

Automated Prioritization for Monitoring and Tracking Service Requests using Named Entity Recognition Technique

Chumpol Mokarat^{1,*} , Pattarak Sawatdee¹, and Pimpika Intutsing¹

¹Department of Information Technology, Faculty of Business Administration and Information Technology, Rajamangala University of Technology Tawan-Ok, Bangkok 10400, Thailand

*Corresponding author: Chumpol Mokarat, chumpol_mo@rmutto.ac.th

Article Information

Article History:

Received: 3 July 2025

Revised: 23 October 2025

Accepted: 7 January 2026

Published: 20 June 2026

Keywords:

Automated Prioritization
Monitoring and Tracking
Named Entity Recognition
Service Requests

Abstract

Service request prioritization in IT service management presents significant challenges in terms of accuracy and efficiency, particularly in Thai-language environments where automated support tools remain limited. This study develops and evaluates a web-based application designed to optimize the management and tracking of organizational service requests. By incorporating automated prioritization through Named Entity Recognition (NER), the system aims to improve operational efficiency and reduce the time staff spend on maintenance-related tasks. In addition to real-time tracking, the application serves as a centralized repository for service request data, enabling in-depth analysis and supporting strategic planning. This capability facilitates more informed decision-making in organizational service management. A key feature of the proposed system is its ability to automatically prioritize incoming service requests based on extracted information. The core component is an NER model fine-tuned using 500 service request samples. Four transformer-based language models, namely BERT-Base-Thai, BERT-Base-Multilingual, WangchanBERTa-Base, and XLM-RoBERTa-Base, were evaluated and compared. The evaluation employed multiple performance metrics, including evaluation loss, precision, recall, F1-score, and accuracy, to determine the most suitable model for the task. Experimental results indicate that BERT-Base-Multilingual achieved the best performance, obtaining an evaluation loss of 0.0272, precision of 0.9888, recall of 0.9946, F1-score of 0.9917, and accuracy of 0.9923. System performance testing further demonstrated that automatic priority assignment required less than 3.5 seconds per request, while service resolution was completed within 48 hours, resulting in an overall user satisfaction score of 4.16 out of 5. The findings confirm the effectiveness of the proposed NER model in accurately identifying multiple entity categories and demonstrate that the developed system successfully enhances service request management while reducing request-tracking time through automated log analysis.

1. Introduction

Educational institutions are entrusted with the responsibility of providing effective teaching and learning environments, which require the availability and readiness of various instructional equipment and information technology resources. However, it is frequently observed that such resources are either damaged or utilized without proper documentation. These issues adversely af-

fect the management and delivery of information technology services within the organization. At Rajamangala University of Technology Tawan-Ok (RMUTTO) (2022), the delivery of teaching and learning requires the utilization of various equipment and resources. Each academic semester necessitates the management of service requests to ensure the readiness and efficiency of overall Information Technology Service Management (ITSM) prior to the commencement of classes. These

services encompass internationally recognized standards and best practices, such as the Information Technology Infrastructure Library (ITIL), which emphasizes service optimization and continuous operational improvement (Axelos, 2019). Transitioning from isolated problem-solving practices within individual departments to an integrated ITSM framework is therefore essential for enhancing organizational service management capabilities. In particular, in addition to concerns regarding speed and accuracy, service request management should support the establishment of systems that promote transparency, reduce redundant work, and facilitate organizational-level strategic decision-making. One of the largest and most dynamic sectors of the global economy is the provision of services, which is essential for creating value for both organizations and service users. To effectively respond to change, organizations must achieve a balance between stability and agility by improving service management through the integration of information technology and emerging technologies (Axelos, 2019). In the past, organizational operations were managed by administrative staff through direct communication channels such as telephone calls and the LINE application, with service requests recorded and tracked using informal documentation methods. However, such practices have resulted in operational delays, inconsistencies in data records, and limitations in categorizing or analyzing requests due to the unstructured nature of the information. Additionally, the organization employs an incident management system for information technology services, which requires accurate and timely information to support incident resolution and restore services to normal operation as efficiently as possible (Petcharat and Puengwattanapong, 2018). This includes the development of incident management approaches within information technology infrastructure environments aligned with ITIL 4 operational guidelines. These frameworks are designed to effectively address ICT-related incidents in educational institutions, with a focus on enhancing the value of ICT services and maintenance activities (Dzemydien.e et al., 2024). Such practices support the continuous operation of interconnected systems within the organization.

Recent research indicates that Information Technology Service Management solutions have increasingly integrated Artificial Intelligence (AI) to address operational challenges and enhance flexibility in service management (Dande et al., 2024; Mao et al., 2021). Artificial Intelligence for IT Service Management (AITSM) focuses on strengthening service resilience and generating additional value throughout service processes. One notable advancement involves the application of Named Entity Recognition (NER) to unstructured text in languages such as Marathi, Chinese, and Thai, enabling the identification and classification of entities from diverse sources, including Wikipedia articles, medical reports, and cybersecurity data (Patil et al., 2020; Zhang et al., 2024; Laosen et al., 2024; Liu et al., 2024; Tian, 2024).

These multilingual and cross-domain implementations employ techniques such as Conditional Random Fields (CRF), Transformer architectures, BigBird, SoftLexicon, and semi-supervised learning methods. In practical applications, NER has been utilized in chatbots and virtual assistants to accurately extract entities such as personal names, dates, and locations, thereby improving the precision of user request processing (Tommy et al., 2020; Chandwani et al., 2023). In addition, research in Thai named entity recognition has consistently identified word segmentation issues and morphological errors as factors that negatively affect NER performance. To address these challenges and improve recognition performance, researchers have proposed the Thai Character Cluster (TCC) approach and developed the BKD Corpus as a standardized dataset for Thai NER research (Sornlertlamvanich and Yuenyong, 2022). Furthermore, a major challenge in NER development is the acquisition of high-quality domain-specific datasets, such as legal, medical, or corporate service management datasets, which often require substantial time and resources to develop. To address this limitation, Bi-directional Long Short-Term Memory (BiLSTM) models have been employed to identify previously unseen entities through contextual learning, thereby reducing the limitations associated with narrowly scoped datasets (Kuntichod et al., 2024). Nevertheless, notable progress has been achieved in the development of tools supporting ITSM, particularly in Incident and Problem Management aligned with ITIL best practices, as well as in Thai NER and Natural Language Processing (NLP) research. Recent advancements include the development of BiLSTM-based architectures utilizing standardized corpora for Thai NER (Sornlertlamvanich and Yuenyong, 2022), the identification of historical Thai named entities from archival textual resources (Laosen et al., 2024), and the recognition and classification of entities in Marathi and Chinese texts (Patil et al., 2020; Zhang et al., 2024), medical records (Tian, 2024), and cybersecurity reports (Liu et al., 2024). However, direct applications specifically focused on service request management within Thai organizational contexts remain limited. This gap highlights the need for a model capable of handling the informal and unstructured characteristics of service request data. Such a model is essential for supporting real-world service request prioritization processes within organizational systems.

Consequently, this research aims to integrate NER techniques into the service request management process using an NLP model optimized for the Thai language and organizational environments. The study provides both technical and practical contributions. From a technical perspective, the study applies and fine-tunes language models for Thai service request analysis. From a practical perspective, the proposed approach establishes a comparative framework against existing organizational prioritization practices. The primary focus is the application of NLP techniques to achieve se-

mantic and syntactic understanding of service request texts, thereby enabling the automatic extraction of relevant information. This approach reduces the manual effort required for request analysis and management. NLP systems are built upon statistical methods and neural network architectures, including Convolutional Neural Networks (CNNs) and deep neural network models capable of identifying complex textual patterns and extracting information from diverse data sources (Vasiliev, 2020). Widely adopted NLP frameworks, such as spaCy, support functions including dependency parsing and Part-of-Speech (POS) tagging. In particular, NER is widely applied to extract key information such as issue types, related equipment, requestors, and urgency levels from service request texts. Furthermore, spaCy is a high-performance open-source library designed for processing large volumes of textual data (Mesquita and Altinok, 2025) and can be adapted for Thai language processing through integration with PyThaiNLP (Phatthiyaphaibun et al., 2023). This capability supports the development of an NER model specifically designed for service request management within Thai organizational environments.

2. Research Materials

In this section, the theoretical foundations and tools utilized for the design and development of this research are presented. These include the spaCy library, Named Entity Recognition (NER), pre-trained Transformer models, and sequeval metrics.

2.1 spaCy Library

spaCy (Mesquita and Altinok, 2025) is a free and open-source Python library designed for advanced Natural Language Processing (NLP). NLP is a subfield of Artificial Intelligence (AI) that focuses on the analysis of text, speech, and other forms of human-generated linguistic information. Textual data often contain references to preceding words, real-world entities, cultural concepts, and contextual information associated with the author or speaker. Designed specifically for production environments, spaCy supports the development of applications capable of efficiently processing and understanding large volumes of textual data. Furthermore, it can be employed for information extraction and the development of natural language understanding systems.

Its features include essential machine learning functionalities such as Tokenization, which segments text into words and punctuation marks; Part-of-Speech (POS) Tagging, which assigns grammatical categories to tokens; and Named Entity Recognition (NER), which identifies and classifies entities within text. Some functionalities within spaCy operate independently, whereas others require trained processing pipelines. These pipelines enable spaCy to generate linguistic annotations, such as identifying nouns, verbs, and other gram-

matical structures. Currently, spaCy provides pre-trained pipelines for multiple languages, including Thai.

spaCy can be integrated with PyThaiNLP (Phatthiyaphaibun et al., 2023), an open-source software project dedicated to Thai language processing. The primary objective of PyThaiNLP is to provide publicly accessible software tools, datasets, and language models for Thai language applications. As a Python library specializing in Thai NLP, PyThaiNLP extends spaCy's functionality through the spaCy-PyThaiNLP package, which provides enhanced support for Thai language processing. A sample processing pipeline based on the spaCy architecture within this framework accepts text as input and produces a Doc object as output, as illustrated in Fig. 1.

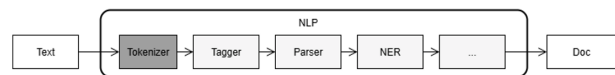


Figure 1. The architecture of spaCy's pipeline (Mesquita and Altinok, 2025).

2.2 Named Entity Recognition (NER)

Named Entity Recognition (NER) (Mesquita and Altinok, 2025) is a Natural Language Processing (NLP) task that identifies and classifies named entities mentioned in text into predefined categories. These entities represent real-world objects and may include persons, locations, organizations, products, dates, and times. A named entity typically refers to a specific object that can be uniquely identified by its corresponding name.

For example, in the sentence "Paris is the capital of France," the system identifies *Paris* and *France* as named entities. In contrast, the word *capital* is not recognized as a named entity because it represents a general concept rather than a specific object. The classification process performed by NER differs from Part-of-Speech (POS) tagging because the set of entity categories can be defined according to application requirements. Common categories supported by NER systems include Person, Location, and Organization. The specific entity types utilized depend on the characteristics of the target corpus and the objectives of the application. An example of the NER process is illustrated in Table 1.

Table 1. spaCy's Named Entity Recognition labels and descriptions (Mesquita and Altinok, 2025).

Label	Description
PERSON	People, including fictional
ORG	Companies, agencies, institutions, and so on
GPE	Countries, cities, states
LOC	Non-GPE locations, mountain ranges, bodies of water
PRODUCT	Objects, vehicles, foods, and so on (not services)

2.3 Transformer Models

Transformer architecture (Tunstall et al., 2022; Mesquita and Altinok, 2025) is a neural network architecture widely used in Natural Language Processing (NLP). It evolved from the traditional encoder-decoder architecture and has gained widespread popularity for processing sequential data, particularly in machine translation tasks. The Transformer consists of two principal components: the Encoder, which converts an input sequence into a sequence of embedding vectors (hidden states) that capture contextual information, and the Decoder, which utilizes the hidden states generated by the encoder to produce an output sequence one token at a time.

The Transformer architecture was designed to address limitations associated with Long Short-Term Memory (LSTM) networks, particularly in handling long sequences and capturing long-range dependencies. During processing, the Transformer converts input text into contextualized vector representations that encode semantic information, sentence structure, and word context. Transformer models are typically pre-trained on large-scale corpora, and the resulting representations can be utilized for various downstream tasks, including text classification, text summarization, question answering, machine translation, and natural language generation.

The Transformer ecosystem includes widely adopted toolkits such as the Hugging Face Transformers API (Hugging Face, 2025). This API supports the downloading, training, and fine-tuning of various pre-trained Transformer models across multiple languages, thereby improving the efficiency and accessibility of NLP model development. Examples of pre-trained models suitable for Thai and multilingual applications include BERT-Base-Thai, BERT-Base-Multilingual, WangchanBERTa-Base, and XLM-RoBERTa-Base.

2.4 sequeval Metrics

The sequeval framework (Nakayama, 2018) is a Python library designed for evaluating sequence labeling tasks. It is commonly used to assess the performance of tasks such as Named Entity Recognition (NER), Part-of-Speech (POS) tagging, and semantic role labeling. The framework computes evaluation scores by comparing predicted labels with reference labels.

The framework requires two primary inputs: *predictions*, which represent lists of predicted labels generated by a sequence labeling model, and *references*, which represent lists of ground-truth labels. Supported tagging schemes include IOB1, IOB2, IOE1, and IOE2.

The sequeval framework returns evaluation statistics at both the overall level and the entity level. Common evaluation metrics include Accuracy, Precision, Recall, and F1-Score.

3. Research Methodology

For this research methodology, the study was structured into the following sequential phases: Overall System Operation, Model Design and Development, and Application Design and Development.

3.1 Overall System Operation

The overall research workflow for monitoring and tracking service requests through automated prioritization using Named Entity Recognition (NER) techniques consists of the following sequential stages: input data collection and preparation, data cleaning and validation, the NER process, and output model generation. The resulting output model is subsequently utilized in the development of a Monitoring and Tracking Service Requests Application.

The proposed application is capable of automatically prioritizing service requests and collecting user feedback when issues occur or when the system is unable to accurately evaluate a service request. This feedback mechanism supports the continuous improvement and refinement of both the NER model and the application to better satisfy user requirements. The overall research workflow is illustrated in Fig. 2.

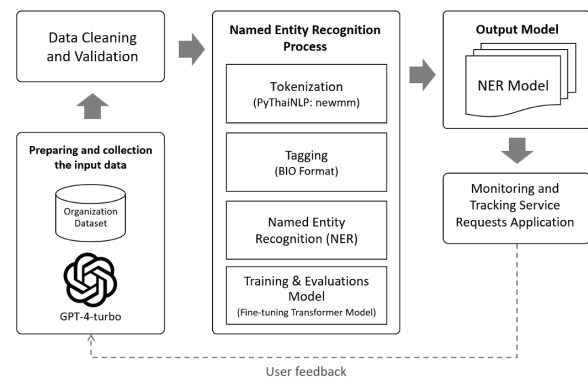


Figure 2. Overall research operation.

3.2 Model Design and Creation

In the model design and creation phase, the process includes the following steps: input data collection and preparation, data cleaning and validation, the NER process, and output model generation. This sequence is illustrated in Fig. 2, with detailed explanations of each step provided below.

3.2.1 Preparing and Collecting Input Data

Data collection and preparation constitute the initial step of the methodology. The research team gathered data from two primary sources: the organization's service request dataset, which was obtained from information provided by faculty members, staff, and students in the Information Technology (IT) program, and a service

request dataset automatically generated by ChatGPT-4o (OpenAI, 2024). The researchers prepared and compiled approximately 500 data instances from these two sources.

Both datasets were subsequently consolidated and carefully recorded to ensure process reproducibility and facilitate data quality auditing. The research team performed the following data preparation procedure: automated data filtering followed by human-in-the-loop validation of the synthetically generated data from ChatGPT. Assessors evaluated the consistency of the data and adjudicated inconsistent cases. In cases of conflict, the data were refined through a systematic data cleaning and verification process to prepare the final high-quality input data for actual model training, as illustrated in Fig. 3.

นักศึกษาสาขาวิชาเทคโนโลยีสารสนเทศ ชั้นปีที่ 1 แจ้งว่าเครื่องพิมพ์หมึกหมดในห้อง 960 ระบบ VPN การเชื่อมต่อมีข้อผิดพลาดจากห้อง 983 ในด้านเรียนวิชาการศึกษาไปนวมกรเว็บ ไม่โครโฟนและลำโพงในห้อง 972 เสียงดังทำให้นักศึกษาและอาจารย์สื่อสารกันไม่ได้ไม่มีประสิทธิภาพ อาจารย์ที่พักในห้อง 961 แจ้งว่าเครื่องพิมพ์เอกสารใช้งานไม่ได้เพราะหมึกหมด เครื่องปรับอากาศในห้อง 963 มีเสียงดังหลังจากได้เปิดใช้งานไปสักระยะ

Figure 3. Input Data Structure Example.

3.2.2 Data Cleaning and Validation

The data cleaning and validation process focuses on the application of appropriate data augmentation techniques. Data augmentation is a crucial strategy for preventing overfitting and functions as a regularization technique that increases the diversity of training data (Shorten et al., 2021). This process enables the model to learn data characteristics more comprehensively and significantly reduces its reliance on specific training instances.

The applied techniques include Easy Data Augmentation (EDA) methods, specifically Random Swap, Random Insertion, Random Deletion, and Random Synonym Replacement. Furthermore, the collected and compiled dataset was thoroughly examined to identify duplicate and anomalous records. This preprocessing procedure ensures that the input data are properly prepared and validated before being utilized in the model development process, as shown in Table 2.

Table 2. List of data augmentation techniques used in the cleaning process.

Technique	Input Data Before Cleaning	Input Data After Cleaning
Random Swap	เครื่องพิมพ์เอกสารหมึกหมดใช้งานไม่ได้ในห้อง 961	เครื่องพิมพ์เอกสารใช้งานไม่ได้ในห้อง 961 หมึกหมด
Random Insertion	Wi-Fi ห้อง 963 ไม่เสถียร	สัญญาณ Wi-Fi ห้อง 963 ไม่เสถียรเลย
Random Deletion	เครื่องปรับอากาศมีเสียงดังเป็นช่วง ๆ	เครื่องปรับอากาศเสียงดังเป็นช่วง ๆ
Random Synonym Replacement	เครื่องคอมพิวเตอร์ไม่ติด	เครื่องคอมพิวเตอร์ใช้งานไม่ได้

Upon completion of the data cleaning and validation processes, the dataset is utilized for NER model development in the subsequent stage, as described below.

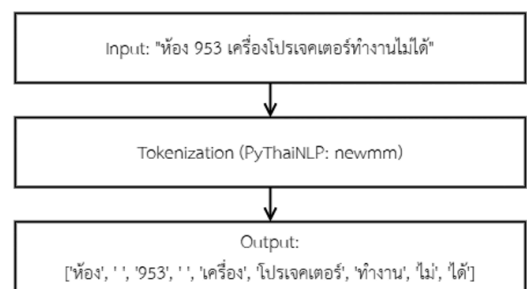
3.2.3 Named Entity Recognition Process

The NER model development process consists of the following sub-phases: Tokenization, Tagging, Named Entity Recognition, and Model Training and Evaluation. A detailed description of each phase is provided below.

1) Tokenization: This phase serves as the initial step before further text processing. It involves segmenting text into smaller units called *tokens*, which may include words, abbreviations, numbers, or punctuation marks. In this research, PyThaiNLP (PyThaiNLP, 2021) was employed for Thai language processing, specifically using the dictionary-based `newmm` tokenizer. This tokenizer provides comprehensive Thai word segmentation based on dictionary matching. For example, the phrase ‘ห้อง 953 เครื่องโปรเจคเตอร์ทำงานไม่ได้’ is tokenized into [‘ห้อง’, ‘ ’, ‘953’, ‘ ’, ‘เครื่อง’, ‘โปรเจคเตอร์’, ‘ทำงาน’, ‘ไม่’, ‘ได้’]. After tokenization, the NER model analyzes groups of tokens to identify entities from the input text. For instance, ‘โปรเจคเตอร์’ may be classified as an EQU (Equipment Entity), as illustrated in Fig. 4.

2) Tagging: This phase involves assigning entity labels to tokens according to the BIO tagging scheme (Jurafsky and Martin, 2008). The labels used in this study include B-EQU (Beginning of an Equipment entity), I-EQU (Inside an Equipment entity), B-ROOM (Beginning of a Room entity), I-ROOM (Inside a Room entity), B-ISSUE (Beginning of an Issue entity), I-ISSUE (Inside an Issue entity), and O (Outside any entity).

The tagging process establishes the target labels used during model training. For example, the sentence ‘เครื่องโปรเจคเตอร์ทำงานไม่เสถียรในห้อง 953’ may be annotated as: เครื่อง (B-EQU), โปรเจคเตอร์ (I-EQU), ทำงาน (O), ไม่ (B-ISSUE), เสถียร (I-ISSUE), ใน (O), ห้อง (O), and 953 (B-ROOM), respectively, as illustrated in Fig. 5.



Input Text: ห้อง 953 เครื่องโปรเจคเตอร์ทำงานไม่ได้									
ห้อง	953	เครื่อง	โปรเจคเตอร์	ทำงาน	ไม่	ได้			

Input Text: ห้อง 961 เครื่องพิมพ์เอกสารหมึกหมด									
ห้อง	961	เครื่องพิมพ์	เอกสาร	หมึก	หมด				

Input Text: เครื่องสำรองไฟเสียงดังเป็นระยะในห้อง 983									
เครื่อง	สำรอง	ไฟ	เสียงดัง	เป็นระยะ	ใน	ห้อง	983		

Figure 4. Tokenization Phase.

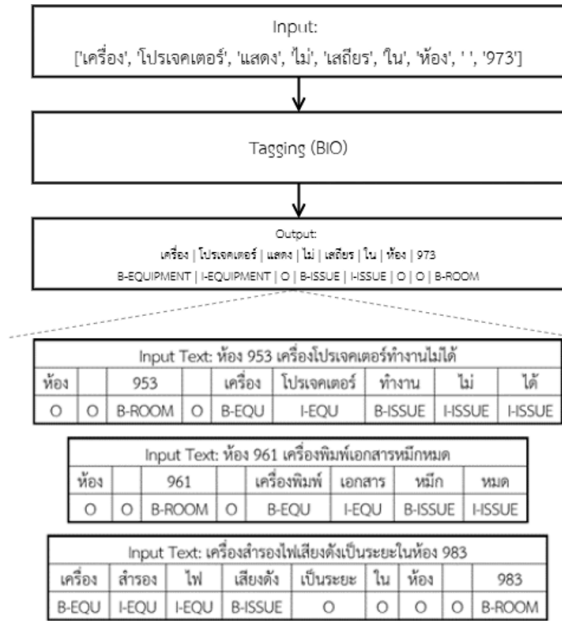


Figure 5. Tagging Phase.

3) Named Entity Recognition: This phase focuses on identifying and classifying entities from the tagged token sequence. Adjacent tokens assigned related BIO labels are combined to form complete entities. For example, the token sequence ['ไม่', 'เสถียร'] tagged as [B-ISSUE, I-ISSUE] is merged into the entity 'ไม่เสถียร', representing an Issue entity.

Named entities provide domain-specific information that can be utilized for subsequent analysis and decision-making processes. In this research, the NER model was developed to identify three entity categories relevant to service request management: Equipment/Materials/Facilities (EQU), Issue Description (ISSUE), and Room/Building Location (ROOM). The entity extraction process is illustrated in Fig. 6.

4) Model Training and Evaluation: For model training and evaluation, the annotated dataset was prepared in BIO tagging format. The Trainer API was utilized for model training, while the seqeval framework (Nakayama, 2018) was employed for performance evaluation. The same hyperparameter configuration was applied to all models, including a learning rate of 5×10^{-5} , 10 training epochs, and an L2 regularization weight of 0.01.

This phase involved fine-tuning pre-trained Transformer models using the service request dataset. Four Thai and multilingual models were evaluated: BERT-Base-Thai, BERT-Base-Multilingual, WangchanBERTa-Base, and XLM-RoBERTa-Base. The dataset was divided into 80% training data and 20% testing data. Most records were collected from internal organizational sources, while additional prototype samples generated by ChatGPT were incorporated to increase data diversity.

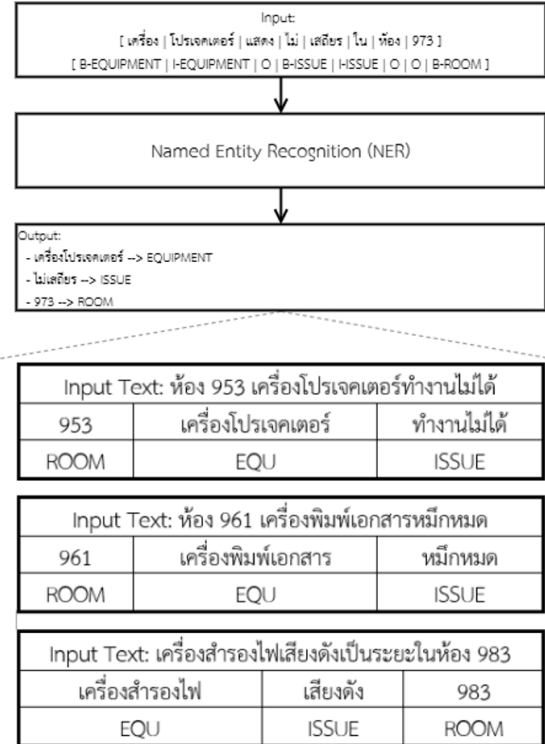


Figure 6. Named Entity Recognition Phase.

Model performance was evaluated using the seqeval framework, which reports Evaluation Loss, Precision, Recall, F1-Score, and Accuracy. The training and evaluation workflow is illustrated in Fig. 7, and the experimental results are presented in Table 3.

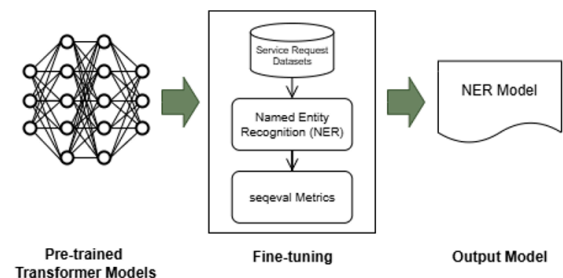


Figure 7. Overview of the fine-tuning process.

3.2.4 Output Model

The output of this process is an NER model stored within a designated directory. The model has undergone training, testing, and performance evaluation using the prepared dataset and is ready for deployment. It is subsequently utilized in the design and development of the Monitoring and Tracking Service Requests Application with automated prioritization based on NER techniques.

3.3 Application Design and Development

For the design and development of the Monitoring and Tracking Service Requests Application with automated prioritization using NER techniques, the research team developed a web-based application. The application consists of a Frontend developed using the React library and a Backend implemented in Python using the FastAPI framework.

The Frontend is responsible for retrieving service request information and communicating with the Backend through API calls. The Backend receives input data from the Frontend and forwards the service request text to the prediction endpoint (`/predict`). The NER model then processes the input text and returns the extracted entities and prioritization results. Subsequently, the processed information is stored in a Firebase database to support service request management and tracking. The overall application architecture is illustrated in Fig. 8.

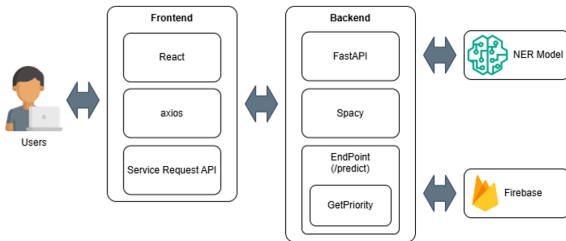


Figure 8. Overview of application operation.

The Backend operation consists of two primary processes: the Service Request Data Extraction process, illustrated in Fig. 9, and the Get Priority workflow, illustrated in Fig. 10.

Figure 9 illustrates the Service Request Data Extraction process within the Backend operation. The process begins when a service request is submitted through a web form. The request data are then transmitted through an API to the NLP application for processing. The NLP application automatically analyzes the service request using NER techniques and returns the extracted entities together with the corresponding prioritization results. These outputs are subsequently utilized by the prioritization algorithm described in Fig. 10.

Fig. 10 illustrates the Get Priority workflow. The process begins with receiving input data consisting of tokens and extracted entities. The workflow defines reference keyword sets associated with equipment, materials, and facilities, together with keyword sets corresponding to three priority levels: High, Medium, and Low. These keyword sets are compared against the extracted entity information obtained from the service request.

If the extracted **EquipmentTexts** are found in the Equipment list and the extracted **IssueTexts** are found in the **IssueHigh** list, the service request is assigned a High priority level. If the extracted **IssueTexts** are

found in the **IssueMedium** list, the request is assigned a Medium priority level. Similarly, if the extracted **IssueTexts** are found in the **IssueLow** list, the request is assigned a Low priority level.

4. Experimental Results

This section presents the performance evaluation of the developed models and the results obtained from the application.

4.1 Model Performance Evaluation

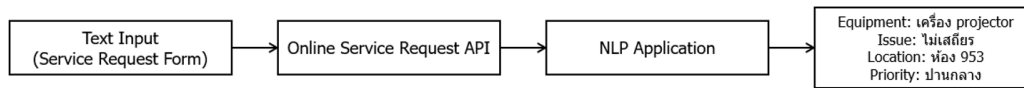
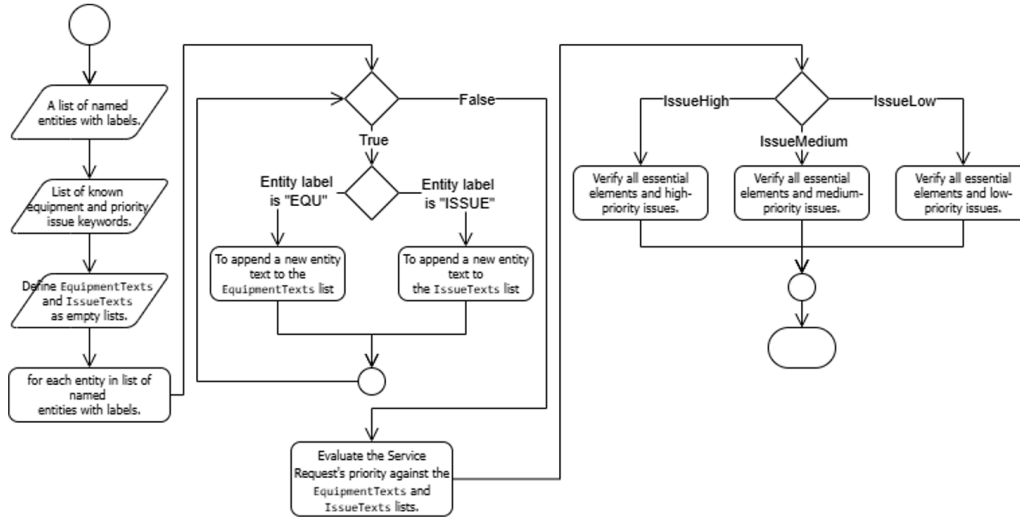
To evaluate the developed models prior to deployment, the research team compared the performance of four NER models suitable for both Thai and multilingual contexts: BERT-Base-Thai, BERT-Base-Multilingual, WangchanBERTa-Base, and XLM-RoBERTa-Base. Model performance was evaluated using Eval Loss, Precision, Recall, F1-Score, and Accuracy. The objective of this evaluation was to identify the most suitable model for developing an application capable of automatically analyzing the priority of user-submitted service requests while supporting service request review and tracking. The evaluation results are presented in Table 3.

Table 3. Comparison of Model Performance with Pre-trained Transformer Models.

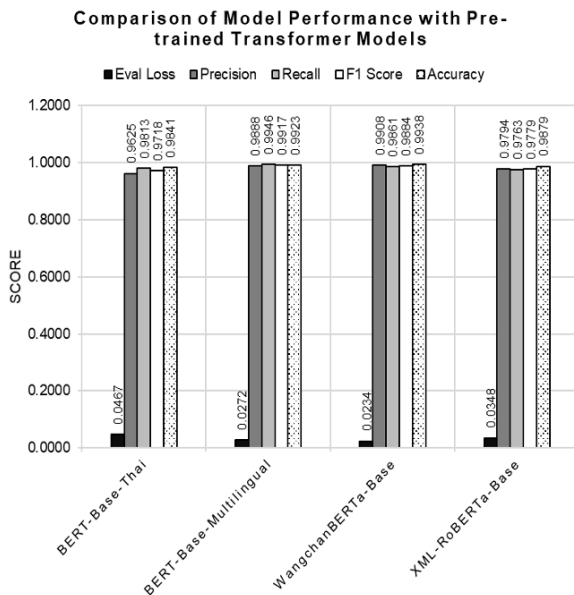
Model Name	Eval Loss	Precision	Recall	F1 Score	Accuracy
BERT-Base-Thai	0.0467	0.9625	0.9813	0.9718	0.9841
BERT-Base-Multilingual	0.0272	0.9888	0.9946	0.9917	0.9923
WangchanBERTa-Base	0.0234	0.9908	0.9861	0.9884	0.9938
XLM-RoBERTa-Base	0.0348	0.9794	0.9763	0.9779	0.9879

Table 3 presents the performance comparison of the evaluated models. The results indicate that BERT-Base-Multilingual achieved the highest F1-Score of approximately 0.9917, followed by WangchanBERTa-Base with an F1-Score of approximately 0.9884 and XLM-RoBERTa-Base with an F1-Score of approximately 0.9779. These results demonstrate strong NER capabilities across all evaluated models. In contrast, BERT-Base-Thai, a Thai-specific model, achieved a lower F1-Score of approximately 0.9718 and exhibited a higher Eval Loss compared with the other models.

Although both multilingual and Thai-specific models achieved high F1-Scores and Accuracy values, the evaluation results indicate that BERT-Base-Multilingual provided the strongest overall performance in terms of effectiveness and robustness. As illustrated in Fig. 11, the model demonstrates strong potential for deployment in Thai and multilingual NER applications. In contrast, certain Thai-specific models still require further optimization to achieve comparable performance levels. These findings highlight the relative strengths of the evaluated models, with BERT-Base-Multilingual achieving the strongest overall per-

**Figure 9.** Service Request Data Extraction Process.**Figure 10.** Get priority workflows.

formance, followed by WangchanBERTa-Base, XLM-RoBERTa-Base, and BERT-Base-Thai, respectively.

**Figure 11.** Comparison of Model Performance with Pre-trained Transformer Models.

Based on the Performance Evaluation of Entity Matching graph, the evaluation results of four models, including XLM-RoBERTa-Base (yellow), WangchanBERTa-Base (gray), BERT-Base-Multilingual (orange), and BERT-Base-Thai (blue), are presented across three entity types: ROOM, IS-

SUE, and EQU (Equipment). When analyzed by entity type, BERT-Base-Multilingual consistently demonstrated strong overall performance compared with the other models.

For the ISSUE entity, BERT-Base-Multilingual achieved an F1-Score of 0.9883, Recall of 0.9873, and Precision of 0.9893, indicating balanced and highly accurate performance. WangchanBERTa-Base and XLM-RoBERTa-Base demonstrated comparable performance for this entity category. For the EQU entity, BERT-Base-Multilingual again achieved the highest performance, with an F1-Score of 0.9927, Recall of 0.9983, and Precision of 0.9872. WangchanBERTa-Base also performed competitively, achieving an F1-Score of 0.9862, Recall of 0.9839, and Precision of 0.9886, suggesting that it is a viable alternative for equipment-related entity recognition.

For the ROOM entity, WangchanBERTa-Base achieved the highest performance, with an F1-Score of 0.9984, Recall of 1.0000, and Precision of 0.9968. These results indicate excellent recognition capability and a strong balance between Recall and Precision. This finding suggests that WangchanBERTa-Base is particularly effective for identifying relatively static entity types such as room identifiers.

Overall, both BERT-Base-Multilingual and WangchanBERTa-Base demonstrated strong entity recognition performance compared with XLM-RoBERTa-Base and BERT-Base-Thai. BERT-Base-Multilingual was particularly effective for identifying diverse and complex entities such as ISSUE and EQU,

whereas WangchanBERTa-Base achieved superior performance for the ROOM entity. The evaluation results are illustrated in Fig. 12.

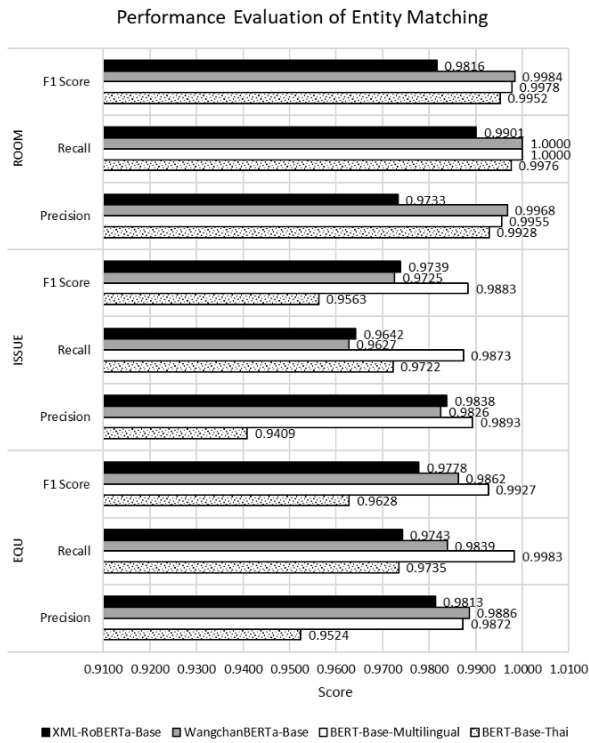


Figure 12. Performance Evaluation of Entity Matching.

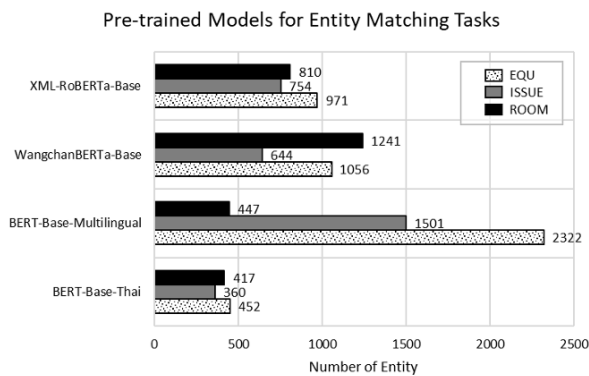


Figure 13. Comparative Analysis of Pre-trained Models for Entity Matching Tasks.

An analysis of the number of detected entities across the three entity categories, namely EQU (blue), ISSUE (orange), and ROOM (gray), indicates that BERT-Base-Multilingual achieved the highest detection counts for two entity categories: EQU with 2,322 instances and ISSUE with 1,501 instances. In comparison, WangchanBERTa-Base achieved the highest detection count for only one entity category, ROOM, with 1,241 instances.

These results suggest that BERT-Base-Multilingual is more effective for identifying entities with greater

variability, such as EQU and ISSUE, whereas WangchanBERTa-Base performs more effectively for relatively fixed entities such as ROOM. Considering the characteristics of the real-world dataset, BERT-Base-Multilingual demonstrates greater comprehensiveness in entity recognition than the other evaluated models. The comparative results are illustrated in Fig. 13.

Furthermore, a bootstrap analysis was conducted to evaluate the stability of model performance. The bootstrap procedure repeatedly sampled data from the original dataset to estimate the distribution of F1-Scores. Five bootstrap iterations were generated using two subsets derived from the training dataset: Subset A (10%) and Subset B (15%). The evaluated models included BERT-Base-Thai (BBT), BERT-Base-Multilingual (BBM), WangchanBERTa-Base (WBB), and XLM-RoBERTa-Base (XMLRBB).

The statistical analysis results indicate that BERT-Base-Multilingual achieved the strongest overall performance, obtaining an F1-Score of 0.9917 and a Recall of 0.9946. Although WangchanBERTa-Base achieved the lowest Eval Loss (0.0027) and slightly higher Precision, BERT-Base-Multilingual demonstrated a more favorable balance between Precision and Recall. Consequently, it exhibited stronger overall effectiveness and generalization capability.

The F1-Score distributions obtained from the bootstrap analysis of both Subset A and Subset B further support these findings. BERT-Base-Multilingual achieved the highest median F1-Score while maintaining a relatively narrow distribution compared with competing models. In contrast, BERT-Base-Thai exhibited a wider distribution, indicating greater performance variability across different bootstrap samples. Although WangchanBERTa-Base achieved a median value comparable to that of BERT-Base-Multilingual, its slightly broader distribution suggests greater sensitivity to variations in the training data.

The evaluation results demonstrate that BERT-Base-Multilingual, which was pre-trained on multiple languages, possesses the capability to learn diverse linguistic representations. This capability enables the model to better capture complex language patterns than monolingual alternatives. Consequently, BERT-Base-Multilingual exhibits strong potential for multilingual NLP applications, particularly in real-world environments characterized by informal and linguistically diverse data, as illustrated in Fig. 14.

4.2 Overall Application Results

The result of the design and development of the Monitoring and Tracking Service Request Application with automated prioritization using NER techniques is a functional web-based system. Users are required to log in before accessing the application functionalities. Upon successful authentication, the main user interface provides the following menu options: Home, Submit Re-

quest, Request List, About Research, Contact Us, and User Profile, as illustrated in Fig. 15.

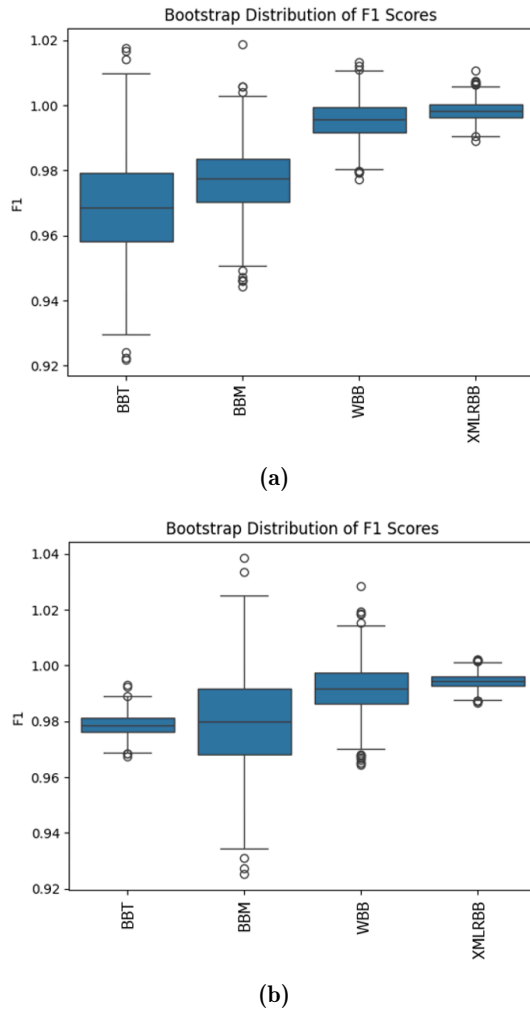


Figure 14. Bootstrap Distribution of F1 Scores with 5 Random Subsets: (a) 10% and (b) 15% of the Training Data.

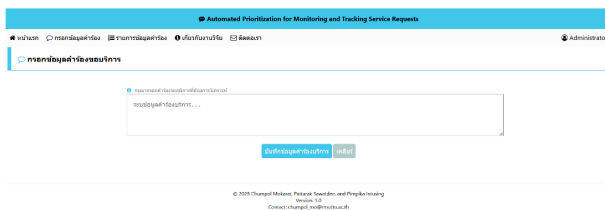


Figure 15. Service request submission screen.

Fig. 15 presents the service request submission interface, where users can specify and submit service requests to the administrator. After entering the required information, the user selects the “Save Service Request” button to transmit the request data to the Backend for processing. Once the request has been processed, the application displays the analysis results, including the identified Tokens, Labels, Confidence Scores, and the

assigned service request priority. The processed information is subsequently stored in the database together with the submitted service request data, as illustrated in Fig. 16.

After the system completes the analysis and prioritization process, users can review previously submitted service requests through the “Service Request List” menu. This interface allows users to track request status and review previously submitted information, as shown in Fig. 17.

4.3 System Performance Testing

The system performance testing results were obtained from end users. The researchers selected a randomly sampled group of 25 participants consisting of Information Technology (IT) students who routinely utilized the service system. The participants were asked to evaluate the software under predefined testing scenarios based on the following performance metrics: priority assignment time, service request resolution time, number of system errors, ease of learning, service continuity capability, and overall user satisfaction, as presented in Table 4.

Table 4 presents the overall system performance evaluation results, indicating that the system operates effectively in terms of time efficiency, operational accuracy, and user satisfaction. Regarding time efficiency, the average time required for service request prioritization was only 3.5 seconds, which falls within the “Rapid” criterion. In addition, the average service request resolution time did not exceed 48 hours, which is considered appropriate for an internal organizational service environment.

In terms of operational accuracy, the system reported an average of no more than two errors, indicating a low error rate. This result is consistent with the high service continuity capability score, which users evaluated at an average of 4.44 out of 5, reflecting the system’s ability to provide reliable and uninterrupted services.

From a User Experience (UX) perspective, the system achieved an average score of 4.04 for ease of learning and 4.16 for overall user satisfaction. These results indicate a favorable level of system performance and suggest that the developed application effectively supports service request management within the organizational environment.

5. Discussion

The results of this research, which focused on developing an application for the automatic monitoring and tracking of service requests using NER techniques and automated service request prioritization, indicate that BERT-Base-Multilingual achieved the strongest overall performance among the evaluated models. The model obtained an Eval Loss of 0.0272, a Precision of 0.9888,

🔍 การวิเคราะห์คำร้องขอบริการ (Service Request Analysis)

Token	Label	Confidence
เครื่องพิมพ์เอกสาร	B-EQU	0.9984
ใช้งานไม่ได้	B-ISSUE	0.9985
962	B-ROOM	0.9978

📌 การจัดลำดับความสำคัญคำร้องขอบริการ (Service Request Priority)

Priority: High

Figure 16. Service request evaluation results screen.

🔍 Automated Prioritization for Monitoring and Tracking Service Requests

🏠 หน้าแรก 🗨️ กรอกรายข้อมูลคำร้อง 📋 รายการข้อมูลคำร้อง 📌 เกี่ยวกับงานวิจัย ✉️ ติดต่อเรา Administrator

📋 รายการข้อมูลคำร้องขอบริการ

รวมข้อมูลคำร้องที่ต้องการค้นหา... 🔍 ค้นหา

รหัสคำร้อง	รายการคำร้อง	ความสำคัญ	สถานะคำร้อง	ดำเนินการ
SR-1002	หม้อจระเข้คอมพิวเตอร์เปิดไม่ติดหลายตัวภายในห้อง 953	Medium	20	📄 รายละเอียด ✍️ แก้ไข 🚫 ลบ
SR-1004	การเชื่อมต่อสัญญาณอินเทอร์เน็ตผ่านสายแลนไม่ติดภายในห้อง 941	High	50	📄 รายละเอียด ✍️ แก้ไข 🚫 ลบ
SR-1005	เครื่องสำรองไฟเปิดไม่ติดในห้อง 982 จึงทำให้ใช้งานคอมพิวเตอร์ไม่ได้	High	50	📄 รายละเอียด ✍️ แก้ไข 🚫 ลบ
SR-1006	Wi-Fi ที่ใช้งานภายในห้อง 942 สัญญาณอินเทอร์เน็ตค่อนข้างช้ามาก ๆ	Low	20	📄 รายละเอียด ✍️ แก้ไข 🚫 ลบ
SR-1007	ห้อง 982 ช่องเสียบสายสัญญาณอินเทอร์เน็ตไม่ค่อยดี ดับ ๆ	Medium	10	📄 รายละเอียด ✍️ แก้ไข 🚫 ลบ
SR-1008	นักศึกษาแจ้งว่าเครื่องคอมพิวเตอร์ในห้อง 942 ทำงานช้ามาก ๆ	Low	10	📄 รายละเอียด ✍️ แก้ไข 🚫 ลบ
SR-1009	โปรเจกเตอร์ห้อง 953 ทางการคิด ๆ ดับ ๆ	Medium	40	📄 รายละเอียด ✍️ แก้ไข 🚫 ลบ

< 1 >

📌 หมายเหตุ: 10 - เปิดคำร้อง, 20 - รับคำร้อง, 30 - ไม่รับคำร้อง, 40 - กำลังดำเนินการ และ 50 - ปิดคำร้อง

Figure 17. Service request lists screen.

a Recall of 0.9946, an F1-Score of 0.9917, and an Accuracy of 0.9923. This performance was achieved despite WangchanBERTa-Base and XLM-RoBERTa-Base demonstrating highly competitive results. When considering both accuracy and reliability in entity recognition across the training and testing datasets, BERT-Base-Multilingual consistently outperformed the other evaluated models.

In particular, BERT-Base-Multilingual demonstrated strong performance in identifying the highly diverse ISSUE and EQU (Equipment) entities. In contrast, WangchanBERTa-Base was more effective in recognizing the relatively static ROOM entity. Furthermore, when considering the maximum number of entities detected within a service request, BERT-Base-Multilingual demonstrated greater capability by accurately detecting both EQU and ISSUE entities, whereas WangchanBERTa-Base was most effective in identifying ROOM entities. These findings suggest that Thai and multilingual NLP models can be effectively employed for service request management within educational institutions, particularly in organizational environments where service requests contain diverse information and

administrative contexts.

The significance of these findings is consistent with previous studies indicating that Artificial Intelligence (AI) can enhance IT Service Management (ITSM) capabilities, particularly in areas such as Configuration Management Databases (CMDBs), organizational resilience, and automated response mechanisms (Dande et al., 2024; Mao et al., 2021). Furthermore, studies involving cybersecurity and unstructured textual data have demonstrated the effectiveness of NER approaches that incorporate semi-supervised learning, active learning, and self-training strategies (Liu et al., 2024). These findings suggest that both BERT-Base-Multilingual and WangchanBERTa-Base are suitable candidates for deployment in semi-structured organizational environments, although additional fine-tuning may further improve performance when adapting the models to new datasets.

The selection of BERT-Base-Multilingual is further supported by its relatively high F1-Score compared with the other evaluated models, indicating a strong balance between Precision and Recall. This characteristic is particularly important in applications where entity recog-

Table 4. System performance testing from end-users.

No.	Metrics	Evaluation Results	Remarks
1	Operation time for priority assignment	Less than 3.5 seconds	Average in Seconds
2	Turnaround time for service request resolution	Less than 48 hours	Average in Hours
3	Number of system errors encountered	Less than 2 cases	Average in Number of Errors
4	Ease of learning the system	4.04	Average Rating (Scale 1–5)
5	Service continuity capability	4.44	
6	Overall user satisfaction	4.16	

dition accuracy directly affects operational decision-making, such as service request management systems. In addition, NER has been successfully applied in chatbot and virtual assistant systems to improve user intent understanding and enhance response quality (Tommy et al., 2020; Chandwani et al., 2023). Consequently, the proposed model also demonstrates potential for deployment in conversational systems that require accurate interpretation of user requests.

NER has also been successfully applied to multiple languages, including Marathi (Patil et al., 2020) and Chinese (Zhang et al., 2024). Comparative analysis of these studies indicates that languages with distinctive linguistic characteristics, such as Chinese and Thai, can benefit from both multilingual and language-specific models. The developed service request monitoring and tracking system demonstrates the practical application of NER techniques for automatically understanding and processing information submitted through service requests. This capability enables real-time contextual analysis and supports the development of intelligent systems that can respond more effectively to user needs.

Regarding multilingual model performance, the experimental results indicate that BERT-Base-Multilingual achieved the strongest overall performance and robustness across the evaluated datasets. The remaining models ranked in descending order of performance were WangchanBERTa-Base, XLM-RoBERTa-Base, and BERT-Base-Thai. This result may be attributed to the multilingual model’s exposure to a diverse range of linguistic patterns during pre-training, enabling effective adaptation to Thai-language service request data within the studied context.

Overall, the developed system successfully satisfied all predefined Service Performance Indicators (SPIs). In terms of time efficiency, the average prioritization time satisfied the “Rapid” criterion, demonstrating the effectiveness of the underlying processing workflow. Similarly, the average service request resolution time remained within the acceptable threshold for an internal

organizational service environment. Regarding operational accuracy, the system exhibited a low error rate, indicating reliable and stable operation during request processing.

These findings are further supported by the high service continuity capability score reported by users. In terms of User Experience (UX), both ease of learning and overall user satisfaction were evaluated at the “Good” level. Collectively, these results indicate that the developed system provides an effective and user-friendly solution for service request management. The findings also provide a strong foundation for future system enhancement and the broader application of NER-based service management solutions within educational institutions.

6. Conclusion

The development of a Service Request Checking and Tracking Application with automatic priority assignment using Named Entity Recognition (NER) was successfully implemented as a web-based application. The Frontend was developed using the React library, while the Backend was implemented in Python using the FastAPI framework and the spaCy library for NER model deployment. The NER model was trained using a dataset consisting of 500 instances, which was divided into 80% training data and 20% testing data. The dataset was primarily collected from internal organizational sources and supplemented with synthetic data generated by ChatGPT.

Performance evaluation was conducted using four Thai and multilingual NER models: BERT-Base-Thai, BERT-Base-Multilingual, WangchanBERTa-Base, and XLM-RoBERTa-Base. The experimental results indicate that BERT-Base-Multilingual achieved the strongest overall performance among the evaluated models, obtaining an F1-Score of 0.9917 and a Recall of 0.9946. In addition, the model demonstrated strong capability in recognizing diverse entity categories, par-

ticularly ISSUE and EQU entities. These results indicate that BERT-Base-Multilingual can effectively capture linguistic patterns within Thai service request data and is suitable for deployment in practical service management applications.

The developed system successfully achieved the research objectives in terms of both technical effectiveness and practical applicability. The experimental results indicate that the average processing time required for service request prioritization was less than 3.5 seconds, while the average service request resolution time remained within 48 hours. Furthermore, the average number of system errors was below two instances. These results demonstrate the capability of the proposed system to streamline service management workflows, reduce procedural redundancy, and decrease staff workload during service delivery operations.

From a usability perspective, the system received positive evaluations from end users. The average score for ease of learning was 4.04, the service continuity capability score was 4.44, and the overall user satisfaction score was 4.16 out of 5. These results indicate that the system is user-friendly and capable of meeting user expectations in terms of both effectiveness and efficiency. The integration of Artificial Intelligence (AI) techniques into the service request management process provided practical benefits to the organization by improving service efficiency and supporting decision-making through automated service request analysis, prioritization, and tracking.

Nevertheless, the present research has several limitations. The experiments were conducted within a single institutional environment and utilized a relatively limited dataset. Consequently, the findings may not fully represent more complex real-world operational scenarios. Additional evaluation in diverse organizational environments is therefore necessary to further validate the robustness, reliability, and generalizability of the proposed system.

Future research should focus on several directions. First, dataset expansion should be conducted to increase both the size and diversity of the corpus, enabling the model to learn more complex linguistic patterns and contextual variations. Such expansion should include service request data collected from multiple departments both within and outside educational institutions. Second, chatbot integration should be investigated to enable real-time service request submission and status tracking. Additional studies should also include stress testing under high-load conditions and long-term user satisfaction analysis. These efforts will contribute to the development of more resilient NER-based service management systems that can be effectively deployed in both public and private organizations while further enhancing service quality and operational efficiency.

Acknowledgments

We extend our sincere gratitude to the Department of Information Technology, Faculty of Business Administration and Information Technology, Rajamangala University of Technology Tawan-ok, Chakrabongse Bhuvanarth Campus, for generously providing the necessary facilities and venue, which were instrumental in the successful completion of this research project and manuscript.

CRedit Authorship Contribution Statement

Chumpol Mokarat: Conceptualization, Methodology, Software, Formal analysis, Validation, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Pattarak Sawatdee:** Data curation, Validation, Software. **Pimpika Intutsing:** Data curation, Validation, Software.

Declaration of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of AI Use

This manuscript includes content generated or assisted by artificial intelligence (AI) tools. Specifically, ChatGPT by OpenAI, and Gemini by Google AI were used to support tasks such as generate sample datasets, language editing, and coding assistance. All AI-generated content was critically reviewed and verified by the authors to ensure accuracy, originality, and compliance with ethical standards.

References

- Axelos (2019). *ITIL Foundation: ITIL 4 Edition*. TSO (The Stationery Office).
- Chandwani, A., Shrivastava, K., Sadashiv, S., Saha, I., and Mishra, P. (2023). Virtual assistant for appointment booking. In *2023 IEEE 8th International Conference for Convergence in Technology (I2CT)*, pages 1–5. DOI: 10.1109/I2CT57861.2023.10126199.
- Dande, F., Li, X., Shofoluwe, M., and McLeod, A. (2024). Artificial intelligence integration in IT service management: An ITIL configuration management process review. In *Proceedings of the 1st World Congress on Industrial Engineering and Operations*

- Management*, pages 464–474, Detroit, USA. DOI: 10.46254/WC01.20240164.
- Dzemydien.e, D., Turskien.e, S., and Šileikien.e, I. (2024). An approach of ICT incident management based on ITIL 4 methodology recommendations. *Baltic Journal of Modern Computing*, 12(3):286–303. DOI: 10.22364/bjmc.2024.12.3.05.
- Hugging Face (2025). Transformers documentation. Accessed: 2025-05-23.
- Jurafsky, D. and Martin, J. H. (2008). *Speech and Language Processing*. Pearson Prentice Hall, 2 edition.
- Kuntichod, W., Lee, W., and Prayote, A. (2024). Unseen named entity recognition for Thai language. In *2024 21st International SoC Design Conference (ISOCC)*, pages 258–259. DOI: 10.1109/ISOCC62682.2024.10762678.
- Laosen, N., Laosen, K., and Paklao, T. (2024). Named entity recognition for Thai historical data. In *2024 21st International Joint Conference on Computer Science and Software Engineering (JCSSE)*, pages 528–533. DOI: 10.1109/JCSSE61278.2024.10613644.
- Liu, Z., Jiang, K., Liu, Z., and Qin, T. (2024). A cybersecurity named entity recognition model based on active learning and self-learning. In *2024 36th Chinese Control and Decision Conference (CCDC)*, pages 4505–4510. DOI: 10.1109/CCDC62350.2024.10587887.
- Mao, H., Zhang, T., and Tang, Q. (2021). Research framework for determining how artificial intelligence enables information technology service management for business model resilience. *Sustainability*, 13(20):11496. DOI: 10.3390/su132011496.
- Mesquita, D. and Altinok, D. (2025). *Mastering spaCy: Build Structured NLP Solutions with Custom Components and Models Powered by spacy-llm*. Packt Publishing, 2 edition.
- Nakayama, H. (2018). seqeval: A Python framework for sequence labeling evaluation.
- OpenAI (2024). ChatGPT. Large Language Model.
- Patil, N., Patil, A., and Pawar, B. V. (2020). Named entity recognition using conditional random fields. *Procedia Computer Science*, 167:1181–1188. DOI: 10.1016/j.procs.2020.03.431.
- Petcharat, T. and Puengwattanapong, P. (2018). Incident management system for IT service. *Life Sciences and Environment Journal*, 19(1):58–66. <https://ph01.tci-thaijo.org/index.php/psru/article/view/74756>.
- Phatthiyaphaibun, W., Chaovavanich, K., Polpanumas, C., Suriyawongkul, A., Lowphansirikul, L., Chormai, P., Limkonchotiwat, P., Suntornitip, T., and Udomcharoenchaikit, C. (2023). PyThaiNLP: Thai natural language processing in Python. In *Proceedings of the 3rd Workshop for Natural Language Processing Open Source Software (NLP-OSS 2023)*, pages 25–36. DOI: 10.18653/v1/2023.nlp-oss-1.4.
- PyThaiNLP (2021). PyThaiNLP documentation.
- Rajamangala University of Technology Tawan-Ok (2022). Rajamangala university of technology tawan-ok. Retrieved 28 March 2025, <https://www.rmutto.ac.th/>.
- Shorten, C., Khoshgoftaar, T. M., and Furht, B. (2021). Text data augmentation for deep learning. *Journal of Big Data*, 8(1):101. DOI: 10.1186/s40537-021-00492-0.
- Sornlertlamvanich, V. and Yuenyong, S. (2022). Thai named entity recognition using BiLSTM-CNN-CRF enhanced by TCC. *IEEE Access*, 10:53043–53052. DOI: 10.1109/ACCESS.2022.3175201.
- Tian, Y. (2024). A model for named entity recognition in colorectal tumor pathological text. In *2024 9th International Conference on Intelligent Computing and Signal Processing (ICSP)*, pages 780–784. DOI: 10.1109/ICSP62122.2024.10743829.
- Tommy, L., Kirana, C., and Riska, L. (2020). The combination of natural language processing and entity extraction for academic chatbot. In *2020 8th International Conference on Cyber and IT Service Management (CITSM)*, pages 1–6. DOI: 10.1109/CITSM50537.2020.9268851.
- Tunstall, L., von Werra, L., and Wolf, T. (2022). *Natural Language Processing with Transformers*. O'Reilly Media.
- Vasiliev, Y. (2020). *Natural Language Processing with Python and spaCy: A Practical Introduction*. No Starch Press, San Francisco.
- Zhang, S., Li, G., Shi, X., Liu, L., and Chen, M. (2024). Chinese named entity recognition with integrated boundary features and location information. In *2024 IEEE 7th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*, pages 565–570. DOI: 10.1109/ITNEC60942.2024.10732932.