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Model Design and Development for a User Support System Using Artificial Intelligence Techniques in Enterprise Resource Planning Software[1]

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Abstract

For organizations, the error-free, consistent, and transparent management of business processes is crucial. Process management relates to the proper handling of data, achievable through enterprise resource planning (ERP) software. This software enables all departments, structured around a central database, to work together. From an organizational perspective, one of the most critical factors for the success of ERP software is its users. Users often require support when using ERP software for various reasons, such as lack of training, experience, or technical issues. Providing this support, whether internally or from external sources, incurs a cost.

This study seeks to determine whether a structure can be developed where users can resolve their support requests independently. To achieve this goal, we propose a model for an intelligent user support system with an AI-based process engine for ERP users. Using this model, unstructured user support requests, created in natural language, are transformed into structured forms using natural language processing techniques and then classified using multi-class machine learning algorithms. The process relevant to the identified class is executed to generate a solution for the user's problem. In this study, 1,000 samples of text written in natural language across 10 different categories, based on real data, were used in the learning process. The data were analyzed using machine learning algorithms (K-Nearest Neighbors, Naive Bayes, C4.5, Support Vector Machine, Random Forest, Sequential Minimal Optimization, LibSVM) and deep learning algorithms (Long Short-Term Memory). The best classification was achieved with Sequential Minimal Optimization (SMO) using TF-IDF weighting. The developed chat and process robot helped convert requests or problems into structured forms and

[1] This study is derived from Hakan Aşan's doctoral thesis titled "Model Design and Development For A User Support System Using Artificial Intelligence Techniques In Enterprise Resource Planning Software"

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provided solutions. In addition to solving the problem through chat or process, technologies such as augmented reality and virtual reality were used.

Keywords: Enterprise Resource Planning, User Support, Artificial Intelligence, Intelligent Enterprise Resource Planning, i-ERP.

JEL Code: M15, O33

1. Introduction

The sustainability of organizations depends on their ability to control their processes. From procurement to production, human resources to marketing, and accounting to financial transactions, each department's processes must be recorded and reported by the system in real-time. Organizations generally achieve this through ERP (Enterprise Resource Planning) software. The need for and usage of ERP systems in organizations is increasing daily. For instance, the ERP software market is expected to reach $86.30 billion by 2027 (Research Allied Market, 2021).

The effective and error-free operation of ERP software is crucial for organizational continuity. ERP software is designed to be user-friendly with easy-to-use features. However, it can be customized to meet diverse needs, potentially increasing its complexity and difficulty in use. Additionally, ERP software, as a living system, may encounter various problems during use. In such situations, ERP users require support. It is generally assumed that ERP software supports two types of needs: one related to software, system, or infrastructure failures, and the other to user errors. Common support needs include a lack of knowledge and the need for recommendations (Vlasov, 2017).

ERP software issues are often attributed to technical reasons, yet technological issues account for less than 10% of the problems regarding system implementation. Organizations typically address this by utilizing their in-house IT departments and external consulting support. This support represents a significant part of the organization's expenses, up to 80%. Additionally, the most commonly required service is ERP application guidance (Panorama Consulting Report, 2020: 22).

Examining ERP installation and usage costs, Mabert et al. (2001) found that consulting represented 30%, hardware and infrastructure 25%, the application team 15%, education 15%, and software 15% of the costs. Similarly, Hurwitz and Associates (2014) found that for 100 users over four years, IT resources accounted for 41%, software 26%, consulting 17%, hardware 7%, education 5%, and infrastructure 4%.

ERP users often face significant difficulties in resolving their requests and issues. This study considers whether a system can be developed where users can independently resolve these problems. The study plans a system where users solve problems using artificial intelligence, marking the beginning of a new era with the perfect integration of AI technologies and ERP software. To describe this integration, the term 'i-ERP' (Intelligent Enterprise Resource Planning) is suggested. i-ERP applications are expected to automate some processes using AI technologies, minimizing the risk of user-associated errors. The collaboration of AI and ERP is anticipated to make significant contributions both sectorally and academically. A UK study revealed that 53% of information systems managers are looking for smarter ERP systems incorporating technologies like machine learning, artificial intelligence, and automation. Additionally, approximately 80% of information technology developers believe machine learning and artificial intelligence will soon replace a significant portion of ERP processes (Biel, 2021).

In this study, the development of an a-ERP application is planned. Based on motivation, a model of an intelligent user support system for ERP users supported by artificial intelligence and a process engine is developed. This model also serves as an example for software developers, system analysts, and designers who wish to develop support systems for users in various fields. Moreover, it is aimed that the use of increasing data in AI's nature and its ability to self-improve will lead to more effective solutions. With the developed structure, all types of user support requests are recorded, which can enable the development of user-oriented education policies.

ERP users in organizations have various reasons for needing support. Meeting support needs can be achieved in various ways. In some cases, it may not be possible to resolve support requests, or they may take a long time to be resolved. These situations also impose a burden on organizations in terms of time and cost. From the organization's perspective, the main problem at this point is the problem of users obtaining the support they need instantly. Starting from this problem, we ask whether a model can be developed using artificial intelligence methods for users to solve their support requests.

2. Literature Review

Organizations use ERP software to manage their business processes and record their data. Although the purposes, modules used, software content, and adaptations made may vary, businesses have a common need for ERP software. ERP software is not merely categorized as computer software; it also represents a culture and a way of doing business. There have been various definitions of ERP software in the literature.

Davenport stated that ERP seamlessly enables the integration of data flow within organizations (which can now be referred to as big data) (Davenport, 1998: 121). Koch defined it as an integrated computer software working on a single, common database that allows departments to easily share information and communicate with each other (Koch, 1999: 1). Blackstone (2010) emphasized the contribution of ERP to internal organizational business processes and, consequently, its advantages in the external environment. Wenrich and Ahmad defined ERP systems as commercial software packages that organize and integrate information and information-based processes within the organization and are adaptable to the dynamics of the business. They also provide reference models or process templates that claim to embody the best existing business practices (Kumar and Hillegersberg, 2000: 23). ERP is a software package consisting of various modules that enable the inter-organizational integration of data through embedded business processes. These software packages can be customized to meet the specific needs of each organization (Esteves and Pastor, 1999: 2). Noureddine and Oualid discussed the impact of ERP on decision-making processes in addition to managing internal business processes (Noureddine et al., 2018: 100). Koch emphasizes that ERP has an adaptable and flexible infrastructure. Many companies use certain modules actively and others passively in their ERP systems in this way. The ERP database and processes are even supported with other software (Koch, 2002: 1).

Based on all these evaluations, a general definition for ERP can be made as follows: “ERP software is designed to centrally manage many business processes in an integrated way through a shared database to organize, design, and manage business processes, as well as provide important reporting for management decision processes. It is a flexible and adaptable software.”

The concept of i-ERP emerged because of the continuous development and evolution of ERP systems over time. The term 'Intelligent Enterprise Resource Planning' has been defined in the literature only recently (Lv et al., 2018). Intelligent ERP systems are designed to enhance efficiency, accuracy, and decision-making capabilities by leveraging advanced technologies such as AI, big data analytics, and machine learning. ERP is an integrated and multi-module application that plans and manages corporate resources (Nur and Putra, 2020). Furthermore, the integration of smart technologies such as artificial intelligence and machine learning into ERP systems enables advanced functionalities and capabilities. For example, it has been proposed to use high-quality enterprise human resource allocation methods based on smart big data (Zhang, 2022). This emphasizes the use of smart technologies to optimize resource allocation. Similarly, the development of virtual reality (VR) technology has affected enterprise human resources management in the age of artificial intelligence and has emphasized the role of smart technologies in improving HR planning and management (Xu and Xiao, 2020).

Intelligent ERP refers to the integration of traditional ERP systems with advanced technologies such as artificial intelligence (AI), big data analytics, and machine learning to improve their capabilities and enable smarter and more efficient management of corporate resources. Intelligent ERP systems combine smart technologies to automate and optimize processes, improve decision-making, and enable predictive and prescriptive analytics. These systems can automatically collect and process data from various sources, such as sensors, IoT devices, and social media, to provide real-time visibility into business operations. Intelligent ERP systems can reduce manual effort and enhance operational efficiency by automating routine tasks and workflows (Pamungkas and Iskandar, 2021; Lv et al., 2018; Jiang, 2022).

The integration of artificial intelligence and machine learning into intelligent ERP systems enables them to learn from historical data and make intelligent recommendations or predictions. For example, they can analyze customer data to identify patterns and preferences, enabling personalized marketing campaigns and increasing customer satisfaction They can also analyze production data to identify bottlenecks and optimize production schedules. Furthermore, intelligent ERP systems enable proactive problem-solving and risk reduction by detecting anomalies or deviations from normal patterns (Pamungkas and Iskandar, 2021; Chiarini, 2020).

The benefits of intelligent ERP go beyond operational efficiency and decision-making. They can also contribute to the overall strategic goals of the organization. For example, intelligent ERP systems can support the implementation of Industry 4.0 initiatives that aim to digitize and automate production processes. Intelligent ERP systems, integrated with cyber-physical systems and leveraging IoT technologies, can enable real-time monitoring and control of production processes, leading to increased productivity and quality. Additionally, they can facilitate the integration of different technologies and systems within the organization, enabling seamless data exchange and collaboration (Chiarini, 2020; Liu et al., 2021; Feisrami and Yunus, 2023).

The International Data Corporation (IDC) outlined the concept of intelligent enterprise resource planning (i-ERP) in 2016, highlighting four key points (Morris et al., 2016):

- These intelligent i-ERP systems employ machine learning algorithms to access the necessary information from extensive data collections.
- i-ERP systems will rely on cloud technology to manage vast and heterogeneous datasets, particularly to aid decision-making processes.
- From a process perspective, these systems will enable users to make better predictions using machine learning and predictive analytics. Furthermore, they facilitate process automation by suggesting the optimal next steps.
- Users will experience substantial differences in user experience because of advancements in user interfaces, natural language processing, and designs prioritizing mobile platforms.

In a study conducted by Silva in the year 2020, the transformation process from ERP to i-ERP was examined. The fundamental characteristics of i-ERP, as illustrated in Figure 1, are outlined in this study.

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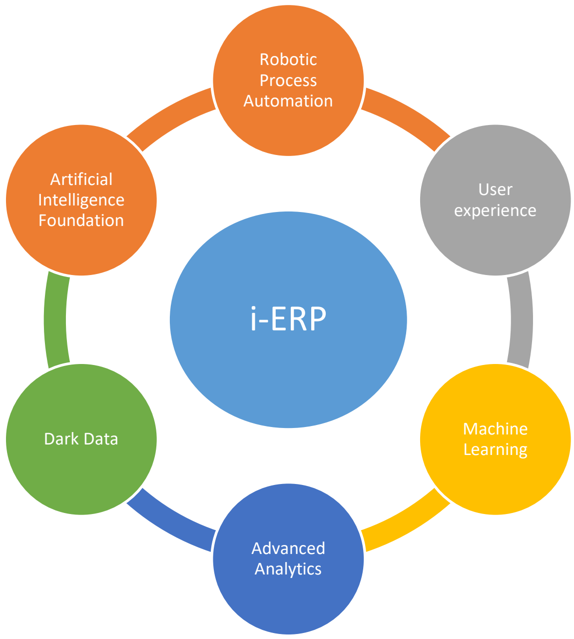
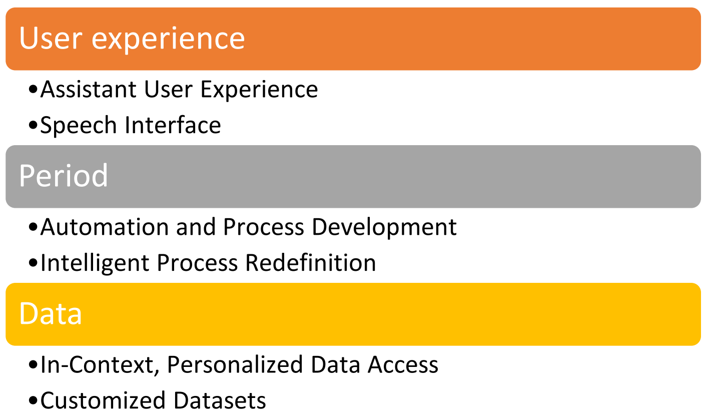
Figure 1: i-ERP Features



Source: Silva, 2020: 15

Morris et al. showed that i-ERP applications have 3 basic dimensions, as shown in Figure 2.

Figure 2: i-ERP Dimensions



Source: Morris vd., 2016:5

Morris et al. In this study, user experience was included as the i-ERP dimension.Silva showed the taxonomy in Table 1 for the development of i-ERP.

Table 1: ERP Development Taxonomy

Level	Feature
Basic ERP	It is entirely run by people. It is pre-configured.
General ERP	It can execute some operations automatically. It has tools that make processes more useful.
Automatic ERP	It contains automated processes that are unstructured. The management of the processes lies with the users. End users receive periodic training.
Semi-Autonomous ERP	Users leave the entire operation of some processes to the ERP software. It has a flexible enterprise application infrastructure. Users receive ongoing training. Advanced analytics and dark data processes are active.
Autonomous ERP	Users have complete confidence in the ERP system. The ERP operational design area is autonomous. In some business line functions such as artificial intelligence, machine learning, advanced analytics, dark data, and user experience, the user works independently.
Intelligent ERP	ERP performance is at the level of a human decision-maker. The system fully suits business scenarios. With cloud technology, connections can be established at the plug-and-play level. The end user is completely specialized in business problems. All ERP processes are based on machine learning and artificial intelligence. It uses ERP features that can be fully adapted to the customer's sensitivity without any intervention.

Source: Silva, 2020: 33-35

In a study by Silva in 2020, a taxonomy for the transition from traditional ERP to i-ERP was developed. Notably, this study emphasizes the automation of processes and the enhancement of user knowledge during this transition.

Artificial intelligence-supported examples in ERP applications have been applied in various commercial and academic fields. For instance, SAP Leonardo, developed by SAP (System Analysis and Program Development), is a digital innovation system that incorporates future technologies such as the Internet of Things, machine learning, blockchain, analytics, and big data, enabling its users to leverage these technologies for various purposes (Schmitz, 2017). Oracle Cloud Infrastructure (OCI) AI Services is a platform that allows developers to create AI applications without requiring them to be data science experts. It offers several services, from natural language processing to visual elements, time series forecasting, and anomaly detection (Pavlik, 2021). Infor Coleman is an example of AI in ERP, using technologies such as natural language processing, smart automation, and machine learning. It can perform various tasks, such as generating the next proposal for a customer or creating demand forecasts for a product (Onvision, 2022).

Logan and Kenyon (1992) used artificial intelligence to improve customer service by developing a software called HELPDESK. This software expanded the first-level problem-solving abilities without the need for additional personnel or training plans. The effectiveness of the developed system was verified through a user survey (Logan & Kenyon, 1992). In a study by Vlasov et al. (2017), a support system for SAP's ERP software was proposed. The study involves the generation of responses to user requests using machine learning algorithms. Various algorithms, such as Naive Bayes, k-nearest neighbors, support vector machines, and MaxEnt, were tested for classifying incoming requests into six categories. This study concentrated on comprehending and addressing requests for user support.

Dong (2021) focused on intelligent financial information systems and data analysis in the realm of ERP and artificial intelligence. Aktürk (2021) conducted a bibliometric study of AI in ERP literature, analyzing 837 publications. The study revealed that the most common topics in AI studies in ERP were "genetic algorithms," "fuzzy logic," and "machine learning."

Anguelov (2021) investigated potential AI applications for ERP, discussing the future developments and threats posed by AI usage in ERP software. The outlook of managers regarding developments in ERP and AI was assessed.

Jenab et al. (2019) discussed the extent to which i-ERP systems could be used in the operations of organizations. They used a decision tree algorithm and found that the model they created significantly improved the decision-making of ERP managers. They also observed that i-ERP software improved the quality of operations and increased competitiveness in the market because of its ability to respond quickly to market demand.

Berhil et al. (2020) identified HR problems and risks determined by experts and focused on computer science applications, especially AI applications, to solve these problems.

Yazgan et al. (2009) proposed an AI-supported model for ERP selection. This study used the Analytic Network Process (ANP) and artificial neural networks.

Tavana et al. (2020) assessed the challenges, issues, applications, and architecture of IoT-based ERP systems. They highlighted how sensors and devices can manage data stored in the cloud through ERP without human intervention. They also evaluated the challenges and opportunities created by the convergence of ERP and IoT with cloud technology.

Haider (2021) wrote a thesis on the use of artificial intelligence in ERP systems. The thesis provided a perspective on AI applications within ERP, offering detailed information on topics such as machine learning, deep learning, and neural networks. It also presented a scenario for creating sales forecasts from historical data using the SAP Analytics Cloud.

NATURAL LANGUAGE PROCESSING AND TEXT MINING

Text mining is a specialized version of data mining. Piatetsky-Shapiro defines data mining as an analytical method that aims to uncover previously undisclosed, hidden, and valuable information by combining disciplines such as statistics, databases, and machine learning (Piatetsky-Shapiro et al., 1996).

Text mining, like data mining, seeks to obtain useful information from data sources by identifying and exploring patterns. In text mining, the source of data is document collections. It works not with structured data, such as data mining, but with unstructured data sets (Feldman et al., 2006: 1). The most significant distinction that sets text mining apart from data mining is that text mining leverages natural language texts (Chunyu et al., 2015: 510).

Today, over 80% of information is stored in the form of text, making text mining a field with high commercial potential for the future (Korde, 2012: 85). Furthermore, approximately 90% of this data remains unstructured, and this unstructured data grows by approximately 55-65% each year. Analyzing these unstructured data is considered highly valuable in a competitive environment (Marr, 2019).

Natural Language Processing

Natural Language Processing (NLP) is used to process human language for specific purposes. It is a set of computational techniques used to analyze one or more levels of naturally occurring textual data (Liddy, 2001: 1).

One of the essential stages of natural language processing is preprocessing. The following processes were used for preprocessing (Miner et al., 2012: 46):

Boundary Determination: The boundaries of the text to be processed are defined (documents, paragraphs, etc.). This step determines how and to what extent the data set dataset should be obtained from different sources.

Tokenization: The text is divided into separate words called tokens. Tokenization is performed by considering spaces, punctuation marks, and some special characters. Each word is assigned a token name after parsing.

Stemming: To standardize and normalize words, their affixes are removed.

Stop Word Removal: Words that did not make a significant difference during analysis were removed from the text. Prepositions, conjunctions, indefinite pronouns, indefinite adjectives, demonstrative adjectives, demonstrative pronouns, and other similar words are considered to stop words (Akbıyık, 2019: 14). However, this process should be carried out carefully, considering the specific dynamics of the problem. For example, in a study classifying X-ray reports in a hospital, words like "Dear," "Doctor," "Hello," and "Sincerely" are removed from the text because they do not differentiate between classes. Nevertheless, this process requires meticulous attention.

Spelling Correction: Texts written in natural language often contain misspelled words or phrases. Correcting spelling errors is essential for accurate analysis. In addition, words with the same meaning but expressed differently are made similar.

Sentence Boundary Detection: Each sentence's end is determined, and sentence endings are marked.

Conversion to Uppercase or Lowercase: To minimize differences throughout the text, the text is converted to lowercase or uppercase. Some programming languages or software packages may be sensitive to the case of letters, and this process helps prevent potential issues.

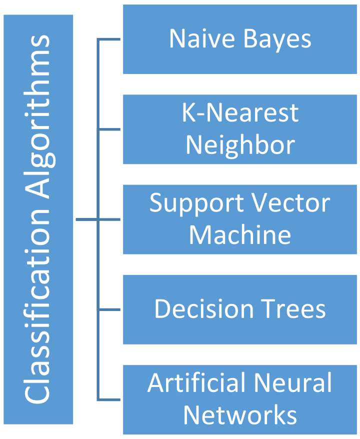
Text Classification with Machine Learning and Deep Learning

Text classification is the process of assigning a text to one of the predefined categories based on the content of the document. It is a supervised learning method (Joachims, 1998). Text classification is used in various fields such as classifying news articles, text filtering, detecting spam emails, and content management (Meena et al., 2009: 28). While the beginning of computer-assisted classification processes can be traced back to the 1960s, the widespread use of text classification began in the early 1990s. Studies during this period were based on expert systems, in which the decisions of an expert were acquired and encoded as classification rules into computer-based systems (Tantuğ, 2012: 2).

There are two main approaches to text classification. The first is based on knowledge engineering, where an expert encodes classification rules as direct, declarative, or procedural statements about classes. The second approach is based on learning from pre-classified example datasets to classify new data. This method is referred to as machine learning because of the computer's learning process. Machine learning is defined as the use of computer systems to optimize a performance criterion using example data or past experiences (Alpaydın, 2015: 3).

The commonly used text classification algorithms are shown in Figure 3 (Akpınar, 2014: 69; Oğuzlar and Kızılkaya, 2019).

Figure 3: Classification Algorithms



Source: (Akpınar, 2014: 69; Oğuzlar and Kızılkaya, 2019).

After the natural language processing step, appropriate weighting and machine learning and deep learning algorithms were applied. For this stage, firstly the literature in Table 2 was examined.

Table 2: Text Classification Studies

No	Year	Name	Author(s)	Weight Method	Validation Method	Algorithms Methods Used	Successful Algorithm Method
1	2016	Performance Analysis of Supervised Machine Learning Algorithms for Text Classification	Mishu and Rafiuddin	-	%60 Training %20 Validation %20 Test	Multinominal NB Bernoulli NB LR SVM Linear SVM Geri Yayılımlı YSA	Backpropagation ANN
2	2017	Automatic Evaluation of Opinions Concerning FATİH Project with Text Mining Methods	Göker and Tekedere	TF-IDF	Cross Validation (K: 10)	NB KEYK J48 (C4.5) SMO RBF Network	SMO
3	2017	A Chatbot Using LSTM-based Multi-Layer Embedding for Elderly Care	Su vd.			LSTM	LSTM Accuracy (%79,96)

4	2018	Comparison Of Multinomial Naive Bayes Algorithm And Logistic Regression For Intent Classification In Chatbot	Setyawan vd.	TF-IDF	%20 Test %80 Training	NB LR	LR
5	2019	Analysis of Social Media Comments an E-Commerce Brands With Text Mining Methods	Işık	-	Cross Validation (K: 10)	NB SMO KNN	KNN
6	2019	A Novel Multi-tier Filtering Architecture and Smart SMS Box for Classification of Turkish Short Messages	Bestil ve Güvensan	-	-	NB Bayes Net (BN) J48 (C4.5) RO	RO
7	2020	Telegram Bot Application with Sequence to Sequence LSTM Model	Işık and Yağcı	-	-	LSTM	LSTM Accuracy (%79) Loss (0,2772)
8	2020	A Machine Learning Framework to Predict NutrientContent in Valencia-Orange Leaf Hyperspectral Measurements	Osco vd.	-	%10 Test %90 Training	K-NN DVM ANN Decision Tree RO Ridge Regression Lasso Regression	RO
9	2020	Building a Medical Chatbot Using Support Vector Machine Learning Algorithm	Tamizharasi vd. .	-	-	DVM NB KEYK	DVM
10	2021	COBY: COVID-19 Telegram Chatbot by Employing Machine Learning Algorithms	Naufaldi vd.	Binary (0/1)	%33 Test %66 Training	NB ANN DVM	ANN (F-Skor) DVM (Accuracy)
11	2021	Turkish News Articles Classification Using Machine Learning Techniques	Uslu ve Akyol	TF	-	DVM RO NB	NB
12	2021	Multilingual Healthcare Chatbot Using MachineLearning	Badlani vd.	TF-IDF	Cross Validation (K: 5)	RO KEYK	RO

						SVM Karar Ağacı MNB	
13	2021	Chatbot for Information Service of New Student Admission Using Multinomial Naïve Bayes Classification and TF-IDF Weighting	Aelani and Gustaman	TF-IDF	Cross Validation (K: 10)	Multinominal NB	Multinominal NB
14	2022	Analysis of Turkish Voice Recordings Data with CountVectorizer and TF-IDF Vectorization Methods as BERT Models on Google Colab Platform and RapidMiner with Machine Learning Algorithms	Tepecik ve Demir	TF TF-IDF	%15 Test %75 Training	RO DVM KA LSTM	NB (TF) DVM (TF-IDF)

Frequently used text classification algorithms in this study were Naive Bayes, k-nearest neighbor, support vector machines, and decision trees were used. In addition, a long-short-term memory (LSTM) artificial neural network, a deep learning algorithm, was also used.

APPLICATION

To be used in the application, 5606 data points were taken from 3 different companies of the same group operating in different sectors. Data were taken from e-mails, messaging software, and a BTSY (Information Technology Service Management English: ITSM) application commonly used by companies. Through interviews with information technology experts, the 10 categories for which support was most requested were determined (Table 3). 100 texts belonging to each category were recorded in the system. Selected categories;

Table 3. Selected categories

Date Unlocking	Printer Errors
Design Issues	New User Identification Requests
Maturity Change	ERP Login Problems
Order Closing Requests	Order Transfer Problems
E-Document Envelope Deletion Requests	Printer Identification Requests

In this study, the model to be developed begins with a problem or request that the user enters the system. Most often, these requests come from a written source such as emails, messages, BTSY, and so on. Even if the requests are made

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via phone or face-to-face meetings, it is observed that the requests are converted into text and recorded due to personnel performance evaluations. All incoming requests consist of unstructured or semi-structured natural language texts. An example of this situation is a request sent via email, as shown in Table 4.

Table 4: ERP User Request Example (E-mail)

Subject	"NETSİS KİLİT KALDIRMA TALEBİ"
Mail Content	"Mert Bey Merhaba, Acil bir müşteri sip. kayıdı atıp sevkiyat raporu almamız gerekiyor.Rica etsem ocak 2020 yılı kilidini kaldırabilir misiniz? Kayıt yapacağım tarih 28/01/2020 Teşekkürler Saygılarımla"

Because the text is obtained from an email, it consists of both the subject and the email content. In such data, the email subject contains very important information and often summarizes the request. Therefore, both the subject and the email content are considered together. When the text is examined in detail, it is observed that there are incorrect words (e.g., 'kayıdı' instead of 'kaydı'), usage errors in punctuation, and frequently used patterns specific to emails. Although this non-structured data is easily understandable for the supporting person, it requires some processing to make it comprehensible for a computer. Natural language processing techniques are applied to convert this text into a structured dataset that the computer can understand.

In the first stage, the dataset is prepared and turned into a single document:

Merging Text: In this stage, each support request coming from different sources is merged into a single sentence. For example, the subject and email content are considered one sentence.

Tokenization: In the data preprocessing stage, each sentence (user request) is first tokenized into words.

Removal of Numerical Expressions: Numerical expressions and words containing numerical expressions are removed. For example, expressions like '12412', 'Company2022', 'F000011234423' are removed from the text.

Removal of Punctuation Marks: Punctuation marks have been removed from the text. Instead of punctuation marks, a space is added to prevent words from being combined. A list of punctuation marks is created for this process.

Conversion to Lowercase: All the letters in the sentence are converted to lowercase to minimize text differences. The language's encoding must be communicated to the software in this process. For example, a code similar to the one below should be used: "sentence = sentence.ToLower(new CultureInfo("tr-TR", false));".

Word Replacement: Some words and abbreviations within the sentence need to be replaced. Some abbreviations or words may be used within the organization. For example, 'sevk' is often used instead of 'irsaliye', and 'fat.' is used instead of 'fatura' within organizations. However, to develop a common language, these words must be transformed. These words are generated by examining the frequency distribution of the entire word list.

Spelling Correction: Due to a busy work schedule, users may misspell words in their messages. Because each incorrect word affects the accuracy of the dictionary differently, these words need to be corrected. The word suggestion function of the Zemberek library was used for this correction.

Separation of Word Roots: Turkish words are usually inflected by adding suffixes at the end. By adding inflectional and derivational suffixes to the root, new words are formed. In Turkish, 'fatura' and 'faturalar' share the same root. By taking 'lar' suffix, it is pluralized. However, it also qualifies the invoice. Therefore, a stemming or lemmatization process is required here. The Zemberek library is used for this process. Although the Zemberek library makes mistakes in some root processes, it is generally considered successful.

Creation of ERP Word Groups: In this stage, it is considered that words within a sentence can together express a meaning. 'Satış fatura' has a specific meaning for ERP. While 'satış' (sales) or 'fatura' (invoice) individually have different meanings, 'satış fatura' represents a distinct concept. To differentiate these word groups, a list has been created. This list is thought to be an important resource for such ERP studies.

Removal of Stop Words: In this stage, some words that are used to ensure the semantic integrity of the sentence but do not make a difference are removed from the sentence. In English, these are called 'Stop Words,' and in Turkish, they are called 'Durak Kelime' or 'Etkisiz Kelime.' For example, conjunctions, prepositions, and pronouns are considered stop words. In this study, three different stopword lists are used. The first list was created for classical Turkish. The second list consists of words that do not affect the ERP for the Turkish language. For example, 'ltd,' 'şti,' 'urgent,' 'kindly,' etc., form a list. The third list contains the specific names of the companies from which this data is obtained. For this purpose, the employee name list has been pulled from the ERP software. The current list has also been added to this. This list may vary according to the study performed.

Binary (0/1) Weighting

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It is a term vector created as 0 or 1 based on whether each term in the expression list is present in the text. The number of times an expression occurs in a category is unimportant. It is represented by a binary expression based on whether it is present in each text.

TF (Term Frequency) Weighting

It is a term vector created as 0 or 1 based on whether each term in the expression list is present in the text.

TF-IDF (Term Frequency-Inverse Document Frequency) Weighting

The TF-IDF method also considers the situation of the expression in other texts. It is not only concerned with whether the word is in the relevant sentence but also with whether it is in other sentences. It is found by multiplying the TF and IDF values.

TF is found as the number of times the term appears in the text divided by the number of terms in the text.

IDF is found as a log (number of texts/number of texts containing the term).

TF-IDF is found as TF * IDF.

The data were analyzed using Python and the WEKA package program. In Python 3.10 in Visual Studio Code, libraries such as numpy, pandas, keras, sklearn, and matplotlib were used. The WEKA 3.8.6 version used the LibSVM library.

K-Nearest Neighbors, Naive Bayes, Sequential Minimal Optimization (SMO), Random Forest, C4.5, LibSVM, and UKSB algorithms underwent a 10-fold cross-validation process.

The verification matrix for 10 different categories is given in Table 5 and Table 6.

Table 5: Category List

a	Date Unlocking	**f**	Printer Errors
b	Design Issues	**g**	New User Identification Requests
c	Maturity Change	**h**	ERP Login Problems
d	Order Closing Requests	**i**	Order Transfer Problems
e	E-Document Envelope Deletion Requests	**j**	Printer Identification Requests

Table 6: Validation Matrix

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	
95	0	1	0	0	0	1	2	1	0	**a**
1	**82**	4	0	3	2	0	2	5	1	**b**
0	5	**95**	0	0	0	0	0	0	0	**c**
0	1	2	**93**	0	0	0	1	3	0	**d**
0	0	0	0	**97**	0	1	1	1	0	**e**
0	1	0	0	0	**85**	0	1	2	11	**f**
0	1	0	0	0	0	**96**	3	0	0	**g**
0	2	1	0	1	0	2	**93**	1	0	**h**
0	0	0	0	0	0	0	0	**100**	0	**i**
0	0	1	0	0	15	0	0	1	**83**	**j**

The highest number of incorrect matches in the verification matrix is observed in order transfer problems. It was thought that this was due to the possibility of the order being used in all other requests.

All analyses were repeated considering TF-IDF calculations. The results are shown in Table 7.

Table 7: Evaluation Criteria by Algorithms (TF-IDF Weighting)

	K-Nearest Neighbor	Naive Bayes	SMO Sequential Minimal Optimization	Random Forest	C4.5 (J48)	LibSVM (Support Vector Machine)	LSTM
Precision	0.870	0.899	0.935	0.885	0.868	0.919	0.929
Recall	0.830	0.886	0.934	0.885	0.867	0.918	0.913
Kappa	0.8111	0.8711	0.9267	0.8722	0.8522	0.9089	0.900
F-Value	0.834	0.886	0.934	0.884	0.866	0.918	0.910
ROC Area Value	0.939	0.991	0.987	0.982	0.952	0.954	0.998
Accuracy (%)	**83**	**88.4**	**93.4**	**88.5**	**86.7**	**91.8**	**91.3**

When the results were evaluated, the highest accuracy rate (Accuracy, F-Measure, Kappa Value) was achieved with the SMO algorithm. In terms of performance metrics, the SMO algorithm appears to be the most successful algorithm for this classification.

The model was also evaluated for overfitting. A 10-fold cross-validation process was used for validation to reduce the likelihood of memorization. In addition, reducing the excessively high number of features helps prevent overfitting. In this regard, two different pruning processes were performed. In the first pruning, words with a frequency value of less than 5 were removed from the feature list. In the second pruning, words that appeared in less than 70% of the texts were removed from the list. However, similar results were obtained even after these pruning processes.

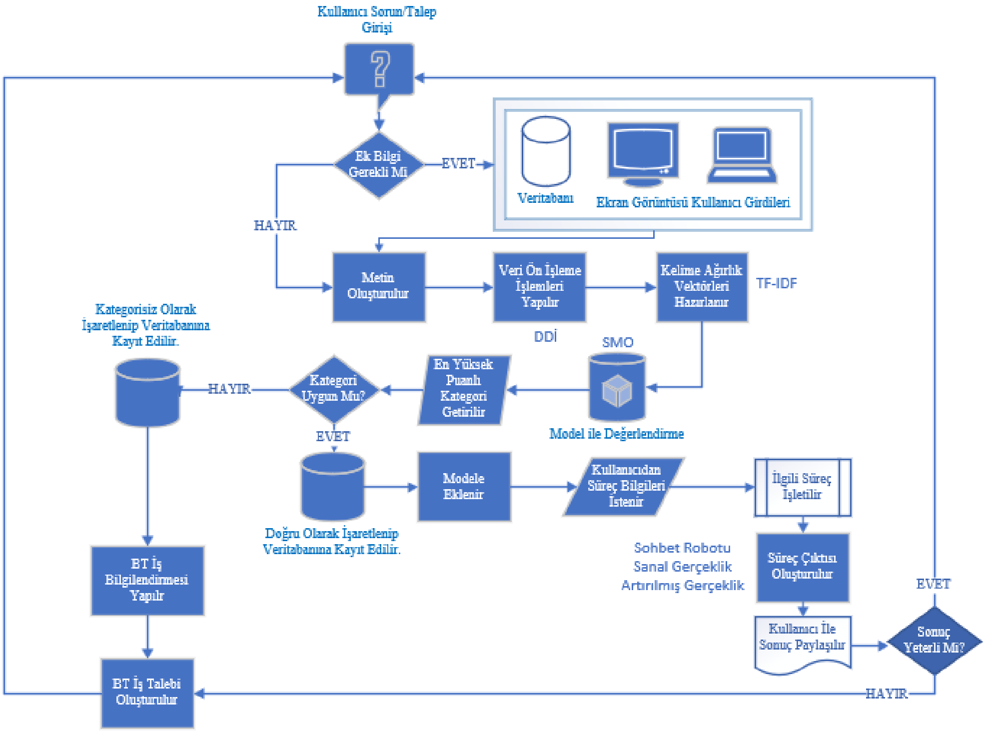
Given the performance metrics, it was decided that the SMO algorithm, which demonstrated high classification performance, is sufficient for developing a support robot. The SMO algorithm was used in the chatbot.

Application Development Phase

Organizations are composed of processes, each with its workflow. These workflows can vary depending on many parameters such as personnel, time, and cost. IT staff or external consultants, who are called upon for support, follow a specific path to resolve support requests. It is not sufficient for the developed software to understand the process. The natural language processing process and classification algorithm, while correctly classifying the support request, are insufficient for solving the support. In addition, after appropriate classification, the relevant process must be created and customized.

The process starts with the BANA.YZ user login and ending with a new support request or a user's conversation is shown in the flowchart in Figure 4.

Figure 4: BANA.YZ Flowchart



We want to express the process shown in Figure 4 step by step:

- The process starts with the user entering the data in the chatbot. Screenshots can be added to the process by the user, and the system can also obtain data from the ERP database if needed.
- All this data is transformed into a text array.
- Data preprocessing is performed.
- The obtained dataset was weighted using the TF-IDF method.
- A new text is tested using a previously trained SMO algorithm. The result is assigned to a class.
- It is confirmed whether the process is correct by the user. If it is incorrect, an email notification is sent. An IT service management record is created. Then, the process returns to the beginning. If it is correct, the relevant process is executed. Raw data and processed data are added to the relevant class.
- The process output is generated.
- The process output is presented to the user.
- It is confirmed whether the result is sufficient. If it is insufficient, a record is created again. If the result is sufficient, the process returns to the beginning to prepare for a new record.

BANA.YZ allows organizations to design their processes with its specially designed and coded process engine. Users can design processes using a drag-and-drop interface without needing any software knowledge. Thus, it provides an infrastructure for users outside the IT department to create their designs.

After BANA.YZ matches support requests with the appropriate process, it directs them to the process engine. The previously designed process design produces various outputs to assist the user. BANA.YZ's support requests can lead to the following actions:

- Display a response text (e.g., "I can't access your waybill because the invoicing process has been completed").
- Perform a database operation (e.g., "Update the due date").
- Establish an API connection (e.g., delete an order from the ERP API).
- Send an email notification (e.g., "An informational email to the Accounting Manager").
- Start or stop a service or program (e.g., "Stop and start the e-Invoice service").
- Create an output (e.g., "Create an Excel file of customers who didn't pay last month").
- Redirect to a virtual reality application. In particular with the increasing number of scenarios, users can receive live support through this feature.
- Redirect to an augmented reality application. Users can see the animations they want to show in reality from their smartphones or tablets.
- Redirect to a video. If the user's support request can be resolved through a video, the user can be assisted by showing the video.
- Redirect to a web address. This address can be on the Internet or intranet. Information can be provided to the user via this address.
- Create a ticket in the IT service management software.

The existence of an unpredictable number of support processes within the organization prevents the system from being fully automated. However, if the system has not yet learned a process related to user support, it will create a support request for the relevant department. In addition, this record is saved as a process that has not yet been learned. After the relevant staff combine similar requests to create a new process, this process also becomes a part of the system.

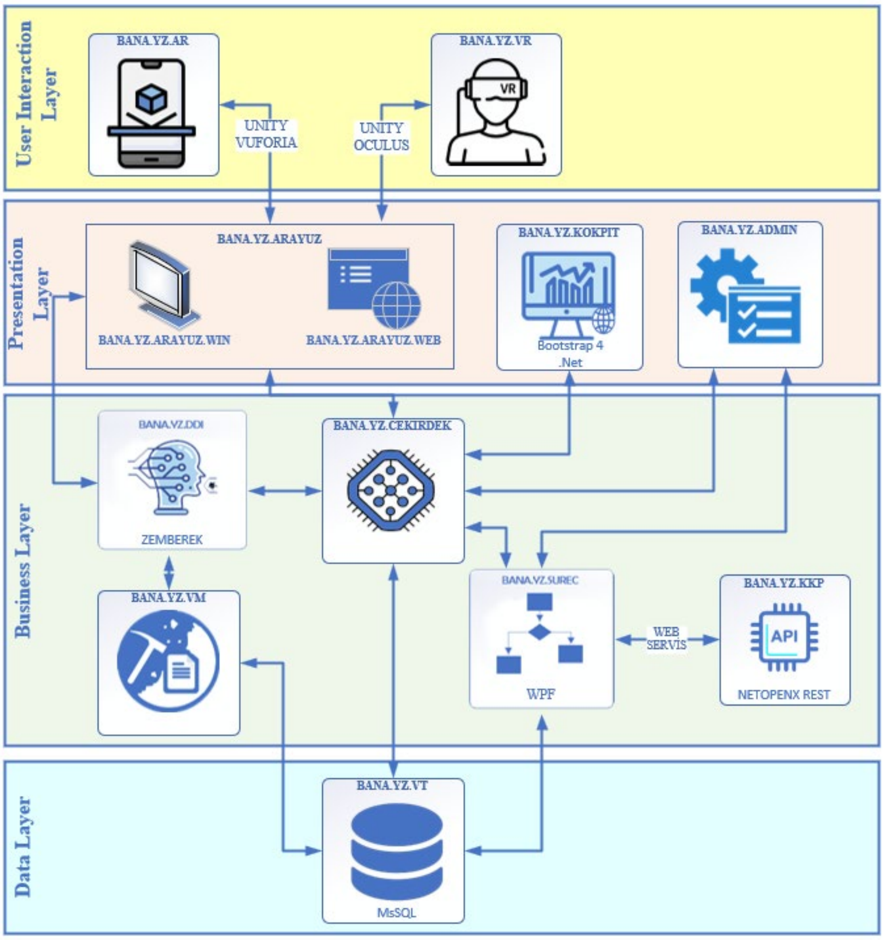
BANA.YZ is also expected to interact with the user as a chatbot, which is why an artificial intelligence programming language called AILM is used. Using this language, BANA.YZ can be taught to handle casual conversations (e.g., "How's the weather today?") alongside ERP support requests.

One of the significant concerns with BANA.YZ is security. For organizations, the operation of the ERP, and data integrity, is essential, and any compromise in this area can lead to vital problems. Furthermore, not everyone should be able to perform transactions related to all processes. Thanks to the designed process engine, approval mechanisms can be activated when necessary. During the login process, the BANA.YZ system performs user verification through the ERP API. Users log in with their ERP username and password. In this way, unauthorized ERP operations are prevented. All operations are performed by

BANA.YZ is logged. This log enables retrospective research to find solutions to problems.

The architectural framework is prepared within the scope of BANA.YZ is shown in Figure 6.

Figure 6: BANA.YZ Architecture



The BANA.YZ application consists of 13 separate subprojects. Each project has different functions (Table 8);

Table 8: Project Layers

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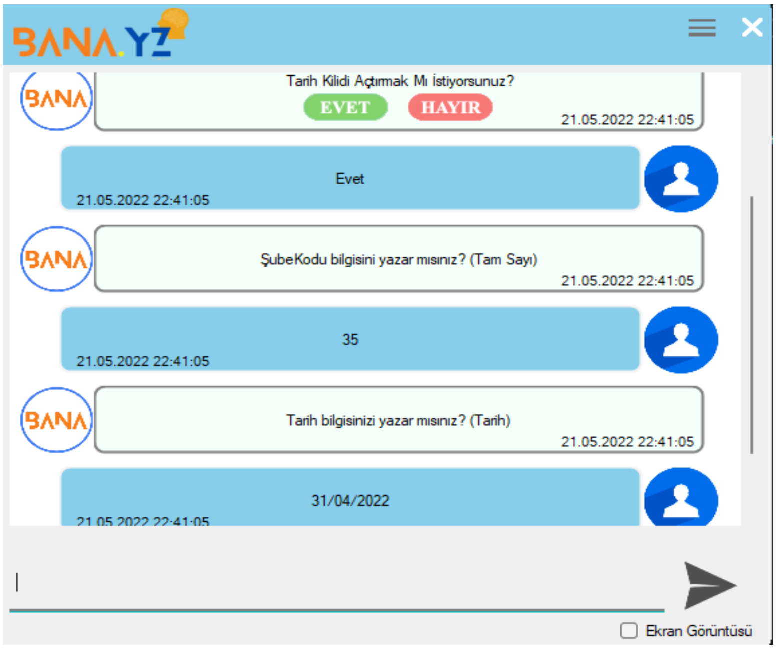
Layer	Project Name	Description
User Interaction Layer	BANA.YZ.AR	User-augmented reality support application
	BANA.YZ.VR	User virtual reality support application
Presentation Layer	BANA.YZ.ARAYUZ • BANA.YZ.ARAYUZ.WEB • BANA.YZ.ARAYUZ.WIN	Interfaces where users interact
	BANA.YZ.KOKPIT	Screens with monitoring screens and reporting for managers and the IT department
	BANA.YZ.ADMIN	Screens where processes are designed
Business Layer	BANA.YZ.SUREC	Library containing the processes of the process engine
	BANA.YZ.DDI	Library with natural language processing operations
	BANA.YZ.VM	Library with data mining operations
	BANA.YZ.KKP (ERP)	Library where the ERP software is interacted with and API services are called
Data Layer	BANA.YZ.VT	Library where all database operations are performed
Test Layer	BANA.YZ.TEST	Application where testing is performed

In addition to these projects, there is the BANA.YZ.CEKIRDEK project, which contains functions common to these projects.

The screen, where users engage in a dialogue with BANA.YZ, is depicted as shown in Figure 7. Users can conduct their conversations through this interface and may include screenshots. The textual expressions in the screenshot are converted into input.

Figure 7: Example Screen



The BANA.YZ user initiates the interaction by entering the discussion screen to address their issue. Initially, it activates the relevant artificial intelligence algorithm to comprehend the user's problem. Based on the output of this AI process, the corresponding workflow is initiated. Essential information within the process is directed to the user through the conversational robot, and responses from the user are collected. The process is applied based on these responses, leading to the resolution of the issue. Feedback is obtained from the user to enhance the model and improve the process. Solutions can be presented to the user in various forms, such textual expressions, executing a specific operation, augmented reality application, or virtual reality application.

CONCLUSION

ERP software holds immense importance for organizations. In a highly competitive environment, sustaining a business is only possible through secure and consistent data recording and analysis. Various factors contribute to the success of ERP usage within an organization, with users being the most critical factor. Smooth usage of the ERP software by users leads to success within the organization. It is common for users to face issues while using ERP software and request support for issue resolution. Traditional methods exist for addressing these requests. Organizations often seek external support or internal support from IT departments to address these issues. However, for organizations with a significant number of employees, it can be quite challenging to address every request on time. Therefore, organizations establish ticketing systems to collect and manage these requests in a centralized. However, in systems where immediate issue resolution is critical, such as ERP, relying solely on ticketing systems can lead to process interruptions. Providing external support for each user request incurs both time and financial costs. Considering all these considerations there is a need for a system that allows users to resolve their support requests independently, without the need for external assistance. To achieve this, artificial intelligence technologies have been employed.

In this study, a model was developed that can understand and act upon a support request when users encounter issues. Techniques such as chatbots, natural language processing, machine learning, and deep learning were employed to develop this model. Using these technologies, a support robot model equipped with its process engine is presented, which can generate solutions to support requests from ERP users. Although the model was designed for ERP, it possesses an adaptable structure suitable for all user support systems.

In terms of limitations, the model is based on the analysis of a specific dataset. Particularly due to the formation of an internal organizational communication culture, it is expected that using the same dataset for another organization may reduce the success rate. However, as the amount of data within the organization increases, it is anticipated that similar successful results are anticipated.

In terms of academic contributions, this study is important for the use of artificial intelligence technologies in a significant field such as ERP. The combination of technologies like natural language processing, machine learning, deep learning, virtual reality, and augmented reality can inspire various research endeavors. The literature review on the problem, the steps developed specifically for ERP in natural language processing, and the comparative presentation of machine learning techniques offer academic value. The developed model can be used in similar software applications that require user support. Moreover, the study emphasizes a new era for ERP by increasing the number of similar studies, indicating the transition to a system where i-ERP systems will automate most processes (e.g., order-invoice-bill transformation, journal voucher entry, generating receipts, user identification, etc.).

Regarding its contribution to the industry, it highlights the significance of a model that allows users to address their support needs immediately in a system where real-time actions are crucial. By preventing ticket systems from becoming congested with routine tasks, this model ensures that more critical issues are noticed and prioritized. Information technology departments are often occupied with handling simple ERP issues, and as a result, they struggle to fulfill their primary responsibility of implementing improvements or new projects. This study is expected to provide value to IT departments in this regard. In addition, it incorporates new technologies such as virtual reality and augmented reality. These technologies, which are often used for educational purposes, can also be considered as an alternative for providing user support. In this sense, this thesis projects into the future.

In the literature and the industry, a greater focus is often placed on customer support as opposed to user support. As a result, in 2018, it was reported that the revenue from customer support services exceeded 20 billion dollars (Khan et al., 2018: 100). Similar studies have been conducted. For example, Özkol et al. (2019) suggested that an AI-supported chatbot would be useful for EBYS users. Vlasol et al. (2017) developed a chatbot model for SAP software that addresses requests and provides responses. In contrast to this thesis, these studies focus on responding to user requests.

In future studies, the use of new technologies can be increased, particularly in parallel with virtual reality and augmented reality. Alternative methods can be explored or developed to address the language structure issues resulting from the Turkish language. Features for receiving and providing support via voice can be developed, particularly for disabled individuals. Research can be conducted to identify issues when users encounter problems, enabling immediate support. New projects can be developed to expand intelligent ERP applications. The study can be extended to ERP companies with specific security protocols. Particularly in organizations that use cloud technology, more accurate response applications can be developed. The integration of support requests through messaging applications frequently used by users can be achieved using APIs, making users capable of sending support requests.

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