Discrete Event Modeling for Operational Management of Restaurants

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Abstract

Models are a tool that allow us to simulate real life systems in a virtual environment to generate scenarios and observe how the system reacts. Restaurant management systems incorporate the concepts of RevPash and Menu Analysis to support difficult decisions in pricing, promotions and resource management. In this paper, using Arena 14.0 software, a discrete event model was designed that incorporates the above concepts and simulates the operations of a restaurant. Based on the proposed model, measures were proposed to improve the restaurant's profitability and scenarios were designed with the possible effects. The value of this proposal lies in the economic advantage that can be obtained with the application of models and Menu Analysis in restaurant management.

Keywords
Simulation, Restaurant Management, RevPash, Menu Analysis and Operations Management.

1. Introduction
Over the last decades, the restaurant industry has experienced a significant growth, mainly in Latin America, where local gastronomy plays an important role in tourism development. According to Kim et al. (2020), the restaurant sector comprises 10% of the workforce in the Americas. In the United States alone, jobs increased from 11.9 to 14.7 million between 2004 and 2017, likewise, industry revenues increased by 81.55%. This boom was expressed in multiple ways in countries such as Peru, for example, where a gastronomic boom was generated that led more than 80,000 young people to choose to study in culinary schools (Matta, 2021).

Despite this formidable growth, restaurant business came to a complete standstill for months due to the global health pandemic generated by COVID-19. This health crisis led to a global economic crisis, impeding tourism and forcing the closure of businesses with physical locations. The economic impact was most severe on low-income households, family businesses and tourism-related companies, where restaurants are located (Gkoumas, 2021). The new situation forced thousands of gastronomic businesses to cease operations and led many others to adapt their operational management to the restrictions and new consumption habits. The most important challenge for the sector is to offer the same value proposition and satisfy customers with a high-quality level of service despite the mandatory prevention measures, since visiting a restaurant has always been more than just satisfying the basic need for food (Madeira et al., 2021).

Faced with this challenge, businesses are looking to maintain their service standards while reducing costs. According to Vieira et al. (2018), low revenue is a problem that becomes more acute if there is also low operating profitability. For that reason, many restaurants reduce the budget of fundamental resources without having the opportunity to analyze the real impact it generates on the business. Considering the current market context, the analysis of operational factors is much more critical for financial viability and is vital in building strategies. It is important to know the business in its entirety; however, according to Heo (2017), traditional operational management indicators do not show the true performance of the company and do not evaluate it correctly. Therefore, appropriate KPIs must be used, which allow multiple variables and efficiency ranges to be related, in addition to being reliable in the face of market uncertainty and compliance with sanitary measures imposed by the authorities.

These needs can be addressed from multiple perspectives. For years, corporations have been creating operational assessment systems and have conclude that not all businesses respond in the same way. As mentioned by Vergara et al. (2019), the complexity of building such systems lies in the randomness of the variables and in identifying how they are related. As a result, modeling with discrete events fits as an adequate methodology to generate an integral system that relates all these variables. In Figure 1, a flowchart presents the study methodology and how discrete event modeling is applied using complex indicators, in order to embrace these industry challenges presented.

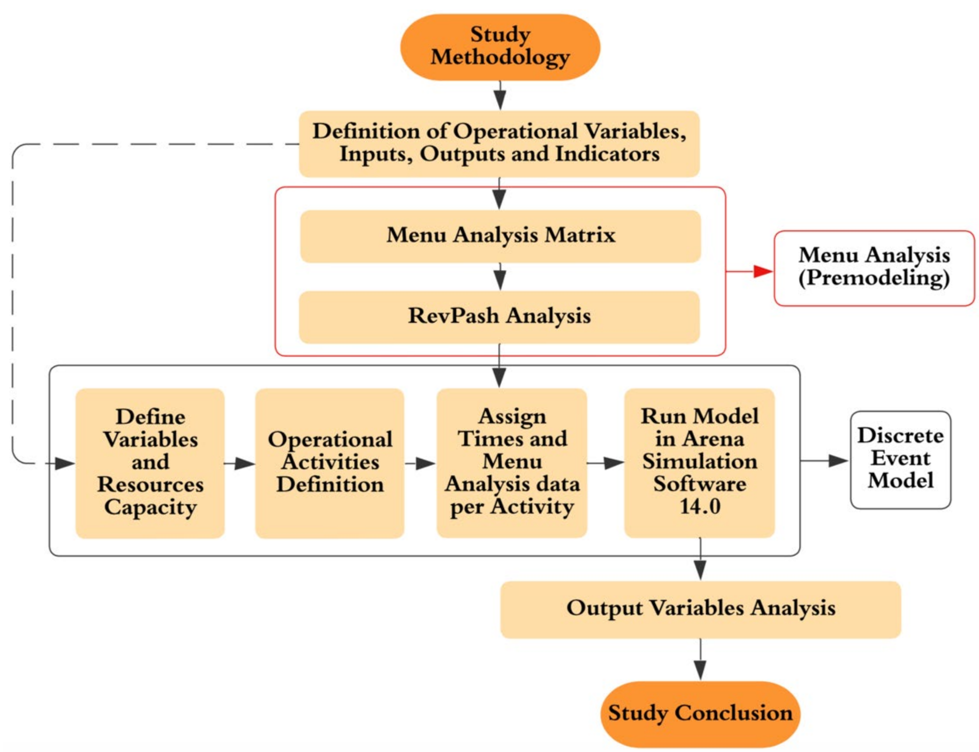

Figure 1. Study Methodology Stages

1.1 Objectives
The main objective of this study was to develop a discrete event model that allows the simulation of post-pandemic operational management of restaurants in order to explain how the context affects the factors of the operations of this type of business, by identifying the most important to guarantee the maximization of profitability in the framework of the new normality.

2. Literature Review
As for all companies, the fundamental objective of restaurants is to optimize their operations to maximize profits. In this regard, Legg et al. (2019) mention that it is not possible to think about improving a process without having an adequate way to measure its performance. They also state that, currently, the most popular indicators to evaluate the management of a restaurant are the Average Turnover per Customer, the Occupancy Rate and the Level of Customer Satisfaction. However, the operation of a restaurant can be synthesized into two factors: the profit obtained from the sale of each dish and the occupancy time of its capacity, which leads to inconsistency, since none of the indicators mentioned combine both factors.

It is for this reason, that Yoonjoung (2017) suggests that restaurant management should be evaluated by a better indicator: RevPash (Revenue per Available Seat Hour), which allows measuring the marginal revenue per unit of time-capacity. To measure and improve the RevPash of restaurants, a discrete event model was developed in the simulation software Arena, since, as mentioned by Vergara et al. (2019), the simulation of discrete events allows the understanding of a system and optimizing its management. The validity of the model was demonstrated by statistical analysis of performance indicators obtained from several simulations under different circumstances and parameters.

This performance evaluation in operational management is not oblivious to market trends. The food sector and restaurants are included in the tourism sector, being essential in the development of hospitality and cultural experience of cities in Latin America. The study conducted by Alonso-Almeida et al. (2015) shows that there is an experiential perspective to measure customer satisfaction, and this perspective varies according to the tourism trend of a locality. With the absence of tourism due to COVID-19, there is no experiential perspective. Erkmen (2019) contributes to this conclusion by noting that, due to the importance of the growth of local gastronomy as a tourism destination attribute, it is crucial to understand what factors contribute to the culinary experience and how this influence traveler satisfaction.

However, these authors focused on an analysis of the most superficial factors of restaurants, considering their value proposition and customer-facing strategy without evaluating the operational implications that this entail. As mentioned by Heo (2017), comprehensive operational indicators are the foundation of the service organizational structure. Not only do they represent how healthy the business is, but they are also the basis for offering differentiation to the target audience.

Operational management starts from understanding the information and resources needed in each step of the service process and in each physical space of a restaurant (Padilla-Solís & Cossa-Cabanillas, 2011). There is a coincidence with Vieira et al. (2018) when it comes to divide this service process and generating a flow, given that both break down operational management into three aspects. The first one is the planning of operations, where a forward projection of the demand is made, therefore, of the resources that will be needed to meet that demand. The second is the execution of operations, where the performance of the customer service processes are evaluated, from the moment the customer arrives at the restaurant until he leaves. Finally, the third aspect is profitability optimization techniques and variable integration systems. Vergara et al. (2019) propose in their discrete event simulation study that the relationship between these processes and the effectiveness in the use of resources impact the efficiency of a model, and that the objective of the model is to achieve the desired level of service.

The purpose of a discrete event model is to simulate the management of a restaurant, not only with operational indicators, but also considering market variables and analyzing competitiveness (Parsa et al., 2019). The objective of considering these variables is that restaurants must have the ability to respond to external crises, in which entrepreneurs cannot control the changes in their environment. Something in line with that is what is currently experienced with COVID-19, where restaurants cannot control the health measures imposed by the government and the growth of new consumption trends by the population (Madeira et al., 2021). Although there have already been many global health crises like the current one, including some with a greater impact on the tourism industry, the current pandemic has different patterns, achieving a social immobilization as never seen before in history (Muller, 2020).

3. Methods

To develop a discrete event model for the simulation of post-pandemic operational management of restaurants, a four-phase methodology was used. First, the variables were determined, defining the input and output data, as well as the key indicators for the model. Subsequently, in the second stage, a first study of the data obtained from operational management was carried out through menu analysis, taking as a reference a restaurant that adapts to the characteristics studied. Then, the third phase of the methodology was the creation of the simulation model using Arena Simulation Software 14.0, this stage being the most important for the research. Finally, the fourth stage included a final analysis and results discussion. These four phases are summarized in Table 1 below:

Table 1. Phases of the proposed methodology

Phase	Scope	Tool
1. Variables definition	Definition of key inputs, outputs and indicators for the creation of the model.	Check List
2. Menu Analysis application	Initial study of data from a Latin American restaurant through Menu Analysis and RevPash indicator.	Menu Analysis, RevPash
3. Modeling	Creation of the Discrete Event Model in simulation software.	Arena Simulation Software 14.0
4. Final analysis	The results were discussed to propose improvements.	Graphic material

3.1 Variables Definition

To properly develop a discrete event model, it was important to recognize the input and output variables. The definition of variables of the model used for this simulation was based on the observation and analysis of the system under study (the restaurant). The main input variables are presented below in Table 2:

Table 2. Model input variables

Variable	Indicator
Demand per hour	Number of customers
Discount per plate	Percentage discount
Simulation time	Simulation hours
Simulation time of day	Simulation start time
Price per plate	Price per plate
Capacity per resource	Quantity per resource
Contribution margin per plate	Contribution margin per plate

The variables described above form the input of the model, which vary according to each restaurant, and this information allows the model to be adapted to different branches and businesses. However, since the 3 simulated scenarios represented the same restaurant, the only variables that were manipulated between each simulation were the demand per hour and the discount per plate. Regarding the output of the model, 2 output variables were taken into consideration with their respective indicators, which are shown in Table 3.

Table 3. Model output variables

Variable	Indicator
Weekly Income	Weekly Income (S/)
Profitability	RevPash

4. Data Collection

A menu is a marketing tool that presents the list of available food and beverages offered by a restaurant. Depending on the options listed on the menu, it represents the totality of purchasing, production, service and marketing decisions for a restaurant. Therefore, it shows the importance of monitoring the performance of each menu item and its specifications in optimizing profitability (Ozdemir & Caliskan, 2014). A common method used by restaurants to review menu effectiveness is the Menu Analysis technique. This technique evaluates the performance of menu items and supports the decision-making process when modifying or introducing new items. Proper menu management essentially contributes to the short-term profitability of the restaurant and aims to increase the contribution margin of each item offered.

4.1 Menu Analysis application

For the proposed study, information was obtained from six menu items of a Latin American restaurant. It was decided to use the dishes shown in Table 4, because they represent the restaurant's entire value proposition and because they are the dishes with the most historical information available.

Table 4. Menu Analysis Matrix

Item	Average Weekly Sales	Popularity	Price (S/)	Margin (%)	Gross Sale (S/)	Net Sale (S/)	Contribution
Beef Sticks	68	Low	20.90	53.59%	1,421.20	761.60	Low
Lomo Saltado	47	Low	45.90	53.92%	2,157.30	1,163.25	Low
Chicken with Potatoes	630	High	25.90	66.80%	16,317	10,899	High
Duck with Rice	151	Medium	51.90	69.36%	7,836.90	5,435.67	High
Classic Salad	522	High	19.90	67.24%	10,387.80	6,984.76	High
Corleone Beef	140	Medium	57.50	63.30%	8,050	5,095.65	High
Total	1,832	-	-	-	46,179.20	30,339.93	-

The classification of the menu items was key in the assignment of scenarios that are simulated in the model. The popularity and contribution of each item allowed us to evaluate the impact they have on profitability.

The restaurant business is based on the combination of two factors: the sale of products, which in this case refers to the dishes and beverages on the menu, and the occupancy time of the local capacity (Padilla-Solís & Cossa-Cabanillas, 2011). Since people tend to eat their main meals, breakfast, lunch and dinner, at certain times of the day, it is inefficient to evaluate the profitability of a restaurant without considering the time factor. It is due to this particularity that RevPash (Revenue per Available Seat Hour) is one of the most appropriate indicators to evaluate the operational management of restaurants, since it measures the marginal contribution per unit of capacity-time.

RevPash is a time-dependent indicator, so the first step in its calculation is to determine the length of the intervals or time periods in which to obtain its values. Likewise, this indicator requires three pieces of information for each customer or group of customers served by the restaurant, which are the start time of the service, the amount paid for everything consumed and the end time. If a customer has stayed in the restaurant for more than one time interval, the amount of his consumption should be distributed among the periods during which he was occupying a table, according to the minutes corresponding to each interval. The RevPash value for each period is the sum of all the amounts or fractions of amounts that were consumed during that time, divided by the available capacity. An example of the calculation of the RevPash is shown below.

In Table 5, data from four customers is presented, with their respective amount spent, start time and end time. This information is helpful to evaluate the RevPash of the restaurant during these four services. In Table 6, RevPash based on the four amounts and 30-minute time intervals from 12:30 to 14:00 hours are shown, showing more details about this indicator.

Table 5. Data for RevPash calculation

Customer	Amount (S/)	Start Time	End Time
1	76.00	12:38	13:22
2	100.00	12:45	13:45
3	84.00	13:00	14:00
4	121.00	13:20	14:25
Total	381.00	-	-

Table 6. RevPash values per time interval

Customer	12:30 - 13:00	13:00 - 13:30	13:30 - 14:00	14:00 - 14:30
1	38.00	38.00	0.00	0.00
2	25.00	50.00	25.00	0.00
3	0.00	42.00	42.00	0.00
4	0.00	18.62	55.84	46.54
Total column	63.00	148.62	122.84	46.54
RevPash	4.20	9.91	8.19	3.10

To better understand how the distribution of an amount is made when a customer occupies more than one time interval, we will show the calculations of the distribution of customer 4. This means that his stay in the restaurant is made up of the last three-time intervals. To allocate the amount between these intervals, the time in minutes that the customer spent in each interval is divided by the duration in minutes of the service, which was 65, and finally the quotient is multiplied by the respective amount spent. The mathematical operations are shown below

$$\text{Interval } 13:00 - 13:30 \ \rightarrow \ \frac{10}{65} \times 121 = 18.62$$

$$\text{Interval } 13:30 - 14:00 \ \rightarrow \ \frac{30}{65} \times 121 = 55.84$$

$$\text{Interval } 14:00 - 14:30 \ \rightarrow \ \frac{25}{65} \times 121 = 46.54$$

The values calculated above coincide with the total amount spent by the customer (121.00). It is important to mention that for this example the capacity of the restaurant was set at 15 seats, so to calculate the RevPash for each time interval the total column in Table 6 was divided by 15.

4.2 Modeling

In the previous phase, using the Menu Analysis and the RevPash study, two fundamental factors were determined for this research. The first one is the dishes whose prices will be subject to discounts and the second one is the strategic time ranges during which those discounts will be applied. To determine the impact that the application of these discounts will have on the restaurant's operations and profitability, a discrete event model was built, which simulates the system in question accurately.

The main advantage of using simulation tools is that they make it possible to recreate a system very close to reality in a virtual environment (Hao et al., 2020). They also allow modifications to be made to the system quickly and without incurring additional costs, instead of having to invest time and money in making such changes in the real system. This makes possible to generate various scenarios of the changes that the system could undergo based on changes in certain parameters or variables, and then analyze each one of them, compare them and finally decide on what will be applied.

With the simulation model, three scenarios were generated by modifying two parameters from the current situation: dish discounts and restaurant demand. The discounts applied to certain dishes were determined by the restaurant's manager, so they are an independent variable; they were determined to be 20%. The extent to which demand varied in response to the discounts applied is unpredictable and uncontrollable, making it a dependent output variable. Three possible cases of how demand could react were considered: no change at all, medium increase and high increase.

The model is flexible, since by changing the parameters, it is able to adapt to the reality of almost any restaurant in an adequate manner. It is a discrete event, non-stochastic model, developed in Arena Simulation Software 14.0, whose main characteristics are the following:

- It considers waiters, cooks, tables and receptionists as resources, allowing the experimenter to modify how many of each there will be.
- It shows the possible impacts that the application of discounts at strategic times would have on the profitability of the restaurant.
- Allows you to set a maximum waiting list size.
- It provides all the necessary information for the calculation of RevPash, total revenue, average length of service and average waiting time.
- Assumes that customers arrive individually or in groups of 2 to 6 people.
- Assume that each customer consumes only one dish from the restaurant's menu.

In order to understand better the model created, it is separated into three main sections. The first one can be seen in Figure 2, begins with the arrival of customers to the restaurant and ends when the waiter takes note of the order and the registration of it in the restaurant's system.

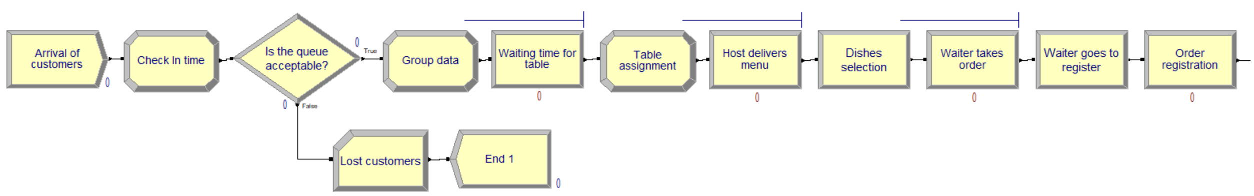

Figure 2. First Section of Model

The second section is showed in Figure 3, contains all the modules that represent the cooking of the dishes and every other activity since the registration of the order until the waiter delivers the dishes to the customers.

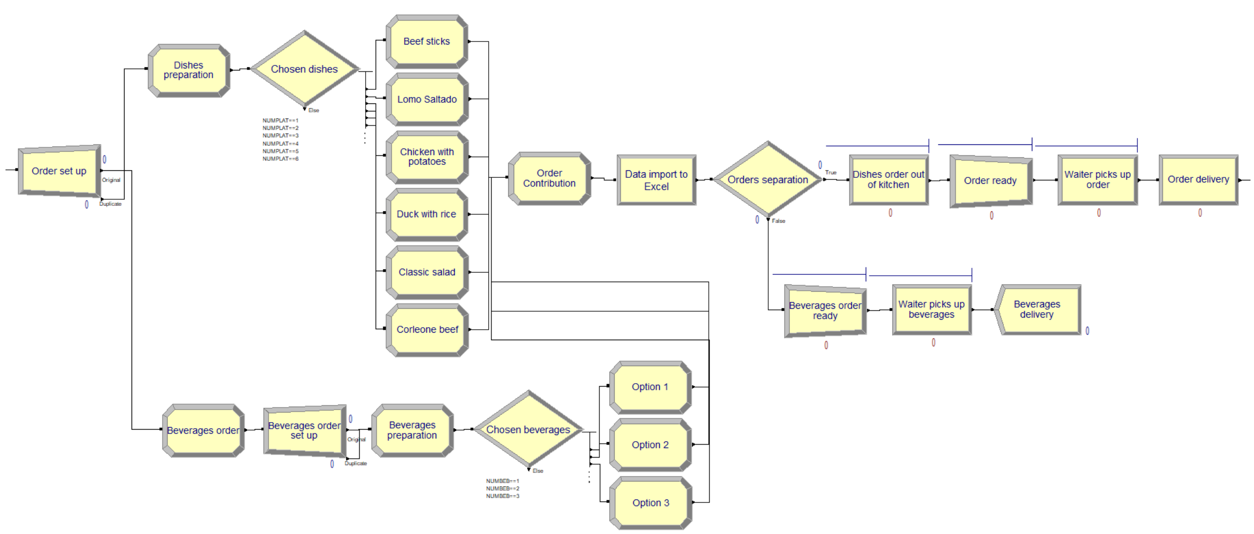

Figure 3. Second Section of Model

The third and last section of the model can be seen in Figure 4, includes the consumption of the food, the payment of the check and when the customers leave the restaurant.

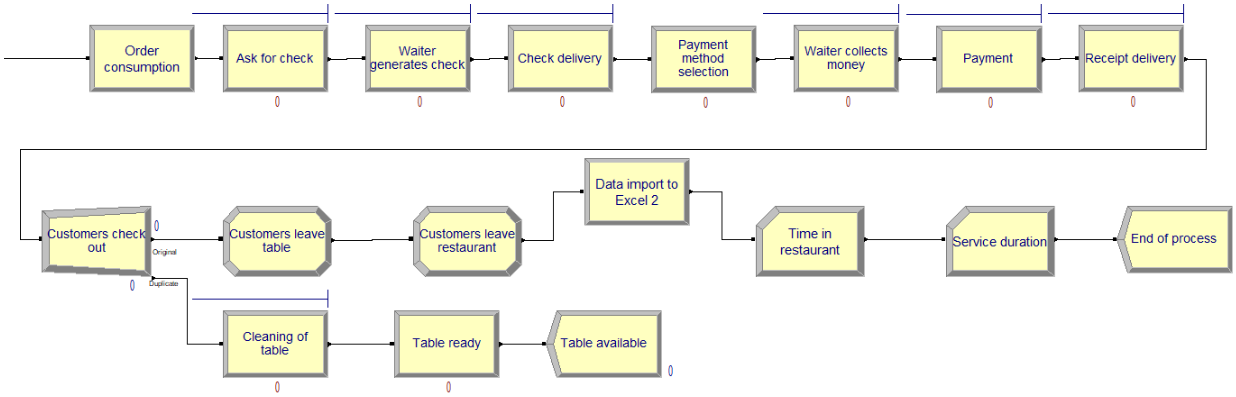

Figure 4. Third Section of Model

The first simulation to which the model was subjected was one that represented the current situation of the restaurant that was studied. The data on daily demand, prices of dishes, number of tables, number of waiters, among others, were obtained directly from the daily operations of the restaurant. As mentioned above, the two indicators that will be analyzed for all simulations are RevPash and weekly revenues. Likewise, each simulation will represent a full week of restaurant operation, from Monday to Sunday; however, only the time range from 12:00 a.m. to 6:00 p.m. will be considered, since these are the main lunch hours. Both indicators obtained from the first simulation, using thirty-minute ranges for the calculation of RevPash, are shown in Table 7:

Table 7. Current situation simulation indicators (RevPash)

Time Range	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
12:00 - 12:30	1.86	1.14	2.48	1.52	2.15	1.51	1.32
12:30 - 13:00	4.25	4.06	3.79	3.70	3.91	3.74	4.13
13:00 - 13:30	5.22	6.33	5.38	5.40	4.84	5.20	6.21
13:30 - 14:00	6.33	6.88	6.10	6.25	5.93	6.25	6.37
14:00 - 14:30	5.98	6.04	5.85	6.15	6.45	6.60	5.84
14:30 - 15:00	5.41	5.87	5.54	5.54	5.79	5.90	5.69
15:00 - 15:30	5.00	5.41	5.06	5.30	5.12	5.20	5.28
15:30 - 16:00	4.70	4.78	4.67	4.99	4.94	5.04	4.87
16:00 - 16:30	4.35	4.29	4.55	4.79	5.03	5.11	4.49
16:30 - 17:00	4.11	4.10	4.75	4.60	4.83	4.61	4.22
17:00 - 17:30	4.15	3.89	4.40	4.78	4.28	4.23	4.23
17:30 - 18:00	4.36	3.99	4.08	4.47	4.50	4.00	4.04
					Weekly Income		56,186.90

From the results shown above, it can be determined that, on average, the hour with the lowest RevPash throughout the week is from noon to one o'clock in the afternoon. However, it is in this range when the first customers of the day start arriving, so this time was not considered for the analysis. That said, the second time interval with the lowest RevPash is from five to six o'clock in the afternoon, so the discounts applied to the menu were valid only during that time range. The change made to the model for the next simulation was to apply a 20% discount, from five to six o'clock, to the two most popular dishes: a quarter chicken and potatoes and the classic salad. The second simulation represents a pessimistic scenario, in which, despite the discounts applied, the demand did not change, and the results were as follows in Table 8:

Table 8. Simulation indicators (RevPash) with no increase in demand

Time Range	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
12:00 - 12:30	1.86	1.14	2.48	1.52	2.15	1.51	1.32
12:30 - 13:00	4.25	4.06	3.79	3.70	3.91	3.74	4.13
13:00 - 13:30	5.22	6.33	5.38	5.40	4.84	5.20	6.21
13:30 - 14:00	6.33	6.88	6.10	6.25	5.93	6.25	6.37
14:00 - 14:30	5.98	6.04	5.85	6.15	6.45	6.60	5.84
14:30 - 15:00	5.41	5.87	5.54	5.54	5.79	5.90	5.69
15:00 - 15:30	5.00	5.41	5.06	5.30	5.12	5.20	5.28
15:30 - 16:00	4.70	4.78	4.67	4.99	4.94	5.04	4.87
16:00 - 16:30	4.35	4.29	4.55	4.79	5.03	5.11	4.49
16:30 - 17:00	4.11	4.10	4.75	4.60	4.83	4.61	4.22
17:00 - 17:30	4.02	3.78	4.25	4.65	4.25	4.15	4.03
17:30 - 18:00	4.12	3.85	3.98	4.39	4.29	3.85	3.88
					Weekly Income		54,174.20

While it is impossible to determine exactly how much demand will vary based on the discounts applied, the third simulation assumed a moderate 15% increase in daily demand for the restaurant from five to six o'clock in the evening. The results of the second simulation are shown in Table 9:

Table 9. Simulation indicators (RevPash) with a 15% increase in demand

Time Range	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
12:00 - 12:30	1.86	1.14	2.48	1.52	2.15	1.51	1.32
12:30 - 13:00	4.25	4.06	3.79	3.70	3.91	3.74	4.13
13:00 - 13:30	5.22	6.33	5.38	5.40	4.84	5.20	6.21
13:30 - 14:00	6.33	6.88	6.10	6.25	5.93	6.25	6.37
14:00 - 14:30	5.98	6.04	5.85	6.15	6.45	6.60	5.84
14:30 - 15:00	5.41	5.87	5.54	5.54	5.79	5.90	5.69
15:00 - 15:30	5.00	5.41	5.06	5.30	5.12	5.20	5.28
15:30 - 16:00	4.70	4.78	4.67	4.99	4.94	5.04	4.87
16:00 - 16:30	4.35	4.29	4.55	4.79	5.03	5.11	4.49
16:30 - 17:00	4.11	4.10	4.75	4.60	4.83	4.61	4.22
17:00 - 17:30	4.17	3.95	4.45	4.89	4.35	4.35	4.44
17:30 - 18:00	4.42	4.03	4.15	4.56	4.62	4.12	4.21
					Weekly Income		57,573.10

In the third simulation it was assumed that the discounts applied would generate a slight increase of 15% in demand; however, there is also the possibility that these discounts would generate a high increase in the number of customers attending the restaurant between five and six o'clock. The fourth simulation will also work with a 20% discount for the same dishes and time interval as the first scenario, but the difference will be that the increase in demand will be 30%, which is a much more optimistic scenario. The impact of this increase in demand on the two indicators is shown in Table 10:

Table 10. Simulation indicators (RevPash) with a 30% increase in demand

Time Range	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
12:00 - 12:30	1.86	1.14	2.48	1.52	2.15	1.51	1.32
12:30 - 13:00	4.25	4.06	3.79	3.70	3.91	3.74	4.13
13:00 - 13:30	5.22	6.33	5.38	5.40	4.84	5.20	6.21
13:30 - 14:00	6.33	6.88	6.10	6.25	5.93	6.25	6.37
14:00 - 14:30	5.98	6.04	5.85	6.15	6.45	6.60	5.84
14:30 - 15:00	5.41	5.87	5.54	5.54	5.79	5.90	5.69

15:00 - 15:30	5.00	5.41	5.06	5.30	5.12	5.20	5.28
15:30 - 16:00	4.70	4.78	4.67	4.99	4.94	5.04	4.87
16:00 - 16:30	4.35	4.29	4.55	4.79	5.03	5.11	4.49
16:30 - 17:00	4.11	4.10	4.75	4.60	4.83	4.61	4.22
17:00 - 17:30	4.21	4.05	4.59	5.01	4.46	4.69	4.62
17:30 - 18:00	4.54	4.15	4.23	4.78	4.79	4.45	4.59
					Weekly Income		61,233.70

5. Results and Discussion

The use of price and profitability optimization systems in restaurants has been discussed by multiple researchers, who approach the subject in different ways and using different tools. The main objective of the present study was to develop a discrete event model that allows the simulation of the operational management of restaurants; after developing the model, it was not only possible to successfully simulate operations, but also to evaluate the impact in operational indicators such as RevPash based on different scenarios.

From the results of the simulation model, under the controlled conditions of increased demand imposed in each of the scenarios, the correct management of discounts allows restaurants to increase their revenues. The value of the discount to be applied is determined by the restaurant's manager, while the time interval for which it will be valid is entirely part of the RevPash analysis. With the results obtained, it was found that this indicator has a direct relation with the weekly revenue generated by the business, a statement that had been exposed by Yoonjoung (2017), in his study of performance indicators in the restaurant industry. This relation is proved in Table 11:

Table 21. Indicators per simulation scenario

Scenario	Average RevPash	Weekly Income (S/)
Initial situation	4.74	56,186.90
Discount without increase in demand	4.72	54,174.20
Discount with 15% increase in demand	4.76	57,573.10
Discount with 30% increase in demand	4.79	61,233.70

In the case of the first scenario, in which the discounts were applied without perceiving an increase in demand, the average RevPash and weekly revenues decreased. This is logical since the number of customers remained constant in relation to the initial situation but the prices of two dishes decreased from five to six o'clock in the afternoon every day, generating a lower value of weekly sales.

As can be seen in Table 11, an improvement in RevPash translates into a better utilization of the restaurant's capacity per working hour, which generates an increase in weekly income. In the second scenario, despite the application of discounts, the average RevPash and weekly income increased because the effect of lower prices was compensated by a greater number of customers, i.e., a higher volume of sales. In the last scenario, under an optimistic perspective, the correct use of discounts allowed the restaurant to increase its revenues by 9% by simply improving its capacity utilization by 1.05%, without the need for a capital investment or the designation of a greater amount of resources.

The study also identified that the hours with the lowest RevPash are the most appropriate for the application of discounts on the restaurant's most popular dishes, which is why a 20% discount was applied between five and six o'clock in the afternoon to the chicken quarter and the classic salad (dishes with the highest popularity). This fact had already been proven by researchers Padilla-Solís and Cossa-Cabanillas (2011), who proposed that dishes with high popularity and good marginal contribution should have a discount in their price during off-peak hours, thus improving demand in that period and consequently capacity utilization. This theory was presented in their study as Menu Engineering, and they built a proposal to base commercial decisions on the four main marketing fundamentals: pricing, product, promotion and place, variables that can also be included in a model and showed in Figure 5:

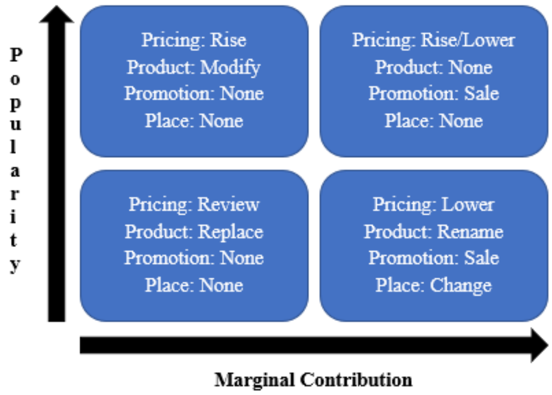

Figure 5. Menu Engineering Matrix

It is also important to highlight the limitations of the model presented. In the discrete event simulation study presented by Vergara et al. (2019), it is possible to measure the desired service level, the competitiveness of the business and make decisions based on resource efficiency. For a future study, it would be important to consider other variables that allow a more in-depth evaluation of operational management and thus obtain indicators that strengthen decision-making, such as utilization per worker and service and waiting times; indicators that would increase weekly income and reduce operational expenses.

Finally, it should be recognized that the results of the model are subject to the randomness of the simulation and that its application may differ in real cases. It is not possible to predict exactly what will happen, but it is possible to generate results that approximate the behavior of indicators such as RevPash and weekly income based on the conditions being considered in the scenarios.

6. Conclusion

This research has documented the simulation of the operational management of a restaurant in Peru. The data used were collected through field observations and with the consent of the company. In that sense, a discrete event model was developed to represent the operations system, quantifying the main variables related to the service offered to customers and the capacity of the premises. The model was used to simulate alternative scenarios of demand variation in the face of the implementation of discounts on the restaurant's dishes during the hour with lowest demand.

The results obtained show that, based on the premise that a discrete event simulation model allows improving the operational management of restaurants, this tool does contribute to decision making in the improvement of performance in this industry. As can be seen in the second and third scenarios, the correct use of discounts in the menu leads to an increase in weekly revenue, if the behavior of demand is favorable according to the simulated conditions.

With respect to the indicators evaluated, it can be concluded that RevPash is a fundamental indicator in the operational analysis of this industry. Not only does it allow us to evaluate the current situation of a restaurant, but also its direct relationship with revenues and the efficient use of resource capacity allow us to consider it as a business driver.

It is important to recognize the limitations of a simulation model and the challenge for future research will be to be able to predict more complex scenarios based on multiple situations. So that the model can contribute to the growth of the industry, especially in times when COVID-19 has stagnated its growth. The reports have been presented to the restaurant's management team with the objective of contributing to its operational management and fostering this growth. Likewise, it is also expected to contribute to the simulation community, especially to users of the Arena Simulation Software tool with modeling situations like those presented in this research.

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