Optimality

www.opt.reapress.com

Opt. Vol. 1, No. 2 (2024) 188–204.

Paper Type: Original Article

Optimizing the Ticket Response Process in Customer Support Systems Using Data-Driven and Machine Learning Methods: A Case Study of IFDA

Hossein Saadati[1,*], Ahmad Hakimi[2]

[1] Macroeconomic and Social Systems Master Student, Kharazmi University, Tehran, Iran; saadatih99@gmail.com.
[2] Department of Industrial Engineering, Shahed University, Tehran, Iran; ahmadhakimi99@yahoo.com.

Citation:

Received: 19 May 2024 *Revised: 11 July 2024* *Accepted: 2 September 2024*	Saadati, H., & Hakimi, A. (2024). Optimizing the ticket response process in customer support systems using data-driven and machine learning methods: a case study of IFDA. *Optimality, 1* (2), 188-204.

Abstract

Effective customer interaction through IT Support Ticketing (ITST) can enhance customer satisfaction, whether human-driven or automated, facilitating collaboration towards common goals. This principle is particularly critical in Information Technology (IT) Services, where clear communication ensures accurate interpretation of requests and efficient resolution of issues. This study employs Machine Learning (ML) algorithms, specifically Natural Language Processing (NLP) and Tag Cloud Representation, to prioritize issues in the support system. The research utilizes data collected from both individual and corporate entities over a one-month period, revealing that common problems predominantly involve password and username retrieval issues. The analysis conducted in this study emphasizes the importance of continuous planning and the integration of additional ML algorithms to enhance the support process further and advance the digitalization of IT systems. This research highlights the critical need for robust IT Service Management (ITSM) strategies to manage increasing ticket volumes and improve Response Times (RT).

Keywords: Machine learning, Tag cloud representation, Response time improvement, Practical applications in IT support, Automated IT support systems, NLP.

1 | Introduction

Effective communication serves as the cornerstone of every successful process, whether human-driven or automated. The ability to comprehend one another and exchange ideas and information facilitates collaboration towards achieving common objectives. This holds especially true in the realm of Information Technology (IT) Services, where clear communication is essential for articulating needs and issues and

Corresponding Author: saadatih99@gmail.com

enabling colleagues to grasp the intricacies of requests thoroughly. A detailed and semantically accurate description increases the likelihood of the message recipient interpreting it correctly and delivering an appropriate solution. Ultimately, the overarching aim of this scenario is to resolve issues or requests efficiently and effectively.

A ticket is the first step in any Service Desk occurrence. An incident, problem, or service request is an example of a service event, and a ticket is a historical record that describes it. The processing of a service event is governed and controlled by tickets. They are employed in the routing of events for resolution among various resources [1].

The Iran Food and Drug Administration (IFDA) fulfils an essential part in ensuring public health by enforcing laws in a variety of industries, including food, cosmetics, and medicines. The obligation emphasizes the need for a strong infrastructure that can handle inquiries for assistance from companies looking for regulatory clearance or direction. But despite the recent paperless system upgrade having improved productivity, there has been a noticeable increase in the number of electronic tickets issued. The IFDA's current workforce faces an important obstacle as a result of the rise in requests, which might result in longer Response Times (RT) and delays in crucial regulatory processes.

A ticket is the first step in the world of Service Desk incidents. It acts like an archive that defines service events by collecting events, difficulties, or service requests. Tickets control the flow of activities among multiple resources and are the basis for the systematic processing of service events [1]. Although they often have helpful information, tickets are typically disorganized. In theory, in order to understand the extra capabilities, new members should review the most important tickets.

On the other hand, this procedure takes a while. Even though tickets are frequently processed one at a time, groups of tickets occasionally show comparable trends [2]. The digitalization approaches implemented by all sectors have resulted in a notable increase in the volume of support requests [3]. A vital tool for successfully and efficiently handling client requests and concerns, Ticket Management Systems (TMS) are utilized by a wide range of companies and associations.

Resolution Time (RT), which is the period that occurs between the time that an issue is logged and when it is fully resolved, is a measure of multiple challenges that modern Customer Relationship Management (CRM) systems encounter. Each of these issues can be overcome with Real-Time Prioritization (RTP), especially when it comes to improving the support ticketing module. Companies are now able to assign customer support interactions to personnel, rank them, and efficiently follow their growth [4].

1.1 | Problem Overview

The IFDA was successfully converted to a paperless system through a recent modernization initiative that used Business Process Management Notation (BPMN) to optimize procedures. Although this digital revolution removed paper-based bottlenecks, it unexpectedly brought about a new problem: a significant rise in the number of electronic inquiries (tickets). The current workforce is unable to handle the rise of demand from enterprises across the country, specifically in light of the small number of experts (4-6) in each field (e.g., medicines, cosmetics). As a result, the time it takes to answer queries has increased greatly, which has an effect on the successful implementation of regulations and can place public health at risk by procrastinating necessary assessments.

The IT department came up with and implemented the ticketing system support. *Fig. 1* illustrates the main operations of this system. All licenses and permits that the Food and Drug Administration has granted are modelled and implemented in businesses using process modelling tools in line with efforts to automate and replace paper-based procedures. This system needs to be carefully analyzed and developed after it is gradually put into operation. Finding the key focal points is the main objective after the process has been described and the process profile has been completed. Graphing the RACI diagram enables a better understanding of the resources and people involved in the process, in addition to the previously discussed tools and visual paradigm software. Following that, a few documents related to the obtained focal points that call for ideas for solutions will be investigated. The reports undergo review to address the challenges and problems that occurred throughout the research.

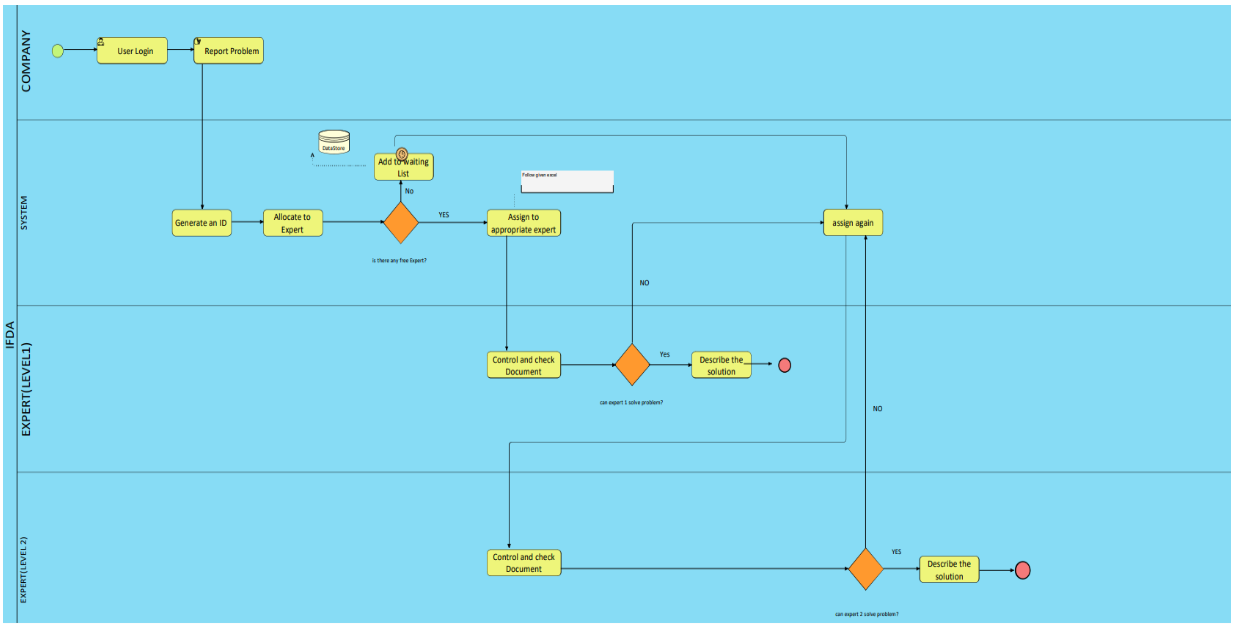

Fig. 1. Process of an IT ticketing system.

The focus of IT Service Management (ITSM) is on the administration and framework for IT service delivery [5]. The investigation covers a large stream of the servicing of IT operations. IT specialists successfully develop an organizational framework for IT services by referring to the IT Infrastructure Library (ITIL) as an approach to IT providing services [6]. Unstructured textual data, or tickets about occurrences, problems, or modifications to IT infrastructure goods and services, is handled heavily by ITIL's several domains, such as Occasion, Problem, and Change Management. The quantity and variety of queries and inquiries that the IFDA's IT department gets daily might severely limit the productivity of its employees. In the digital age, migrating from paper-based procedures to modern information systems has become routine. However, the IFDA has launched a ticketing system to offer its customers online assistance. The first step towards resolving the previously described problems is the deployment of this system.

Fig. 2. GUI of Khedmat system.

1.2 | Significance of Research

The previously described ticketing system has been meticulously developed through a number of collaborative meetings, including experts in the field. The framework aims to deal with the variety of requirements of clients at different phases while upholding the ideals of continual development. However, the scattered requests, a lack of classification, and inadequate user explanations of the problems they face have forced the IFDA's Research and Development (R&D) department to adopt specific algorithms and regression models. The research methodology section will include a thorough explanation of these techniques.

According to an examination of the current system logs, waiting in line for the information system is one of the main bottlenecks in the process mentioned earlier. Due to the shortage of experts in such situations, the system cannot forward a case to a specific expert if the total number of cases assigned to it exceeds a particular limit; instead, it will allocate the case to the selected individual at another time. In addition, if a suitable specialized department is not selected or explained improperly in relation to the activity, it can result in several challenges, including unresolved problems remaining open, misleading responses, and even the need to speak with another expert in a different department or area of expertise for advice or details.

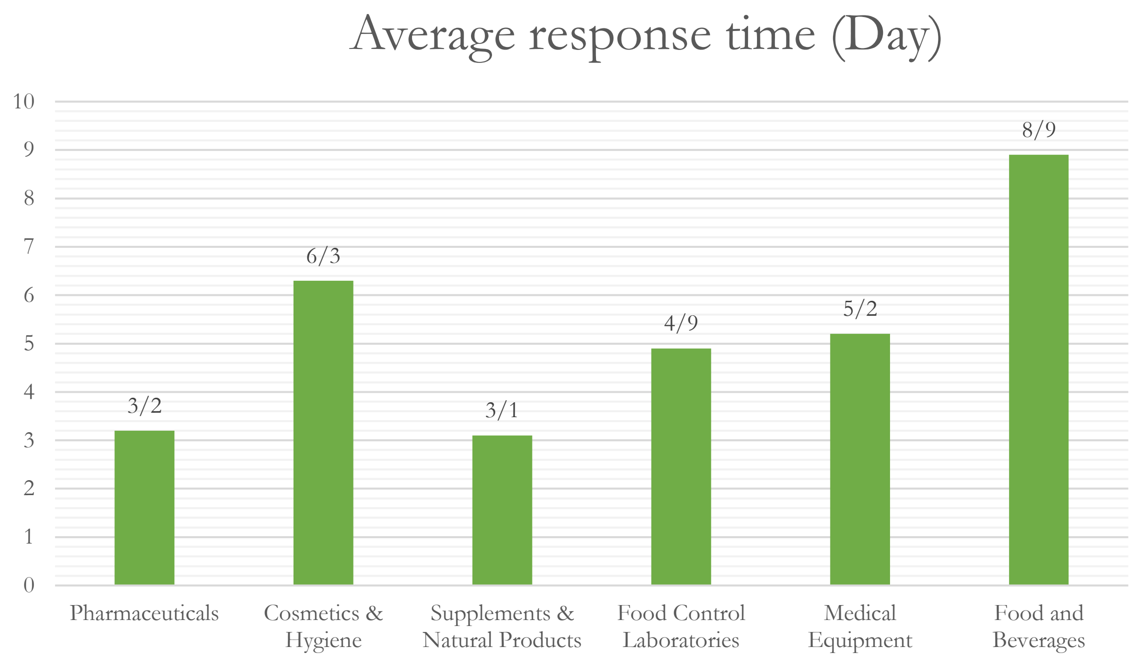

Fig. 3. Average response time (days) for inquiries to IFDA departments (Source: IFDA data).

The average response time (in days) for questions sent to the several IFDA departments is shown in *Fig. 3*. The departments are classified on the x-axis, and the average response time is measured on the y-axis. Among all the specialities shown in the chart, the Department of Food and Beverage and the Department of Cosmetics and Hygiene stand out for having the longest resolution timeframes. The cause for this prolonged response time is probably due to a great deal of questions that these business large number of companies generate. However, the IFDA cannot simply increase staff to handle the increasing volume of inquiries due to financial constraints. This requires a more systematic and productive method. The IFDA is looking at using Machine Learning (ML) and Artificial Intelligence (AI) to develop an original approach to ticket-setting priorities, having recognized the potential benefits of these technologies.

There has never been a greater need to use modern technology to automate regulatory processes, especially given the mistakes that are common in data collecting and use. This change offers a solution to the growing issue of regulatory organizations' dwindling internal staffing levels along with simplifying operations [7].

This study contributes to the ongoing pursuit of enhanced customer support experiences. By leveraging Tag Cloud Representation for ticket prioritization, IFDA can expedite issue resolution, improve resource allocation within its IT service desk, and ultimately enhance customer satisfaction. Furthermore, the research emphasizes the importance of continuous improvement. The exploration of additional ML algorithms alongside NLP presents a promising avenue for further optimizing the digitalization of IFDA's customer support system, leading to a more robust and efficient service experience for its customers. Additionally, the main research question of this study: how can customer support systems be optimized in a way that responses to submitted tickets are faster and more effective? is practically addressed in Section 4.

The rest of the paper is structured as follows. Section 2 provides the literature review, and in Section 3, the research methodology is explained. Section 4 provides the answer to the main research question (data analysis). Finally, the conclusion and policy implications of the paper are stated in Section 5.

2|Literature Review

Any business, given the current level of digitization, has a wide range of applications, many of which have grown continuously. Massive and complex IT service environments are needed to serve such a portfolio [8]. These advancements highlight the critical role that IT support systems play in the support functions of any firm [9]. Tickets serve as the most significant means for interaction between clients and the personnel in charge of monitoring service, enabling the resolution of any issues or events. These kinds of dealings occur in almost every sector of the economy. However, complaints and requests for assistance for IT-related issues are the most common examples [1]. Ticket Automation (TA) can be defined as the collection of automated systems that aim to reduce the number of steps between the submission of a ticket and its resolution. The rising complexity of IT services used by businesses has drawn attention to the automatic classification of IT issues [10].

The initiation of a problem ticket within the helpdesk support system is carried out by the end user, who chooses a category and provides a description. Nevertheless, the manual selection of the ticket category by the end user introduces the risk of misrouting tickets to incorrect resolver groups. The E-ticketing system, endorsed by the Federal Highway Administration's Every Day Counts (EDC) program, uses software tools to track electronically and archive data regarding the quantity of construction materials procured by State Transportation Agencies (STAs) through unit bid contracts based on weight [11].

The rapid evolution of technologies, particularly driven by contemporary AI, has significantly transformed the world, ideally to the advantage of humanity. AI is being applied to address numerous real-world challenges, benefiting society in various ways. Notable examples include industrial automation, intelligent virtual assistants, autonomous vehicles, cancer diagnostics, and advanced Enterprise Resource Planning (ERP) systems [12].

The advent of ML has opened avenues for automating ticket classification, thereby facilitating the prediction of the time required to resolve cases [13], [14]. Various ML algorithms have been integrated into Service Ticketing Systems (STS) to achieve this goal. In previous research, an in-depth linguistic analysis was conducted on ITIL Change Management (CHM) ticket texts from the IT CHM ticket processing department of a large enterprise with over 200,000 employees worldwide [10]. This study utilized detailed linguistic representations of the ticket texts to implement a rule-based approach for predicting process complexity [15]. Several automatic document classification methods have been developed using supervised learning techniques, as documented in prior studies [16]. For instance, Revina et al. [17] proposed a method employing Support Vector Machines (SVM) to detect commits carrying safety risks automatically. Diao and Bhattacharya [18] utilized Word2Vec and a Convolutional Neural Network (CNN) to classify functional and non-functional requirement documents. Additionally, Pingclasai et al. [19] introduced a technique for categorizing bug reports using supervised learning and topic modelling methods like Latent Dirichlet Allocation (LDA). However, it is worth noting that labelled training data preparation can be a costly endeavour. Moreover, in cases where the context of the software development project is not predetermined, the derivation and creation of labels pose significant challenges.

Al-Hawari and Barham [20] in a ML-based help desk system for ITSM was introduced to enhance the performance of the German Jordanian University IT staff in addressing technical ticket issues. This system employs a ML model to automatically classify tickets by utilizing the title, description, and comments of each ticket. Specifically, TF-IDF is applied for tokenization and feature extraction, while the SVM algorithm is used for the classification task.

A recent study introduced a SVM classifier that integrates various features such as Bag-Of-Words (BOW), POS-tag, synonyms, and entity types [21]. This research aligns closely with the objectives of our investigation, particularly regarding the extraction technique employed to analyze diverse features within each question. However, it's noteworthy that the dataset utilized in the study is the Hierarchical Classification Standard, which differs from the focus of our research, centred on the dataset specific to helpdesk support systems. Additionally, Rodríguez-Robayo et al. [22] introduced a Tree-Based Convolutional Neural Network (TBCNN) tailored for programming language processing. A pivotal study, the National Cooperative Highway Research Program (NCHRP) Synthesis 450, sheds light on the significant discrepancy between the expanding scope of regulatory responsibilities and the diminishing workforce available to fulfil them [23], [24].

The categorization of questions stands as a pivotal component within the realm of question processing as it determines the appropriate type of response. The classification of answers assumes significant importance in Question Answering Systems, delineating the specific information that needs to be retrieved from a knowledge base [25]. Assigning a text to a set of pre-defined categories is known as text classification, sometimes known as categorized text or language tagging. Human specialists have traditionally completed this type of task. For instance, expert text classification is still frequently used in qualitative studies such as indexing or coding [26]. However, as the volume of text data increased, scientists' and practitioners' emphasis turned to methods that were automated. Three primary categories of automatic text classification techniques exist rule-based, ML-based and hybrid systems that combine both of them. Software development and maintenance ticket classification have been investigated to address issues like precise ticket allocation and prioritizing, forecasting time and quantity of possible tickets, and preventing duplicate requests [27], [28]. Showcase the feasibility of extracting tags possessing collective utility from the amalgamation of individually and freely assigned tags, thereby autonomously resolving tag ambiguity issues [29]. Various machine-learning techniques are explored for email filtering and classification. Additionally, SVM and Artificial Neural Networks (ANN) have been employed by other researchers [30]. Research indicates that the Neural Network (NN) footprint can be significantly reduced with only moderate performance degradation across various tasks such as image recognition [31], natural language understanding and speech recognition. Various techniques have been proposed to achieve this, including integer quantization [32], hashing, vector quantization [33], and matrix factorization. NN models often need to be executed rapidly to minimize user-perceived latency. This is particularly crucial for applications involving continuous interactions with customers, such as virtual assistants [34].

Delivering top-notch customer service is paramount in both service-based industries and businesses. It's imperative to prioritize customer satisfaction by providing optimal assistance. The IT service delivery of every company heavily depends on the efficiency of its helpdesk. Consequently, numerous enterprises employ intelligent helpdesk solutions to enhance the quality of customer service, recognizing its critical importance [35]. A customer's request for assistance from a service provider's help desk is referred to as a support ticket. These are necessary resources for all contemporary companies to manage their interaction with clients and include incident reports, service tickets, and customer complaints [11].

In recent years, the adoption of helpdesk support systems has emerged as a prevailing trend across industries, offering a structured approach to managing support services. A plethora of open-source applications catering to helpdesk support has already permeated the market, providing organizations with readily available solutions to facilitate their support endeavours. Management can peruse these options and select the most suitable helpdesk support system based on the unique requirements and objectives of their business operations [13]. The service desk creates a ticket once it recognizes the situation as an incident. The incident report, the user's name and contact information, the date and time of the occurrence, and other details should all be included in the ticket. Categorization, ordering, and the actions the service desk takes may all be included in the logging process. The process of categorization entails giving the occurrence of at least one subcategory and a category [21].

In a helpdesk system, a crucial element is a Question and Answering (Q&A) system, housing question data that serves as the primary information for processing to ensure effective implementation of Q&A activities. Hence, there is a necessity to organize existing questions to facilitate accurate and prompt responses. A question, in this context, refers to a linguistic expression utilized to seek information [36].

Numerous methods for categorizing questions have been explored and put into practice, particularly within customer service domains. Three primary strategies are commonly employed for question classification tasks: these include 1) ML approaches, 2) rule-based techniques, and 3) hybrid methodologies that combine elements of both [39].

Pingclasai et al. [19] conducted a comparative analysis of four algorithms: 1) Multinomial Naïve Bayes, 2) Logistic Regression, 3) K-nearest Neighbor, and 4) SVM. Their findings indicated that the SVM exhibited the highest accuracy rate of 87% when compared to Logistic Regression (81%), Multinomial Naïve Bayes (69%), and K-nearest Neighbor (67%) on the training dataset. Notably, the SVM classifier demonstrated consistent performance across various service desk ticket data samples, achieving a satisfactory level of accuracy. The implementation of the suggested automated ticket classifier system promises enhancements in end-user satisfaction, customer happiness, and the efficient utilization of support resources. Additionally, it facilitates faster ticket RTs and fosters business growth.

Table 1. Overview of design techniques and key findings in tag cloud research.

Author(s)	Design Technique	Key Findings
[11]	Clustering	Semantic grouping does not improve efficiency for visual location of tags.
[11]	Clustering	Applied clustering techniques to tag cloud design.
[37]	Alphabetical, semantic, and random designs	Alphabetical design was the best rated.
[22]	Manipulable design	Users can manipulate typography, position, orientation, and color of tags.
[28]	Tag location (first quadrant)	Tags in the first quadrant are most remembered.

Table 1 summarizes various design techniques used in tag cloud research and the key findings associated with each approach. It highlights the impact of different designs on user efficiency, memory, and interaction with tag clouds.

3 | Research Methodology

As highlighted at the outset of this study, the growing integration of AI into business and daily life underscores the critical importance of AI explainability. Understanding AI system decisions is crucial for building trust and effectively addressing errors made by such systems. Our research focuses on the ITIL Change Management-based IT ticketing process of a large telecommunications company. Implementing changes in the IT infrastructure involves interventions in the organization's IT environment, functions, and user experience each time a change is made.

3.1 | Case Study

There are many different types of research methodologies, but each has its benefits. Research topics that centre on how and why are suitable for case studies. For a number of reasons, scenarios are crucial in research. By providing specific, contextual information that is frequently ignored by more general surveys or experiments, they aid in the development of theories. This is particularly useful in exploratory study, which aims to generate unique ideas and questions.

Furthermore, case histories add fresh data to enhance and broaden previous hypotheses. They are also essential for theory testing since they enable scholars to assess the constraints and applicability of theoretical conceptions in practical contexts. Through the observation of interactions between troubles, actions, and outcomes made possible by this practical application, an in-depth understanding of the phenomenon being studied is provided.

The IFDA plays a crucial role in safeguarding public health by regulating and supervising a wide range of industries, including pharmaceuticals, food, and cosmetics. To enhance its regulatory capabilities, the IFDA has implemented a system known as the Tracking, Tracing and Authentication Control (TTAC). It is for monitoring and tracing health-related products. This system aims to prevent the distribution and sale of counterfeit and smuggled goods. The primary focus of the TTAC system is to create a centralized database to permanently record the ownership and temporal and spatial identity of a product throughout the supply chain.

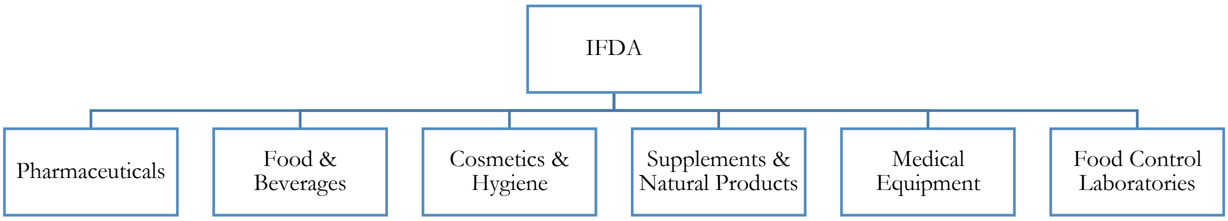

Fig. 4. Departments of IFDA.

In the context of this research, the case study method was applied to analyze the IFDA's Tracking, Tracing, and Authentication Control (TTAC) system. The TTAC system, which comprises 23 subsystems operating in five different categories, is designed to prevent the distribution and sale of counterfeit and smuggled goods by creating a centralized database to permanently record the ownership and temporal and spatial identity of products throughout the supply chain.

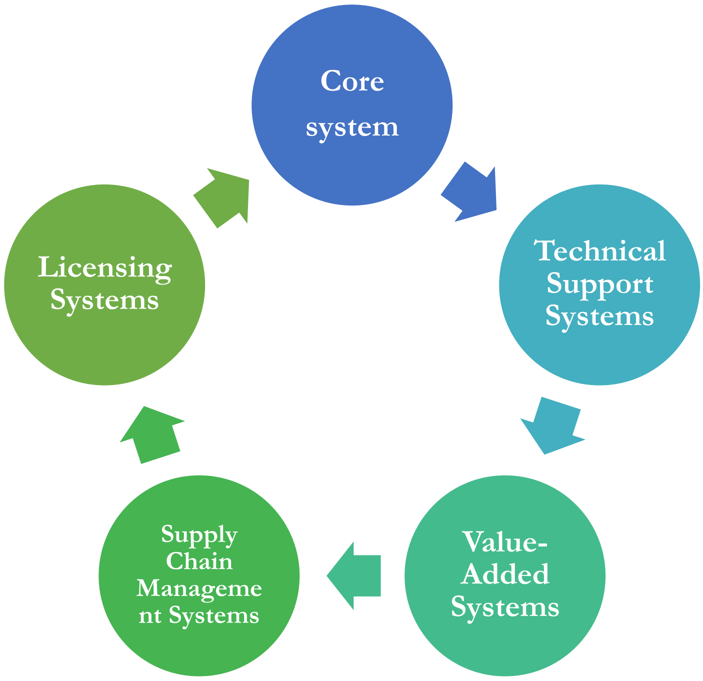

Fig. 5. Architecture of TTAC.

3.2 | Data Collection

The data collected for this study was sourced from tickets submitted by users within the Food and Drug Ticketing System. Given the high volume of incoming requests, we focused exclusively on system (entity) data over one month as our case study. This approach allowed us to manage the data effectively while ensuring the relevance and accuracy of our findings.

3.3 | Machine Learning

Predictive analytics entails leveraging historical data and statistical models to anticipate future events of unknown nature. The concept of predictive analytics has garnered significant attention in recent years, driven by the proliferation of data and advancements in technologies like AI, ML, and business intelligence. By harnessing predictive analytics, organizations can effectively tap into past and present data to accurately predict trends and behaviours, providing insights into future occurrences ranging from seconds to days or even years ahead [23].

Supervised Learning is a learning function that maps inputs to outputs based on a given example of input-output pairs. Supervised Learning is a function of the training data labels that exist in a set of training examples. This algorithm requires external assistance from a supervisor. The input dataset will be separated into two parts: 1) train, and 2) test. There will be an output variable in the training dataset that must be predicted or categorized. Draws a pattern from the training dataset and applies it to the test dataset for prediction or classification [26].

3.4 | Natural Language Processing

Natural Language Processing (NLP) is a significant field of AI which investigates the connections between people and computers through natural language. It explores basic approaches to understanding the meaning of lexical, phrasal, and textual expressions. These approaches include grammatical and semantic processes like as syntactic parsing, semantic translation, and lexical analysis. Moreover, NLP aims to create several applications, including text production, dialogue systems, information retrieval, Machine Translation (MT), and recommendation engines. In industries like search engines, virtual assistants, corporate analytics, and customer support systems, NLP integration is essential. The history of NLP dates back to the 1950s. In the beginning of NLP research, rule-based methods were used to build NLP systems, including word/sentence analysis, QA, and MT [20], [29].

3.4.1 | Tag cloud representation

A novel approach for metadata creation, known as tagging, has emerged. Tagging-based systems enable users to categorize web resources by adding freely chosen keywords or tags to facilitate their retrieval at a later time. Tagging functions not only as an individual categorization process but also as a social indexing mechanism and a collective knowledge construction activity. By sharing resources along with their associated tags, users contribute to the generation of an aggregated tag index referred to as a folksonomy. Folksonomy is defined as a space of keywords. When folksonomy is used, searchers can access the resources previously tagged through two principal paradigms: 1) Information Filtering (IF), and 2) Information Retrieval (IR) [11].

3.4.2 | Evaluation metrics

Aouiche et al. [38] defined the entropy of a tag cloud as follows:

$$\mathrm{Entropy(T)} = -\sum_{t \in T} p(t) \log\{p(t)\}, \tag{1}$$

where

$$p(t) = \frac{\mathrm{weiqht(t)}}{\sum_{t \in T} \mathrm{weiqht(t)}}. \tag{2}$$

Entropy quantifies the weight disparity between tags. If it is low, the tag cloud is significant or effective. If, on the contrary, it is high, the weights of the tags are uniform, which visually is not very informative. A tag cloud will be effective if it consists of significant tags [18]. According to Sinclair and Cardew-Hall [39], various methods of tag generation should be reviewed, including aspects such as tag size and tag usefulness. They argue that a ranking system is essential for the selection of tags to be displayed in the tag cloud.

$$\mathrm{TagSize} = 1 + C.\frac{\mathrm{Log}(f_i - f_{min} + 1)}{\mathrm{Log}(f_{max} - f_{min} + 1)}, \tag{3}$$

where f_i is the tag frequency, f_{min} and f_{max} are the minimum and maximum frequencies, respectively, and C is a constant which determines the maximum text size.

This section of the article delves into the analysis of the employed methods and addresses the posed inquiries to present a practical and effective approach for addressing the research problem. Leveraging ML algorithms, this section explains the methods that were used and gives practical solutions to the challenge that was explored. By examining actual cases in the appropriate field, these evaluations give investigators the chance to identify trends and subsequently acquire expertise for closing the understanding gap between theory and practice. Therefore, the practical strategy used in this part helps to improve understanding and effectiveness while solving real-world problems in the sector.

As we became familiar with the systems related to the Food and Drug Administration in the previous section, we will now, considering the various subsystems under the TTAC system for transferring implementation experiences in the regulatory industry in the health sector, randomly implement and introduce one of the targeted systems called Entities.

Applicants create a task list for registering technical managers' details. After submission, In the Entity system. Food and Drug Administration reviews and approves the information, issuing an activity license. Company managers can then search for and send employment requests to licensed technical managers, who can accept or reject these requests.

4 | Solution and Implementation

This section of the article delves into the analysis of the employed methods and addresses the posed inquiries to present a practical and effective approach for addressing the research problem. Leveraging ML algorithms, this section explains the methods that were used and gives practical solutions to the challenge that was explored. By examining actual cases in the appropriate field, these evaluations give investigators the chance to identify trends and subsequently acquire expertise for closing the understanding gap between theory and practice. Therefore, the practical strategy used in this part helps to improve understanding and effectiveness while solving real-world problems in the sector.

As we became familiar with the systems related to the Food and Drug Administration in the previous section, we will now, considering the various subsystems under the TTAC system for transferring implementation experiences in the regulatory industry in the health sector, randomly implement and introduce one of the targeted systems called Entities.

In the Entity system, by executing the Request for Technical Manager Qualification operation by the applicant, a task list is created for them. The technical manager information registration task list is specifically designed for completing the personal information, educational, and work history of technical managers. Additionally, the registration task list for the CEO is specifically designed for registering legal companies active in the health sector. This task list includes the personal information of the CEO and board members, along with the registered company information. After registering and submitting the technical manager's information in the system, the information review process is carried out by the Food and Drug Administration experts, and if the information is approved, an activity license for the technical manager is issued. After the activity license is issued, company managers can search for the relevant technical manager and send an employment request to them. The technical manager, by viewing the applicant companies' information in the system, can accept or reject the employment requests.

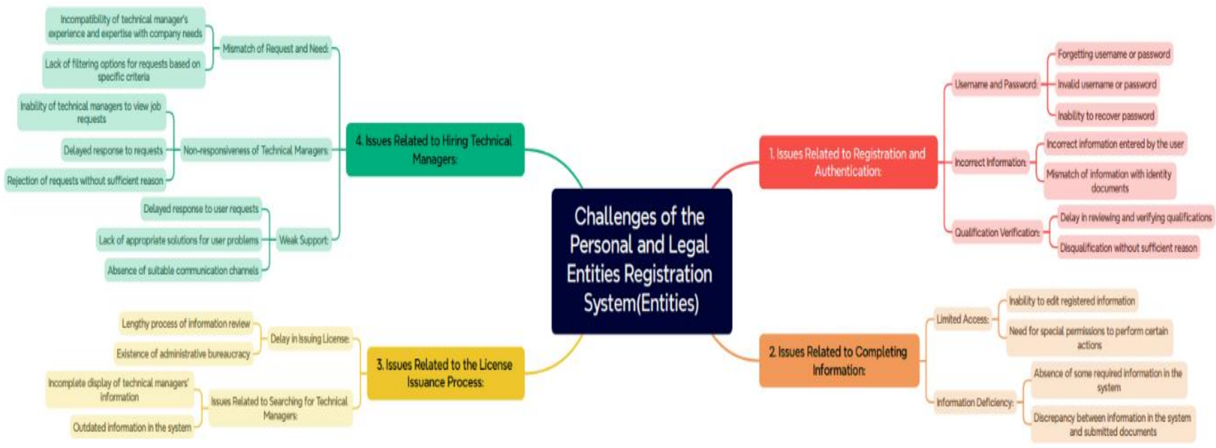

Fig. 6. Mapping the challenges of entity registration.

In *Fig. 6*, to facilitate and expedite the response to registered tickets, we will categorize and classify them, and in the continuation of the article, we will discuss how this categorization is used in the applied algorithms.

In this section, we provide a detailed solution to optimize customer support systems, addressing the main research question of this study:

Q1: How can customer support systems be optimized in a way that responses to submitted tickets are faster and more effective?

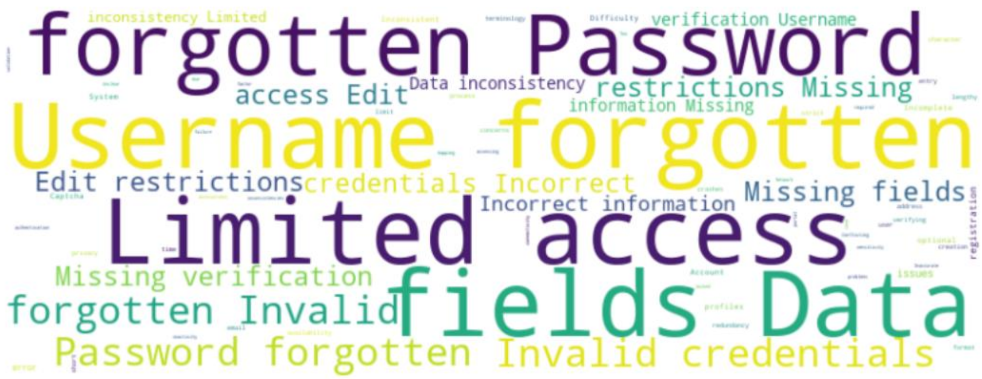

Fig. 7. Tag cloud representation.

Given the heavy workload in the Ian Food and Drug Administration (IFDA), the presence of specialized departments with numerous requests, the submission of duplicate tickets, the outbreak of infectious diseases such as COVID-19, and several other factors, the need to improve the customer service support system became critically important. Support systems for users require precise prioritization to respond effectively and efficiently to submitted tickets. To address this, we conducted group meetings with experts from specialized departments to gather and document their feedback. Subsequently, in collaboration with IT engineers and utilizing the Tag Cloud Representation technique, the status of open tickets in the system was graphically displayed to the responsible experts in a structured format.

The Tag Cloud Representation technique helps categorize tickets based on frequently used keywords and similar topics. This method enables experts to identify high-priority tickets and respond appropriately quickly. Additionally, by displaying frequently asked questions in the users' dashboard, duplicate ticket submissions are prevented, thereby reducing the workload.

Using this technique resulted in:

I. Increased efficiency and productivity: experts were able to respond faster to more important tickets with proper prioritization.

II. Reduction in duplicate tickets: by displaying frequently asked questions to users, the number of duplicate tickets decreased, reducing the workload for experts.

III. Improved user satisfaction: rapid and effective responses to tickets led to higher user satisfaction.

IV. Better resource management: with fewer duplicate tickets, the organization's resources were managed more optimally.

Statistics indicate that the implementation of this method has led to a decrease in the number of submitted tickets and an improvement in the quality of responses. These measures have significantly enhanced the efficiency and reduced the workload of the support units. All the code related to this section, written using the Jupyter framework, has been included in the attached file submitted with this paper for the journal.

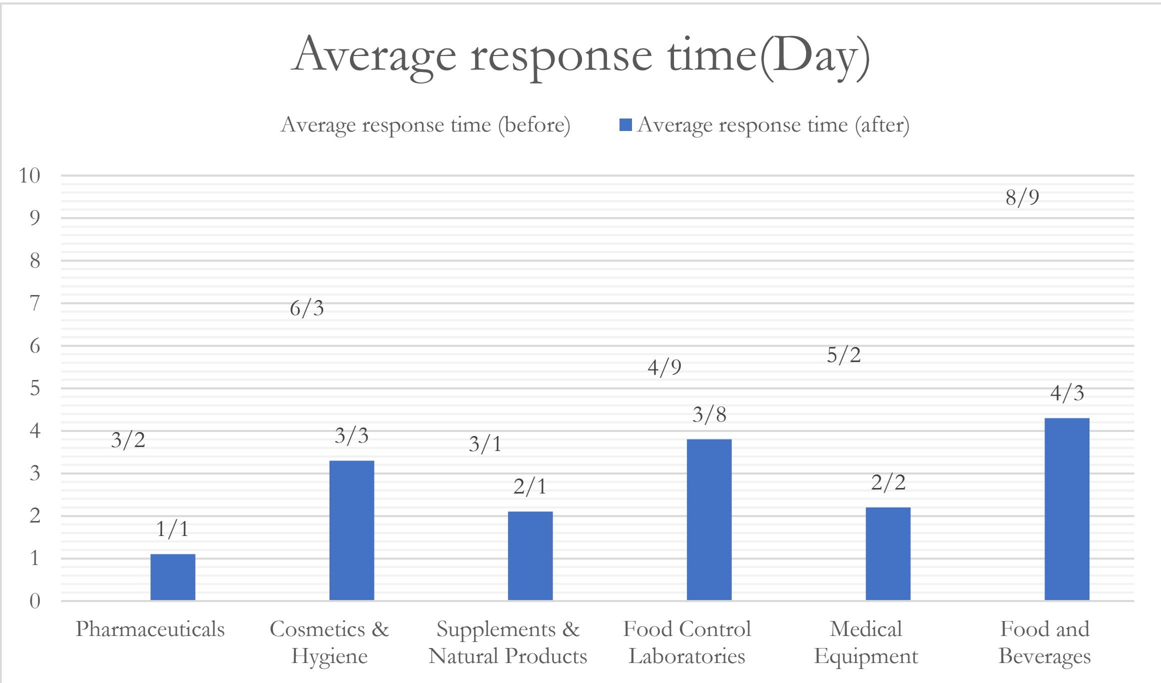

Fig. 8. Research findings.

5 | Conclusion

The limitations identified across studies addressing behaviour pattern analysis in ticketing systems span several aspects. These include challenges such as noisy data affecting pattern recognition, limitations in handling technical terms impacting accuracy, algorithmic constraints hindering ticket classification, computational resource requirements for expedited learning, the need for periodic training set adjustments, absence of ground truth annotations for sentiment analysis, dataset constraints, the necessity to evaluate system performance over longer time scales and under varying settings, and the initial handling of unstructured noisy data. Addressing these limitations collectively would require strategies ranging from data preprocessing techniques to algorithmic enhancements and resource optimization to ensure accurate and efficient behaviour pattern analysis in ticketing systems.

This paper explores the limitations and potential solutions for behaviour pattern analysis in ticketing systems. By analyzing user interactions within ticketing systems, organizations can gain valuable insights into customer behaviour, identify potential issues, and improve overall service delivery. However, several challenges hinder the accuracy and efficiency of current behaviour pattern analysis methods.

This investigation points up a number of major shortcomings in previous research on behavior pattern analysis in ticketing systems. Some of these challenges are:

I. Noisy data: ticketing system data can be riddled with errors and inconsistencies, impacting pattern recognition algorithms [14].

II. Technical terminology: the presence of technical terms within tickets can hinder the accuracy of analysis, as classification algorithms may not readily understand these terms.

III. Algorithmic constraints: current classification algorithms might struggle to effectively categorize tickets due to inherent limitations in their design [1].

IV. Computational resources: training and running complex algorithms often require significant computational resources, impacting processing speed and scalability.

V. Training set maintenance: the performance of behaviour pattern analysis systems can degrade over time if the training data sets are not periodically adjusted to reflect evolving user behaviour and system configurations.

VI. Sentiment analysis challenges: the absence of ground truth annotations for sentiment analysis within ticketing data makes it difficult to assess user emotions and satisfaction accurately [40].

VII. Dataset constraints: dataset limitations, such as size and representativeness, can restrict the generalizability of findings and hinder the development of robust behaviour pattern analysis models.

By addressing these challenges and implementing the proposed solutions, researchers and practitioners can develop more accurate and efficient behaviour pattern analysis systems for ticketing systems. This will ultimately lead to improved customer service delivery and enhanced decision-making within organizations.

The provision of support services throughout the entire application system development process stands as a cornerstone for organizational success. Both technical and management support play indispensable roles in guaranteeing the seamless evolution and ultimate triumph of an application system. From the initial user requirement phase through programming development, system testing, and culminating in the final support stage, ongoing assistance is imperative to shepherd the system to its full maturity. Indeed, the continuity of support services is essential for sustaining the relevance and functionality of an application system over time.

A ML system for categorization and ranking incoming calls can be developed by exploiting the IFDA's huge collection of previous inquiries and replies. The platform may evaluate incoming inquiries and assign priority levels depending on public health impact and urgency by developing models on earlier data. This ensures prompt attention to critical issues, optimizing resource allocation and regulatory decision-making. When an ML-based ticket prioritizing system is effectively implemented at the IFDA, it can optimize the utilization of resources, simplify workflows, and greatly speed up RT for severe public health concerns. By using ML to find patterns in questions, human specialists can focus on deeper issues, which increases productivity and eliminates backlogs.

The IFDA has strong databases that are used to publicly label ML algorithms like K-Nearest Neighbours (KNN) and others. This enables improved performance comparison and exploitation. Moreover, through the development of a multi-year strategy and the setting up of appropriate performance measures, the Support Ticketing system can be improved by giving priority to ongoing improvement.

The high volume of inquiries encountered in the transitioned paperless environment at the IFDA necessitates a novel solution. Implementing a ML system for ticket prioritization offers a promising approach. By leveraging its vast dataset of past inquiries and resolutions, the IFDA can develop a system capable of intelligently classifying and prioritizing incoming tickets based on urgency and potential public health impact. This innovative solution holds the potential to enhance public health protection, optimize resource allocation within the IFDA, and improve customer service for businesses seeking regulatory guidance. Further R&D are crucial to refine this approach and ensure its successful integration within the IFDA's regulatory framework.

Author Contribution

The conceptualization and ideas for the study were developed by H.S. The data collection and formal analysis were also carried out by H.S. Funding for the research was acquired by A.H. Both A.H. and H.S. were involved in the investigation phase. Methodology development, software programming, and the creation of computer code and supporting algorithms were handled by H.S. Validation and review were conducted by A.H., while the original draft of the manuscript was written by H.S. The review and editing process was completed by A.H.

Data Availability

The data used in this research study is derived from the ticketing system of the IFDA. The FDA retains the ownership of this data. Given the nature of the data, which includes information related to the production lines of certain pharmaceuticals and specific drug-related details, sharing this data poses significant risks and potential harm. Despite our trust in your esteemed journal, we must adhere to these confidentiality constraints. However, we have included the relevant Python software codes in the appendix for the journal's review.

Conflicts of Interest

The author declares no conflict of interest. The data utilized in this study were obtained from the ticketing system of the IFDA. Access to this data was granted under strict confidentiality agreements, and the IFDA retains full ownership of the data. Therefore, the data cannot be shared publicly or with third parties without explicit permission from the IFDA.

References

[1] Hertvik, J. (2020). *Service desk TIPS explained: Ticket, incident, problem, service request.* https://www.bmc.com/blogs/ticket-vs-incident-vs-problem-vs-service-request/

[2] Mani, S., Sankaran, A., & Aralikatte, R. (2019). Deeptriage: exploring the effectiveness of deep learning for bug triaging. *Proceedings of the ACM India joint international conference on data science and management of data* (pp. 171–179). Association for Computing Machinery. https://doi.org/10.1145/3297001.3297023

[3] Kurnaedi, D., Oktora, E., Dharmawan, E., Nasrullah, I., & Drajat, M. (2022). Web-based IT helpdesk ticketing system at PT. Dayacipta Kemasindo. *Bit-tech: binary digital-technology*, *5*(2), 121–127. https://doi.org/10.32877/bt.v5i2.617

[4] Mani, S., Sankaranarayanan, K., Sinha, V. S., & Devanbu, P. (2014). Panning requirement nuggets in stream of software maintenance tickets. *Proceedings of the 22nd ACM sigsoft international symposium on foundations of software engineering* (pp. 678–688). Association for Computing Machinery. https://doi.org/10.1145/2635868.2635897

[5] Orta, E., Ruiz, M., Hurtado, N., & Gawn, D. (2014). Decision-making in IT service management: a simulation based approach. *Decision support systems*, *66*, 36–51. http://dx.doi.org/10.1145/2635868.2635897

[6] Fontes, M., Nascimento, W., Carvalho, K., Moreira, E., Cardoso, M., & Montoni, M. (2014). Improving the software factory contracting process in the public area: the rio de janeiro city hall's experience. *2014 9th international conference on the quality of information and communications technology* (pp. 152–155). IEEE.

[7] Newcomer, C., Withrow, J., Sturgill, R. E., & Dadi, G. B. (2019). Towards an automated asphalt paving construction inspection operation. *Advances in informatics and computing in civil and construction engineering: proceedings of the 35th CIB w78 2018 conference: it in design, construction, and management* (pp. 593–600). Springer. https://doi.org/10.1007/978-3-030-00220-6_71

[8] Paramesh, S., & Shreedhara, K. S. (2019). It help desk incident classification using classifier ensembles. *ICTACT journal on soft computing*, *9*(04), 331–346. DOI:10.21917/ijsc.2019.0276

[9] Agarwal, S., Aggarwal, V., Akula, A. R., Dasgupta, G. B., & Sridhara, G. (2017). Automatic problem extraction and analysis from unstructured text in IT tickets. *IBM journal of research and development*, *61*(1), 4–41. https://doi.org/10.1147/JRD.2016.2629318

[10] Rizun, N., Meister, V., & Revina, A. (2020). Discovery of stylistic patterns in business process textual descriptions: it ticket case. *33rd international business information management association conference* (pp. 2103–2113). IBIMA. https://ibima.org/accepted-paper/discovery-of-stylistic-patterns-in-business-process-textual-data-it-ticket-case/

[11] Hassan-Montero, Y., & Herrero-Solana, V. (2024). *Improving tag-clouds as visual information retrieval interfaces*. https://doi.org/10.48550/arXiv.2401.04947

[12] Rizun, N., Revina, A., & Meister, V. (2019). Method of decision-making logic discovery in the business process textual data. *International conference on business information systems* (pp. 70–84). Springer.

[13] Harun, N. A., Huspi, S. H., & Iahad, N. A. (2021). Question classification framework for helpdesk ticketing support system using machine learning. *2021 7th international conference on research and innovation in information systems (ICRIIS)* (pp. 1–7). IEEE. https://doi.org/10.1109/ICRIIS53035.2021.9617077

[14] Chagnon, C. J., Trapp, A. C., & Djamasbi, S. (2017). *Creating a decision support system for service classification and assignment through optimization* [presentation]. Twenty-third americas conference on information systems (pp. 1–5). https://scholar.archive.org/work/qhgkenuucff4lp4brdv3ox3kcm/access/wayback/http://aisel.aisnet.org:80/cgi/viewcontent.cgi?article=1393&context=amcis2017

[15] Revina, A., & Rizun, N. (2019). *Multi-criteria knowledge-based recommender system for decision support in complex business processes*. https://mostwiedzy.pl/pl/publication/multi-criteria-knowledge-based-recommender-system-for-decision-support-in-complex-business-processes,150018-1

[16] Dekhtyar, A., & Fong, V. (2017). Re data challenge: requirements identification with word2vec and tensorflow. *2017 IEEE 25th international requirements engineering conference (RE)* (pp. 484–489). IEEE.

[17] Revina, A., Buza, K., & Meister, V. G. (2020). It ticket classification: The simpler, the better. *IEEE access*, *8*, 193380–193395. https://doi.org/10.1109/ACCESS.2020.3032840

[18] Diao, Y., & Bhattacharya, K. (2008). Estimating business value of it services through process complexity analysis. *NOMS 2008-2008 IEEE network operations and management symposium* (pp. 208–215). IEEE.

[19] Pingclasai, N., Hata, H., & Matsumoto, K. (2013). Classifying bug reports to bugs and other requests using topic modeling. *2013 20th asia-pacific software engineering conference (APSEC)* (Vol. 2, pp. 13–18). IEEE.

[20] Al-Hawari, F., & Barham, H. (2021). A machine learning based help desk system for IT service management. *Journal of king saud university-computer and information sciences*, *33*(6), 702–718. https://doi.org/10.1016/j.jksuci.2019.04.001

[21] Prasetio, R. T., Ramdhani, Y., & Alamsyah, D. P. (2021). Scrum method in help-desk ticketing and project management system. *2021 3rd international conference on cybernetics and intelligent system (ICORIS)* (pp. 1–6). IEEE. https://doi.org/10.1109/ICRIIS53035.2021.9617077

[22] Rodríguez-Robayo, K. J., Méndez-López, M. E., Molina-Villegas, A., & Juárez, L. (2020). What do we talk about when we talk about milpa? A conceptual approach to the significance, topics of research and impact of the mayan milpa system. *Journal of rural studies*, *77*, 47–54. https://doi.org/10.1016/j.jrurstud.2020.04.029

[23] Bottou, L., Curtis, F. E., & Nocedal, J. (2018). Optimization methods for large-scale machine learning. *SIAM review*, *60*(2), 223–311. https://doi.org/10.1137/16M1080173

[24] Houssein, E. H., Mohamed, R. E., & Ali, A. A. (2021). Machine learning techniques for biomedical natural language processing: a comprehensive review. *IEEE access*, *9*, 140628–140653. https://doi.org/10.1109/ACCESS.2021.3119621

[25] Cortes, E., Woloszyn, V., Binder, A., Himmelsbach, T., Barone, D., & Möller, S. (2020). An empirical comparison of question classification methods for question answering systems. *Proceedings of the twelfth language resources and evaluation conference* (pp. 5408–5416). European Language Resources Association (ELRA).

[26] Basha, S. M., & Rajput, D. S. (2019). Survey on evaluating the performance of machine learning algorithms: Past contributions and future roadmap. In *Deep learning and parallel computing environment for bioengineering systems* (pp. 153–164). Elsevier. https://doi.org/10.1016/B978-0-12-816718-2.00016-6

[27] Carpinteiro, O. A. S., Lima, I., Assis, J. M. C., de Souza, A. C. Z., Moreira, E. M., & Pinheiro, C. A. M. (2006). A neural model in anti-spam systems. *Artificial neural networks--icann 2006: 16th international conference, athens, greece, part II 16* (pp. 847–855). Springer. https://doi.org/10.1007/11840930_88

[28] Ye, Y., Lee, B., Flynn, R., Murray, N., & Qiao, Y. (2017). HLAF: heterogeneous-latency adaptive forwarding strategy for peer-assisted video streaming in ndn. *2017 IEEE symposium on computers and communications (ISCC)* (pp. 657–662). IEEE. https://doi.org/10.1109/ISCC.2017.8024603

[29] Awad, W. A., & ELseuofi, S. M. (2011). Machine learning methods for spam e-mail classification. *AIRCC's international journal of computer science and information technology*, *3*(1), 173–184. DOI : 10.5121/ijcsit.2011.3112

[30] Yayah, F. C., Ghauth, K. I., & Ting, C.-Y. (2022). The Performance Of Classification Method In Telco Customer Trouble Ticket Dataset. *IAENG international journal of computer science*, *49*(2). http://www.iaeng.org/IJCS/issues_v49/issue_2/IJCS_49_2_05.pdf

[31] Yang, N., Wu, G., MacEachren, A. M., Pang, X., & Fang, H. (2023). Comparison of font size and background color strategies for tag weights on tag maps. *Cartography and geographic information science*, *50*(2), 162–177. https://doi.org/10.1080/15230406.2022.2152098

[32] Denton, E. L., Zaremba, W., Bruna, J., LeCun, Y., & Fergus, R. (2014). *Exploiting linear structure within convolutional networks for efficient evaluation*. https://doi.org/10.48550/arXiv.1404.0736

[33] Gong, Y., Liu, L., Yang, M., & Bourdev, L. (2014). *Compressing deep convolutional networks using vector quantization*. https://doi.org/10.48550/arXiv.1412.6115

[34] Jaderberg, M., Vedaldi, A., & Zisserman, A. (2014). *Speeding up convolutional neural networks with low rank expansions*. https://doi.org/10.48550/arXiv.1405.3866

[35] Sujata, S., & Ramya, M. (2020). Real-time IT help desk ticket classification using deep learning approach. *International journal of scientific and technology research*, *9*(4), 239–244.

[36] Paramesh, S. P., & Shreedhara, K. S. (2019). Automated it service desk systems using machine learning techniques. *Data analytics and learning: proceedings of dal 2018* (pp. 331–346). Springer.

[37] Abakouy, R., En-Naimi, E. M., El Haddadi, A., & Lotfi, E. (2019). Data-driven marketing: how machine learning will improve decision-making for marketers. *ACM international conference proceeding series* (pp. 1–5). Association for Computing Machinery. DOI: 10.1145/3368756.3369024

[38] Aouiche, K., Lemire, D., & Godin, R. (2009). Web 2.0 olap: from data cubes to tag clouds. *Web information systems and technologies: 4th international conference* (pp. 51–64). Springer. https://doi.org/10.1007/978-3-642-01344-7_5

[39] Sinclair, J., & Cardew-Hall, M. (2008). The folksonomy tag cloud: when is it useful? *Journal of information science*, *34*(1), 15–29. https://doi.org/10.1177/0165551506078083

[40] Mandal, A., Malhotra, N., Agarwal, S., Ray, A., & Sridhara, G. (2019). Automated dispatch of helpdesk email tickets: pushing the limits with AI. *Proceedings of the AAAI conference on artificial intelligence* (Vol. 33, pp. 9381–9388). IAAI. https://doi.org/10.1609/aaai.v33i01.33019381