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# How does technological innovation impact the service time and the attraction of new customers in the financial sector? Evidence from an emerging economy

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## Abstract

Due to safety perceptions, Colombian banking clients prefer to visit bank branch offices instead of other channels. Thus, there are long waiting for lines at branch offices. Considering the need for more tools for strengthening and streamlining client service, the number of financial clients tends to diminish. In this context, this paper aims to measure the impact of technological innovation on the clients' waiting time and the attraction of new customers. We propose a simulation-based methodology to analyze customer behaviors and forecast the diffusion effect on mobile app adoption. Furthermore, our study provides managerial insights and future research lines.

**Keywords** Banking clients · Service level · Mobile App · Agent-based simulation · Bass diffusion model

## 1 Introduction

The financial sector, an industry historically steeped in tradition, is presently undergoing a paradigm shift characterized by an explosion of products, services, and information,

posing significant challenges in processing and management. In a society that is increasingly structured and demanding, individuals are eager to evaluate and compare various products and services. This has led to a complex landscape where designing tools to gauge and enhance the service level and the number of served clients is becoming ever more intricate, especially with the introduction of intangible products where the delivery environment plays a pivotal role in adding value (PwC 2019; Maechler et al. 2018; Gómez 2008).

Traditionally, customer service in the banking sector relied heavily on physical branches, call centers, and ATMs, offering standardized solutions with a primary focus on metrics such as loyalty, retention, and referrals. The modern iteration, however, leverages digital technologies such as mobile applications, web platforms, chatbots, and social media, offering 24/7 accessibility and personalization, thus shifting the focus towards customer experience metrics such as ease, speed, and delight. This shift has not only introduced innovative business models but also intensified competition, with new entrants like FinTechs and Big Tech challenging the incumbents with lower costs and innovative solutions (Patel 2023; PwC 2019; Maechler et al. 2018).

Amidst this evolving landscape, it becomes imperative for financial institutions to adapt and innovate, aligning their services to understand better and anticipate customer needs and demands. Thus, establishing technological innovations

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within existing business models emerges as a crucial strategy to maintain a competitive edge (Aguirre 2015).

In this context, the Bass diffusion model, proposed by Frank Bass in 1969, presents itself as a potent tool to study the adoption patterns of new products or technologies within a population (Bass 1969). Based on Everett Rogers' Diffusion of Innovations theory, this model delineates two types of adopters: innovators and imitators. The Bass diffusion model encapsulates the nuances of adoption patterns and facilitates the analysis of marketing strategies or environmental factors in the diffusion process.

The Bass diffusion model has found applications across diverse fields, including consumer durables, industrial goods, pharmaceuticals, telecommunications, energy, and social innovations (Baviskar et al. 2023; Horvat et al. 2020; Kusuma and Suryanegara 2019). Recent developments of the Bass diffusion model include explanatory parameters and extensions to incorporate system dynamics and feedback loops, which enable a more nuanced understanding of the diffusion process and the creation of effective interventions to promote adoption (Baviskar et al. 2023; Tani et al. 2022; Sokele and Moutinho 2018). Despite the extensive application of the Bass diffusion model in various fields, its application in understanding the evolutionary dynamics of customer service in the banking sector remains underexplored. Existing studies have primarily focused on adopting new products or technologies, leaving a gap in the literature concerning the analysis of customer service strategies and their impact on the service level, and the number of served clients in the banking sector.

This study addresses the identified research gap by dissecting the complex dynamics of customer service evolution in the banking sector and analyzing the factors that serve as drivers or barriers to diffusion. Therefore, this research aims to facilitate the formulation of strategies for more effective attraction and retention of clients. The study is developed on the following research question:

How the use and adoption of a mobile application impact the service times and the attraction of new clients in the financial sector?

To respond to the research question, we propose and implement a methodology supported by the agent-based version of the Bass diffusion model. In particular, the agent-based simulation has proven to be a tremendously helpful technique for modeling complex systems, particularly social systems (Zapata-Roldan and Sheikh 2020; Lee et al. 2019; Gilbert 2019; Ahrweiler 2017; Macal 2016; Macal and North 2014; Edmonds 2000). This type of simulation evaluates the actions and interactions of autonomous individuals within an environment, determining their effects on the system (Borshchev and Filippov 2004). Readers are referred to the works by Will et al. (2020) and Klein et al. (2018), as reviews of agent-based modeling for exploring social

interactions. On the other side, the Bass diffusion model has demonstrated its simplicity and flexibility in examining the influence of information on consumers' decisions to adopt a new product. In addition, this model perfectly captures how consumers change their choices over time (Wei et al. 2022).

The integration of both models, i.e., the agent-based model and the Bass diffusion model, allows us to determine the attraction of new clients due to better service levels. Thus, our proposed methodology deals with competing paradigms to forecast the demand effects and customer behaviors of the diffusion of innovative products or technologies (Rand and Stummer 2021; Abedi 2019; Massiani and Gohs 2015; Rand and Rust 2011). Unlike other demand prediction models, this model does not require historical sales information of the products (Rand and Rust 2004).

The main contributions of this paper are as follows:

- We propose and implement a methodology to study customer behaviors and forecast the diffusion effect on customer adoption of a banking App due to better service levels.
- An agent-based version of the Bass diffusion model was designed to study customer behaviors and forecast the diffusion effect on customer adoption of a banking App due to better service levels.
- A novel methodology for service operations is developed. The proposed methodology is flexible for studying any service operation that involves interaction between entities within an artificial environment reflecting the real-world system.
- Performance indicators, including served clients, service level, service time deviation, and average system occupancy rate, were analyzed.
- A real-life problem with real-life data was considered for validating the proposed methodology.

The rest of this paper is structured as follows: Section 2 provides a review of the related literature. Section 3 describes the problem under study. Section 4 presents the proposed methodology, including an explanation of the mobile App, the descriptive formulation, and the simulation model employed to evaluate the effectiveness of the Application. Section 5 presents the analysis of the results, and Section 6 provides theoretical and managerial insights for academics and practitioners interested in the studied problem. Finally, Section 7 presents concluding remarks and opportunities for further research.

## 2 Literature review

Most real-world systems are too complex to be evaluated analytically (i.e., using mathematical methods to obtain exact information on the question of interest). Those

systems must use simulation, where data are gathered to estimate the desired characteristics of the model (Law et al. 2015).

Simulation is applied to a wide range of problems and sectors, principally for the designing of manufacturing industries or modification of plants/production lines (Villanueva 2008). In the logistic sector, simulation has been used to design transportation flows of people or materials and optimization of platforms or terminals (Bernardi et al. 2020; Ozdemir and Kumral 2019; Rahimikelarijani et al. 2018; Solano-Charris and Paternina-Arboleda 2013). In addition, simulation has applications in scenarios such as hospitals, urban developments, police, banking sector, among others (Ataee Gortolmesh et al. 2020; Zapata-Roldan and Sheikh 2020; Samitas et al. 2018; Omogbai and Saloniitis 2016; Krause et al. 2004).

In this context, simulation is a flexible tool that enables us to evaluate different alternatives of system configurations and operating strategies to support decision-making (Negahban and Smith 2014). The literature can distinguish several types of simulation models: discrete simulation or continuous simulation, deterministic or stochastic simulation, static or dynamic simulation, agent-based simulation, etc. da Silva Meireles et al. (2022) present a review of the most used methodologies to study customer behavior in the face of service innovations. This section presents the literature review dedicated to studies that have used simulation (1) to explore operational strategies to improve service quality and (2) to evaluate customer behaviors due to the inclusion of new products. The databases explored were Web of Science, Elsevier, and Scopus, which are considered one of the largest citation databases. The search equation was formed by the following keywords: service quality, customer behavior, acceptance of new products, and agent-based simulation. The literature review is limited to studies published between 2000 and 2022.

## 2.1 Methodologies for improving service quality

Generally, one of the most used tools to evaluate policies to improve service quality by considering social patterns is based on simulation. For example, Tian et al. (2022) proposed an agent-based simulation to model individual customers with different behaviors. The results showed that it is essential to assess the level of satisfaction of current and potential customers. In addition, the authors recognized the importance of developing hybrid models to capture industry dynamics and social patterns. In this context, multi-agent simulation can be used to model the behavior of the sector, considering competitors and customer behaviors.

Rand and Stummer (2021) proposed an agent-based simulation to model the behavior of customers and competitors when a new product is introduced in the market.

Rand and Stummer (2021) used the Bass diffusion model to simulate the interaction between customers and competitors. The authors concluded that the integration of agent-based simulation and Bass diffusion modeling is helpful for critically evaluating the new product's impact on the market and service quality.

Additionally, Malhotra and Mukherjee (2004) presented an analysis that demonstrated the positive impact on employee satisfaction that the inclusion of new technologies has. Findings indicated that job satisfaction and organizational commitment of employees have a significant impact on the service quality delivered. Following this research line, Jalilian et al. (2021) developed an agent-based simulation to optimize service provision. The model considered the interaction of various substitute products and how they affect service delivery. Jalilian et al. (2021) addressed a case study for a banking institution in Iran. The authors concluded that simulation allows representing the interaction between customers and new products for evaluating service quality.

## 2.2 Modeling of customer behaviors due to the inclusion of new products

Complementary to the previous subsection, this section focuses on modeling customer behaviors. For example, Dostov et al. (2022) developed a system dynamics model to evaluate the impact and acceptance of fast payment services. The authors recognized that the acceptance of any system depends on a maturation process in the market. Dostov et al. (2022) implemented the Bass diffusion model to model different customer behaviors. They used historical data from Great Britain to evaluate the acceptance of the fast payment service. The authors demonstrated that the proposed hybrid model can reproduce the behavior of fast payment system acceptance.

Sava and Marković (2017) developed an agent model to evaluate customer behaviors in an online marketplace. The study focused on representing the decision-making process of customers associated with the use of the online platform. The authors modeled the following parameters as a random variable: gender, customer age (integer random values between the range of 18 and 60 years), income levels, sensitivity to advertisements, information transfer between customers, and sensitivity to a specific product attribute. The proposed model was designed to evaluate the online sales system, customer behaviors, and the impact of customers on the performance of the system.

Considering the attributes of various products, Theerthaana and Sheik Manzoor (2020) studied a portfolio of investment projects offered by a financial organization. The authors presented a simulation model where they integrated the Bass diffusion model. The authors analyzed the behavior of customers when faced with a set of investment projects. The objective of the study was to evaluate the impact of the

type of information transferred to customers and between customers. The results showed that investment projects have a better acceptance when the project provider shares the information risk associated with the project.

In particular, the combination of agent-based simulation and diffusion modeling has been frequently applied in the context of the supply chain (Backs et al. 2021), control and promotion of emerging firms to collaborative environments (Yu et al. 2020), product design (Zapata-Roldan and Sheikh 2020; Lee et al. 2019; Negahban and Smith 2018; Hu et al. 2018) and evaluating the impact of product innovations or operating policies on the market (Amini et al. 2012; Bohlmann et al. 2010). Despite the existing literature on agent-based simulation models, there remain opportunities for applying these models to new product diffusion (Rand and Stummer 2021).

The reviewed studies show that most studies focus on modeling clients' decisions to purchase a product. One of the main objectives of these studies is to attract new clients and evaluate the quality of service. However, there is a lack of studies related to assessing the adoption of a complementary service that supports the provision of the business-leading service.

### 3 Generalities of the Colombian financial market and problem description

In the Colombian financial market, there are 27 banking establishments, 6 financial corporations, and 14 commercial financing companies, among other financial entities (Superintendencia de Industria y Comercio 2020). According to the degree of access to financial services, Bogotá is the city with the highest banking access in the country up to 98.7%, and the second one in terms of financial products up to 86.9% (Superintendencia Financiera de Colombia 2018).

As stated in the last Colombian financial inclusion report, the use of technological channels has increased over the years (Superintendencia Financiera de Colombia 2018). In fact, 2018 was the first year in which Internet operations exceeded those carried out in physical branches by handling 49.8% of all transactions (Superintendencia Financiera de Colombia 2018). Thus, ensuring digital and innovative solutions for the near future is of paramount importance for banking establishments.

Technological solutions are valuable tools for the financial inclusion of under-served populations and those groups whose needs are not being met by the traditional system (Superintendencia Financiera de Colombia 2018). However, the limited access to products and services offered by banks through virtual platforms makes bank offices necessary, for instance, the capacity of withdrawal operations and the provision of other banking services.

According to the statistics of financial institutions, client complaints, and claims are related to the insufficient capacity of bank tellers to perform a bank transaction safely and quickly. Additionally, due to the high perceived risk, building users' initial trust is crucial to facilitating their adoption and usage of mobile banking (Zhou 2012).

Regarding this context, financial institutions must anticipate the behavior of the demand to enhance the service level and thus, retain and attract new clients, and motivate the inclusion of digital tools in the financial sector (Aguirre 2015).

#### 3.1 Problem description

This study is carried out in a Colombian banking establishment. The bank has more than 70 years in the country and currently has 30 branches across Colombia. In this paper, the city of Bogotá is selected due to its highest level of banking activity. Here, the problem of long waiting times for clients at branch offices and the limited capacity of the system to cover all demands are addressed. The objective is to represent the current situation of three bank branches and evaluate whether or not the use of a mobile application impacts service levels for financial clients. The clients of the banking sector in Colombia feel safer making the transfers in the bank offices. As a result, there are many clients in the bank office, which generates long waiting times for clients.

We consider more than one financial service to represent the current system, i.e., payments (40%), deposits (35%), withdrawals (17%), check account balance (5.5%), transfers (2%), and international transfers (0.7%) (Superintendencia Financiera de Colombia 2014). These transactions have maintained stable behavior in the last few years in Colombia.

The service level is defined as the client's waiting time before being served at the bank office. For the analysis, the bank branch offices in the downtown area of the city were strategically considered. The model considerations and parametrization of the case study are provided in the following sections.

#### 3.2 Queue problem considerations

Bank branches classify clients into permanent clients and potential clients. Permanent clients are those with accounts/products opened in the same bank. Potential clients are the people who use the bank occasionally (e.g., for the payment of public services). The setting of system variables and model assumptions are presented below:

- The service levels of bank branches are classified into general and preferential lines.

- Each bank branch office has a client arrival rate (expected number of arrivals per unit of time).
- Each bank branch office has an associated number of bank tellers and a capacity for attending the clients.
- There are a limited number of transactions per client.
- All bank tellers have the same service rate per transaction.
- Each client has a bank branch office preference and a monthly frequency for doing the transactions.
- Each transaction is associated with preferred days depending on a probability distribution.
- Each client only performs one transaction at a time.
- When a client cannot make a transaction or does not want to wait, the client exits the system.

## 4 Simulation-based methodology

We implement a discrete-event and agent-based simulation model to represent the current scenario. The simulation model compares the current system (Scenario A) and the one where the mobile App is implemented (Scenario B). The system represents the process of performing transactions by bank tellers. The process starts when a client enters the banking establishment to do a transaction and it ends after the transaction is done or when the client decides to exit the system without doing it.

The bank operation system is composed of a limited number of bank tellers, a general line, and a preferential line. The

general line serves potential clients, while the preferential line serves permanent clients. A bank teller is assigned to the preferential line if at least one permanent client is in the system. When there are no permanent clients in the system, all bank tellers serve the general line. The service and waiting times depend on the number of transactions to be processed and follow the rule FIFO - first in first out (Larson 1987). Clients are considered agents to model the behavior between potential and permanent clients. Figure 1 describes the structure of our proposed methodology.

For scenarios A and B, the system operation is analyzed utilizing discrete events to determine the queues' behavior and, afterward, the bank tellers' behavior. The number of bank tellers changes according to the bank branch policy.

### 4.1 Scenario A: current scenario

Figure 2 describes the current system process. A truncated normal distribution for clients' arrival time at branch offices is considered due to the statistical distribution fitting. Once a client is in the system, they evaluate whether to wait in line. If the number of clients in the row exceeds the occupancy perception (i.e., 40 clients in the queue), the client decides not to make the transaction and leaves the system (see Fig. 1).

The following steps describe the logic process when a client decides to do a transaction in a bank office:

1. Is the client a permanent client?

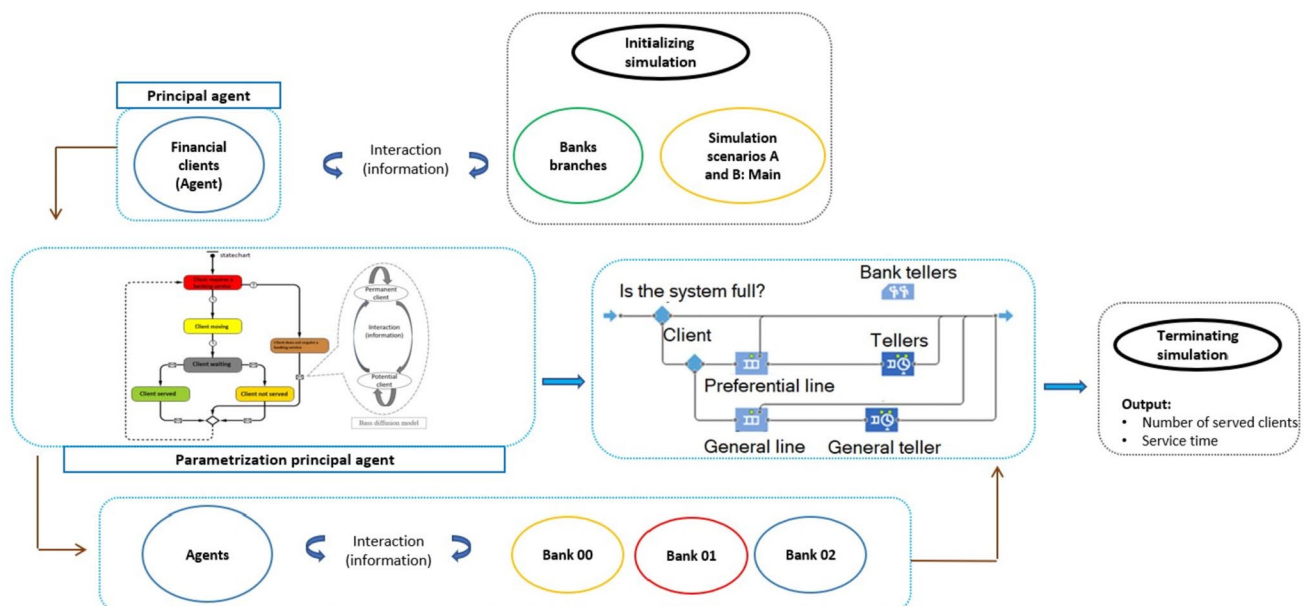


Fig. 1 Framework of our methodology

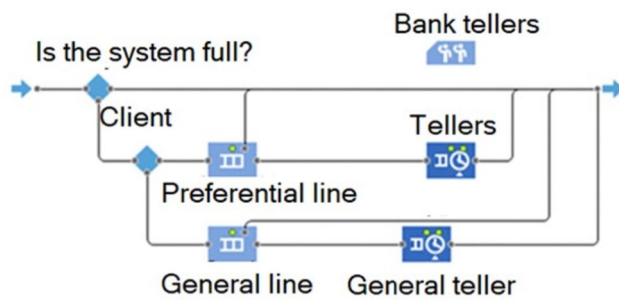


Fig. 2 Model structure for scenario A

- (a) Yes, the permanent client goes to the preferential client line.
  - (b) No, the potential client goes to the general client line.
2. The client is placed in the waiting line.
  3. The client remains in the waiting line.
  4. Is the client served?
    - (a) Yes, the client leaves the system.
    - (b) No, evaluates how long the client has been in line. Is the waiting time greater than the maximum waiting time (parameter)?
      - (i) Yes, the system is full, and the client exits the system without performing the bank transaction.
      - (ii) No, the steps are repeated from step 2.

## 4.2 Scenario B: proposed scenario

Figure 3 presents scenario B. Scenario B considers the same parameterization as the current scenario. The process starts when a client enters the system. The client uses the mobile App to select a bank branch for doing a transaction.

The following rules describe the selection process:

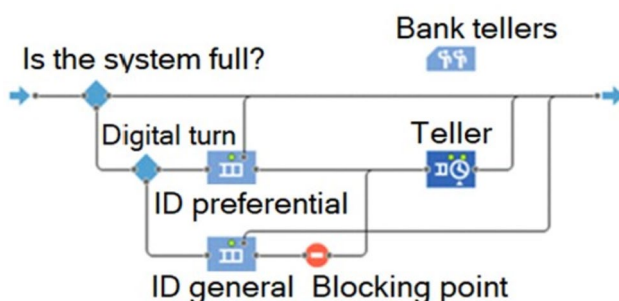


Fig. 3 Model structure for scenario B

1. Each client and bank branch office have a different geographical location. When a client needs to make a transaction, the current location becomes the origin of a set of paths that connect each bank branch office. The sum of those path lengths defines the distance between the current position of the client and the bank branch office.
2. The client's location is a random variable.
3. The distance is converted to time units assuming a walking speed of 4 km/h (Chi and Schmitt 2005).
4. The client searches in the mobile App for available bank offices.
5. Clients prefer the bank branch office with the shortest path.
6. Based on the list of available banks in step 4, the App evaluates the occupancy of all bank offices and suggests the ones with less occupancy.
7. The client selects the preferred bank office, and the App evaluates how much time the client takes to get to a bank office and complete a transaction.
8. The App generates a place in a digital queue for the client.
9. An attribute allows differentiating the type of client. Is the client a permanent client?
  - (a) Yes, are there any potential clients in the system?
    - (i) Yes, a permanent client is assigned to a preferred position (i.e., earlier placement in the digital queue) than the one assigned to potential clients.
    - (ii) No, assign placement in the digital queue following the FIFO rule.
  - (b) No, assign placement in digital queue following the FIFO rule.

Once the client selects a bank and has a place in a digital queue, the client arrives at the bank and does the transaction. The service performance depends on the number of bank tellers available to serve the client. The service time will be the sum of the exponential probability distributions by transaction type and quantity. The operating time is the sum of the service and travel time.

## 4.3 Behavior of financial clients

The Bass diffusion model is considered to identify how the use and adoption of a mobile Application are diffused among financial clients. The current process starts once the client arrives at the selected bank branch office. All clients entering the system require a bank transaction. A low service level is defined as the initial state for the client in the system. A potential client can become a permanent client for a bank

branch office when its service level is high. Otherwise, the user must wait until someone refers to the bank's services.

Clients will have a contact rate determined by the number of times a client refers a banking establishment to a random related contact (Dunbar 1992). The service level depends on the success of the transaction and the waiting time. When the transaction is completed with a waiting time less than or equal to the expected time by the client, the service level is high. On the contrary, if the waiting time exceeds the maximum expected waiting time, the client decides not to carry out the banking transaction at that bank branch office; thus, the client leaves the system, and the service level is low.

Figure 4 represents the status change of a client. A client can continue to be a permanent client if the service level is high. If the client receives a low service level, the permanent client will become a potential client. The transition from potential to permanent clients occurs through an information transfer between permanent and potential clients. Equation 1 formally describes the Bass diffusion model. The  $F_t$  refers to the number of clients who have adopted the App at the time  $t$ , the parameter  $p$  indicates the proportion of spontaneous adoptions given by external variables, and  $q$  represents the proportion of adoptions given by imitation (transfer information).

$$F_t = \frac{1 - e^{-(p+q) \cdot t}}{1 + \frac{q}{p} \cdot e^{-(p+q) \cdot t}} \quad (1)$$

The client's behavior depends on the bank occupation level (occupancy perception) and its proximity. Once the client is at a bank office, he decides to stay in line or leave the bank office according to the waiting time perception. For each permanent client, a variable is assigned that counts the number of times the client is served or

not. When a permanent client has been served five consecutive times, they give references of the bank office to potential clients (i.e., information transfer). When a permanent client has not been served three times, they become a potential one. If the potential client completes six unattended services, the client decides not to visit the bank branch again.

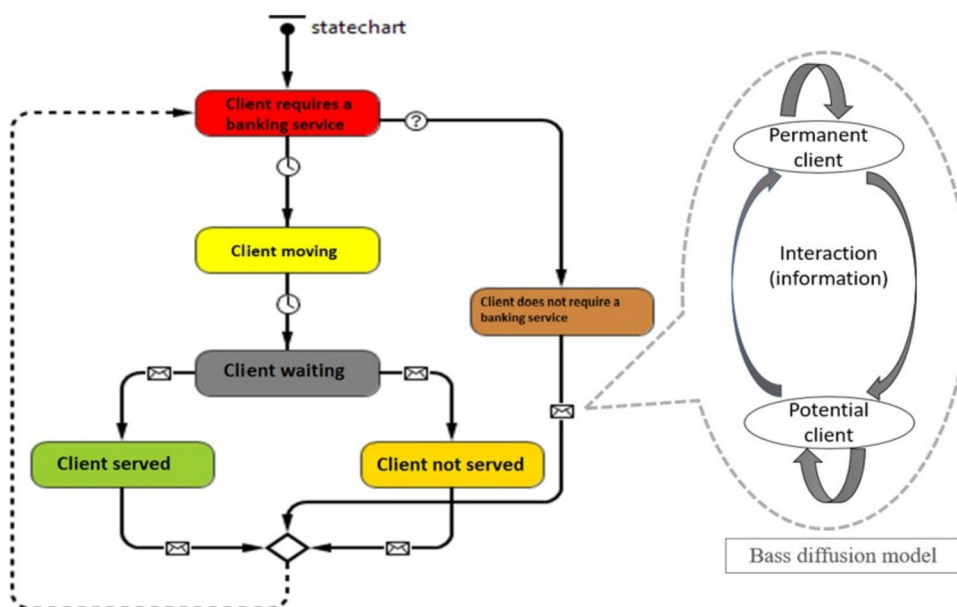
## 5 Numerical experiments and results

The simulation model is implemented in the AnyLogic® simulation tool in an Intel Core i5, 2.5 GHz, 8 Gb RAM. The data were constructed from the Bank's financial data reports. Three banking establishments denominated as bank 0, bank 1, and bank 2 are considered. The banking establishments are in the center of Bogotá, Colombia. Table 1 shows the parametrization of the simulation models:

In the computational experiments, the service level, and the number of served clients are provided as performance criteria for evaluating scenarios A and B. This section details the experimentation and results. The experimental phase is divided into two parts:

1. Analyze the effect on the average number of clients in the banking system. The analysis is done by testing the following research hypothesis:
  - (a) There is no significant difference between the current and proposed scenario in terms of the average number of served clients in a day.
2. Analyze the effect on service times in the banking system. The analysis is done by testing the following research hypothesis:

**Fig. 4** Exemplification of the service level in the bank, information transfer and transition between types of clients (Bass diffusion model)



**Table 1** Parameters for simulation models

Parameters	Value
Bank branches	Bank 0 Bank 1 Bank 2
Number of bank tellers: Bank 0 (servers)	4
Number of bank tellers: Bank 1 (servers)	3
Number of bank tellers: Bank 2 (servers)	4
Preference probability the bank 0	0.46
Preference probability the bank 1	0.27
Preference probability the bank 2	0.27
Line capacity: Bank 0 (general line, preferential line) clients	(120, 50)
Line capacity: Bank 1 (general line, preferential line) clients	(70, 40)
Line capacity: Bank 2 (general line, preferential line) clients	(52, 28)
Maximum waiting time (min)	30
Occupancy perception (clients)	40
Number of peak hours (H)	2
Days of the month and frequency of the financial client's transactions	Private information provided by the financial sector
Number of transactions type	[1, 7]
Service time per transaction (transaction 1..., transaction 7) (min)	(1; 2; 1.2; 3; 3; 2.4; 3.2)
Transactions per client (standard deviation=2)	[1, 5]

- (a) There is no significant difference between the current and proposed scenarios in terms of service time deviation in a day.

### 5.1 Tuning parameters for the simulation model

This section defines the simulation horizon and the number of runs required to study the system. The simulation horizon of the model is 247 days (i.e., working days) and 10 runs. A total of 1,000 clients are assumed, considering the Colombian annual projection. Permanent clients constitute 4.2% of the total clients. Particularly, in scenario B, the system becomes saturated, and the proportion of permanent clients rises to 9.2% after 60 days. As a result, the planning horizon is defined in 60 days. Tables 2 and 3 show the results for Scenario A and B, respectively.

According to the results, the number of served clients in the three bank branches is greater in scenario B than in scenario A (see Fig. 5). This behavior is justified considering that clients select the preferred bank branch (the closer one with the shorter estimated waiting time).

Next, the number of simulations to run is determined statistically to capture the behavior of financial consumers (i.e., the Bass diffusion model). In this study, the number of clients served in the system follows a normal  $\sigma = 103$ , with a 95% confidence level and an allowable error of 4 clients. Equation 2 describes the calculation of the number of runs in the system.

$$n = \frac{Z^2 \cdot \sigma^2 \cdot N}{Z^2 \cdot \sigma^2 + e^2 \cdot (N - 1)} \quad (2)$$

$$= \frac{1.94^2 \cdot 103 \cdot 60}{1.94^2 \cdot 103 + 4^2 \cdot (60 - 1)} \approx 18 \text{ runs}$$

where  $Z$  is the distance from the mean of a standard normal distribution,  $\sigma$  represents the standard deviation of the number of clients in the system,  $e$  shows the allowable error and  $N$  is the number of days considered for the simulation, i.e., 60 days. According to the results, 18 runs are needed for scenarios A and B.

### 5.2 Performance metric: impact on the total number of served clients

To analyze the impact on the total served clients, Table 4 shows the results of the simulation models for scenarios A and B. Figure 6 shows that in scenario B, the number of served clients in the system is greater than in scenario A.

A  $t$ -student test (see Eq. 3) is performed to statistically compare scenarios A and B and determine if there is a significant difference in the average number of clients entering a banking establishment and being served per day. Table 5 presents the parameterization of the simulation model for both scenarios.

$$t = \frac{(\mu_{\text{scenarioB}} - \mu_{\text{scenarioA}})}{sp \cdot \sqrt{\frac{1}{n_{\text{scenarioB}}} + \frac{1}{n_{\text{scenarioA}}}}} \quad (3)$$

**Table 2** Simulation results for scenario A

Experiment	Bank Branch Office	TPC	SPC	CPL	SC	SLP	TBT	LOA	AQPL	CaPL	URPL	AQGL	CaGL	URGL
1	BANK 00	6069	259	266	1273	97%	4	95%	0	50	0%	25	120	21%
	BANK 01	5883	192	203	989	95%	3	96%	0	40	0%	26	70	37%
	BANK 02	5635	206	214	1211	96%	4	96%	0	28	0%	25	52	48%
2	BANK 00	6038	248	252	1217	98%	4	95%	0	50	0%	26	120	22%
	BANK 01	5572	153	161	945	95%	3	95%	0	40	0%	27	70	39%
	BANK 02	5657	169	177	1315	95%	4	96%	0	28	0%	25	52	48%
3	BANK 00	6080	252	260	1183	97%	4	95%	0	50	0%	24	120	20%
	BANK 01	5734	156	166	911	94%	3	95%	0	40	0%	25	70	36%
	BANK 02	5553	162	170	1224	95%	4	96%	0	28	0%	25	52	48%
4	BANK 00	5993	268	274	1337	98%	4	96%	0	50	0%	25	120	21%
	BANK 01	5745	174	183	907	95%	3	96%	0	40	0%	26	70	37%
	BANK 02	5645	187	194	1280	96%	4	95%	0	28	0%	26	52	50%
5	BANK 00	6011	255	261	1285	98%	4	95%	0	50	0%	25	120	21%
	BANK 01	5757	164	174	1056	94%	3	95%	0	40	0%	27	70	39%
	BANK 02	5289	179	186	1262	96%	4	95%	0	28	0%	26	52	50%
6	BANK 00	6001	261	269	1254	97%	4	95%	0	50	0%	26	120	22%
	BANK 01	5611	162	171	954	95%	3	95%	0	40	0%	26	70	37%
	BANK 02	5644	174	183	1297	95%	4	96%	0	28	0%	25	52	48%
7	BANK 00	6027	265	272	1198	97%	4	95%	0	50	0%	25	120	21%
	BANK 01	5724	167	175	975	95%	3	95%	0	40	0%	25	70	36%
	BANK 02	5578	175	185	1278	95%	4	95%	0	28	0%	26	52	50%
8	BANK 00	5999	241	249	1211	97%	4	95%	0	50	0%	26	120	22%
	BANK 01	5659	155	165	933	94%	3	95%	0	40	0%	26	70	37%
	BANK 02	5597	164	172	1294	95%	4	95%	0	28	0%	25	52	48%
9	BANK 00	6023	251	256	1259	98%	4	95%	0	50	0%	25	120	21%
	BANK 01	5711	155	164	948	95%	3	95%	0	40	0%	26	70	37%
	BANK 02	5612	168	176	1301	95%	4	95%	0	28	0%	26	52	50%
10	BANK 00	6031	258	265	1275	97%	4	95%	0	50	0%	26	120	22%
	BANK 01	5694	174	183	924	95%	3	96%	0	40	0%	27	70	39%
	BANK 02	5634	182	190	1278	96%	4	96%	0	28	0%	26	52	50%

TPC Total permanent clients, SPC Served permanent clients, CPL Clients in preferential line, SC Served clients, SLP Service level for permanent clients, TBT Total bank tellers, LOA Level of occupation of ATMs, AQPL Average queue in preferential line, CaPL Capacity of preferential line, URPL Utilization rate of preferential line, AQGL Average queue in general line, CaGL Capacity of general line, URGL Utilization rate of general line

where the  $\overline{\mu_{\text{scenarioA}}}$  and  $\overline{\mu_{\text{scenarioB}}}$  are the average of total clients in the system for scenarios A and B, respectively. The  $sp$  value is the standard deviation and  $n_{\text{scenarioA}}$  and  $n_{\text{scenarioB}}$  are the number of runs for each scenario.  $S_{\text{scenarioA}}$  and  $S_{\text{scenarioB}}$  are the standard deviation for each scenario. Equation 4 shows the calculation of  $sp$ .

$$sp = \sqrt{\frac{(n_{\text{scenarioB}} - 1) \cdot S_{\text{scenarioB}}^2 + (n_{\text{scenarioA}} - 1) \cdot S_{\text{scenarioA}}^2}{n_{\text{scenarioA}} + n_{\text{scenarioB}} - 2}}$$

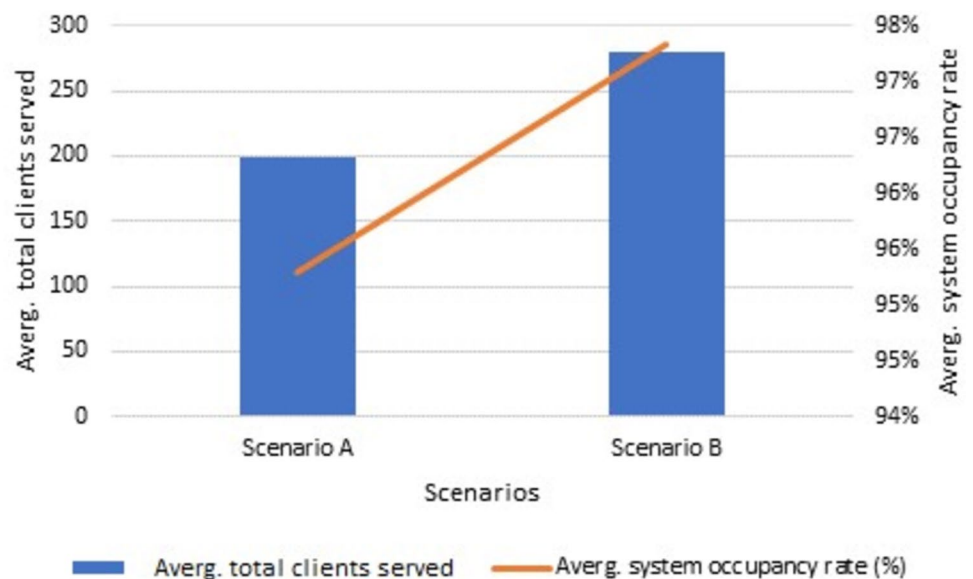
$$sp = \sqrt{\frac{(18 - 1) \cdot 8.6^2 + (18 - 1) \cdot 9.2^2}{18 + 18 - 2}} = 8.957 \quad (4)$$

The value of the  $t$ -student test is -27.06, then  $p < 0.001$ . Results allow us to conclude that there is no evidence to affirm that the average number of clients entering the system is the same for both scenarios, i.e., there is a difference in the system performance of scenario A and scenario B. Figure 6 shows that in scenario B, the number of served clients in the system is greater than in scenario A. Additionally, we compared means to determine which is the best scenario (scenario with the most significant number of served clients). Equation 5 describes the difference between  $\mu_{\text{scenarioA}}$  and  $\mu_{\text{scenarioB}}$  with a confidence interval of 95%.  $v_1$  and  $v_2$  represent the degrees of freedom for scenario A and B, respectively.

**Table 3** Simulation results for scenario B

Experiments	Bank Branch Office	SC	CPL	PPCS	T	POT
1	BANK 00	343	389	88%	4	98%
	BANK 01	271	318	85%	3	97%
	BANK 02	284	330	86%	4	97%
2	BANK 00	331	381	87%	4	98%
	BANK 01	236	281	84%	3	97%
	BANK 02	250	293	85%	4	97%
3	BANK 00	331	382	87%	4	98%
	BANK 01	238	283	84%	3	97%
	BANK 02	246	288	85%	4	97%
4	BANK 00	351	396	89%	4	98%
	BANK 01	254	299	85%	3	97%
	BANK 02	263	307	86%	4	97%
5	BANK 00	338	387	87%	4	98%
	BANK 01	243	289	84%	3	97%
	BANK 02	259	301	86%	4	97%
6	BANK 00	341	394	87%	4	98%
	BANK 01	246	288	85%	3	97%
	BANK 02	258	299	86%	4	97%
7	BANK 00	345	390	88%	4	98%
	BANK 01	243	291	84%	3	97%
	BANK 02	256	296	86%	4	97%
8	BANK 00	319	365	87%	4	98%
	BANK 01	236	280	84%	3	97%
	BANK 02	243	286	85%	4	97%
9	BANK 00	331	379	87%	4	98%
	BANK 01	235	279	84%	3	97%
	BANK 02	252	295	85%	4	97%
10	BANK 00	338	388	87%	4	98%
	BANK 01	257	301	85%	3	97%
	BANK 02	262	304	86%	4	97%

SC Served clients, CPL Clients in preferential line, PPCS Proportion of preferential clients served, T Tellers, POT Percentage of occupancy of tellers

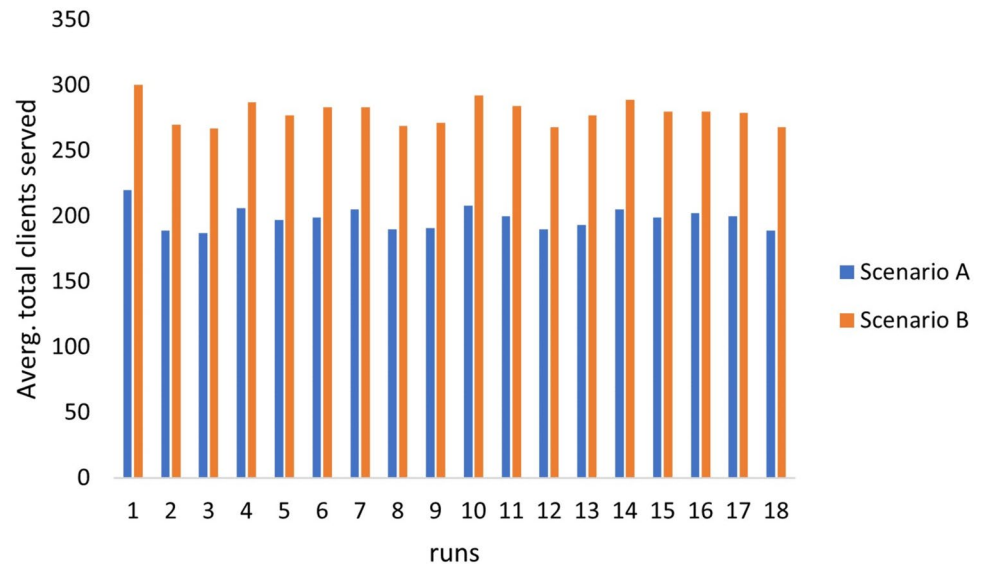
**Fig. 5** Average total clients served and Average system occupancy rate overall bank branches

**Table 4** Simulation of the scenarios A and B: served clients

Scenario A				Scenario B			
Experiments	Bank branch office		Served clients	Experiments	Bank branch office		Served clients
1	BANK	00	263	1	BANK	00	346
	BANK	01	189		BANK	01	270
	BANK	02	209		BANK	02	283
2	BANK	00	244	2	BANK	00	327
	BANK	01	151		BANK	01	234
	BANK	02	171		BANK	02	249
3	BANK	00	249	3	BANK	00	333
	BANK	01	148		BANK	01	229
	BANK	02	163		BANK	02	238
4	BANK	00	265	4	BANK	00	345
	BANK	01	170		BANK	01	249
	BANK	02	182		BANK	02	266
5	BANK	00	253	5	BANK	00	336
	BANK	01	165		BANK	01	244
	BANK	02	174		BANK	02	251
6	BANK	00	267	6	BANK	00	351
	BANK	01	159		BANK	01	243
	BANK	02	172		BANK	02	256
7	BANK	00	269	7	BANK	00	348
	BANK	01	164		BANK	01	244
	BANK	02	181		BANK	02	258
8	BANK	00	243	8	BANK	00	320
	BANK	01	159		BANK	01	239
	BANK	02	168		BANK	02	248
9	BANK	00	248	9	BANK	00	331
	BANK	01	153		BANK	01	236
	BANK	02	173		BANK	02	247
10	BANK	00	261	10	BANK	00	341
	BANK	01	178		BANK	01	263
	BANK	02	184		BANK	02	271
11	BANK	00	254	11	BANK	00	338
	BANK	01	168		BANK	01	251
	BANK	02	179		BANK	02	263
12	BANK	00	241	12	BANK	00	327
	BANK	01	155		BANK	01	234
	BANK	02	175		BANK	02	244
13	BANK	00	249	13	BANK	00	333
	BANK	01	158		BANK	01	242
	BANK	02	171		BANK	02	257
14	BANK	00	263	14	BANK	00	344
	BANK	01	169		BANK	01	257
	BANK	02	182		BANK	02	266
15	BANK	00	253	15	BANK	00	337
	BANK	01	161		BANK	01	245
	BANK	02	183		BANK	02	259
16	BANK	00	264	16	BANK	00	343
	BANK	01	162		BANK	01	241
	BANK	02	181		BANK	02	256
	BANK	00	259		BANK	00	339

**Table 4** (continued)

Scenario A				Scenario B			
Experiments	Bank branch office		Served clients	Experiments	Bank branch office		Served clients
17	BANK	01	163	17	BANK	01	242
	BANK	02	178		BANK	02	255
	BANK	00	243		BANK	00	323
18	BANK	01	152	18	BANK	01	235
	BANK	02	173		BANK	02	246

**Fig. 6** System performance in terms of number of served clients for scenarios A and B

$$\begin{aligned} \mu_{\text{scenarioB}} - \mu_{\text{scenarioA}} &\in \overline{\mu_{\text{scenarioB}}} - \overline{\mu_{\text{scenarioA}}} \pm t_{1-\frac{\alpha}{2}, v_1+v_2-2} \cdot sp \cdot \sqrt{\frac{1}{n_A} + \frac{1}{n_B}} \\ \mu_{\text{scenarioB}} - \mu_{\text{scenarioA}} &\in 198 - 279 \pm 2.032 \cdot 8.957 \cdot \sqrt{\frac{1}{9}} \\ -87 &\leq \mu_{\text{scenarioB}} - \mu_{\text{scenarioA}} \leq -75 \end{aligned} \quad (5)$$

The results show that the difference between  $\mu_{\text{scenarioA}}$  and  $\mu_{\text{scenarioB}}$  is between -85 and -75. According to the results, scenario B generates a significantly higher number of served clients than Scenario A.

### 5.3 Performance metric: Impact on the service duration time

The impact on the service duration time for scenarios A and B are presented in Table 6.

Considering these results, we evaluate whether there is no significant difference in the deviation of the service times of the financial clients served in a day for scenarios A and B. To do so, we evaluate if the variances of the system follow a Fisher – Snedecor distribution. The theoretical  $F$  value is  $F_{0.025;17;17}=0.3740$  and  $F_{0.975;17;17}=2.673$

assuming a confidence level of 95%. The calculated value is set to 2.49 ( $F_{\text{calculate}} = \frac{s_{\text{scenarioB}}^2}{s_{\text{scenarioA}}^2}$ ). Notice that  $F_{0.025;17;17} \leq$

$F_{\text{calculate}} \leq F_{0.975;17;17}$ . Thus, it allows us to conclude that there is sufficient evidence to affirm that the variance in service time in scenario B and the current scenario are significantly different. Considering Eq. 3 and a significance level of 0.05, the  $t$ -student test is performed to determine the difference between the average service time for both scenarios. The probability value is 476.57, then  $p < 0.001$ . Therefore, there is sufficient evidence to conclude that there is a significant difference in the average service duration time comparing scenarios A and B. Next, we compute the difference between  $\mu_{\text{scenarioA}}$  and  $\mu_{\text{scenarioB}}$  which represent the average service duration time (minutes) in scenarios A and B, respectively. The difference

**Table 5** Parameterization of the simulation model for both scenarios

Statistical value	Scenario A	Scenario B
$X$	198	279
$\sigma$	8.6	9.2
$n$	18	18

**Table 6** Total service time per bank, in scenarios A and B

Scenario A				Scenario B			
Experiments	Bank branch office		Service time [min.]	Experiments	Bank branch office		Service time [min.]
1	BANK	00	7233	1	BANK	00	4044
	BANK	01	7011		BANK	01	3948
	BANK	02	7062		BANK	02	3936
2	BANK	00	7144	2	BANK	00	4038
	BANK	01	7036		BANK	01	3926
	BANK	02	7083		BANK	02	3928
3	BANK	00	7146	3	BANK	00	4041
	BANK	01	7017		BANK	01	3921
	BANK	02	7073		BANK	02	3940
4	BANK	00	7158	4	BANK	00	4033
	BANK	01	7041		BANK	01	3910
	BANK	02	7089		BANK	02	3960
5	BANK	00	7152	5	BANK	00	4029
	BANK	01	7027		BANK	01	3903
	BANK	02	7062		BANK	02	3954
6	BANK	00	7168	6	BANK	00	4035
	BANK	01	7021		BANK	01	3912
	BANK	02	7076		BANK	02	3940
7	BANK	00	7178	7	BANK	00	4056
	BANK	01	7023		BANK	01	3944
	BANK	02	7084		BANK	02	3955
8	BANK	00	7171	8	BANK	00	4028
	BANK	01	7043		BANK	01	3927
	BANK	02	7070		BANK	02	3926
9	BANK	00	7178	9	BANK	00	4044
	BANK	01	7026		BANK	01	3936
	BANK	02	7046		BANK	02	3928
10	BANK	00	7033	10	BANK	00	4041
	BANK	01	7012		BANK	01	3930
	BANK	02	6950		BANK	02	3926
11	BANK	00	7153	11	BANK	00	4021
	BANK	01	7043		BANK	01	3904
	BANK	02	7056		BANK	02	3937
12	BANK	00	7159	12	BANK	00	4046
	BANK	01	7052		BANK	01	3948
	BANK	02	7044		BANK	02	3941
13	BANK	00	7135	13	BANK	00	4032
	BANK	01	7017		BANK	01	3932
	BANK	02	7026		BANK	02	3939
14	BANK	00	7158	14	BANK	00	4044
	BANK	01	7044		BANK	01	3927
	BANK	02	7049		BANK	02	3934
15	BANK	00	7151	15	BANK	00	4056
	BANK	01	7036		BANK	01	3937
	BANK	02	7038		BANK	02	3953
16	BANK	00	7133	16	BANK	00	4043
	BANK	01	7009		BANK	01	3935
	BANK	02	7032		BANK	02	3927
	BANK	00	7142		BANK	00	4038

**Table 6** (continued)

Scenario A				Scenario B			
Experiments	Bank branch office		Service time [min.]	Experiments	Bank branch office		Service time [min.]
17	BANK	01	7026	17	BANK	01	3918
	BANK	02	7043		BANK	02	3949
	BANK	00	7138		BANK	00	4039
18	BANK	01	7019	18	BANK	01	3923
	BANK	02	7022		BANK	02	3926

between  $\mu_{\text{scenarioA}}$  and  $\mu_{\text{scenarioB}}$  is between 3.095 min and 3.122 min. Thus, it is concluded that scenario B presents better performance. Figure 7 shows the system performance of scenarios A and B. It can be observed that the service duration times are better in scenario B.

## 6 Theoretical and managerial implications

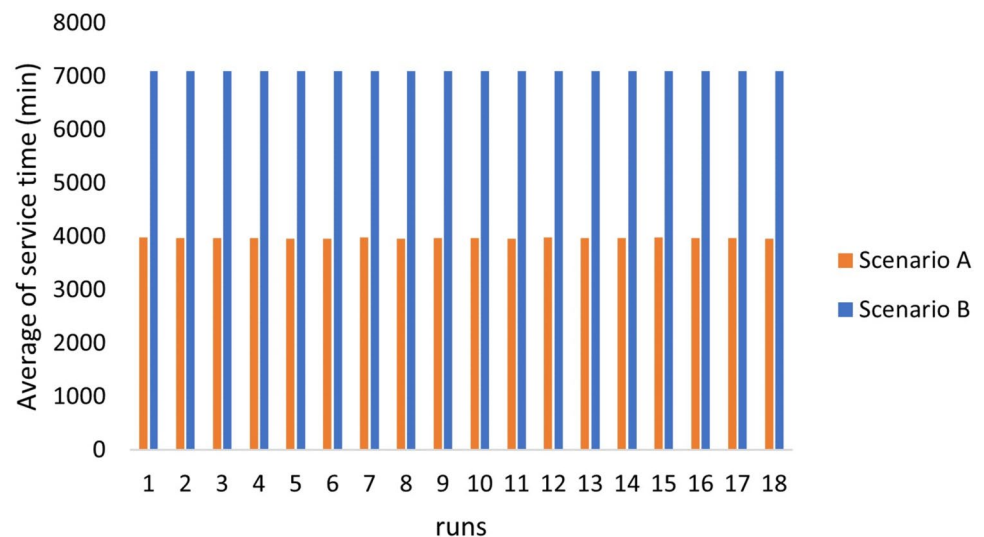
This study offers pivotal theoretical and managerial implications, underlining the potential extensive applicability of the proposed method in diverse contexts, for example, the adoption of tangible products such as food, clothing, cars, and beverages, among others, and the adoption of intangible products, such as consulting, transportation, insurance, etc. Besides, the proposed methodology offers a blueprint for future research to explore and expand upon this synergistic integration in other economic sectors, e.g., primary and secondary.

Furthermore, the studied problem revitalizes the discussion on the contrasting schemes of customer services in the banking sector, providing a contemporary lens to analyze and comprehend the dynamic of consumer behaviors in the digital era. The proposed model, validated with real-world data, offers a robust framework for future research to explore the variegated

facets of technology adoption and diffusion, expanding the horizons of the traditional Bass diffusion model.

From a managerial standpoint, the findings from this research wield significant implications for practitioners in the banking sector and beyond. The developed mobile application serves as a harbinger of a transformative wave in customer service optimization, showcasing the immense potential of leveraging technological innovations to enhance the service level and the number of served clients. Financial institutions can glean invaluable insights from this study to fine-tune their service delivery mechanisms, fostering a seamless and enriched customer experience.

Moreover, the insights garnered from this study can be instrumental in guiding policy formulation and strategy development, aiding financial institutions to navigate the complex landscape of the digital revolution adeptly. The flexibility of the proposed methodology allows for its adaptation and implementation, serving as a versatile tool for organizations to optimize their operations and strategize their technological integration endeavors. This adaptability highlights the potential for a broader application, opening avenues for cross-industry collaborations and fostering innovation in service delivery mechanisms, heralding a new era of technology-driven transformation in service delivery and companies' excellence.

**Fig. 7** System performance in terms of service time duration

In summary, this research contributes to the theoretical discourse and offers tangible and actionable insights for academics and practitioners, underscoring the extensive potential applicability of the proposed method. Future research can build upon this foundation, exploring the myriad avenues for innovation and optimization in the ever-evolving landscape of the digital era.

## 7 Conclusions

This article presented a methodology based on simulation to evaluate the impact of using a mobile App for reducing banking clients' waiting time. The results provide evidence of the App impact on the service levels of the agents involved in the process (i.e., clients) and its effect on the attraction of new clients. Our study contributes a nuanced understanding of the existing literature, highlighting the potential of mobile applications to improve not only their operational performance but also the service experience. This fact is aligned with the identified research gap, where the application of technology in enhancing customer service experiences in the banking sector remains underexplored.

Despite the contributions of this work, future research lines include:

- Identify and create forecast models for transactional loads by banking establishments, which allows them to identify the annual, monthly, and daily behavior of the entity.
- To optimize the operation cost of adding bank tellers to accomplish the service promise.
- To balance the number of bank tellers in bank branch offices.
- Generate and evaluate campaigns or strategies so that the use of these transactional platforms and/or financial services (such as mobile banking) can achieve widespread implementation.
- Expand the research to other service areas of the financial institution such as service platform, credit areas, etc.
- Finally, implement the proposed methodology for tangible and intangible products and other economic sector.

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**Data availability** Not applicable.

## Declarations

**Conflict of interest** The authors have no competing interests to declare that are relevant to the content of this article.

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