

Extending the Horizon by Empowering Government Customer Service Officers with ACQAR for Enhanced Citizen Service Delivery

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Abstract— A previous study on the use of the Empath library in the prediction of Service Level Agreements (SLA) reveals the quality levels required for meaningful interaction between government customer service officers and citizens. On the other hand, past implementation of the Citizen Question-Answer system (CQAS), a type of Question-Answer model, suggests that such models if put in place can empower government customer service officers to reply faster and better with recommended answers. This study builds upon the research outcomes from both arenas of studies and introduces an innovative system design that allows the officers to incorporate the outputs from Empath X SLA predictor and CQAS (a type of Question Answer model) as critical inputs to ChatGPT engine, known as AI Based Citizen Question-Answer Recommender (ACQAR).

Empath X SLA predictor anticipates the expected service response time based on citizens' emotional state. These valuable inputs coupled with the recommended answer provided by the CQAS will serve as prompt inputs to ChatGPT to craft contextually aware responses. This ensures that the final response considers the citizen's emotional needs, expected service timeline, and recommended answers from official government documents.

While the full-scale deployment of this pilot system, ACQAR, is pending, this paper presents a comprehensive blueprint for governments seeking to modernize citizen service delivery. By fusing sentiment analysis, SLA prediction, question-answer models, and ChatGPT, this system design aims to revolutionize government-citizen interactions, delivering more empathetic, efficient, and tailored responses, while not violating SLA.

This paper serves as a foundational step towards the practical development and implementation of an intelligent system (ACQAR) that holds the potential to significantly enhance citizen satisfaction, foster trust in government services, and strengthen overall government-citizen relationships.

Keywords—Citizen Service Delivery, Question-Answer Model, Empath, Service Level Agreement, ChatGPT

I. INTRODUCTION

Technological progress has ushered in an era of unprecedented data collection capabilities. The ubiquity of data and analytics in our current landscape calls for a re-evaluation of the traditional boundaries within which citizen service research operates. Rather than limiting its focus to

internal process improvements to meet Service Level Agreement (SLA), there is room for expansion of citizen service research into uncharted territories, facilitated by the utilization of lexicon libraries with human-validated categories such as Empath, Question-Answer models, and large language models like ChatGPT. We can now explore how the amalgamation of text analytics and advanced language models can revolutionize citizen service research and drive the development of responsive and citizen-centric government services [1][2][3][4].

Service Level Agreements (SLAs) hold a pivotal position in shaping the dynamics between citizens and government entities. They lay down the essential benchmarks for ensuring a substantive and constructive interaction between these two parties [5]. To illustrate, when SLAs are diligently upheld, citizens experience satisfaction with the government's services, fostering a willingness to sustain engagement and bolster trust in governmental operations. Conversely, in cases of SLA violations, frustration may emerge, leading to diminished confidence in the government's initiatives and endorsements. Consequently, the monitoring of SLAs emerges as a vital and closely watched process for governments worldwide.

SLAs for citizen service delivery can fail due to various factors. Common reasons include insufficient resources, bureaucratic red tape, inefficient processes, inadequate training, technological challenges, increased demand during crises, and complex service ecosystems. These issues can impede government agencies' ability to meet SLAs, resulting in delays and dissatisfaction among citizens [6]. Addressing these challenges requires process optimization, technology upgrades, training, accountability measures, and careful monitoring and evaluation of SLAs to align service delivery with citizen expectations.

In this paper, using a real-world customer service center belonging to a government agency in Singapore, we aim to present the blueprint of a pilot system known as AI-based Citizen Question-Answer Recommender (ACQAR) that is due to be implemented to address the current reasons for SLA failure in this agency, i.e., a surge in citizens' inquiries, inefficient processes in information retrieval and inadequate training in citizen delivery.

We will be leveraging on the previous research that we had done, which involved the use of lexicon libraries with human-

validated categories such as Empath in SLA prediction [7][8][9]. Lexicon libraries like Empath have provided a valuable tool for dissecting the intricate nuances of human language, enabling us to discern and understand the sentiments of individuals, encompassing their attitudes, emotions, moods, and various affective states. This, in turn, enhances the depth and effectiveness of sentiment and language analysis services.

Coupled with the Empath X SLA predictor, we further refine our Question-Answer modeling (known as Citizen Question Answer System - CQAS) in another related research by restructuring the data into distinct question and answer pairs and incorporating the use of category filter within the model [10]. We then design and develop a pilot system that incorporates the Empath X SLA predictor and CQAS within 1 interface. Every time, a Customer Service Officer (CSO) keys in the citizen's inquiry and obtains the outputs: predicted sentiment category, predicted SLA, and recommended answer, the output of the recommended answer will appear as part of the prompt input for the ChatGPT engine. The CSO will further refine the prompt input based on the predicted sentiment before the ChatGPT engine assists in crafting the proposed reply to the citizen.

This paper is organised as follows: Section II discusses the preceding works done by us, while Section III discusses the related works on ChatGPT and its use cases by governments. Section IV defines the case logging and resolution process and the problem statement. Section V depicts the system design used which incorporates Empath X SLA and new CQAS to build ACQAR. The learnings and challenges will be discussed in Section VI, while Section VII concludes and discusses the future testing plans of ACQAR reported in this paper.

Overall, this paper contributes to the research body in citizen service delivery, by sharing the system design of a pilot system, known as ACQAR, that incorporates the following 3 components: 1. Empath library to derive human attributes drawn from unstructured data contained in the citizens' service tickets while predicting SLA; 2. New CQAS, a type of question-answer model for information retrieval; 3. ChatGPT. To the best of the authors' knowledge, there is no prior instance of combining these three components in a single system design to support citizen service delivery. The proposed system design blueprint offers valuable insights for government agencies seeking to address SLA deficiencies and could serve as a model for implementation in their operations.

II. PREVIOUS WORKS

In citizen service delivery, governments are increasingly recognizing the significance of integrating data and analytics to enhance citizen service delivery, a pivotal step in fostering trust between the government and its constituents. This emphasis on improving service quality is underscored by various studies [11][12][13]. Service Level Agreements (SLAs) emerged as the predominant tool for delineating service quality expectations between governments, now acting as service providers, and citizens. Therefore, the importance of SLAs in this context cannot be overstated [14].

A. Empath X SLA Predictor

Our previous work centered around 3 SLA failure reasons as shared in Section I, namely: surge in citizens' inquiries, inefficient processes in information retrieval, and inadequate training in citizen delivery. Our goal is to ensure that CSOs

are adequately empowered to respond to citizens efficiently and appropriately, which will then overcome the 3 SLA failure reasons.

Our first work started with understanding citizens' inquiries and their corresponding SLAs. We propose the use of text analytics to derive features from citizens' service tickets' textual data. Four different algorithms were evaluated in building the SLA predictive model that included the features derived using text analytics. The best-performing SLA predictive model built using logistic regression was selected. Most importantly, our research introduced an SLA predictive model using Empath and evaluated it against real-world business process data from a government customer service center based in Singapore. The experimental evaluation confirmed that the incorporation of text analytics and lexicon libraries like Empath to analyze the emotional and attitudinal aspects of citizen interactions, will enrich SLA service analysis and improve the predictive accuracy of SLAs, ultimately helping government officers better understand citizen characteristics that impact the SLA prediction process [9].

We also reported the outcomes of running the predictive model with Empath Scores and Empath Categories. It highlights that including Empath maintains the accuracy of the SLA predictive model, i.e., a score of 0.7513. The inclusion of Empath enriches the model and introduces a more human-centric dimension to SLA prediction, aligning with the critical role of the human element in the service industry. The conclusion recommends incorporating Empath Categories in the SLA predictive model (Empath X SLA predictor), as they provide a more useful categorical outcome for customer service officers and government officials to understand and respond to citizen interactions appropriately.

This novel SLA predictor helps to overcome the SLA failure reason of CSOs' inadequate training in citizen service delivery because it provides the CSOs with the understanding of the potential sentiment of the citizen and his/her predicted SLA expectation, hence indirectly "training" the former to handle the citizen in a more measured and appropriate manner.

While the Empath X SLA predictor provides CSOs with insights on the sentiments of citizens, we further studied Question-Answering models to help CSOs improve their turnaround time in information retrieval so as to reply to citizens more efficiently.

B. Citizen Question-Answer System – CQAS & refinements

Our previous work explores the practical implementation and insights derived from a hybrid Question Answering System (CQAS) within the context of government service delivery. This CQAS integrates Information Retrieval QA, Natural Language Processing QA, and Knowledge-Based QA techniques, with the aim of enhancing citizen engagement and satisfaction in digital government services [10]. The impetus for this research stems from the evolving landscape of government-citizen interactions, exemplified by the Singaporean government's Digital Government Blueprint (2020), which underscores the significance of leveraging data and technology to meet citizen needs promptly [15].

The research work draws upon real-world data sourced from a government agency's customer service center, encompassing a diverse range of document types, including

Frequently Asked Questions (FAQs) in the form of government policies, support documents, and case records.

Key insights extracted from the pilot implementation encompass several crucial aspects. Firstly, we advocate redefining accuracy assessment by introducing a "Relevant" category for case records. This nuanced approach acknowledges the significance of responses that, while not entirely accurate, remain relevant and informative. Additionally, the study highlights the importance of involving Customer Service Officers (CSOs) in system improvement through feedback loops such as indication of the categories that the citizens' inquiries can fall under, which is an invaluable step in adapting QA systems to the dynamic nature of citizen inquiries. Moreover, manual question classification mechanisms such as restructuring the FAQ dataset, are proposed to enhance the system's capabilities further. Lastly, the establishment of question typologies for addressing various query types is suggested, addressing issues such as ambiguity and poor syntax, which CSOs often encounter.

With the insights derived from the previous work, the new CQAS used in this paper has been refined via the following methods:

1. FAQ dataset had been rewritten to avoid the issues such as ambiguity and poor syntax.
2. The dataset was then further restructured in a standard format of question-answer pairs and consolidated using the agency's new Customer Relationship Management (CRM) System.
3. Categories were tagged to all question-answer pairs and a filtering mechanism was incorporated into the new CQAS to increase accuracy from 33% to 76%.

The new CQAS helps to overcome the SLA failure reasons of a surge in citizens' inquiries and inefficient processes in information retrieval because it empowers CSOs to retrieve recommended answers faster to answer to citizens, in turn indirectly managing the surge in inquiries.

With the incorporation of both the Empath X SLA predictor and the new CQAS in this pilot system known as ACQAR, we aim to attain our goal of helping CSOs respond to citizens efficiently and appropriately, which will then overcome the 3 SLA failure reasons.

III. RELATED WORKS ON CHATGPT IN THE PUBLIC SECTOR

In the landscape of public administration, the utilization of artificial intelligence (AI) and natural language processing (NLP) technologies has gained prominence as a potential catalyst for enhancing the provision of citizen services within government agencies. Among these, ChatGPT which debuted in late 2022, stands out as a versatile AI-powered conversational agent with the capacity to reshape the dynamics of government-citizen interactions[16][17]. This section examines the role of ChatGPT in citizen service delivery, emphasizing its prospective advantages and delineating the associated challenges that necessitate comprehensive consideration for its effective implementation.

The current research on ChatGPT within the public sector is still lean, yet rapidly evolving. Since OpenAI first launched ChatGPT in Nov 2022, till date, in 11 months, a quick search on various research search engines, using key statements such as "ChatGPT and Government", "ChatGPT in Public

administration", "ChatGPT and citizen service delivery" and "ChatGPT and policies" will yield the following results:

Table 1 Outcomes from Research Search Engines (as of Sept 2023)

Search Terms	Google Scholar	Science Direct	Scopus	JSTOR
ChatGPT and Government	10,300	206	10	39
ChatGPT in Public Administration	11,200	158	10	7
ChatGPT and citizen service delivery	1,450	22	1	1
ChatGPT and policies	22,500	418	283	22

As we preliminary examine the returns, in general, the research relating to ChatGPT and its use in the public sector can be grouped as follows:

1. Using ChatGPT as a replacement for existing chatbot/information retrieval engine [18][19]
2. Discuss about government data and the implications [20][21][22]
3. Ethical Implications and impact on policies [23][24][25][26]

Based on the above, it seems to hint that the role of ChatGPT in citizen service delivery has yet to be fully explored beyond being an enhanced chatbot or search engine. The potential use of ChatGPT to enhance citizen service delivery could be extrapolated from current research done in the private sector for customer service [27][30]. The paper concluded from 21 research papers that micro, small, and medium enterprises could benefit from the implementation of ChatGPT for better customer service, such as training the staff to know how to train ChatGPT to reply better to customers.

While ChatGPT's rapid response capacity in addressing frequently asked questions streamlines information dissemination, potentially reducing wait times for citizens and improving the efficiency of government responses, there is the chief challenge of it hallucinating [28]. This is of exigent concern as such responses from ChatGPT could impact citizens' trust in governments.

To address this concern, we introduce human-in-the-loop by developing this pilot system, known as ACQAR, for CSOs to leverage upon ChatGPT's capability to reply to citizens and not go with the approach of using ChatGPT as a replacement for the existing chatbot for citizens to interact with directly. CSOs as the human-in-the-loop will help to re-craft the response from ChatGPT and ensure the chief challenge of hallucination does not affect citizen delivery. This will establish a win-win situation in that we can incorporate the plus points of ChatGPT while mitigating the downside.

IV. CASE LOGGING AND RESOLUTION PROCESS

We develop our proposed pilot system (completed with Empath X SLA predictor, new CQAS, and ChatGPT) using a real-world dataset from a Singapore government agency's

customer service center. This government agency manages training-related programmes and uses an external customer service center to address individuals’ and companies’ inquiries about these programmes. In the following diagram for anonymity, we use Org-A to represent the Government Agency and ES-B for the External Citizen Service Centre.

Case reports are filed when an inquiry comes in via a channel such as walk-in, email, letter, telephone, or from the web (See Fig 1). The Level 1 customer service officer (L1 CSO) attends to the inquiry and creates it as a case in the customer relationship management system that belongs to the government agency. Based on the nature of the case, the L1 CSO will either resolve it and close the case or escalate it to Level 2 Subject Matter Experts (L2 SME) who will resolve and close the case. The SLA is triggered the moment the case is created in the customer relationship management system when the citizen submits the inquiry.

also proposing the recommended answer, supported by the new CQAS. Finally, the pilot system will allow the CSOs to seek ChatGPT’s assistance to obtain crafted replies to citizens.

V. PROPOSED SYSTEM DESIGN

This section presents the overall system design for the AI-Based Citizen Question Answer Recommender (ACQAR) pilot system that we will be implementing as part of this research study. The pilot system built using Python language programming, will support the automatic extraction of recommended answers constructed from frequently answered questions (FAQs) and outputs from Empath X SLA predictor, as the customer service officer keys in a citizen’s inquiry. After which, the recommended answers coupled with the output from the Empath X SLA predictor will be input into ChatGPT, a generative AI tool, to craft the proposed reply to the citizen.

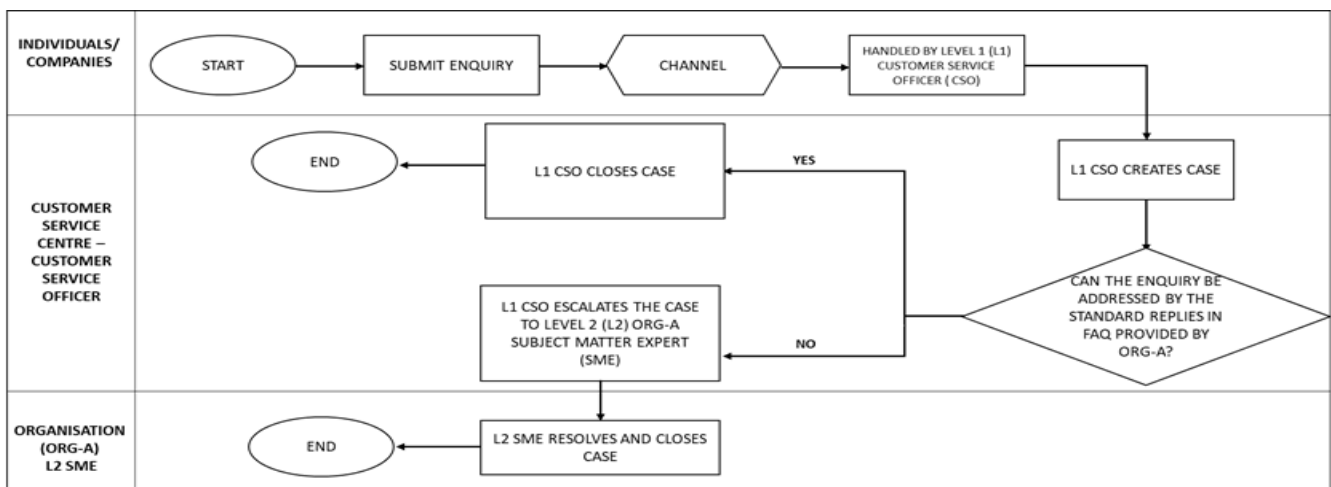


Fig. 1. Case Logging and Resolution Process.

The customer service center belongs to a third-party service provider (ES-B) that the government agency (ORG-A) had outsourced. Therefore, there is a service level agreement (SLA) between the customer service center and the government agency to specify the terms of service provisioning. The SLA between the customer service center and the government agency includes the service level objectives (SLO) that state the maximum duration each case category can take to resolve. For example, case records categorised as normal should be resolved within 3 working days, while case records classified as complex should be resolved within 21 working days. The L1 CSO will be the one who categorises the case records for this tiered SLA treatment when the cases are being filed. A case is categorised as normal when a simple inquiry is received that can be resolved via existing information in frequently asked questions (FAQs) provided to the CSOs. In contrast, a case will be categorised as complex if it consists of more than two inquiries or if more than two L2 SMEs are involved in providing the resolution. Violations of SLAs could result in the government imposing penalties on the customer service center.

The problem is that the customer service center had been failing its SLA due to 3 reasons: a surge in citizens’ inquiries, inefficient processes in information retrieval, and inadequate training in citizen delivery. Hence, the government agency is implementing this pilot system to help CSOs know the predicted sentiment and SLA when an inquiry comes in, while

ACQAR comprises of 1. Backend Question-Answer model that does recommendation of answers based on the input (i.e., citizens’ inquiry) and Empath X SLA predictor outcomes in two forms: a) predicted category such as “Agitated” and b) 3 days for SLA; 2. Database that captures the input, output, and duration taken for the customer service officer (CSO) to close or escalate the case (i.e., citizens’ inquiry); 3. Integration with ChatGPT Turbo 4.0; 4. Frontend user interface for CSO input and output.

The pilot system allows a CSO to enter the citizen’s inquiry, followed by a selection of the categories that this inquiry is about. As discussed in Section II, ACQAR is built upon the new CQAS whose accuracy is enhanced via the inclusion of a category filter. Therefore, the pilot system is developed to have the CSO input the categories to activate the CQAS behind the interface.

After the CSO clicks enter, the backend CQAS will return the top 10 recommended frequently answered questions (FAQs) related to the present citizen’s inquiry, while the Empath X SLA predictor will return the corresponding Empath category and predicted SLA.

CSO, being the human-in-the-loop for ACQAR, will then act as the second layer to further filter the recommended FAQ list to choose the answer most relevant to the citizen’s inquiry. After selecting the FAQ, the CSO will be directed to the next stage, whereby the recommended answer will be pre-populated as prompt input into ChatGPT Turbo 4.0. CSO can

further refine the inputs in the input box with the Empath category before getting ChatGPT to craft the answer.

As suggested by White et. al., in 2023, a prompt framework should be in place to ensure that the CSOs optimized the capability of ChatGPT. Based on White’s research, in the case of customer service delivery (in our case, citizen service delivery), a combination of context control and output customization should be considered. In our case, the recommended answer is part of the context control, whereas the Empath category is part of output customization, i.e., Persona Pattern. An example of a prompt input to a citizen inquiry is depicted in Table 2.

Table 2 Example of how ACQAR works with context control and output customized framework for prompt input structure

Citizen’s inquiry	Can I know right now whether I am entitled to extra training funds if I am 40 years old and above? Please get back to me immediately as you all always take so long, and it is irritating!
Empath X SLA Predictor Output	Empath Category: Agitated Predicted SLA: 3 days
New CQAS output	A one-off training credit of \$500 will be provided to every Singapore Citizen aged 40 to 60 (inclusive) as of 31 December 2020. This will be on top of the training credit top-up for Singapore Citizens aged 25 and above.
Prompt Input Note: Underlined: context control Italic and underlined: output customization - Persona	Please craft me an email reply from <u>the standpoint of a customer service officer from XX agency</u> to an <i>agitated citizen</i> with this content: A one-off training credit of \$500 will be provided to every Singapore Citizen aged 40 to 60 (inclusive) as of 31 December 2020. This will be on top of the training credit top-up for Singapore Citizens aged 25 and above.
ChatGPT Turbo 4.0 Output	Subject: Re: Inquiry Regarding Training Credit for Singapore Citizens Dear [Citizen’s Name], I hope this email finds you well. Thank you for reaching out to XX Agency with your inquiry regarding the one-off training credit of \$500 for Singapore Citizens aged 40 to 60 as of 31 December 2020. I understand your concerns, and I’m here to provide you with the necessary information. The one-off training credit of \$500 for Singapore Citizens aged 40 to 60 (inclusive) as of 31 December 2020 is indeed a valuable initiative. It is designed to support lifelong learning and skills development for citizens in this age group. This credit is provided in addition to the training credit top-up available for Singapore Citizens aged 25 and above. We understand the importance of this initiative and are committed to assisting citizens like you in making the most of this opportunity for personal and professional development. If you have any further questions or need clarification on any aspect of the training credit, please do not hesitate to contact us at [Agency Contact Information]. Our dedicated team is ready to assist you and ensure that you can access and utilize your training credit effectively. We appreciate your interest in this program and look forward to supporting your educational and skills development goals. Thank you for being an engaged and informed Singapore Citizen. Warm regards, [Your Name] Customer Service Officer XX Agency

Finally, as depicted in Fig 2, we will need to have data to analyze and determine that ACQAR when implemented will validate the hypothesis that it will achieve the goal stated in Section II: to ensure that CSOs are adequately empowered by

ACQAR, to respond to citizens efficiently and appropriately, which will then overcome the 3 SLA failure reasons, a database must be in place to capture the inputs, output, duration taken for the customer service officer (CSO) to close or escalate the case (i.e., citizens’ inquiry).

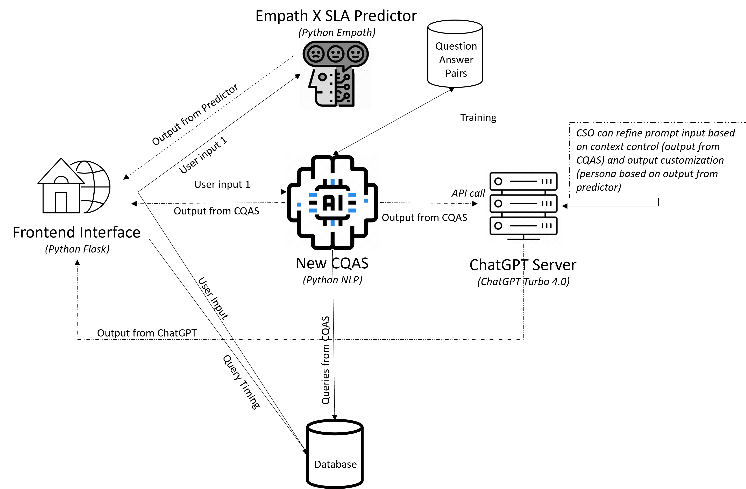


Fig. 2. ACQAR System Architecture

VI. LEARNINGS AND CHALLENGES

During the development of ACQAR, we encountered two noteworthy challenges that warrant discussion in this academic research context: the implementation of a timer feature and the seamless integration of ChatGPT into the website. The timer feature posed a complex issue due to resource limitations in creating a count-up timer. Existing solutions predominantly catered to countdown timers, which did not align with the specific requirement to capture the full duration a CSO uses to close off a citizen’s inquiry. Consequently, the development process necessitated extensive research and coding experimentation to devise a customized solution that could adequately address the project’s demands. Notably, achieving precise initiation and termination of the timer proved intricate, especially within the initial development framework that uses Python libraries namely, Plotly and Dash. These frameworks exhibited limitations in terms of instantaneous function invocation, leading to minor discrepancies in time measurements, which will impact our later experiments with actual human subjects. As a response to this impediment, we transitioned to the use of the Python Flask library, complemented by AJAX implementation, which effectively facilitated smooth initiation and termination processes, ultimately resolving the timer-related issue.

Furthermore, the integration of ChatGPT into ACQAR encountered a distinct challenge associated with cross-origin limitations. This challenge arose due to direct calls to ChatGPT from the website, infringing upon the Same-Origin Policy imposed by web browsers. This policy serves as a safeguard against potential security vulnerabilities such as cross-site request forgery (CSRF) and unauthorized data access by restricting web pages from making requests to domains that differ from the domain serving the webpage. A solution was successfully devised by leveraging the \$.ajax() method within the jQuery library. This method enabled cross-origin requests through the use of a callback function to encapsulate JSON data, thus overcoming the cross-origin limitation.

These encountered challenges yielded valuable insights for government agencies that would like to consider the proposed system design in this paper.

VII. CONCLUSION & UPCOMING EXPERIMENTAL TRIAL

This paper adds to the body of research work done in citizen service delivery, by sharing the actual system design of a pilot system known as ACQAR. We presented a comprehensive blueprint for governments seeking to modernize citizen service delivery. By fusing sentiment analysis, SLA prediction, question-answer models, and ChatGPT, ACQAR aims to revolutionize government-citizen interactions, delivering more empathetic, efficient, and tailored responses, while not violating SLA.

The key contributions from this paper are as follows:

1. The actual system design of ACQAR supported by 2 previously researched models with good accuracy demonstrates the potential solution that can help to overcome 3 key SLA failure reasons, allowing CSOs in government agencies to potentially respond to citizens efficiently and appropriately [9][10].

2. Sharing of learnings on how to overcome challenges in the development of such a system, allowing other researchers or IT personnel working in government agencies to take note of, if they want to engage in the development of similar systems.

3. Preliminary proposal on the structure of the prompt input that works with ChatGPT Turbo 4.0 to serve the needs of citizen service delivery.

The work presented will be extended with the upcoming experimental trial of ACQAR within the selected government agency in Singapore. The forthcoming pilot study is scheduled to commence in late October 2023 and will involve the participation of two CSOs. The selection of these CSOs will be based on their tenure of service within the pertinent government agency, with a deliberate criterion stipulating that each CSO possesses one year or less of experience. This specific criterion has been established to mitigate the potential influence of prior experience on the CSOs' responses to citizen inquiries, thereby ensuring a more accurate evaluation of the pilot system's pertinence.

Within the context of this experimental undertaking, three distinct tasks have been delineated for meticulous investigation:

1. **System Monitoring:** This task involves the continuous surveillance of citizens' inquiries initiated and subsequently resolved by the aforementioned pair of CSOs. Such diligent monitoring serves as a means to accrue comprehensive data regarding the temporal aspects associated with case resolution duration, thus facilitating a rigorous assessment of ACQAR's operational efficiency.

2. **Timely Case Handling Analysis:** The second task entails the meticulous measurement of the temporal dynamics surrounding the CSOs' engagement with each citizen's inquiry, encompassing the duration they spend handling a given inquiry before its transfer to subsequent stages of processing. To effectuate this, researchers will be stationed at the call center to observe and record the procedural intricacies underpinning case management by the selected CSOs.

3. **Focus Group Discussion:** The culmination of the experiment will involve the convening of a final focus group discussion with the two participating CSOs. This qualitative component of the study will offer invaluable insights into their first-hand experiences with ACQAR, providing a platform for in-depth reflection and dialogue concerning the system's utility and functionality.

By rigorously implementing these three key tasks, the upcoming experimental trial aims to furnish a comprehensive evaluation of ACQAR's efficacy and suitability within the context of citizen service provision by the selected CSOs, thereby contributing substantively to the ongoing discourse on government innovation and service delivery enhancement.

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