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Enhancing Line Chatbot Experiences: Utilizing Thai Question-Answering Systems to Enrich Dialogue with Unpredictable Questions

Worachet Uttha[1,*]
[1] Faculty of Science and Technology, Nakhon Pathom Rajabhat University

Abstract

Chatbots have gained popularity in recent years as a means of engaging with people using natural language, especially Line Chatbot, which has 290,000 active chatbots in Thailand. With such a high number of active chatbots in Thailand alone, Line Chatbot has become a prominent player in the chatbot market. The main problem with chatbot construction is processing unpredicted questions. Even if Dialogflow, as a natural language understanding tool, can assist us in finding users' intentions, it is not good enough. In this work, we intend to enhance Line chatbot experiences by utilizing the pre-trained Thai Question Answering model as the NLP service that talks with the chatbot via the RESTful API. The major task is to deal with the message that Dialogflow cannot find the user's intention. With this strategy, we can improve the chatbot's ability to answer unexpected or complex questions, offering more accurate and relevant responses. By incorporating the Thai Question Answering model, the chatbot may exploit its pre-trained expertise to better understand and reply to user queries, boosting the overall user experience. The results show that the system met the specified requirements and consistently provided users with meaningful information.

Keywords: Line Chatbot, Thai Question Answering, Natural Language

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1. Introduction

Chatbots have gained significant popularity in recent years as they provide automated responses and assistance to users in various industries such as customer service, healthcare, e-commerce, and education [1]–[4]. Question-Answering Systems (QAS), on the other hand, are designed to retrieve relevant information from large databases or knowledge bases to answer specific questions. In many universities in Thailand, constantly responding to students' inquiries is the duty that staff must execute on a daily basis. This task can be time-consuming and overwhelming for staff, especially during peak periods. By developing chatbots that are capable of handling complex inquiries, universities can alleviate some of the burden on their staff while still providing timely and personalized support to students. However, the effectiveness of these chatbots heavily relies on their dialogue capabilities. Most chatbots cannot manage unanticipated queries or sophisticated interactions, generating annoyance for users. As a result, institutions are investing in advanced natural language processing algorithms and machine learning approaches to increase the dialogue capabilities of their chatbots. By training these chatbots on vast datasets and using contextual awareness, universities want to boost their chatbots' capacity to handle a wide range of queries and deliver individualized advice to students, but the training's cost on a large dataset is very high.

This research aims to create a more efficient and cost-effective solution for universities, reducing the need for extensive training and resources for staff members and focusing on enhancing their ability to respond to unpredicted questions within a specific context.

*Corresponding author; e-mail: wuttha@webmail.npru.ac.th

By studying new techniques and strategies, this research intends to improve the NLP model's capacity to handle complex inquiries and provide appropriate responses. The goal is to enhance the overall chatbot experience and enable universities to offer individualized advice and support to students.

2. Literature Review

2.1 Chatbot

A chatbot [5] refers to a software application that has the capability to imitate a dialogue like that of a human being, either through written text or spoken language. Chatbots can be categorized into three distinct classifications, which encompass rule-based, generative, and retrieval-based models. Rule-based chatbots rely on pre-established rules to decide the appropriate responses to user input, whereas generative chatbots employ neural networks to produce novel responses. Retrieval-based chatbots use a mechanism that selects responses from a pre-existing database of responses in accordance with the user's input.

In the context of university chatbots, in addition to the presence of intelligent chatbots, prioritizing user experience is crucial to fostering a sense of comfort and engagement among students when interacting with the university's digital platforms. The field of user experience design is centered around the enhancement of platform layout, navigation, and functionality in order to provide an intuitive and user-friendly experience. The incorporation of a visually appealing and user-friendly interface enhances the likelihood of student engagement with the chatbot, hence facilitating the acquisition of proactive assistance. Furthermore, the integration of consistent feedback and updates from students can contribute to enhancing the user experience and tailoring it to their specific needs and preferences. The utilization of a chatbot within the Line application is deemed appropriate in this particular context due to its capability to seamlessly integrate into the platform and provide students with a familiar user experience. The Line Application's chatbot, with 54 million active users in Thailand [6], can be programmed to give individualized advice and help depending on each student's particular progress and goals. In addition, the inclusion of interactive elements such as flex message, quick reply, imagemap, template message, and multimedia support serves to enrich the overall learning experience and adds an element of excitement for students. Incorporating a chatbot into the Line application has the potential to significantly enhance the efficacy and user-friendliness of the platform, particularly for students in search of aid and support.

2.2 NLP & Thai Question Answering System

Natural language processing (NLP) is used in chatbots to make it easier to understand and answer user questions by considering the question's context and the meaning behind the words used. The comprehension of intricate aspects of human language enables chatbots to deliver responses that are both precise and pertinent, enhancing the user experience by ensuring a seamless and gratifying interaction. The Thai language is characterized by complicated tonal distinctions and grammatical structures, posing a significant obstacle for natural language processing (NLP) technology [7]. Thai natural language processing (NLP) has been developed using many methodologies, such as rule-based, statistical, and deep learning techniques [8].

Question answering (QA) and natural language processing (NLP) are two fields within artificial intelligence (AI) that focus on understanding and generating human language. NLP aims to enable computers to understand, interpret, and generate meaningful human language through tasks like text classification, entity recognition, machine translation, text generation, sentiment analysis, and part-of-speech tagging. QA, a specific application of NLP, focuses on extracting answers from textual or structured data in response to user queries. QA systems can range from simple

keyword-based searches to advanced models using deep learning techniques. Recent advancements in NLP have improved the performance of QA systems, making them well-suited for various NLP tasks.

The Thai Question answering system [9] is a cutting-edge technology that uses artificial intelligence to generate accurate, relevant answers to various Thai language inquiries. Thai language faces challenges in natural language processing due to its grammatical structures. Despite this, Thai question-answering systems use various methodologies, including rule-based systems, statistical models, and deep learning architectures, to provide precise responses. However, their precision and scalability are limited by the availability of training data [9]–[12].

2.3 Dialogflow

Dialogflow [13] is a service provided by Google that facilitates the advancement of natural language processing and serves as a foundation for constructing chat interfaces for websites, mobile applications, widely-used messaging platforms, and Internet of Things (IoT) devices. Dialogflow has the capability to establish connections with many platforms such as Alexa, Facebook, Twitter, Slack, Cortana, and Line. Through this integration, Dialogflow is able to receive messages from users and afterwards employ its translation functionality to analyze the content of these messages. The primary objective of this analysis is to discern the intentions of the users and subsequently categorize them into distinct intents. Developers will possess the capability to formulate suitable solutions for users. The aforementioned solutions encompass both static and dynamic responses, facilitating developers in the creation of a program that supports their job by utilizing their preferred programming language and establishing connections with their own database. Moreover, different segments that are implemented within a secure Hypertext Transfer Protocol Secure (HTTPS) are subjected to encryption measures, thereby guaranteeing the prevention of unauthorized data theft. A potential security threat known as a "man-in-the-middle attack" is being discussed.

2.4 Related Works

Balderas et al. [1] proposed using a chatbot to provide initial support and facilitate communication between students and the university during the COVID-19 pandemic. They create the chatbot using DialogFlow and connect it to Google AppScript as a webhook to retrieve more information. The results of the testing, which involved over 160 students and staff members from student services, are in favor of chatbots as a potential tool for communication in developing emergency situations.

Illescas-Manzano et al. [3] implemented a chatbot via Facebook Messenger and the ManyChat platform, demonstrating that a chatbot on the platform positively impacts lead capture. The study concludes that incorporating a chatbot can be a powerful tool for obtaining consumer information, facilitating two-way communication, and facilitating sales for companies.

Chandra et al. [4] developed a chatbot for university admission using a question-answering system based on the sequence-to-sequence model. They train this model using a dataset of conversations from university admissions. Their approach is to combine sequence-to-sequence with an attention mechanism to give a response to the given question. The model achieves a high BLEU score of 41.04, but an attention mechanism technique using reversed sentences improves it to 44.68.

3. Design and Development

Line Chatbot is an AI program that uses natural language processing and machine learning to provide personalized assistance and information. It can be developed using the Line messaging platform and Dialogflow, a cloud-based platform that integrates AI technologies for intelligent chatbot applications. One

limitation of chatbots is their ability to accurately understand and respond to complex or ambiguous questions. Additionally, chatbots may struggle with providing relevant and contextually appropriate answers, especially when faced with a wide range of diverse questions.

This section aims to elucidate the process involved in the creation of an application that integrates a Thai chatbot with a question-answering system. The NPRU Smart Campus Chatbot system combines chatbot and question-answering technology to provide students with natural language responses. The system consists of three actors: high school students, university staff, and university students as described in Figure 1. Students can inquire about admission requirements, programs, and deadlines, while university staff can assist with administrative tasks. University students can access course schedules, grades, and campus events. The Line Messaging API offers various message types, making it user-friendly and interactive. The system also integrates with other apps and services, allowing students to access relevant information and resources. This prototype aims to provide students with precise, succinct responses in a natural language format.

Additionally, the API allows for easy communication between students and faculty members, enabling them to schedule appointments or seek academic guidance conveniently. With its versatile features and user-friendly interface, the Line Messaging API enhances the overall efficiency and effectiveness of university operations.

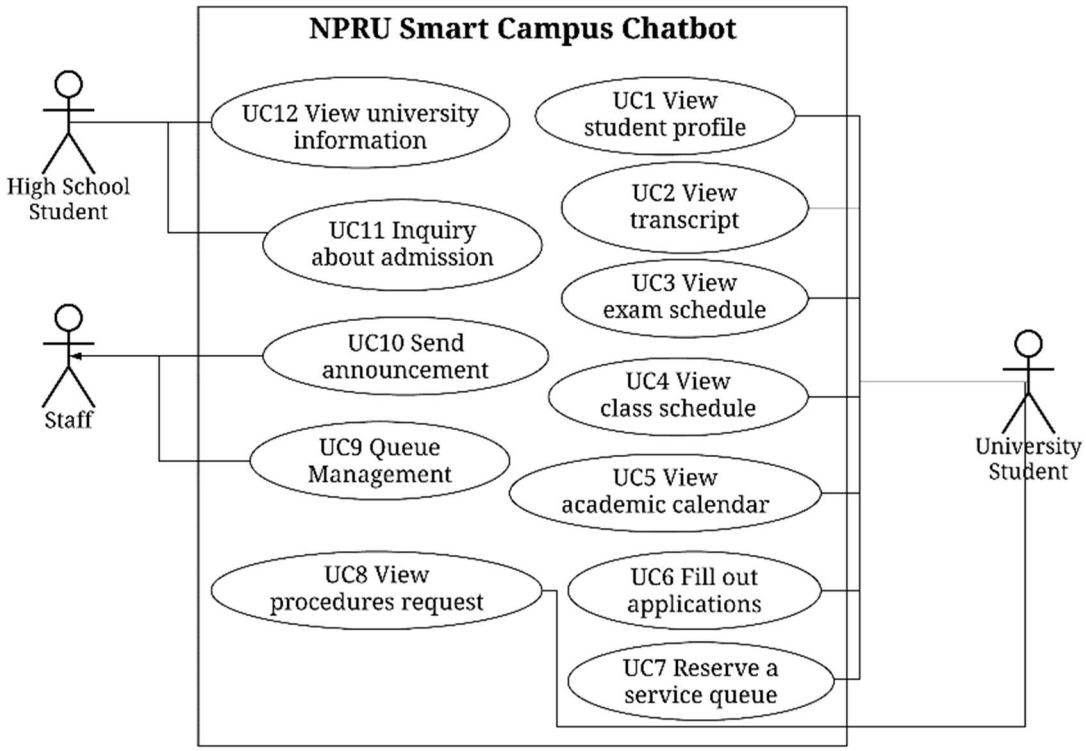

Figure 1. Use case Diagram of NPRU Smart Campus Chatbot

3.1 System Architecture & Implementation

The adoption of a multi-tier architecture design pattern was chosen for the implementation of the NPRU Smart Campus Chatbot. Multi-Tier Architecture [14], alternatively referred to as N-Tier Architecture, is a prevalent design pattern in software development. Its purpose is to partition the many components of an application into independent levels, or tiers. Each layer within the organizational structure is assigned distinct duties and possesses a clearly delineated set of responsibilities. This architectural methodology contributes to the enhancement of scalability, maintainability, and flexibility in intricate software systems. The quantity of tiers may exhibit variability, while the prevailing multi-tier systems often encompass three tiers: presentation, application (business logic), and data tiers.

The system is divided as shown in figure 2: 1) The Presentation Tier, which uses the Line chatbot as a channel to engage with the user, can send messages through the chat room, and when the processing system is completed, the results are sent through the Line application. 2) The Application Logic Tier, constructed using Node.js, operates as a Webhook or Application Gateway that coordinates with the Presentation Tier and Resource Manager Tier. For example, when the user requests their grade, the chatbot will send a service request to the webhook. The system then connects to the database to search for information from the Resources Manager Tier level, then generates the results that are appropriately prepared, thereby distributing the results to users via the online application, etc. In the application logic tier, there is another component, the Dialogflow API, which shifts the natural language processing function (NLP) to the application, so the user is directed back to a webhook processor in order to complete the processing process. 3) The Resource Manager Tier is created utilizing the CodeIgniter framework, a PHP framework that serves as a REST API. Webhook can access the database by using this API. The Resource Manager layer includes the integration of the NLP service with two additional services. The two technologies under discussion encompass the Dialogflow API and Thai QAS. The implementation of the Thai Question Answering System (QAS) utilizes FastAPI, a Python framework that facilitates the transmission of unforeseen queries and their corresponding context via a RESTful API. The primary objective of this function is to acquire the suitable response from the Dialogflow API, then utilized for generating a reply to the user.

The incorporation of the Natural Language Processing (NLP) service with the Dialogflow Application Programming Interface (API) and Thai Question Answering System (QAS) facilitates enhanced language processing and comprehension with improved efficacy and precision. By leveraging the Dialogflow API, the system demonstrates the ability to perform an analysis and interpretation of the user's queries, afterwards providing relevant responses. The functioning of the Thai Question Answering System (QAS) is greatly enhanced since it allows for effective handling of unanticipated queries and the provision of contextually appropriate responses. In aggregate, these technologies enhance the system's capacity to generate solutions that are both significant and advantageous in resolving user enquiries. Moreover, the partitioning of the system into these three tiers provides improved structuring, expandability, and manageability of the software. The independent development and upkeep of each layer enable the smooth integration of novel functionalities or error corrections without causing disturbances to the overarching system.

3.2 User Interaction with Dialogflow API

Dialogflow is a Natural Language Understanding (NLU) engine to enable users to develop intelligent chatbots effortlessly. It provides developers with an API to interact with the chatbot and retrieve user inputs. This allows users to have a conversational interaction with the chatbot, asking questions or issuing commands. The Dialogflow API

analyzes these inputs and returns suitable replies depending on the stated intents and entities. This enables a more human-like and intuitive user experience. In our scenario, students can submit messages to the chatroom to inquire about any information described in Figure 1. The chatbot may seek more information to grasp the context, and then Dialogflow will determine the genuine intention of the student and transfer it to the API gateway to build an automatic answer in case it cannot fulfill the replies by itself and give it back to the student.

One of the challenges that chatbot developers have to address is that we cannot foresee every user query as it is a chat and users can send any text to the chatroom. In order to emulate people, chatbots have to deal with unpredicted questions. To address this difficulty, developers can utilize machine learning methods to train the chatbot on a wide range of probable user queries. By regularly feeding it with new data and analyzing its performance, the chatbot can learn to recognize patterns and create acceptable responses, even for unexpected requests. Additionally, developers can also include natural language processing techniques to help the chatbot grasp the underlying meaning and context of user queries, enabling it to offer more accurate and relevant answers. In order to accomplish this, we need a supercomputer with great performance, a huge dataset to feed and train the model, and additional time to train the model. Each of these costs a lot, which a tiny firm such as a government agency cannot offer. In order to address this issue, we proposed an alternative solution. Our approach entails developing Thai Question Answering System APIs based on pre-trained models that offer sophisticated machine learning capabilities while minimizing the work and time required for training. By employing these APIs, we can reduce the need for a supercomputer on-premises. This approach helps small companies like government agencies harness the benefits of NLP without paying extravagant fees.

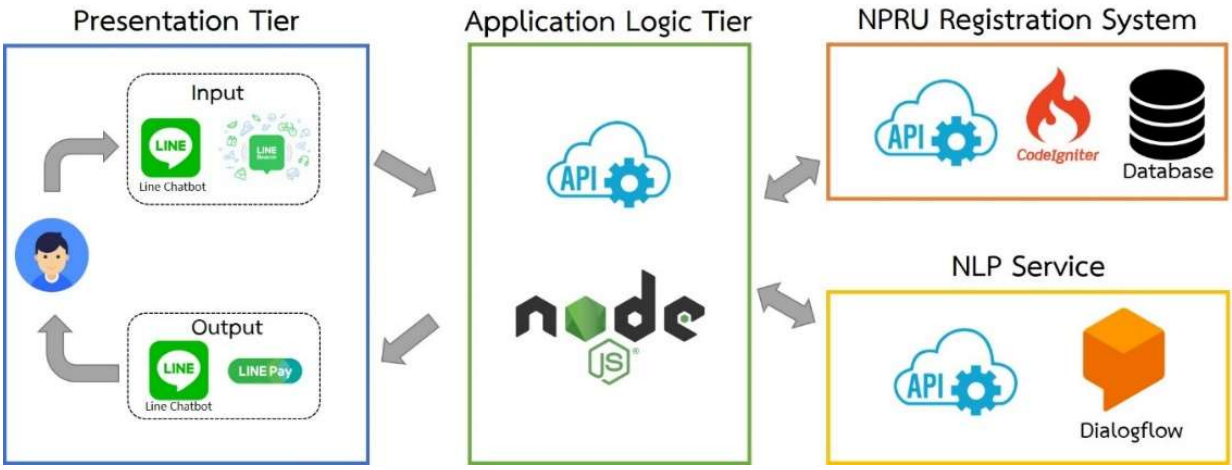

Figure 2. NPRU Smart Campus Chatbot's System Architecture

3.3 NLP Service Combination

As mentioned before, NLP services are developed using a pre-trained Thai question-answering model. According to Thammarak's advice [15], the development of a RESTful API included the use of the WangchanBERTa-QA-Thaiqa_Squad pre-trained model. WangchanBERTa [16], one of the top BERT-based [17] models for Thai NLP, specializes in a variety of NLP tasks and has been tailored especially for comprehending Thai. In the areas of named entity recognition, text

categorization, and question answering, it has produced cutting-edge results. WangchanBERTa's robust features have greatly increased Thai NLP and made it a useful tool for developers and researchers working with Thai. The utilized model in this study is the Wangchanberta-base-att-spm-uncased model, which is then fine-tuned using the Thaiqa_squad dataset. The Wangchanberta-base-att-spm-uncased model's fine-tuning method uses the Thaiqa_squad dataset to help it do better at answering questions about open-domain themes. The Nvidia DGX-1, consisting of 8 units of a 32GB GPU, was utilized to train this model. It took around 125 days to train the model on a big 78.5GB dataset consisting of 360,000 training steps. There are 4,000 questions in the Thaiqa_squad dataset for training and 74 questions for development, both of which NECTEC generated and PyThaiNLP converted to SQuAD format.

We use FastAPI [16], a Python framework that allows us to easily deploy and serve WangchanBERTa-QA-Thaiqa_Squad for Thai NLP applications. FastAPI is widely recognized for its outstanding performance and scalability, making it a very desirable choice for efficiently handling the significant workload associated with NLP activities. FastAPI offers the functionality to create efficient and reliable APIs for seamless integration of WangchanBERTa-QA-Thaiqa_Squad into various applications. The combination of WangchanBERTa-QA-Thaiqa_Squad and FastAPI offers developers a streamlined and effective method to leverage the sophisticated functionalities of Thai NLP. This methodology enables the creation of NLP services that possess the capability to provide precise responses to inquiries posed in the Thai language. Developers have the ability to leverage pre-trained models and enhance their performance by fine-tuning them with pertinent data, enabling the creation of robust and efficient NLP applications. Not only does this practice result in time and energy conservation, but it also allows enterprises and people to obtain NLP capabilities at a significantly reduced expense in comparison to the development of their own models.

In summary, students have the ability to submit inquiries to the chatbot through the Line application. Subsequently, our webhook will intercept the text and transmit it to the DialogFlow API for the purpose of ascertaining the student's intention, provided it aligns with the predefined messages outlined in Figure 1. The webhook is responsible for generating responses for students. However, in situations where DialogFlow is unable to identify the true intention of the student (such as an unexpected inquiry), the webhook will transmit this question in a log format together with relevant context to the Thai QA service. The Thai QA service analyzes queries and contexts to provide accurate responses, even if Dialogflow fails to understand them. This integration enhances the effectiveness and reliability of the student support system.

4. Chatbot Evaluation

Software testing is crucial in software engineering to ensure the quality and reliability of a chatbot. Various testing methodologies, such as unit testing, integration testing, and acceptance testing, help identify and rectify potential issues during the development process. Regular evaluations and software testing are essential for creating a resilient and effective chatbot. In this study, two tasks were evaluated: assessing the chatbot's performance in understanding and providing accurate responses to user inquiries and evaluating the accuracy of Thai question-answering responses. This comprehensive evaluation ensures the chatbot's efficacy and reliability before deployment.

Black box testing [17] is a widely used method for assessing software development life cycles, focusing on program functionality without examining its internal architecture. This method ensures chatbot efficacy and compliance with user expectations. It detects potential defects, allowing for modifications

before release. Precision, recall, and F1 score metrics [18] are used to assess the accuracy and comprehensiveness of QA systems, identifying areas for improvement and ensuring the system meets requirements.

5. Result & Discussion

In this research, the output is in the form of a Line chatbot for Nakhon Pathom Rajabhat University's Office of Academic Promotion and Registration. The chatbot can provide information on course registration, academic information, and other relevant topics. The system's performance was evaluated through black box testing techniques and analysis of response accuracy and timeliness. Overall, the Line chatbot proved to be a valuable tool for streamlining administrative processes and improving user satisfaction. Users can learn more about Nakhon Pathom Rajabhat University outside of the provided topics by asking questions regarding the campus facilities, extracurricular activities, and student support services. The chatbot was created with the support of the Thai QA service using data accessed from Nakhon Pathom Rajabhat's websites to provide thorough information on the university's history, goals, and vision, as well as the numerous faculties and departments accessible for students to choose from. Additionally, users can also seek information on admission guidelines, scholarships, and forthcoming events. With the Line chatbot's ability to address a wide range of inquiries, it acts as a comprehensive resource for prospective and present students alike.

We used precision, recall, and F1 score metrics. TP refers to true positives, which are the number of correct answers given by the system. FP refers to false positives, which are the number of incorrect answers given by the system. FN refers to false negatives, which are the number of correct answers not predicted by the system. When calculating recall, divide TP by the sum of TP and FP. When calculating precision, divide TP by the sum of TP and FN. The F1 score is the harmonic mean of precision and recall, providing a balanced measure of the system's performance. It is formulated as follows:

$$(1)\ Precision = \frac{TP}{(TP + FP)}$$

$$(2)\ Recall = \frac{TP}{(TP + FN)}$$

$$(3)\ F1 = \frac{2\ x\ Precision\ x\ Recall}{(Precision + Recall)}$$

Our dataset is composed of 100 questions and their corresponding answers. After evaluating the model, we got: 1) true positives (TP): 65 questions; 2) false positives (FP): 20 questions; and 3) false negatives (FN): 15 questions. Therefore, when evaluating our model, we got the recall score of 0.7647 indicates that our system successfully identified approximately 76.5% of the correct answers in the dataset. This signifies that our model has reasonably good predictive capabilities. The precision score of 0.8125 shows that our system accurately predicted around 81.25% of the correct answers. The F1 score of 0.7879 emphasizes the balance between precision and recall, providing an overall assessment of our system's performance, considering both false positives and false negatives.

During the evaluation of the chatbot, we assessed its performance by considering factors such as response time, user satisfaction, and error rate. We tested the chatbot with a diverse set of user queries and measured its ability to provide accurate and relevant responses. The results showed that the chatbot had high response accuracy, a low error rate, and a quick response time. Users reported high satisfaction levels with the chatbot's performance, indicating that it effectively understood their queries and provided helpful responses. These positive results demonstrate the chatbot's effectiveness in meeting user expectations and its ability to perform well in real-world scenarios.

6. Conclusion

In this research, we provided a Thai chatbot that integrated the Thai Question Answering System as a component of the NLP service to aid the personnel at Nakhon Pathom Rajabhat University's Office of Academic Promotion and Registration. By employing the pretrained Thammarak model that is accessible on huggingface, this strategy may handle unexpected queries and save money on constructing a new Thai question-answering model, which is a good trade-off between accuracy and cost-effectiveness. The chatbot has demonstrated encouraging results in terms of its capacity to offer accurate and fast responses to user queries, therefore boosting the efficiency and effectiveness of the office's operations. Additionally, the integration of the Thai Question Answering System has enabled the chatbot to continuously learn and improve its performance, ensuring that it remains up-to-date and reliable in aiding workers. Overall, this research contributes to the rapid development of NLP technology in the Thai language and establishes an example for future developments in this field. The results showed that the system met the specified requirements and consistently provided users with meaningful information. However, there were a few areas identified that needed improvement, such as the system's response time and the accuracy of certain responses, especially long questions, or long answers. These findings will help guide future enhancements to the system and ensure that it continues to deliver precise and dependable responses.

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