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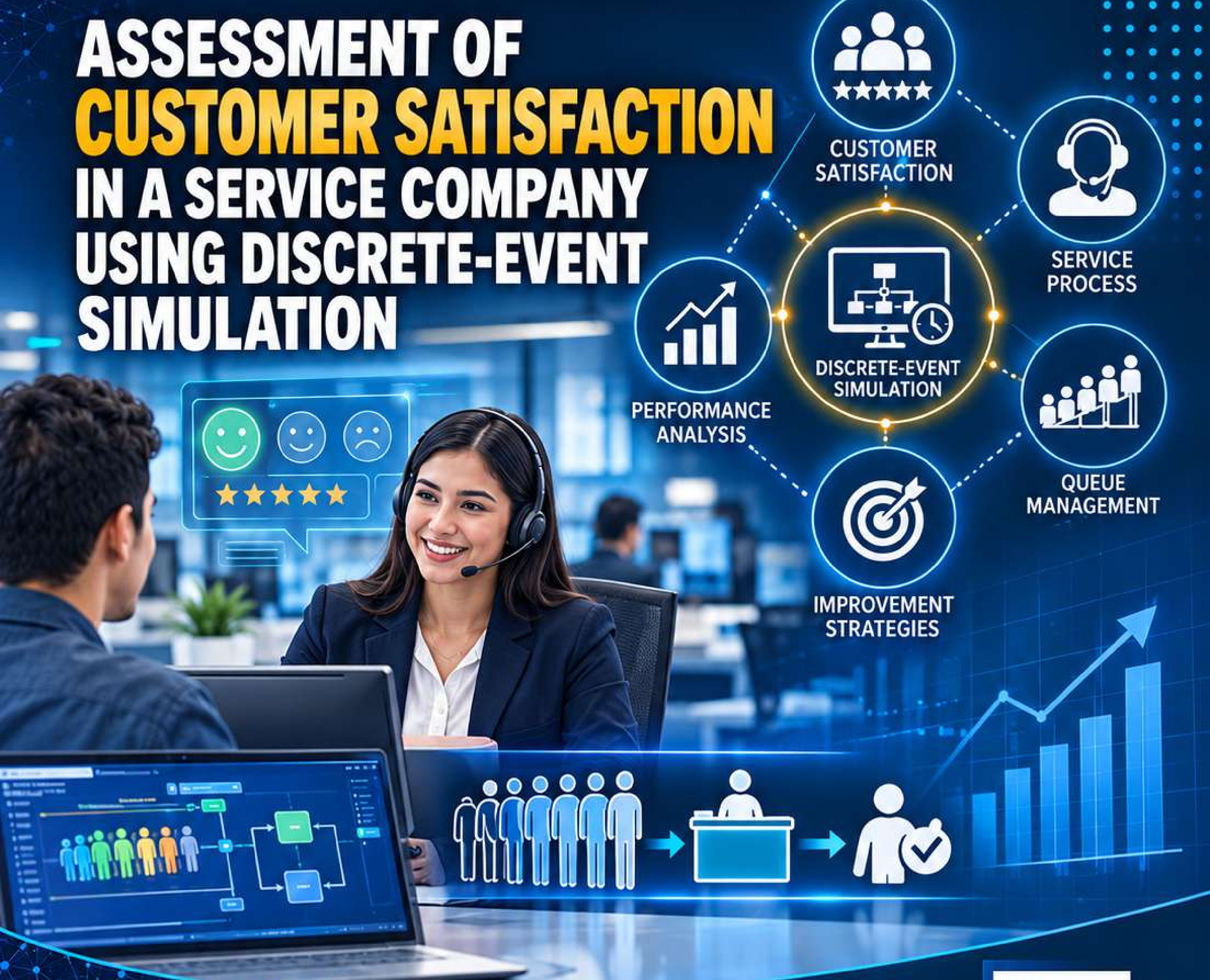

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ASSESSMENT OF CUSTOMER SATISFACTION IN A SERVICE COMPANY USING DISCRETE-EVENT SIMULATION

EVALUACIÓN DE LA SATISFACCIÓN DEL CLIENTE EN UNA EMPRESA DE SERVICIOS APLICANDO LA SIMULACIÓN DE EVENTOS DISCRETOS

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Abstract— This article presents an analysis of wait times in the university cafeteria using ProModel. The simulation shows that even when the cafeteria's capacity demand is met (in this case, with 75% efficiency and no customer abandonment), the distribution of time within a single resource provider can operate inefficiently. Customers wait an average of nearly 12 minutes to receive a service that takes 9 minutes and 306 seconds longer than it should, which lowers their assessment of service quality.

The researchers used the SERVQUAL framework to determine that the issue was not a lack of resources, but rather a misalignment between peak demand and service supply. Instead of hiring more employees, their recommendation is to implement flexible scheduling with the current workforce during peak hours. Finally, they recommended that future research integrate these simulations with direct assessments of customer satisfaction.

Keywords— Mathematical model, Quantitative method, Service enterprise, Simulation, Statistical analysis.

Resumen— Este artículo presenta un Análisis del tiempo de espera en el comedor universitario utilizando ProModel. Puede observarse a partir de la simulación que incluso cuando se satisface la demanda de capacidad del comedor (en este caso, con un 75% de eficiencia y sin abandono de clientes), la distribución del tiempo dentro de un único proveedor de recursos puede operar de manera ineficiente. Los clientes permanecen en espera durante un promedio de casi 12 minutos para recibir un servicio que dura 9 minutos 306 segundos más de lo que debería tardar lo cual reduce su evaluación de la calidad.

Los investigadores utilizaron el marco SERVQUAL para determinar que no se trataba de una falta de recursos, sino de una desalineación entre la demanda máxima y la oferta de servicio. En lugar de más empleados, su recomendación es la programación flexible con la fuerza laboral actual durante las horas pico. Por último, recomendaron que las investigaciones futuras integren estas simulaciones con evaluaciones directas de la satisfacción del consumidor.

Palabras Clave— Análisis estadístico, Empresa de servicios, Método cuantitativo, Modelo matemático, Simulación.

INTRODUCTION

For enterprises that rely on providing services to generate revenue, customer satisfaction is the most core performance indicator, which directly links three key dimensions that determine the survival or demise of an enterprise: the first is whether customers will continue to choose the enterprise's services, that is, customer retention; the second is the public's evaluation of the enterprise's brand, that is, brand reputation; the last is whether the enterprise can avoid the risk of being eliminated by the market and sustain its operations long-term. To maintain its competitiveness in a fiercely competitive market, an enterprise must never arbitrarily modify its existing service processes after all, even adjusting a queuing numbering rule or adding a new service window could trigger chain reactions across the entire system and cause disruptions. Before actually implementing any changes to real-world processes, the enterprise must first obtain a reliable tool to simulate in advance all scenarios that may arise in the entire service process after the changes, identify potential problems, and only then proceed with implementation.

Discrete-event simulation, referred to as DES, is exactly such a quantitative analysis tool. It does not require the enterprise to conduct any experiments in its physical brick-and-mortar stores or service outlets. Instead, it only requires building an identical simulation model of the real service system, and then this virtual model can be used to calculate all operational metrics that the enterprise cares about: for example, how many people will queue up, how long everyone will wait to receive service, the maximum business volume that the entire system can handle, and whether resources such as labor and site space are being utilized efficiently. The entire process of calculation and analysis will never disrupt the normal operation of real business activities such as offline brick-and-mortar stores and online customer service, and will not cause any inconvenience to actual customers. The following sections will sequentially explain the background, rationale, objectives, and limitations of this study.

International Background

Currently, a method called discrete event simulation is commonly used internationally to optimize customer service experience. A concrete application case of this method was implemented in Colombia in 2020 — researchers Heredia-Acevedo, Ceballos, and Sánchez-Torres used Simul8® software to build a complete service process simulation model for a local SME operating in the fast food industry. Through this model, they identified optimization directions that could shorten customers' waiting time, but at the same time, they also pointed out the limitations of this method: it cannot accurately reproduce the complete processes of those pure service-oriented scenarios.

Similarly, Mendoza Casseres, González Conde, Corcho Martínez, and Berdugo Alonso used discrete-event simulation to analyze the queuing problem in the emergency room of a healthcare provider in

Barranquilla, finding that disorganized scheduling directly affected patient stay times and referrals, which negatively impacted patients' perception of the service received.

In Brazil, da Rocha Nascimento, dos Santos, da Silva, Bueno, and Machado (2021) applied discrete-event simulation using Arena software to improve queue management at a bank branch ( ), demonstrating that reassigning staff significantly reduced wait times and increased satisfaction among users of the financial service.

In Indonesia, Firmansyah and Saputra (2021) studied the effect of implementing a queueing system on customer satisfaction, concluding that reducing perceived wait times has a direct and positive impact on customers' assessment of the service they received.

In Malaysia, a study published in the International Journal of Industrial Management applied discrete-event simulation to optimize a hypermarket's queuing system, showing that congestion at the cash registers, caused by insufficient staffing, significantly reduced customer satisfaction, and that simulating different scenarios allowed for the proposal of a more efficient resource configuration (Application of Discrete Event Simulation for Enhancing Queuing System at Lotus Alor Setar, 2025).

In Turkey, Aslan and Özderiir (2021) developed a simulation application for a university student dining hall, demonstrating that modeling arrival and service times makes it possible to anticipate the formation of lines and design strategies to improve the user experience of the food service.

In the United States, Curin, Vosko, Chan, and Tsimhoni (2005) used discrete-event simulation to reduce service time at a high-demand fast-food restaurant on a college campus, achieving significant reductions in wait times by reconfiguring the workstations.

Finally, Kumar (2005) analyzed, from an empirical perspective, the competitive impact of improving service processes on customers' waiting experiences in retail markets, demonstrating that the perception of waiting time is a critical determinant of satisfaction and repurchase intent.

Latin American Context

In the national context (Peru), various studies have examined the application of discrete-event simulation in service companies with the aim of improving customer service and satisfaction. Sotelo Seguil (2017), in his thesis for the degree of Industrial Engineer at the Pontifical Catholic University of Peru, designed and implemented a discrete-event simulation model to improve public safety services in the district of

San Martín de Porres, concluding that the model made it possible to identify feasible improvements in the allocation of operational resources.

Similarly, a study conducted at the Pontifical Catholic University of Peru used discrete-event simulation to evaluate the level of service in the in-person customer service operations of a telecommunications company, finding that simulating different staffing scenarios made it possible to reduce wait times and increase the customer satisfaction metric reported by the company.

Similarly, at César Vallejo University, a discrete-event simulation model was developed to reduce wait times in the outpatient department of a public hospital in Chimbote; the results showed reductions of over 90% in the average wait time in line, which led to a substantial improvement in the satisfaction of the patients treated (Calla Delgado, 2020).

Complementarily, Gutiérrez, Ramos, Uribe, Ortega-Loayza, Torres, Montesinos, and León (2009) analyzed the relationship between wait time and user satisfaction at the central pharmacy of a general hospital in Lima, concluding that there is a significant association between the two variables, which supports the relevance of addressing service times as a strategy for service improvement.

In the consumer goods sector, a thesis from the Pontifical Catholic University of Peru applied discrete-event simulation to the cookie production and packaging process at a consumer goods company, with the goal of increasing the process's productivity and profitability, demonstrating the tool's usefulness beyond purely production-related processes.

Meanwhile, Tamashiro Tamashiro and Yacarini Vadillo (2023), in a study published in the journal *Industrial Data* of the National University of San Marcos, applied a discrete simulation model using ProModel software to improve the productivity of a Peruvian manufacturing company's production process, after first evaluating the impact of these improvements on the satisfaction of the process's internal customers.

In the financial sector, Alarcón Bozzo and Díaz Aroco (2018), in their undergraduate thesis at the Universidad Peruana del Norte, designed a simulation system to reduce wait times in the operations area of a bank branch in Cajamarca, demonstrating that simulation allows for anticipating the effects of different service configurations on the quality of service as perceived by the customer.

Study Objective

The objective of this study is to evaluate customer satisfaction at a service company by applying a discrete-event simulation model that represents the service process, identifies the critical factors affecting wait and service times, and proposes improvement scenarios that contribute to increasing the level of satisfaction perceived by customers.

Rationale for the Study

From a practical standpoint, this research is justified because it provides the service company under study with an analytical tool that allows it to anticipate the behavior of its service processes without incurring the costs or risks of experimenting directly on the actual system, which is particularly valuable in organizations where operational errors have an immediate impact on the customer experience. As noted by da Rocha Nascimento, dos Santos, da Silva, Bueno, and Machado (2021), discrete-event simulation allows organizations to test alternative service configurations and anticipate their effects on customer satisfaction before implementing them, thereby providing management with objective information for decision-making.

This study conducts a theoretical integration, combining queuing theory, simulation methods, and classic evaluation models to connect the quality of service processes with customer satisfaction, filling the theoretical gap between the two.

The core foundational framework supporting the entire study is the SERVQUAL model, which was proposed by Parasuraman, Zeithaml, and Berry in (1988). Under the definitions of this model, customer satisfaction is not a vague perception score, but a clear gap value: on one side is the customer's expectation of the service before receiving it, and on the other side is the actual perception generated after the customer completes the service experience. The gap between these two is the core source of satisfaction. To measure this gap, assessments must be carried out from five dimensions, namely reliability, responsiveness, assurance, empathy, and tangibility. The simulation model used in the study can conduct assessments one by one against the specific conditions of these five dimensions, and can also make predictions for future changes in these dimensions.

The research method adopted in this study uses a set of modeling and simulation processes specifically designed for the field of industrial engineering. This set of processes is not pieced together arbitrarily; it has undergone validity verification. Anyone who operates step by step in accordance with the requirements of the process can repeatedly produce the same results. The entire process contains six interconnected steps in sequence: data collection, distribution fitting, conceptual model construction, verification, validation, and scenario analysis.

As Law (2015) pointed out, to ensure that research results can truly and reliably reflect the actual system, the two steps of verification and validation must be completed correctly and well—if mistakes are made in these two steps, all conclusions drawn afterward cannot be aligned with the real system in reality, and the results of the entire study will therefore be untenable.

Study Limitations

This study has several limitations, these deficiencies directly affect the scope of application of the research conclusions, and the conclusions cannot be applied in all scenarios.

First, we only analyzed the situation of a single company, and the research results obtained cannot be generalized to the scenarios of other organizations, let alone directly apply this set of conclusions to more different environments.

Second, all the research data we used only came from a fixed period of time, and the probability distribution calculated from these data may shift with changes in customer demand and seasonal patterns, which will not be consistent with the actual situation.

Third, when we measured customer satisfaction, we only relied on the two indicators of waiting time and service level, and the subjective perceptions that affect users' core judgments on service quality were all omitted and not included in the satisfaction assessment.

Finally, the simulation software we selected has its own limitations. It cannot support us to fully reproduce the complexity of the real system that we need to restore in the research, and the level of detail that can be ultimately achieved is restricted by the software itself from beginning to end.

DEVELOPMENT

Research Paradigm

This research was conducted under the positivist paradigm, which assumes the existence of an objective reality that can be measured, quantified, and explained through the application of the scientific method. This paradigm is relevant to the study insofar as the assessment of customer satisfaction is approached through observable variables and a simulation model that allows for the numerical representation of the service system's behavior, thereby minimizing the researcher's subjective influence on the results obtained. In this regard, Hernández-Sampieri and Mendoza (2018) note that the quantitative approach, characteristic of the positivist paradigm, begins with an idea that is progressively refined; once the objectives and research questions are defined, hypotheses and variables are established, a plan is devised to test them, and the variables are measured within a specific context, with the aim of identifying patterns of behavior and testing theories through statistical analysis of the collected data.

Level of Research

The study was conducted at a descriptive level, since its purpose was not to deliberately manipulate the variables of the real system, but rather to characterize the behavior of the customer service process at the university cafeteria based on the observed data, and subsequently represent it using a simulation model that would allow for a description of its performance in different operational scenarios. In this regard, Arias (2012) defines descriptive research as research whose purpose is to characterize a fact, phenomenon, individual, or group in order to establish its structure or behavior, without necessarily explaining the causes that give rise to it.

Participants

This study was conducted on the premises of the campus cafeteria of a public university in Mexico. All observation subjects were regular patrons of this cafetería long-time repeat customers who frequented the establishment. The study focused on the details of the service these regular customers received at the cafeteria. Researchers recorded a total of 68 complete sets of observation data, which were used to estimate three customer-related values: first, the time customers arrived at the store; second, the total length of time customers spent from the start to the end of receiving service; third, the level of customers' satisfaction with that service instance. The estimation results calculated from these observation data could reach a confidence level of 90% this value is an indicator used to measure the reliability of the estimation results, and the original text only provided this value without adding any additional explanations.

Procedure

Data collection took place during the January–June 2025 semester, a period during which direct observations were made at various times of high and low customer traffic, with the aim of capturing the natural variability of the service process. During this stage, customer arrival times, service times at each service point, the number of people in line, and relevant incidents in the process were recorded; this information was subsequently used as input for building and calibrating the simulation model. Data collection was conducted in a non-intrusive manner, taking care at all times not to disrupt the normal flow of service.

Ethical Considerations

The study was conducted in accordance with the ethical principles governing research involving human subjects, ensuring respect for the dignity, privacy, and well-being of the participants at all times. Customer observation was conducted anonymously, without recording any personal data that would allow for their identification , and the information collected was used exclusively for academic purposes and to improve the service, safeguarding the confidentiality of the data obtained. Furthermore, prior authorization was obtained from the authorities responsible for the university cafeteria to conduct the observation of the process; every effort was made not to interfere with the establishment’s normal operations; and the research was conducted at all times in accordance with the principles of scientific integrity, avoiding the manipulation or alteration of the collected data and respecting the authorship of the sources consulted.

Procedure for Data Analysis and Statistical Analysis

Researchers first collected three types of data: the time customers arrived at the store, the time required to prepare and serve each customer's order, and the store's actual operational performance. These data could not be used directly; they first had to be fitted into an existing probability distribution model to eventually build a simulation model capable of replicating real scenarios, laying the groundwork for subsequent research.

After completing the model, they used the ProModel software to carry out specific simulation work. They first reproduced the entire customer flow process of the coffee shop in the software—they could accurately simulate the full movement path of customers from entering the store, placing orders, picking up meals, to leaving. Through this simulation, they first evaluated the store's current actual operational status, then projected the level of operational improvement that different types of adjustments to the store would bring about respectively.

However, before using this model for any formal analysis, they did not dare to apply it directly; instead, they conducted two rounds of verification and checks. They compared the results output by the model with the store's real daily operational conditions, and then cross-checked them against various indicators used to measure customer satisfaction. Only after confirming that the model's results were accurate and fully capable of supporting subsequent analysis did they officially launch the follow-up research work.

Data Analysis

This section presents and interprets the results obtained from running the discrete-event simulation model developed in ProModel software, corresponding to the service process at the university cafeteria under study. The analysis is organized around three complementary areas: the behavior of the customer flow entering the system, the overall productivity of the service process, and the composition of the cycle time experienced by the customer, with the aim of identifying the factors that influence perceived satisfaction and of providing quantitative evidence to support opportunities for system improvement.

Customer Flow Behavior

Table 1 presents the results obtained:

Table 1. *Customer Flow Behavior***.**

Customer Flow Indicator	Value
Successful Arrivals (successfully served)	36
Arrivals in the system (in process at the end of the run)	12
Failed arrivals (rejected or abandoned)	0

Source: Author's *own analysis*.

During the simulated period, the system recorded a total of 36 successful arrivals—that is, customers who entered the café and completed the service cycle without incident. Additionally, 12 arrivals remained in the system at the end of the simulation run; these correspond to customers who were at some stage of the process—waiting, being served, or leaving—without having yet completed their service cycle when the observation period ended, and whose inclusion is important to avoid underestimating the actual load the system faced. After this simulation, all customers who were originally supposed to access the service successfully entered the system. Not a single customer failed to complete their visit; not one person was left out.

Although everyone waited for a considerable amount of time, and many customers queued for a long stretch before it was their turn to receive service, the carrying capacity of this system fully accommodated the needs of all customers, not losing a single guest. Even though everyone waited a long time, the maximum workload the system could handle remained sufficient, and there was never a situation where it could not accommodate more people.

For the upcoming system upgrade, there is no need to worry about the system being unable to accommodate more users, nor to patch any capacity loopholes. We only need to focus on improving the user experience for customers.

System Productivity

Table 2 presents the process's productivity.

Table 2. *System Productivity*.

Performance Indicator	Value
System Productivity	75%

Source: Author's *own work*.

The model estimated a productivity rate of 75% for the simulated service point, defined as the proportion of the total simulation time during which the service resource was effectively occupied serving customers. This value indicates a reasonably high utilization of the installed capacity , but at the same time shows that a quarter of the server's available time was not devoted to direct customer service, either due to periods of inactivity or interruptions associated with the dynamics of the process. This level of production efficiency is very common in service industries with fluctuating demand, and university canteens are a typical example of such scenarios. After all, the number of diners in a university canteen inherently fluctuates with class start and end times: during peak hours, long queues form at service counters, while during off-peak hours, staff may not receive a single order for hours on end. This alternating pattern of slack and busyness in production efficiency is by no means an exceptional case across all service industries where demand shifts constantly.

Using this single indicator alone cannot lead to the conclusion that the service suffers from low efficiency or wasted resources. One cannot fixate on this single figure to hastily judge that the establishment's service is poorly run, that idle staff constitute a waste of resources—this single indicator is fundamentally incapable of supporting such a conclusion.

To determine whether employees' idle time actually impacts customer experience, this indicator must be evaluated alongside the total duration of a customer's visit, from entering to exiting the establishment. Only by measuring the two indicators together can one clarify whether the idle time when staff are not

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working truly slows down diners' entire process and diminishes their experience. Relying solely on the aforementioned production efficiency indicator cannot yield a reliable conclusion.

Composition of the Customer Cycle Time

Table 3 presents the behavior of the process times.

Table 3. *Breakdown of the customer cycle time***.**

Cycle Time Component	Average Duration
Average Service Time (Total Cycle)	21.60 min
Waiting time in line	11.84 min
Actual service time (effective service)	8.85 min
Hold time	0.62 min
Server downtime	12.75 min

Source: Author's *own calculations*.

The average service time recorded by the model was 21.60 minutes, a figure that represents the complete cycle experienced by the customer from the moment they enter the system until the end of their service. When breaking down this value into its constituent parts, we see that the wait time in the queue amounts to 11.84 minutes—a figure that accounts for the largest proportion of the total cycle and, in relative terms, is the most decisive factor in customer satisfaction, since it corresponds to a period during which the user remains inactive, waiting to be served, without receiving any direct value from the service.

In contrast, the actual service time—that is, the period during which the customer actually receives the service—was 8.85 minutes, a figure considerably lower than the wait time. This ratio highlights a significant imbalance within the process: for every minute the customer spends being served, they spend nearly an additional minute and a half waiting for that service—a situation that, if left unaddressed, can progressively erode the perception of service quality, even when, as noted in the previous section, no customer actually abandoned the system. The process stalled for 0.62 minutes, which is a mere over 30 seconds of lag. This data indicates that the downstream link further along the sequence encountered a temporary restriction, making it unable to process the incoming business at the originally planned speed. In addition, there was a cumulative 12.75 minutes of server downtime. Adding up this period of shutdown, the overall idle rate reached 25% — to put it plainly, throughout the entire service cycle, normal work could not be carried out for a full quarter of the time. This idle situation occurred because there were not enough customers requiring service.

The core finding of this study is that two seemingly completely contradictory scenarios — long wait times and extensive service idleness — actually coexist. On one hand, customers have to queue for a very long time before receiving service; on the other hand, there is still a huge amount of time where servers or service staff are idle and unable to start work. This coexistence of abnormal circumstances shows that all problems stem from uneven demand distribution, not insufficient total service capacity. It is not that the total volume of service that can be provided cannot support the visiting customers, but that the time periods during which people in need of service arrive are extremely uneven: they either crowd in all at once, clogging the entire process, or no one comes for ages, leaving staff waiting idly. The optimization work to be carried out next must focus on two tasks: adjusting demand to make it more even, and dynamically allocating resources, rather than blindly increasing the total service capacity. Do not follow the old path of expanding capacity by adding more servers and more staff. First smoothing out the time gaps in demand, then flexibly deploying backup resources in line with changes in passenger flow, is the correct direction to solve the problem.

Discussion

The results obtained through the discrete-event simulation model allow us to compare the behavior of the university cafeteria's service system with the findings reported in previous research that has addressed similar issues in different contexts and service sectors, thereby enabling us to assess both the consistency of the results obtained and the specific contribution this study makes to existing knowledge regarding the relationship between processing times and customer satisfaction.

First, the complete absence of failed arrivals recorded in the system studied is consistent with the findings reported by Heredia-Acevedo, Ceballos, and Sánchez-Torres (2020), who, by simulating the customer-process at a fast-food SME in Colombia, concluded that discrete-event simulation allows for the early identification of whether installed capacity is sufficient to absorb demand, thereby preventing customer loss before intervening in the actual system. In the case of the café analyzed, this favorable result suggests that, unlike other service contexts where saturation is the main problem, the establishment's capacity does not, on its own, represent a structural constraint on service.

However, the finding regarding the marked difference between the waiting time in line (11.84 minutes) and the actual service time (8.85 minutes) is consistent with the observations of Kumar (2005), who argues that the perception of waiting time is a critical determinant of customer satisfaction in retail settings, regardless of how efficiently the service itself is delivered. This approach takes on particular relevance in the present study, insofar as the system evaluated does not exhibit obvious deficiencies in the duration of the actual service, but rather in the proportion of time the customer remains inactive before being served, which reaffirms that satisfaction does not depend solely on the server's speed, but on the comprehensive management of customer flow.

Similarly, the 75% productivity level obtained in the simulation, along with a server downtime of 12.75 minutes, aligns with the findings reported by da Rocha Nascimento, dos Santos, da Silva, Bueno, and Machado (2021) in their study on queue management at a Brazilian bank branch, where they identified that the coexistence of periods of staff inactivity with prolonged customer wait times is not due to a lack of resources, but rather to an uneven distribution of demand throughout the business day. This consistency reinforces the interpretation that the central problem of the system under study relates to the synchronization between staff availability and peak customer traffic times, rather than to the quantity of available resources.

Along the same lines, the findings are also consistent with the study by Firmansyah and Saputra (2021), who concluded that reducing perceived wait times directly affects customers' assessment of the service received, even when the actual service time remains unchanged. Similarly, the behavior observed in the composition of the customer cycle time is comparable to that described for the " " queuing system at a hypermarket in Malaysia, where congestion caused by occasional staff shortages at certain times significantly reduced customer satisfaction—a situation that was addressed by simulating alternative resource allocation scenarios (Application of Discrete Event Simulation for Enhancing Queuing System at Lotus Alor Setar, 2025).

At the national level, the results of this study align with those reported by Calla Delgado (2020) in the outpatient department of a public hospital in Chimbote, where the application of a discrete-event simulation model revealed that wait times were the most critical component of the care cycle, and with the findings of Gutiérrez et al. (2009), who found a significant association between wait time and user satisfaction in a hospital pharmacy service in Lima. This consistently supports the interpretation that wait time—and not necessarily service time—is the variable with the greatest impact on the perception of quality in various types of service organizations within the Peruvian context.

Likewise, the results obtained at the university cafeteria are consistent with those reported in the research conducted at the Pontifical Catholic University of Peru on in-person service at a telecommunications company, in which simulating different staffing scenarios made it possible to reduce wait times and improve the satisfaction indicator reported by the organization. This suggests that, as in the present study, interventions aimed at balancing human resource availability with demand variability constitute a more effective strategy than simply expanding installed capacity.

From a theoretical perspective, the results obtained can be explained in light of the SERVQUAL model proposed by Parasuraman, Zeithaml, and Berry (1988), in which the responsiveness dimension—understood as the willingness to attend to and provide service promptly—constitutes one of the most decisive gaps between customer expectations and perceptions. The findings of this study suggest that, although actual service time does not represent a weakness in the system, the perception of service responsiveness could be compromised by long wait times, which would reduce the overall evaluation of this dimension by customers of the university coffee shop.

Finally, the methodological consistency of the results obtained is also supported by Law (2015), who emphasizes that the validity of a simulation model depends largely on whether its outputs reliably reflect the relationships that actually occur in the real system. In this regard, the observed correspondence between the results of this study and the findings reported in research conducted in different sectors and countries—healthcare, banking, telecommunications, retail, and food service—constitutes further evidence of the robustness of the model developed, insofar as the same behavioral pattern—characterized by the predominance of wait time over service time—is consistently repeated across diverse service systems.

Conclusions

The application of the discrete-event simulation model to the service process at the university cafeteria made it possible to achieve the objective set forth in this study by quantitatively evaluating customer satisfaction based on the observed behavior in terms of wait times, service times, and system occupancy, without the need to directly intervene in the establishment's actual operations during the study period.

First, it is concluded that the system's installed capacity is sufficient to meet the recorded demand, as no failed arrivals occurred during the simulated period. This result rules out insufficient resources as the primary cause of potential customer dissatisfaction and shifts the focus to how those resources are distributed throughout the service day.

Second, it is concluded that the factor that most significantly affects the total duration of the service cycle is the wait time in the queue, which far exceeds the actual time spent being served. This disproportion constitutes the study's most significant finding, as it demonstrates that the perception of customer satisfaction in the evaluated system depends to a greater extent on the time customers spend waiting to be served than on the duration or quality of the service received once service begins.

Third, it is concluded that the productivity level achieved—75%—along with the downtime identified on the server, reveals the existence of periods of idle capacity that coexist with moments of greater congestion. This indicates that the system's problem stems from a y mismatch between the availability of service resources and the variability of demand throughout the semester analyzed, rather than a structural limitation in the number of staff or available service points.

Fourth, it is concluded that discrete-event simulation is an appropriate and reliable tool for evaluating customer satisfaction in service companies, as it allows for the integrated representation of variables that, in isolation, would not provide a sufficient explanation of the phenomenon under study, and enables the projection of improvement scenarios on a quantitative basis before modifying the actual system.

Finally, it is concluded that the results obtained lay a solid foundation for guiding future interventions in the university cafeteria's service system, particularly regarding the dynamic management of staff during peak periods, with the aim of reducing customer wait times without compromising the efficiency achieved in the use of available resources.

As a first line of future research, it is recommended to develop and evaluate, using discrete-event simulation, different scenarios for dynamic staffing based on the peak time slots identified during the semester, with the aim of determining the resource configuration that will significantly reduce customer wait times without increasing the service's operating costs or affecting the system's current level of productivity.

As a second line of future research, it is suggested to complement the quantitative approach of this study by incorporating instruments for directly measuring customer satisfaction—such as surveys based on the

SERVQUAL model—which would allow for comparing the results obtained through simulation with users' actual perceptions regarding the dimensions of reliability, responsiveness, security, empathy, and tangible service elements, thereby enriching the comprehensive understanding of the phenomenon of satisfaction in service companies.

Conflict of Interest

The authors declare that they have no conflicts of interest.

Data Availability

All datasets relevant to the results of this study are available in their entirety in the article.

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This study was not funded by any organization.

Statement on Generative AI

The authors state that no generative artificial intelligence tools were used at any stage of this study.

References

Alarcón Bozzo, G. C. A., y Díaz Aroco, T. (2018). *Diseño de un sistema de simulación para reducir el tiempo de espera en el área de operaciones de la empresa INTERBANK Agencia Cajamarca* [Tesis de pregrado, Universidad Peruana del Norte]. Repositorio institucional UPN. https://repositorio.upn.edu.pe/

Application of Discrete Event Simulation for Enhancing Queuing System at Lotus Alor Setar. (2025). International *Journal of Industrial Management, 19*(4), 197-209. https://doi.org/10.15282/ijim.19.4.2025.11959

Arias, F. G. (2012). *El proyecto de investigación: Introducción a la metodología científica* (6.a ed.). Editorial Episteme. https://www.formaciondocente.com.mx/06_RinconInvestigacion/01_Documentos/El%20Proyecto%20de%20Investigacion.pdf

Aslan, E., y Özderiir, N. (2021). Bir Üniversite Öğrenci Yemekhanesinde Simülasyon Uygulaması. *Kahramanmaraş Sütçü İmam Üniversitesi Sosyal Bilimler Dergisi, 18*(2), 965-978. https://doi.org/10.33437/ksusbd.629888

Calla Delgado, V. F. (2020). Simulación de eventos discretos para reducir el tiempo de espera en el área de consulta externa de un hospital público. *INGnosis*, *6*(1), 16-26. https://www.researchgate.net/publication/350455179

Curin, S. A., Vosko, J. S., Chan, E. W., y Tsimhoni, O. (2005). *Reducing service time at a busy fast food restaurant on campus*. Proceedings of the 2005 Winter Simulation Conference, 2628-2635. https://doi.org/10.1109/WSC.2005.1574562

da Rocha Nascimento, M. A., dos Santos, L. M., da Silva, A. M., Bueno, R. C., y Machado, S. T. (2021). Discrete event simulation applied to single queue management: A case study at a bank agency. *Independent Journal of Management & Production*, *12*(9), S831-S842. https://doi.org/10.14807/ijmp.v12i9.1632

Firmansyah, F., y Saputra, A. C. (2021). Effect of the implementation of queue system on customer satisfaction. *Bongaya Journal for Research in Management*, *4*(1), 1-7. https://doi.org/10.37888/bjrm.v4i1.245

Gutiérrez, E., Ramos, W., Uribe, M., Ortega-Loayza, A., Torres, C., Montesinos, D., y León, O. (2009). Tiempo de espera y su relación con la satisfacción de los usuarios de la farmacia central de un hospital general de Lima. *Revista Peruana de Medicina Experimental y Salud Pública*, *26*(1), 61-65. http://www.scielo.org.pe/scielo.php?script=sci_arttext&pid=S1726-46342009000100011

Hernández-Sampieri, R., y Mendoza, C. (2018). *Metodología de la investigación: Las rutas cuantitativa, cualitativa y mixta*. McGraw-Hill Interamericana. http://www.biblioteca.cij.gob.mx/Archivos/Materiales_de_consulta/Drogas_de_Abuso/Articulos/SampieriLasRutas.pdf

Heredia-Acevedo, D., Ceballos, Y. F., y Sánchez-Torres, G. (2020). Modelo de simulación de eventos discretos para el análisis y mejora del proceso de atención al cliente. *Investigación e Innovación en Ingenierías*, *8*(2), 44-61. https://doi.org/10.17081/invinno.8.2.3639

Kumar, P. (2005). The competitive impact of service process improvement: Examining customers' waiting experiences in retail markets. *Journal of Retailing*, *81*(3), 171-180. https://doi.org/10.1016/j.jretai.2005.07.004

Law, A. M. (2015). *Simulation modeling and analysis* (5.a ed.). McGraw-Hill Education.

Mendoza Casseres, D. A., González Conde, M., Corcho Martínez, R. A., y Berdugo Alonso, A. (2018). Aplicación de la simulación discreta en el área de urgencias de una institución prestadora de servicios de salud. *INGENIARE*, (21), 55-71. https://dialnet.unirioja.es/servlet/articulo?codigo=6118796

Parasuraman, A., Zeithaml, V. A., y Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, *64*(1), 12-40.

Pontificia Universidad Católica del Perú. (2015). *Diagnóstico y mejora de procesos utilizando simulación de eventos discretos en una empresa de consumo masivo* [Tesis de pregrado]. Repositorio institucional PUCP. https://tesis.pucp.edu.pe/repositorio/handle/20.500.12404/6229

Pontificia Universidad Católica del Perú. (2016). *Mejora del nivel de servicio en la atención presencial en una empresa de telecomunicaciones empleando simulación de eventos discretos* [Tesis de pregrado]. Repositorio institucional PUCP. https://repositorio.pucp.edu.pe/items/61592350-0670-47d5-9a22-b0784cd77a96

Sotelo Seguil, M. G. (2017). *Diagnóstico y mejora para el servicio de la seguridad ciudadana en el distrito de San Martín de Porres mediante simulación de eventos discretos* [Tesis de pregrado, Pontificia Universidad Católica del Perú]. Repositorio institucional PUCP. https://tesis.pucp.edu.pe/repositorio/handle/20.500.12404/9055

Tamashiro Tamashiro, E., y Yacarini Vadillo, C. J. (2023). Aplicación de un modelo de simulación discreta para mejorar la productividad del proceso de producción en una empresa manufacturera. Industrial Data, 26(1), 303-332. https://www.redalyc.org/journal/816/81676820017/html/

Universidad César Vallejo. (2019). *Diseño de un modelo de simulación de eventos discretos para reducir el tiempo de espera del cliente en la empresa Super Taxi Elegant* [Tesis de pregrado]. Repositorio institucional UCV. https://hdl.handle.net/20.500.12692/29070

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Validation	Del Socorro Corral María

Formal Analysis	Silva Máynez Lucia Xiomara, García Aguirre Ilse Aydee
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Data Curation	Silva Máynez Lucia Xiomara, García Aguirre Ilse Aydee
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Writing - Review and editing	Del Socorro Corral María
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Supervision	Reyes Ledezma Daniela María, Medina Molina Yearim
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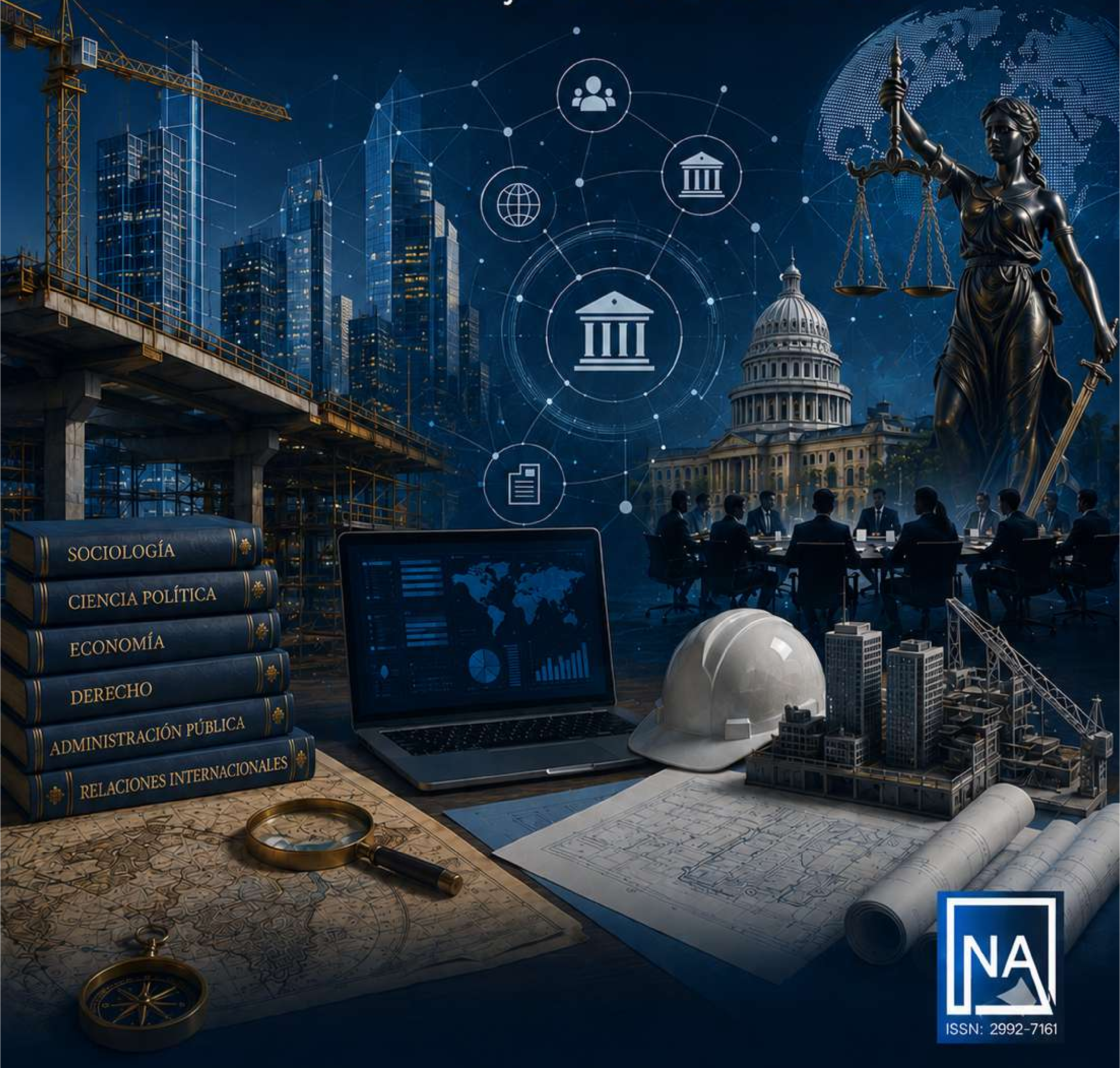

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