International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Artificial Intelligence Model for Citizen Service in Mixed-Economy Companies

[1]William Higuera Paz, [2]Fabiola Sáenz Blanco

Submitted: 18/07/2023 **Revised**: 08/09/2023 **Accepted**: 25/09/2023

Abstract: In a competitive and constantly evolving world, excellence in customer service is critical to business success; however, the management of PQRS (Petitions, Complaints, Claims, and Suggestions) can be challenging. In this context, data-driven artificial intelligence, artificial intelligence emerges as a powerful transformational tool in this area, using natural language processing algorithms and data analytics, and can provide personalized and rapid responses, thereby improving the customer experience. Similarly, machine learning is critical as it enables automation and improves the quality of responses; furthermore, machine learning systems can analyze large volumes of information, identify patterns and trends, and learn from feedback. These systems can understand the content of requests and generate accurate and relevant responses, adapting to the needs of each user, optimizing customer service, and improving problem resolution. This thesis presents a practical approach for mixed-economy companies interested in optimizing their customer service processes as follows: data-driven artificial intelligence can drive operational efficiency and overall business success; the combination of industrial engineering and artificial intelligence offers opportunities to optimize processes; and simulation and data analytics facilitate decision making, empowering industrial engineers to efficiently optimize processes.

Keywords: *Machine Learning, Artificial Intelligence, Automated Learning, Data Analysis, Natural Language Processing, and Continuous Improvement*.

1. Introduction

In the current context, the interaction between citizens and mixed economy companies plays a fundamental role in the development and efficiency of measuring the performance of such organizations. Citizen service is driven as a key aspect of strengthening the relationship between the government and its citizens. However, the increasing volume of queries and requests received by these entities may hinder efficient and personalized attention.

Service companies, like many other companies in various sectors, have faced difficulties in the development of their business management due to the adversities arising during the years 2020 and 2021, mainly due to the pandemic.

One of the difficulties highlighted in these companies is the decrease in demand for their services. This is reflected in the business pulse report prepared by DANE in the year 2021, which ratifies how companies in the services sector have seen their share of demand reduced from 66% in April 2020 to 42.8% in March 2021 (DANE, n.d.)

Taking into account the results of the DANE, companies have maintained their focus on traditional activities without considering the new needs of the market. The decisions taken have not demonstrated efficiency, efficacy, flexibility, or speed in the face of the events generated by the pandemic, which has led these entities to face an economic crisis.

The Chamber of Commerce of Bogota has presented the results of the growth in the creation and renewals of the commercial registration of Colombian companies during 2019 and 2020. Unfortunately, a decrease of 11% was evidenced, which translates into the closure of 54,838 companies. This decrease represented a worrying sign for the country's business panorama (BOGOTA CHAMBER OF COMMERCE, n.d.)

In response to this problem, artificial intelligence (AI) and natural language processing (NLP) have emerged as innovative and promising solutions to improve the citizen service process. These advanced technologies offer the possibility of automating and streamlining the response or assignment of queries and requests, thus providing a faster and more satisfactory experience for citizens.

Artificial intelligence, based on machine learning algorithms, can understand and analyze large volumes of data generated by citizens. This deep understanding capacity allows the identification of patterns and trends, facilitating the classification and prioritization of inquiries

1Ingeniero industrial (Universidad Central de Colombia), Especialista en costos y presupuesto (Universidad la Gran Colombia), Estudiante de Maestria de ingeniería industrial. whiguerap@ucentral.edu.co – ORCID: https://orcid.org/0009-0008-3768-3446

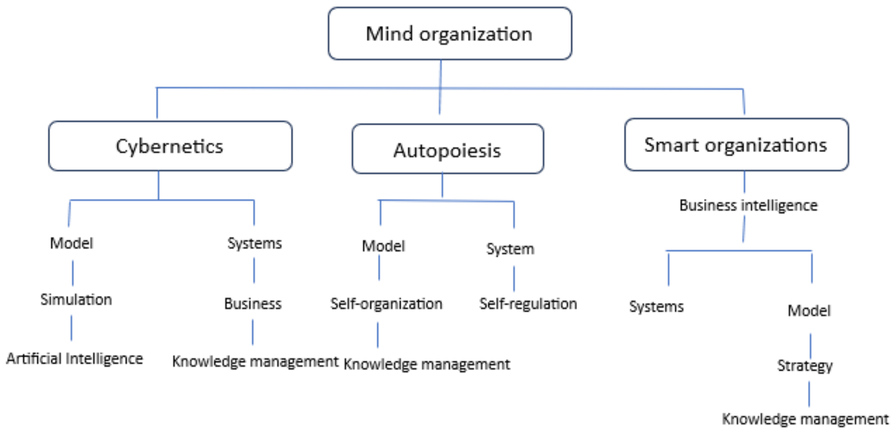
2Ingeniera Industrial (Universidad Distrital Francisco José de Caldas), Doctora en Dirección de Empresas (Universidad de Oviedo, Asturias – España), Postdoctora en Innovación (Colciencias - Universidad Distrital), Docente Titular Tiempo Completo Facultad de Ingeniería Universidad Distrital "Francisco José de Caldas".Bogotá D.C. (Colombia) –(Author) – ORCID: https://orcid.org/0000-0003-0040-1296

and requests received. In addition, artificial intelligence can generate accurate and personalized responses, adapting to the individual needs and preferences of citizens.

On the other hand, natural language processing focuses on understanding and generating human language. Through text and voice analysis, this branch of artificial intelligence allows entities to interpret queries and requests formulated in natural language, eliminating communication barriers and facilitating a more fluid and effective interaction with citizens.

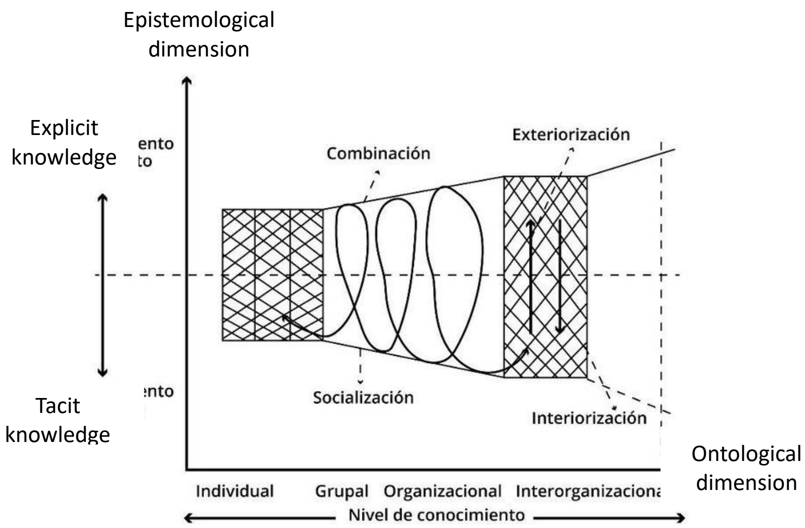
2. Theoretical Background

Based on the UNESCO thesaurus, the keywords necessary to carry out a scientometric search of research related to models or systems developed for artificial intelligence have been determined.



Knowledge is a term that has been approached over time from many philosophical and management perspectives. This pre-project focuses on the organization as Davenport indicated in 2001 informing about the "information age", but he also clarified that there are no models, methodologies, and others for the use and appropriation of knowledge (Yolima et al., 2006).

Different researchers have focused on the development of a new class of leaders who are empowered by individual knowledge and who find the means to use it in organizations. Among the outstanding research in knowledge management is that of Nonaka and Takeuchi in 1995 on their proposal for the creation of organizational knowledge. The main premise of this theory is that knowledge starts from the individual and through interactions allows the development of organizational knowledge.



Nonaka and Takeuchi's theory reviewed from the epistemological and ontological axes determined that there are two types of knowledge: tacit and explicit (Ruth et al., 2017).

They conceptualized these terms as follows:

Tacit Knowledge: This knowledge arises from experience and is difficult to transfer.

Explicit Knowledge: This is the knowledge that has the advantage of being written and transferred. In organizations, it is found in manuals, procedures, instructions, and others.

From the aforementioned premise about the interaction between individuals, it is observed that the creation of knowledge arises dynamically through the interaction between two types of knowledge. As organizations evaluate the behavior of these types of knowledge, they seek to convert them into something formal that can be shared among individuals, while promoting the development of new experiences to generate innovative practices.

According to Nonaka and Takeuchi's description in 1995, specific modes of knowledge conversion are identified: socialization, externalization, combination, and internalization. Each of these modes triggers a process by which knowledge is transformed and disseminated within the organization.

Socialization: Conversion from Tacit to Tacit, which is reflected in the organizational culture.

Externalization: Conversion from Tacit to Explicit. This conversion generates the standardization of the process of good business practices.

Combination: Explicit to Explicit Conversion. It is the development of information processing

Internalization: Conversion from Explicit to Tacit. This is the development of organizational learning.

Considering that companies are teams formed by individuals with the ability to create knowledge, feedback, and learn, it can be deduced that by applying the general theory of systems, it can be affirmed that the system (the company) shares the same properties as the individuals. In other words, the characteristics of learning, feedback, and knowledge creation present in individuals extend to the functioning of the business system (Martín-De Castro & López Sáez, 2004).

Likewise, it can be premised that the individual generates individual knowledge and through a series of capacities of acquisition, generation, use, and transfer of knowledge, skills, and habits generates intelligence, while in organizations knowledge, by generating a series of organizational capacities, becomes intellectual capital or organizational intelligence (Lourdes Quiroga, n.d.). From this ideology authors such as Maturana, in 2002, expressed that the company is "(...) subjects that learn, and that do so to evolve, adapt and respond to the demands of a cultural environment characterized by instability, virtuality and multiplicity of expectations, which demands from them an extraordinary adaptive skill" (De Comunicación et al., 2018). In this framework, organizations express that they are entities in continuous learning, without the importance of size.

Researchers such as Pelufo and Catalán in 2002 recognized knowledge management as a discipline and expressing as an objective: "(..) to generate, share and use the tacit knowledge (Know-how) and the explicit (formal) existing in a certain space, to give answers to the needs of individuals and communities in their development" (Adrián Ramírez et al., n.d.). Thus, Pelufo and Catalán focused on the need for knowledge management, which is determined by six linear processes for management, namely:

1. Initial diagnosis
2. Definition of objectives
3. Production of organizational knowledge
4. Storage and Updating
5. Circulation and utilization of knowledge
6. Performance measurement

In the application of artificial intelligence, organizational knowledge collected and stored during initial diagnosis and knowledge production can be used to train machine learning models. The efficient circulation and utilization of knowledge allow for improved decision-making and more accurate responses to natural language processing tasks.

In addition, performance measurement, as the ultimate process in knowledge management, is essential to evaluate the effectiveness of artificial intelligence and natural language processing models implemented in an organization. This allows for continuous feedback and adjustment of the systems, improving their performance and adaptability.

In the conception of the term "scientific and cybernetic intelligence", the term "brain organization" was developed from the metaphor proposed by Gareth Morgan (1986), who relates brain functions with the management performed by an organization in search of self-organization. This metaphor was based on the comparison of a machine with a brain, an idea previously explored by Gordon Rattray Taylor, using the results of Karl Lashley's (1935) experiment on the removal of portions of the brain in rats trained to run mazes.

Lashley's experiment revealed that, as long as the visual part of the animal's brain was not removed, he could destroy 90% of the cortex and the animal still found its way out of the maze. Unlike a machine, a living organic system maintains its functionality at a lower capacity when a part of the main system is removed. From this concern about the possibility of designing organizations to be as flexible, resilient, and inventive as the brain, Gareth Morgan posed the question: "Is it possible to design organizations in such a way that they can be as flexible, resilient, and inventive as the brain?

This question was addressed by representatives of information processing and cybernetics theories, as well as by advances in artificial intelligence and natural language processing. Through the contributions of Wiener in 1948, Ashby in 1952, and Beer in 1972, the mission of cybernetics was defined as the exchange of information between machines and organisms, allowing the self-regulation of behavior to maintain an objective state (Arnold-Cathalifaud, 2008).

Today, artificial intelligence and natural language processing have become fundamental tools for knowledge management in organizations. These technologies enable the automation of cognitive tasks, the analysis of large volumes of information, and data-driven decision-making.

For example, through the use of machine learning algorithms, artificial intelligence can identify patterns and trends in the data collected, facilitating the detection of opportunities and challenges in the business environment. Likewise, natural language processing enables organizations to extract relevant information from documents, reports, or customer interactions, contributing to a better understanding of available knowledge and its subsequent management. In the context of the brain organization, these artificial intelligence and natural language processing technologies are integrated to enhance an organization's ability to adapt, learn, and make decisions, enabling more effective knowledge management and greater self-regulation in its operation.

George Miller, Eugene Galanter, and Karl Pribram in 1960 made a contribution to cybernetics with the TOTE (Test - Operation - Test - Exit) algorithm. This analogical algorithm points out that human mental activity is guided by conscious and unconscious goals. When we set a goal, we perform a TEST to evaluate whether it is achieved. If it is not achieved, we OPERATE to modify the situation or take action to move closer to the goal. Once the TEST judgments have been met, proceed to EXIT, to generate a new TEST in a different situation (Zegarra Salas, 2019).

Thus, Morgan summarizes the behavior of systems as brains in four basic principles:

1. Systems must recognize the environment.
2. Systems must communicate information between their components.
3. The system must recognize deviations in its functionality.
4. The system must recognize the pertinent actions to act upon each possible deviation.

By applying these principles, the aim is to achieve an organization that can adapt and learn from its environment like that of a brain, which favors self-regulation and continuous improvement in its operation.

3. Methodology

The research is framed as applied research to address the problem related to decision-making in a mixed economy entity. To validate this approach, an independent variable and intervening variables will be used through the design of an artificial intelligence model.

Regarding the nature of the research, two main types of research are identified. First, exploratory research aims to delve into under-researched topics to develop specific knowledge. Secondly, descriptive research is used to characterize the results of previous exploratory research.

In terms of the data used, the research is based on both quantitative and qualitative approaches. The phenomena will be evaluated through mathematical tools for quantification, as well as through detailed descriptions that allow a deeper understanding of the actions of the actors involved in the research, their motivations, values, and principles based on the organizational culture. For this, qualitative methods and methodologies will be used.

Through scientometric research, several variables relevant to the development of a model have been identified.

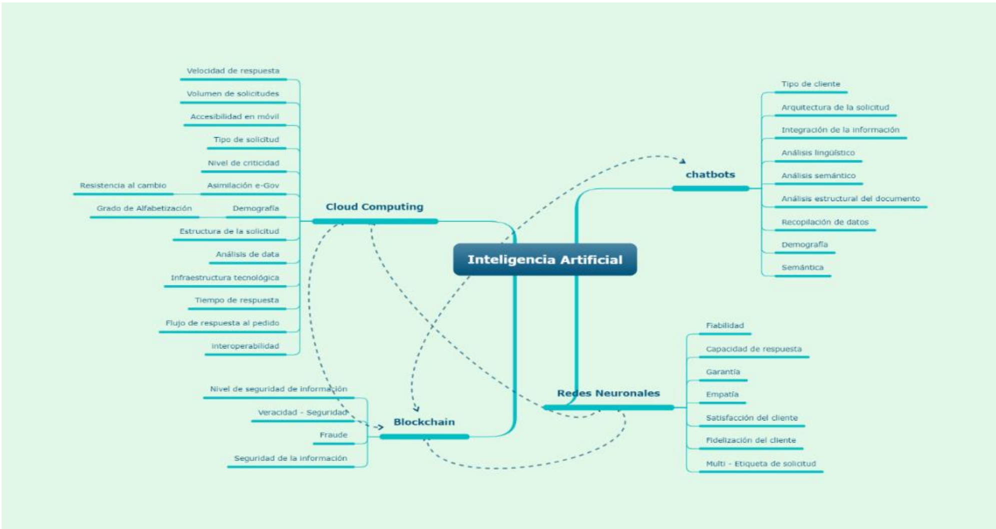
Article	Variables
Design of the use of chatbot as a virtual assistant in banking services in Indonesia (Effendi & Susanto, 2019)	Structure of the request Semantic Analysis Request response flow Empathy
The TRISEC framework for optimizing conversational agent design across search, experience, and credence service contexts (Blazevic & Sidaoui, 2022)	Structure of the application Linguistic analysis Request response flow
An intelligent knowledge-based chatbot for customer service (Ngai et al., 2021)	Customer knowledge, Response time
DialogueBERT: A Self-Supervised Learning based Dialogue Pre-training Encoder (Z. Zhang et al., 2021)	Structure of the application Information Security Fraud
CASExplorer: A Conversational Academic and Career Advisor for College Students (Lee et al., 2021)	Structure of the request Semantic Analysis Request response flow
AI-based chatbots in customer service and their effects on user compliance (Adam et al., 2021)	Structure of the request Semantic Analysis Request response flow Interoperability
Power User Sensitivity Analysis and Power Outage Complaint Prediction (Ding et al., 2021)	Reliability Responsiveness Empathy Warranty Multi - Labels
Developing smart devices with automated Machine learning Approach: A review (Patel et al., 2022)	Structure of the request Semantic Analysis Request response flow Demographics Multi - Tags
A Chatterbot Based on Genetic Algorithm: Preliminary Results (Orellana et al., 2021)	Structure of the request Semantic Analysis Request response flow Interoperability Multi - Tags

Artificial Intelligence for Public Sector: Chatbots as a Customer Service Representative (Adnan et al., 2021)	Structure of the request Semantic Analysis Request response flow Multi - Tags
Real-Time Data Science Decision Tree Approach to Approve Bank Loan from Lawyer's Perspective (Rajesh et al., 2020)	Volume of responses Volume of requests Technological infrastructure Response times Multi - Labels
An Intelligent Chatbot System Based on Entity Extraction Using RASA NLU and Neural Network (Windiatmoko et al., 2020)	Structure of the request Semantic Analysis Criticality level Document structure analysis Request response flow Multi - Tags
A Restless Bandit Model for Resource Allocation, Competition, and Reservation (Fu et al., 2018)	Structure of the request Semantic Analysis Request response flow Data analysis Information security levels Veracity
E-governance for Public Administration (Kaluti & Rajani, 2021)	Service Category e-Gov Literacy level Demographics
Electronic Public Services in the AI Era	Availability Privacy of information Reliability Transparency Interactivity
Customer support chatbot using Machine Learning (Madana Mohana et al., 2021)	Volume of requests Response speed
Research on Intelligent Robot Engine of Electric Power Online Customer Services Based on Knowledge Graph (B. Zhang et al., 2020)	Structure of the request Semantic Analysis Request response flow Multi - tags Keywords

Automatic update strategy for real-time discovery of hidden customer intents in chatbot systems (Rebelo et al., 2022)	Type of requests Model update time Most likely customer intent Number of times the keyword Cluster
Intention model-based multi-round dialogue strategies for conversational AI bots (Tian et al., 2022)	Knowledge base Data collection
Development of Dialogue Management System for Banking Services (Rustamov et al., 2021)	Intention Tagged Type of response
Machine learning algorithms for teaching AI chatbots (Tebenkov & Prokhorov, 2021)	Data analysis Multi - Tags

These variables, carefully selected and analyzed, provide a solid basis for the creation of a scientific and systematic approach to a more accurate understanding of the key factors influencing the proposed model.

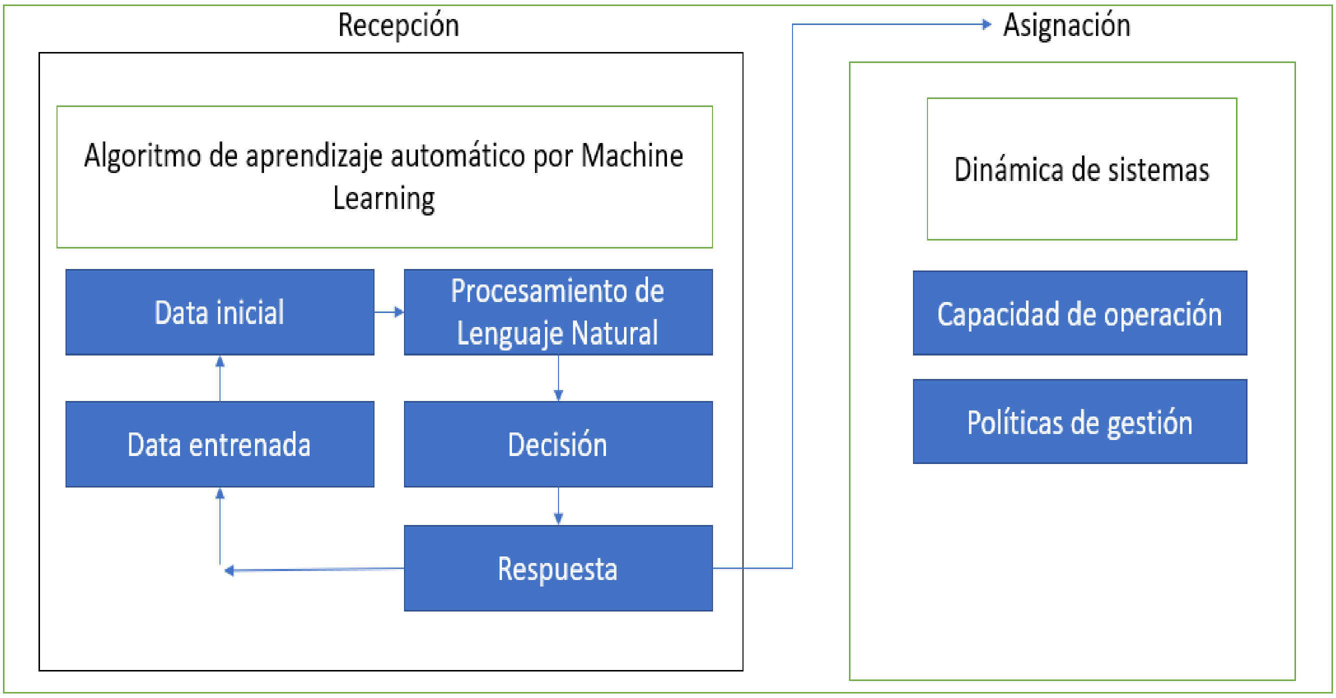
for the creation of a scientific and systematic approach to gain a more precise understanding of the key factors influencing the proposed model. By integrating these variables into the research, a solid and well-founded framework is established, capable of shedding light on the complexity of the subject in question and providing an adequate structure for the development and validation of the proposed model.

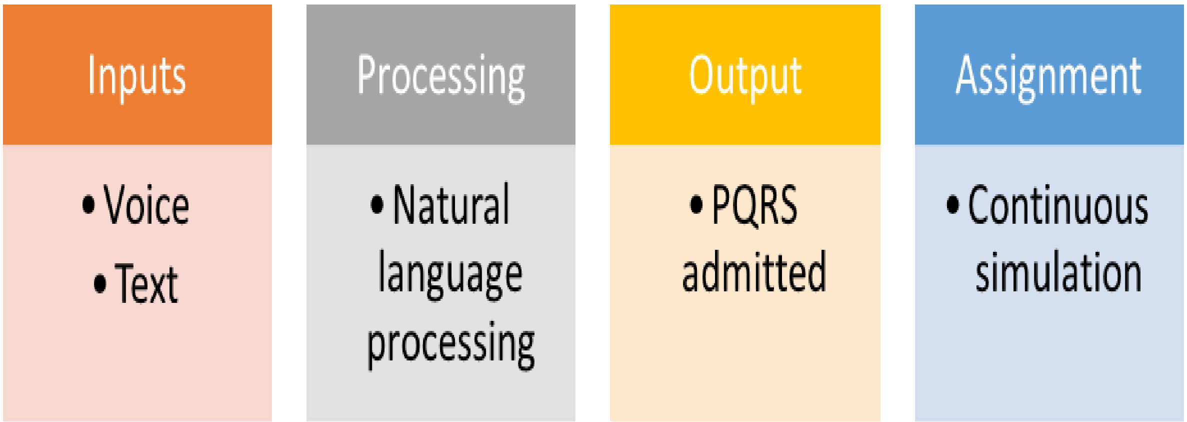


The Artificial Intelligence Model in citizen service for mixed economy entities is based on the variables developed in chatbots and neural networks, a methodology for the assignment of requests, complaints, claims, and suggestions (PQRS) with two main stages: reception and assignment.

In the first stage, an approach is implemented that focuses on the essential activities for the PQRS assignment process. To achieve this, a Machine Learning (ML) model with natural language processing (NLP) was used, which allows the identification of requests in an efficient way. In the second stage, the allocation is performed considering the dynamics of admitted requests, taking into account the operational capacity and management policies that may influence the increase or decrease of capacity. In this context, the principles of brain organization are applied, seeking to adapt the allocation process in a flexible and resilient manner, similar to how a brain adjusts and learns to maintain its optimal functioning.

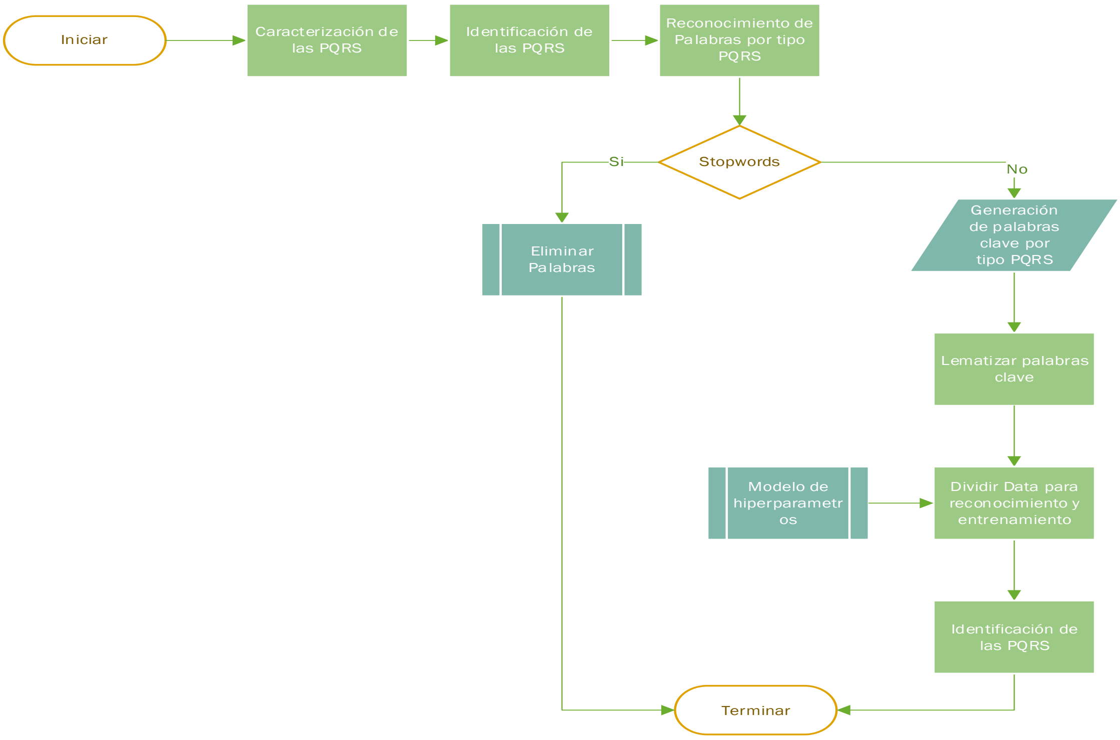
The following is the integral model developed:





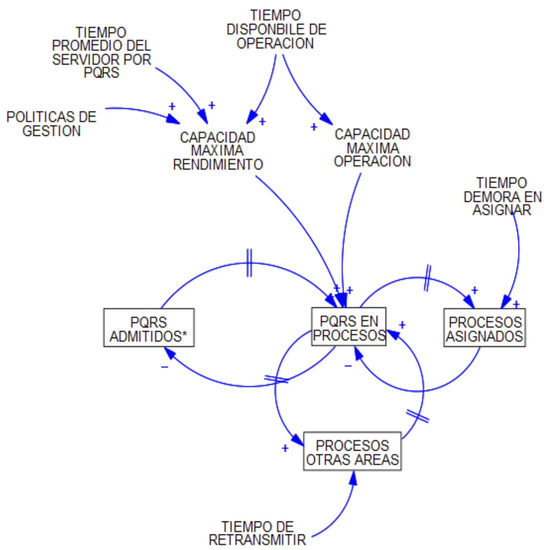
Once the model architecture has been defined, it is important to highlight that the operation is performed using the programming language known as Python for natural language processing (NLP). Python has a large number of popular libraries such as NLTK (Natural Language Toolkit), SpaCy, and TensorFlow, among others, these libraries provide a wide range of functionalities for analysis, tokenization, labeling, lemmatization, attribute detection, and recognition generation of data analysis algorithms. Its open-source nature and broad support in research groups also ensure constant support, frequent updates, and a wealth of resources and tutorials available online. In summary, the choice of Python as the programming language in the thesis provides significant advantages in terms of availability of specialized libraries, ease of use, and an active community that fosters collaboration and continuous development

Natural language processing is carried out in the assignment phase through the following algorithm:

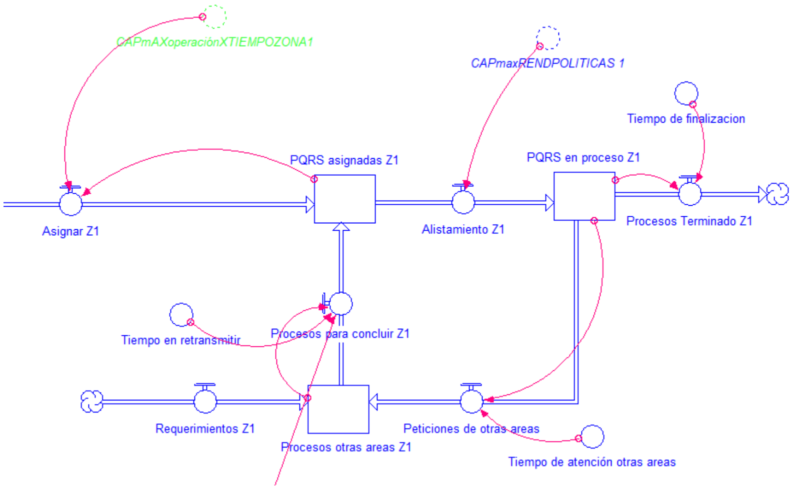


Through the application of natural language processing, the result of the previous algorithm reveals the admitted PQRS. The execution of this algorithm enables a precise and systematic evaluation, defining the characteristics of each category and fulfilling a series of predefined criteria for its collection. This classification process, driven by natural language analysis, speeds up efficient and objective identification, contributing significantly to informed decision-making and the maintenance of quality standards in the admission of PQRS.

Through the PQRS admitted, the operation of a mixed economy entity is determined using system dynamics, which is a methodology used to understand and analyze the operation in the long term. This methodology is based on a causal analysis to elaborate the creation of mathematical models that represent the interactions and relationships between different variables and components of the entity. Through these models, it is possible to simulate various scenarios and evaluate how changes in one part of the system affect other areas. This makes it possible to understand the complex interconnections and feedback that influence the functioning of the entity, identify possible points of conflict or inefficiency, and design strategies to optimize its performance. In this way, the system dynamics is in the PQRS assignment phase that provides a comprehensive and long-term perspective, which helps to take action and implement changes that have a positive impact on the value chain. The causal analysis of the PQRS process is presented below.



At present, the entity for the case study has four agencies by zones, which have their respective operating and performance capacities. The following is the modeling of the zone operation.



Equations

$$x = PQRS$$

$$i = Zone\ number$$

PQRS ASSIGNED TO THE ZONE

$$Fe = AssignZ_i + Processes\ to\ conclude\ Z_i$$

$$Fe = Max.operating\ capacity\ per\ time\ Z_i + \frac{Processes\ in\ other\ areas\ Z_i}{Time\ in\ Retransmit\ Z_i}$$

$$Fs = Enlistment\ Z_i = Capacity\ Max.performance\ Management\ policies\ Z_i$$

$$\frac{dx}{dt} = Max.operation\ by\ time\ Z_i + \frac{Processes\ in\ other\ areas\ Z_i}{Time\ in\ Retransmit\ Z_i} - Cap\ Max.performance\ Management\ policies\ Z_i$$

PQRS IN PROCESS IN THE AREA

$$Fe = Enlistment\ Z_i$$

$$Fe = Capacity\ Max.performance\ Management\ policies\ Z_i$$

$$Fs = Finished\ processes\ \ Z_i + Requests\ to\ other\ areas\ \ Z_i$$

$$Fs = \frac{PQRS\ in\ process\ Z_i}{Completion\ Time} + \frac{PQRS\ in\ process\ Z_i * Transfer\ factor\ to\ other\ areas}{Attention\ time\ of\ other\ areas}$$

$$\frac{dx}{dt} = Capacity\ Max.performance\ Management\ policies\ Z_i - \frac{PQRS\ in\ process\ Z_i}{Completion\ Time} - \frac{PQRS\ in\ process\ Z_i * Transfer\ factor\ to\ other\ areas}{Attention\ time\ of\ other\ areas}$$

PQRS IN PROCESS IN THE AREA

$$Fe = Requirements + Requests\ to\ other\ areas\ \ Z_i$$

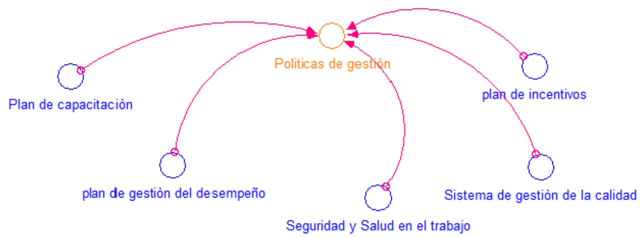
$$Fe = BINOMIAL(10,2,5) + \frac{PQRS\ in\ process\ Z_i * Transfer\ factor\ to\ other\ areas}{Attention\ time\ of\ other\ areas}$$

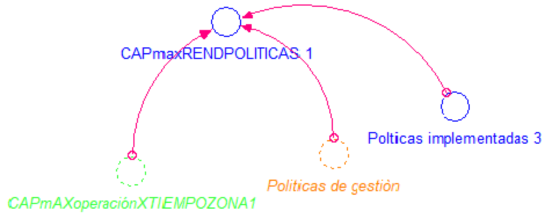
$$Fs = Processes\ to\ conclude\ Z1$$

$$Fs = \frac{Processes\ in\ other\ areas\ Z_i}{Time\ in\ Retransmit\ Z_i}$$

$$\frac{dx}{dt} = BINOMIAL(10{,}2{,}5) + \frac{PQRS\ in\ process\ Z_i * Transfer\ factor\ to\ other\ areas}{Attention\ time\ of\ other\ areas} - \frac{Processes\ in\ other\ areas\ Z_i}{Time\ in\ Retransmit\ Z_i}$$

The capacity of the operation by performance is based on the operation capacity by time, the policies implemented in the area, and the management policies established in a theoretical way.





Equation

$$Management\ policies = Training\ Plan + Performance\ Management\ Plan + Occupational\ Health\ and\ Safety + Quality\ Management\ System + Incentive\ Plan$$

$$Cap.Max.Opera.perPerPerformance\ Z_i = Max.operating\ capacity\ per\ time\ Z_i * \frac{Policies\ implemented}{Management\ policies}$$

Discussion of results

By processing the data, the data were divided into two parts for testing and for training, it is always necessary to give a greater amount of data to the training since the model will take the examples from there to make future predictions. After dividing the data, the tests of the different models to be developed are applied. For the artificial intelligence model, five tests were performed, which are: Logistic regression, support vector machines, random forests, k nearest neighbors, and Gaussian Naive Bayes. To evaluate each test, the accuracy metric was used to define which model is the most convenient for the prediction processes, the following table shows those obtained with each model.

Model	Accuracy
Logistic regression	0.666
Support vector machines	0.283
Random forests	0.533
K nearest neighbors	0.383
Gaussian Naive Bayes	0.466

With this development carried out with machine learning and natural language processing, which automatically classifies requests, the reception times per area became zero. Taking into account the dates of the filings through the platform, it was determined that the average time of reception and definition of admitted PQRS is 5.14 days.

In the reception phase, through the analysis of system dynamics, it has been possible to reveal a notable change in the results of the process. A considerable decrease of 7.4% has been determined in comparison with the previous volume of PQRS in the process. This achievement has materialized through an innovative strategy: the efficient execution of filing and validation activities, facilitated by natural language processing.

In this way, it is possible to define a continuous improvement in the reception process for mixed economy entities, generating a decrease in the development and response times of admitted PQRS.

Conclusions

When analyzing the different models, Logistic Regression obtains the highest accuracy index, reaching a value of 0.66. Although this performance is considered moderate, it is advisable to use it to make predictions on previously unseen data sets. To further improve performance, it is essential to obtain feedback from the data in a balanced way, encompassing several additional features to generate a larger number of categories. To achieve more robust results, a larger and more diverse dataset, encompassing a wider variety of classes, is required. This approach would allow to retrain the models and obtain significant improvements in the results.

In case it is not feasible to modify or expand the dataset in a different entity, one option to 'improve' the results would be to consider eliminating the class 'requests for access to public information'. Since this class has very precise information and from different cases, its inclusion in the model generates noise and does not contribute relevant information in a meaningful way. However, it is important to note that this action would only have a limited effect in improving the results.

For the case of Central de Inversiones S.A., it is recommended to use Logistic Regression due to its moderate performance. As a follow-up, it is recommended to generate new categories that are more explicit and not general, allowing the model to perform more efficiently, although it can be determined that by further categorizing the input information there is a possibility that neural networks with layers that identify unique characteristics in the typology should be used.

References

[1] Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 427–445. https://doi.org/10.1007/S12525-020-00414-7

[2] Adnan, S. M., Hamdan, A., & Alareeni, B. (2021). Artificial Intelligence for Public Sector: Chatbots as a Customer Service Representative. *Lecture Notes in Networks and Systems*, *194 LNNS*, 164–173. https://doi.org/10.1007/978-3-030-69221-6_13/COVER

[3] Adrián Ramírez, C., María, M., Carmen, D., Moreno, H., Herrera Tapia, F., & Pérez Sánchez, A. (n.d.). *Gestión territorial para el desarrollo rural Construyendo un paradigma*.

[4] Arnold-Cathalifaud, M. (2008). LAS ORGANIZACIONES DESDE LA TEORíA DE LOS SISTEMAS SOCIOPOIéTICOS. *Cinta de Moebio*, *32*(32), 90–108. https://doi.org/10.4067/S0717-554X2008000200002

[5] Blazevic, V., & Sidaoui, K. (2022). The TRISEC framework for optimizing conversational agent design across search, experience, and credence service contexts. *Journal of Service Management*, *33*(4–5), 733–746. https://doi.org/10.1108/JOSM-10-2021-0402/FULL/PDF

[6] CAMARA DE COMERCIO DE BOGOTA. (n.d.). *Al cierre de 2020 las empresas de Bogotá y la Región cayeron 11 % - Cámara de Comercio de Bogotá*. Retrieved May 28, 2021, from https://www.ccb.org.co/Sala-de-prensa/Noticias-CCB/2021/Enero/Al-cierre-de-2020-las-empresas-de-Bogota-y-la-Region-cayeron-11

[7] DANE. (n.d.). *Encuesta Pulso Empresarial*. Retrieved May 28, 2021, from https://www.dane.gov.co/index.php/en/estadisticas-por-tema/comercio-interno/encuesta-pulso-empresarial

[8] De Comunicación, F., De Fin, T., Máster, D. E., Corona León, G. A., & Uk, A. (2018). *MICROEMPRESAS TURÍSTICAS EN SEVILLA CORE View metadata, citation and similar papers at core*. Universidad de Sevilla.

[9] Ding, J., Shi, Y., Zhu, R., Wei, X., Chen, B., & Yu, J. (2021). Power User Sensitivity Analysis and Power Outage Complaint Prediction. *Journal of Physics: Conference Series*, *1852*(2), 022052. https://doi.org/10.1088/1742-6596/1852/2/022052

[10] Effendi, P. M., & Susanto, T. D. (2019). Test of Citizens' Physical and Cognitive on Indonesian E-Government Website Design. *Procedia Computer Science*, *161*, 333–340. https://doi.org/10.1016/J.PROCS.2019.11.131

[11] Fu, J., Moran, B., & Taylor, P. G. (2018). A Restless Bandit Model for Resource Allocation, Competition and Reservation. *Operations Research*, *70*(1), 416–431. https://doi.org/10.1287/opre.2020.2066

[12] Kaluti, M., & Rajani, K. C. (2021). E-governance for Public Administration. *Lecture Notes in Electrical Engineering*, *698*, 1059–1065. https://doi.org/10.1007/978-981-15-7961-5_98

[13] Lee, T., Zhu, T., Liu, S., Trac, L., Huang, Z., & Chen, Y. (2021). CASExplorer: A Conversational Academic and Career Advisor for College Students. *ACM International Conference Proceeding Series*, 112–116. https://doi.org/10.1145/3490355.3490368

[14] Lourdes Quiroga, A. (n.d.). *Gestión de información, gestión del conocimiento y gestión de la calidad en las organizaciones*. Retrieved May 11, 2021, from http://scielo.sld.cu/scielo.php?script=sci_arttext&pid=s1024-94352002000500004

[15] Madana Mohana, R., Pitty, N., & Lalitha Surya Kumari, P. (2021). Customer support chatbot using machine learning. *Advances in Intelligent Systems and Computing*, *1177*, 445–451. https://doi.org/10.1007/978-981-15-5679-1_42/COVER

[16] Martín-De Castro, G., & López Sáez, P. (2004). *Dinámicas de aprendizaje organizativo Measuring and Reporting National Intellectual Capital View project A BIBLIOMETRIC ANALYSIS OF INTELLECTUAL CAPITAL (1990-2016) View project*. https://www.researchgate.net/publication/28120539

[17] Morgan, G. (n.d.). *IMÁGENES DE LA ORGANIZACIÓN*. Retrieved April 15, 2021, from

http://institutocienciashumanas.com/wp-content/uploads/2020/03/IMAGENES_DE_LA_ORGANIZACION.pdf

[18] Ngai, E. W. T., C. M. Lee, M., Luo, M., Chan, P. S. L., & Liang, T. (2021). An intelligent knowledge-based chatbot for customer service. *Electronic Commerce Research and Applications*, *50*, 101098. https://doi.org/10.1016/J.ELERAP.2021.101098

[19] Orellana, C., Tobar, M., Yazán, J., Peluffo-Ordóñez, D., & Guachi-Guachi, L. (2021). A Chatterbot Based on Genetic Algorithm: Preliminary Results. *Communications in Computer and Information Science*, *1455 CCIS*, 3–12. https://doi.org/10.1007/978-3-030-89654-6_1/COVER

[20] Patel, S. A., Patel, S. P., Adhyaru, Y. B. K., Maheshwari, S., Kumar, P., & Soni, M. (2022). Developing smart devices with automated Machine learning Approach: A review. *Materials Today: Proceedings*, *51*, 826–831. https://doi.org/10.1016/J.MATPR.2021.06.243

[21] Rajesh, D. P., Alam, M., Tahernezhadi, M., Vikram, C., & Phaneendra, P. N. (2020). Real-Time Data Science Decision Tree Approach to Approve Bank Loan from Lawyer's Perspective. *Proceedings - 19th IEEE International Conference on Machine Learning and Applications, ICMLA 2020*, 921–929. https://doi.org/10.1109/ICMLA51294.2020.00150

[22] Rebelo, H. D., de Oliveira, L. A. F., Almeida, G. M., Sotomayor, C. A. M., Magalhães, V. S. N., & Rochocz, G. L. (2022). Automatic update strategy for real-time discovery of hidden customer intents in chatbot systems. *Knowledge-Based Systems*, *243*, 108529. https://doi.org/10.1016/J.KNOSYS.2022.108529

[23] Rustamov, S., Bayramova, A., & Alasgarov, E. (2021). Development of Dialogue Management System for Banking Services. *Applied Sciences 2021, Vol. 11, Page 10995*, *11*(22), 10995. https://doi.org/10.3390/APP112210995

[24] Tebenkov, E., & Prokhorov, I. (2021). Machine learning algorithms for teaching AI chatbots. *Procedia Computer Science*, *190*, 735–744. https://doi.org/10.1016/J.PROCS.2021.06.086

[25] Tian, J., Tu, Z., Li, N., Su, T., Xu, X., & Wang, Z. (2022). Intention model-based multi-round dialogue strategies for conversational AI bots. *Applied Intelligence*, *52*(12), 13916–13940. https://doi.org/10.1007/S10489-022-03288-8/METRICS

[26] Windiatmoko, Y., Rahmadi, R., Hidayatullah, A. F., & Jiao, A. (2020). An Intelligent Chatbot System Based on Entity Extraction Using RASA NLU and Neural Network. *Journal of Physics: Conference Series*, *1487*(1), 012014. https://doi.org/10.1088/1742-6596/1487/1/012014

[27] Yolima, D., Buitrago, F., Alfonso, M., & Castrillón, G. (2006). *La gestión del conocimiento*.

[28] Zegarra Salas, W. (2019). "La Matemática Recreativa Con Números Racionales En El. In *Universidad Cesar Vallejo*. Universidad Cesar Vallejo. https://repositorio.ucv.edu.pe/handle/20.500.12692/34328

[29] Zhang, B., Lin, H., Zuo, S., Liu, H., Chen, Y., Li, L., Ouyang, H., & Yuan, B. (2020). Research on Intelligent Robot Engine of Electric Power Online Customer Services Based on Knowledge Graph. *ACM International Conference Proceeding Series*, 216–221. https://doi.org/10.1145/3390557.3394312

[30] Zhang, Z., Guo, T., & Chen, M. (2021). DialogueBERT: A Self-Supervised Learning based Dialogue Pre-training Encoder. International Conference on Information and Knowledge Management, Proceedings, 3647–3651. https://doi.org/10.1145/3459637.3482085

[31] Leo, L. M. ., Simla, A. J. ., Kumaran, J. C. ., Julalha, A. N. ., & Bhavani, R. . (2023). Blockchain based Automated Construction Model Accuracy Prediction using DeepQ Decision Tree. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1), 133–138. https://doi.org/10.17762/ijritcc.v11i1.6060

[32] Mr. Dharmesh Dhabliya, Mr. Rahul Sharma. (2012). Efficient Cluster Formation Protocol in WSN. International Journal of New Practices in Management and Engineering, 1(03), 08 - 17. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/7

[33] Soundararajan, R., Stanislaus, P.M., Ramasamy, S.G., Dhabliya, D., Deshpande, V., Sehar, S., Bavirisetti, D.P. Multi-Channel Assessment Policies for Energy-Efficient Data Transmission in Wireless Underground Sensor Networks (2023) Energies, 16 (5), art. no. 2285, .