even if the positions were almost identical. The sales of product C increased by 10% on the new lunch menu. Probably, this change occurred because the picture and font size became larger. In this way, one can discuss the effects of menu book design on customer choice using large amounts of purchase data.

Another interesting finding of this experiment was the change in average customer spending. A restaurant industry representative reported to the author that Japanese customers tend to consider average prices of products on the menu, although the assertion was not proved. If this supposition is correct, then customers might roughly calculate the average price by checking some products on the menu. Figure 2.7 extracts price information from Fig. 2.6. If customer eyes could be attracted by the upper part of menu, then they might perceive average prices of products lower in the left menu. Actually, the average customer spending amount changed from 825 yen (left menu) to 844 yen (right menu). Although this hypothesis should be investigated further, the price on the menu is also expected to include important information for customers to choose products in a restaurant.

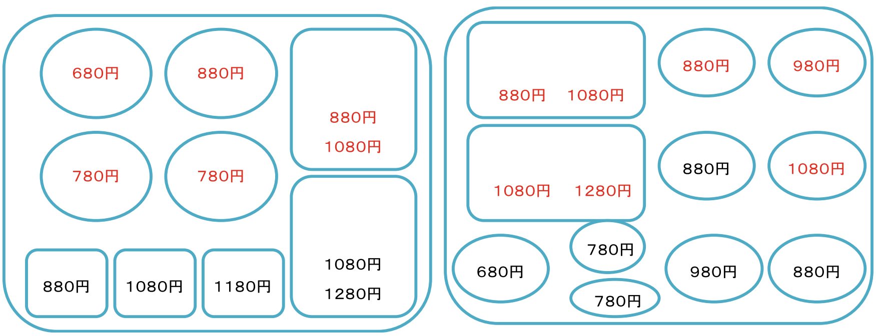

Fig. 2.7 Prices of products on two menus

2.4 Technology for Customer Contact

As discussed above, the menu book can strongly influence a customer's choice of products. However, other important problems persist even if we understand how customers choose products from a menu. Many customers, especially new customers, choose products based on their expectations rather than their experiences. Therefore, even a best-selling product is not necessarily the most satisfying product. Moreover, for modeling of customer needs and behaviors, one must consider the diversity of customer preferences and the reasons underlying customer satisfaction.

Against that backdrop, we introduced an interactive device using a tablet computer for customer contact. It recommends products and elicits data related to customer needs and satisfaction through natural interaction (Takenaka 2012, 2013). Figure 2.8 portrays screenshots of this device. The left panel shows promotion of some products. The right panel shows a customer satisfaction rating for a product after eating.

Figure 2.9 shows customer rating results for some products of a Japanese restaurant chain. The products are best-selling products of the restaurant chain according to comprehensive purchase data. Customers' subjective ratings vary according to the product type. For example, product A is a dish that includes tofu. Over 50% people awarded it a "Gold Prize". However, further investigation reveals that the satisfaction felt by repeat customers and new customers might differ. Figure 2.10 shows the difference of rating for the product. This product is appreciated more by repeat customers than by new customers. Moreover, other data acquired using this device show that repeat customers choose this product more often than new customers do. Therefore, this product has the potential to enhance customer satisfaction.

As discussed above, it is important to verify customers' decision-making mechanism of choosing a product and their evaluation of it after eating. The gap separating high expectations and lower evaluation can result in disappointment. Moreover, repeaters' choices of products give great information to elucidate product value even if they do not evaluate products explicitly.

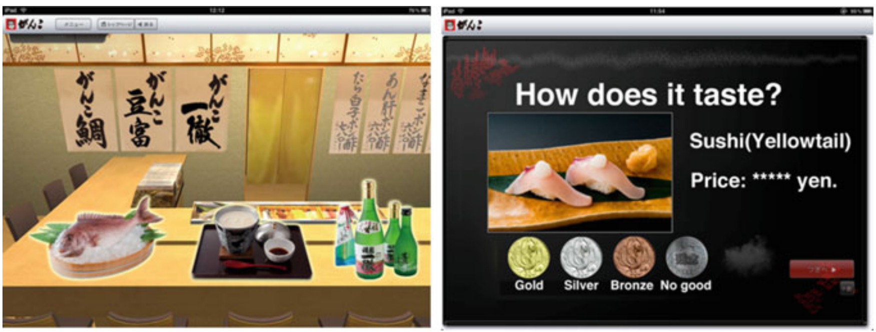

Fig. 2.8 Screenshots: promotion of products (left), customer satisfaction rating to each product after eating (right)

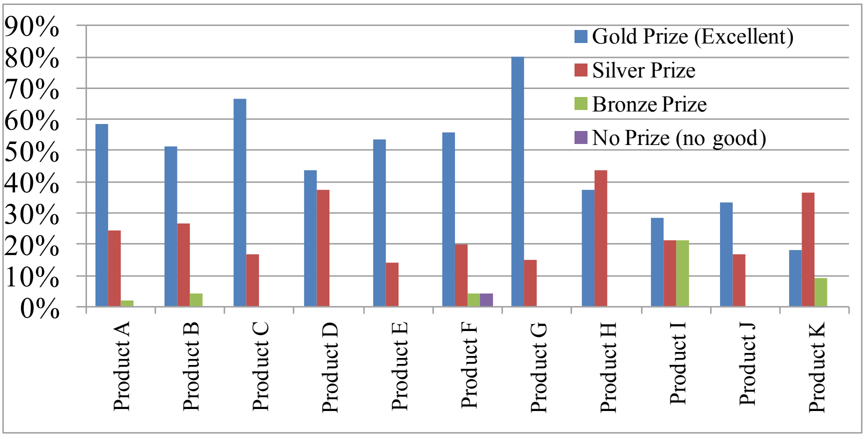

Fig. 2.9 Sample of customer ratings for hot-selling products of the restaurant chain

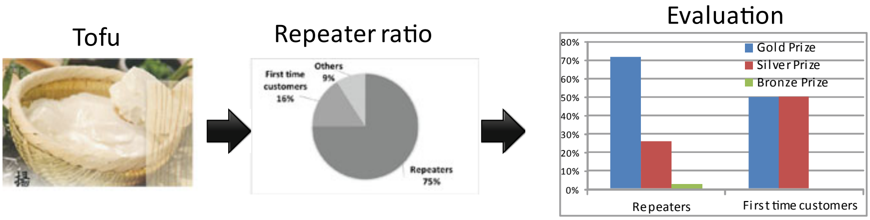

Fig. 2.10 Customer product ratings, comparing repeaters and new customers

2.5 Customer Satisfaction Mechanism

Earlier sections described how we can analyze customer behaviors based on data acquired at actual restaurants. For example, we can use purchase data combined with environmental data for demand forecasting, which is an important task for restaurant businesses. Moreover, it presents a research example of how one can verify the menu design effects for the customer's choice of products, combining menu design and purchase data.

However, it remains insufficient to elucidate customer needs and satisfaction because purchase data do not tell us why and which types of customers purchased those products. It is still not common in restaurants that each customer's behavior is recorded using membership systems, although recent rapid digital transformation including digital money might change the current situation in the near future. At present, it remains difficult for us to ascertain differences between behaviors of repeat customers and those of first-time customers. The research example of the customer contact device introduced in Sect. 2.4 highlights challenges to acquisition of customer feedback, including their on-site satisfaction.

Furthermore, customer satisfaction for a restaurant is not only affected by the quality of products (meals). Customers also evaluate other factors such as service quality, hospitality of staff members, and atmosphere of the restaurant including cleanliness. Overall satisfaction to a restaurant has often been represented by the willingness to revisit and willingness to recommend.

The authors have investigated those mechanisms underlying customer satisfaction to the restaurant based on large-scale mystery shopping survey data conducted by MS & Consulting Co. Ltd. A Structural Equation Modeling (SEM) method was used to analyze the relations among factors related to customer satisfaction. We used 3500 mystery shopping survey data of Japanese restaurants of several kinds including Japanese pub restaurants (Izakaya), family restaurants, and fast-food restaurants. We used many possible models through a trial and error process. Figure 2.11 presents a model that illustrates causal relations among factors related to customer satisfaction. We used some well-known measures of fit for the assessment of model fit, including Root Mean Square Error of Approximation (RMSEA) or Goodness of Fit Index (GFI). For this model, GFI was 0.923; RMSEA was 0.131. Most researchers concur that a GFI of 0.9 or more indicates good fit, although an RMSEA of 0.1 or more denotes a poor fit. Therefore, this model is not the best fit, but it can be a reasonable model.

As the model indicates, restaurant owners should enhance customer satisfaction to increase loyal customers who often revisit and recommend their restaurants to friends. For this end, not only satisfaction with products but also hospitality of staff members and atmosphere of restaurant including cleanliness are important. Moreover, continuous assessment of customer satisfaction based on behavior data and questionnaire survey data and long-term strategies to improve services are fundamentally important. Furthermore, it is important to consider customer diversity. CRM with individual customers will be more important for restaurants to survive and thrive in worldwide competition of restaurant businesses.

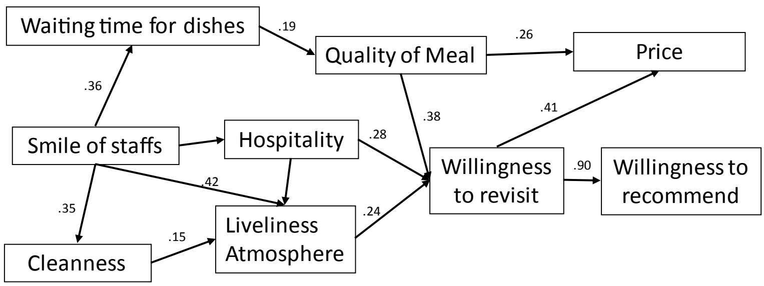

Fig. 2.11 Structure of customer satisfaction in restaurants

As introduced in this chapter, scientific methods based on actual data can help restaurant managers to create new services continuously based on changing customer needs.

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