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Demonstration of the application of an integrated digital platform in acute ischemic stroke emergency care and evaluation of its effectiveness

Xiaolin Hou[1], *Huarui Zhang*[1], *Juan Yang*[1], *Li Zhao*[1], *Xiaoyu Wu*[1], *Xiaoping Tu*[1,*] *and Yi Zhao*[1]

[1] General Hospital of Ningxia Medical University, Yinchuan, Ningxia Hui Autonomous Region, 750004, China

SUMMARY: *The development of digital technology is facilitating the smart emergence of stroke emergency care. Deep learning MCDE techniques and algorithms based on QoS have been used in this paper to create an integrated digital platform to improve the effectiveness and efficiency of acute ischemic stroke emergency response. The MCDE method learns various heterogeneous medical knowledge to create a stroke medical knowledge graph, which serves as a repository of resources to rapidly query. Together with a QoS-based service selection algorithm, it computes ideal emergency medical intervention combinations. With its application to acute ischemic stroke treatment, the combined platform recorded DTP, DTT, and DNT performance rates of 6.29 +1.03, 20.48+3.74, and 17.35+5.12 respectively. Efficacy of thrombolytic treatment was 91.86%. Integrated digital platform-assisted emergency care allows quicker and more accurate emergency response compared to the conventional emergency interventions.*

KEYWORDS: *MCDE; QoS analysis services; integrated digital platform; knowledge graph; stroke emergency care*

1 Introduction

AIS is a term used to define a clinical condition resulting in an interruption of brain blood flow due to different factors that result in focal cerebral tissue ischemia, hypoxic necrosis and consequent neurological deficit that develops quickly. It is the leading cause of strokes and constitutes about 60 percent to 80 percent of all strokes [1-4]. The onset is abrupt and its course rapid; without prompt and efficient medical response, it would significantly affect patient prognosis and could even be fatal. The most important thing in order to improve patient outcomes is prompt and effective emergency care [5-7].The paper of reference [8] gives up-to-date information on risk factors of AIS and addresses the clinical importance of new vascular risk factors in AIS patients. Reference [9] notes that AIS is affected by variables like gender and age with the emphasis that precise characterization of AIS plays an important role in enhancing relevant guidelines, preventive interventions and allocation of resources. Reference [10] considers a prospective cohort study of AIS patients, which follows the occurrence of acute myocardial infarction among them and calculates the 5 year cumulative incidence and risk according to risk factors such as age and AIS. Reference [11] describes the clinical features and properties of AIS, defining it as an acute neurological symptom that begins abruptly and peaks in a short time, but noting difficulties of detailed diagnosis and treatment. Reference [12] groups AIS causes and its causative agents and presents AIS management approaches in details.

*HXL8587496221@163.com
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Reference [13] covers AIS evaluation and the latest developments in management across the continuum of care beginning with prehospital care to care in the emergency department to acute hospital care and post-stroke rehabilitation.

Integrated digital platforms are also important players in medical services and management due to the constant technological advances and innovations happening in the healthcare sector [14]. Integrated digital platform means a system that applies information technology to combine and administer healthcare resources, provide medical services and support making decisions [15, 16]. It aims at increasing the effectiveness of health care, better quality of medicine, and better quality of patient-provider interaction as well as more comfort and ease in health care service provision to medical facilities, doctors, and patients [17-19]. An integrated digital platform allows the alignment of AIS emergency data within and outside hospitals and the automatic collection and documentation of critical time intervals. The integrated digital platform mainly comprises a prehospital mobile treatment system and an in-hospital stroke treatment system. The prehospital mobile treatment system runs on the 120 ambulances, which allow real-time synchronization of the vitals of the patients, stroke assessment status, and basic patient information to the hospital. This system allows remote hospital registration and has a stroke map that helps 120 navigate accurately [20-24. Hospital-based stroke treatment system can be loaded on the smartphones, iPads, and hospital computers using the personal employee ID login [25]. The system integrates with the hospital laboratory management system and picture archiving and communication system (PACS). The radiology department is held back when the patient is informed of prehospital admission and they hold onto a CT scan until the patient arrives so that they can be scanned immediately. The laboratory needs to perform five coagulation tests and upload the results to the system [26-29]. At the same time, the system automatically registers and documents critical time points, which makes possible quality control analysis of such milestones. The AIS treatment team may use this system to conduct quality control analysis and then implement quality improvement activities [30-32]

The reference [33] created a green smartphone platform to integrate the on-site assessment, hospital recommendations and pre-hospital notifications so as to streamline and standardize the entire AIS emergency management process. Its effectiveness in implementation has been tested, which proves its usefulness to the AIS emergency management. The reference [34] describes a smartphone application that helps emergency medical staff perform on-site assessments and refer AIS patients, optimizes the use of resources and shortens the time of patient admission. The reference [35] investigates the use of artificial intelligence and robotics in healthcare, and the possible application thereof to the AIS processes. It discusses stages of the AIS healthcare process such as prehospital diagnosis, transportation of the patient, treatment modalities and AI application. Reference [36] intended to assess the viability and usefulness of the Neuron Emergency Room Mobile Information System. Its application in a comprehensive stroke unit of AIS patients confirmed its usefulness in assisting AIS treatment management. Reference [37] is a communication platform based on web browsers and mobile applications. It connects appropriate members of the stroke care pathway and ensures coordinated flow of information during AIS treatment. Reference [38] designed a distance communication system to facilitate the management of strokes and assessed the effectiveness of the JOIN smartphone application system in accelerating the sharing of clinical and imaging information to help plan the treatment of stroke. Reference [39] presented a technical solution to the workflow of remote-assisted treatment in AIS patients, which sought to minimize the time between the onset of symptoms and the start of treatment using telemedicine. The reference [40] states that the move towards digital healthcare is positively effective in enhancing medical care services. To treat stroke, this involves prompt, coordinated, and sustained treatment across different levels of healthcare systems. Reference [41] presents the systematic introduction of the STROKE5.0 platform and its influence. This platform supports early symptom detection, effective emergency care, and effective hospital management with the help of smart decision-making system, which plays a significant role in improving the quality of care and resource allocation in AIS care. The goal of Reference [42] is to co-develop a multi-component digital technology support system involving AIS patients and clinicians to prevent AIS recurrence. The questionnaire surveys highlight the paramount significance of increased monitoring of health and lifestyle indicators.

This paper employs the MCDE approach to process diverse stroke medical knowledge data within an integrated digital platform. Through entity-attribute alignment and similarity calculations, a stroke disease dictionary is established, linking knowledge entities to graph structures to enhance knowledge accuracy. Combining the TransE and TransD models, knowledge entities are stored as triples within the knowledge graph, completing its embedding and holistic modeling. Service availability during emergency response is calculated using a service QoS utility function. A QoS-based service selection algorithm solves single or multiple uncertain emergency medical service demands, identifying optimal rapid response solutions.

2 Development of an Integrated Digital Platform for Acute Ischemic Stroke

2.1 Design of an Integrated Digital Platform for Stroke Care

Based on the clinical needs and management requirements for patients with acute ischemic stroke, this platform is primarily divided into five modules: stroke screening, stroke emergency care, stroke units, follow-up care, and health education. Information across these modules is interconnected, collectively forming a comprehensive, closed-loop information management system covering the entire care pathway.

2.1.1 Stroke Screening

Screening of stroke has two major steps involved. The first step is the initial screening that mainly consists of preliminary evaluation of patients to determine the ones who are likely to develop stroke. The initial screening generally comprises gathering general data on patients, asking about medical and family history, performing a basic physical examination, and assessing lifestyle practices.

After the first screening has been completed, the doctor will decide whether a repeat test of rescreening should be performed. Rescreening entails a thorough and comprehensive examination of patients who have tested positive in the initial screening to ascertain their particular degree of stroke risk. Additional complex laboratory tests, imaging studies, and special assessment measures can be included as part of the re-screening process.

The findings of the re-screening assist doctors to decide on the type of health intervention that is suitable to every patient. The interventions might be in the form of lifestyle changes, drugs, or surgical interventions with the overall aim of lowering the risk of stroke and promoting health in general.

The services of stroke screening can be provided by medical professionals to different patient populations or can be done separately by patients or their families. The self-screening could be done through an online integrated digital platform whereby a patient or family member would self-assess on the basis of the guidelines of the platform. Nevertheless, one should bear in mind that the results of self-screening might contain certain margins of error. Consequently, it is advised that once a person has undergone self-screening, they should get more information and assurance on their condition using professional medical care providers.

The platform is essential in the stroke screening procedure. To patients, the platform gathers and monitors screening data, sorts patients into different management groups depending on their results and allows them to monitor their health in real-time. It allows the creation of personalized interventions appropriate to every category of patients. Physicians can use data analysis in order to provide the effective management and follow-up of the screening. The platform assists doctors in learning more about their patients stroke risks using the information technology platforms to record, manage, and analyze real time data, and hence come up with specific treatment plans. It allows the objectives of early detection and early treatment, which will decrease the incidence of stroke and disability. Also, the platform offers educational materials related to health, and it will assist patients and their families in gaining more knowledge about stroke-related information and signs, so that they would have more self-management and preventive skills.

2.1.2 Stroke Emergency Care

Emergency care of strokes mainly consists of giving emergency treatment to stroke victims. The ideal golden treatment window of stroke is no more than 6.0 hours because the shorter the duration between the onset of symptoms and proper treatment, the better the prognosis, and less disability and death rate. Introduction of 5G technology into integrated digital platforms introduces new opportunities into stroke emergency care. Time management is therefore an area of extreme importance during the stroke emergency cycle. Any delay in either step can potentially lose the opportunity to treat optimally. Through the combination of the hospitals existing emergency care processes with the latest industry best practices, a customized and efficient green channel to provide stroke emergency care was developed. Such a green channel is intended to reduce delays in treatment so that patients may be treated in the shortest time possible.

Initially, the integrated digital platform should log the time taken to initiate and conclude each of the important steps of the process in real time such as the reception of patients, starting evaluation, imaging testing, verification of diagnosis, development of treatment plan, and execution of treatment. The information is of great importance in the future medical quality control and process optimization. Secondly, the platform should gather and sort out diverse operational data created in the process of urgent care, including vital signs, examination findings, and medications history.

By accurately coordinating the stroke emergencies with the assistance of the integrated digital platform, a full knowledge map of cerebrovascular diseases can be built. The study allows monitoring all stages of the patient emergency journey in real time to provide timely and effective medical care. At the same time, data support offered by the platform constantly improves the emergency procedures and raises the percentage of standardized treatment within the golden hour (the first hour after the stroke). It will decrease the level of death and disability among patients.

2.2 Construction of a Stroke Knowledge Graph Based on the MCDE Method

2.2.1 Modeling Medical Knowledge on Stroke

MCDE is used in research on building stroke knowledge graphs as an entity-relation extraction and completion approach based on deep learning to improve the coverage and accuracy of knowledge graphs. The construction of the stroke medical knowledge graph involves several stages. First, human intervention is employed to build a stroke disease dictionary, which in this step serves as the foundation for constructing the stroke ontology knowledge base. This paper designs a classification system for stroke-related concepts by surveying authoritative standard medical terminology collections both domestically and internationally. The relationship classification system within the stroke ontology is derived from annotation and analysis of medical cases. Through comparative evaluation, a preliminary stroke disease dictionary is established. Subsequently, the stroke knowledge graph is constructed. Guided by the stroke disease dictionary, attribute and relationship data—including symptoms, treatment methods, medications, and emergency measures—are extracted from specialized medical websites and public repositories like Baidu Baike. A hybrid approach combining manual annotation and automated extraction processes this highly structured data to build the stroke medical knowledge graph ontology. Following knowledge graph modeling and knowledge processing, the semi-automated construction of the medical knowledge graph for stroke was achieved.

Once the construction methodology is determined, a comprehensive structure is formed. The framework uses a semi-automated construction design pattern that has a cyclic iterative pattern and each iteration contains the following steps: graph pattern design, knowledge extraction, knowledge graph modeling, and knowledge processing. This design allows updating the knowledge graphs in a sustainable way that creates a new version every time an iteration is performed. As a result, the knowledge graph is becoming more flexible to the intricate situations faced in the acute ischemic stroke emergency treatment.

2.2.2 Knowledge Fusion

Knowledge fusion in the process of constructing knowledge graphs can be realized in various ways, and in this study, knowledge fusion in stroke knowledge graphs is mainly carried out through entity attribute alignment and entity linking with the help of similarity calculation. Entity alignment is an indispensable part of knowledge fusion, in which the entities in the knowledge base of heterogeneous data sources that match the stroke ontology are entity-aligned with the entities with globally unique identifiers, and then the entities are linked to the stroke knowledge graph through methods such as entity attribute alignment. Since this paper proposes to formulate a dictionary of stroke diseases, the step of entity alignment has already been completed in the phase of data extraction, so the phase of entity attribute alignment mainly focuses on the alignment of attributes.

1) Attribute Alignment

The role of this step of attribute alignment is to improve the accuracy of entity linking. Since there are fewer attributes in the stroke domain, this paper constructs an attribute mapping table based on the stroke ontology library constraints to align entities of the same type with different expressions of the same attribute. After aligning the attributes of entities from different data sources, the attribute values are normalized using the constraint specifications in the schema layer of the Stroke Ontology Library.

After aligning the attributes from heterogeneous data sources, the attribute values are normalized according to the constraint specifications in the schema layer. In this study, the attributes are categorized as follows: numeric, interval, entity-object-list, string, and boolean. These attribute values are normalized and structured according to the following constraints: the unit of measure of numeric attribute values is unified; spaces and line breaks in string attribute values must be deleted; for interval attribute values, the upper and lower limits are retained and stored in lists; entity object attribute values are stored in lists without attribute alignment operations.

2) Entity Link

After completing the work of attribute alignment and normalization of attribute values, the semantic similarity of the result of attribute alignment is chosen to be calculated to determine the relationship with the entity nodes in the Knowledge Graph to decide whether to link to the Knowledge Graph or not. In the case of stroke medicine entities, this study calculates the similarity of the attribute values for each of the different classes mentioned above as a way of deciding whether to link to the entities in the knowledge graph or not. For two entities W_1 and W_2, the corresponding aliases and names are merged into the name sets S_1 and S_2, respectively. The similarity is calculated according to the following formula (1), and those with high similarity are linked to the entities in the knowledge graph.

$$Sim\left(W_1, W_2\right) = \frac{k}{1+N} \max\left(\sum_{i \in W}^{N} \sum_{j \in W2}^{N} \frac{2 \times lcs(i, j)}{L_i + L_j} \right) \tag{1}$$

Here, $lcs(i, j)$ denotes the length of the longest common subsequence between names i and j, where N is an adjustable parameter and k serves as a weighting parameter to mitigate the impact of excessive similarity within the name set.

3) Knowledge Integration

Knowledge integration in medical knowledge graphs involves incorporating structured knowledge and information from public knowledge bases into existing knowledge graphs. Based on knowledge integration methods, this paper outlines the process for merging public knowledge bases into the stroke knowledge graph: knowledge extraction, concept matching, entity alignment, and knowledge evaluation. Concept Matching and Entity Alignment are the steps that consist of normalizing knowledge acquired by the Chinese symptoms database through manual definition of the stroke disease dictionary. Assessing the consistency and accuracy of the extracted knowledge is done using knowledge evaluation.

2.2.3 Knowledge Graph Embedding

On the medical knowledge graph of acute ischemic stroke, every piece of medical knowledge is expressed as a triplet of the form <*head*, *relation*, *tail*>, with head being the head entity node, tail being the tail entity node, and relation being the relationship between nodes. Figure 1 is an example of the acute ischemic stroke knowledge graph.

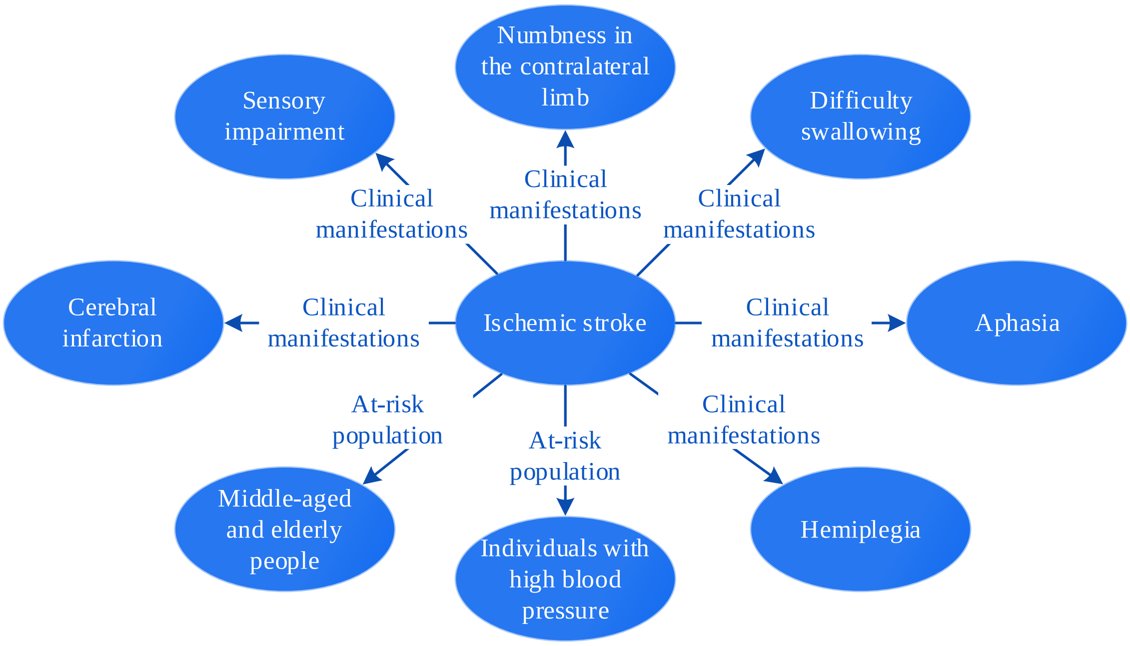


Figure 1: Example of Knowledge Graph for Acute Ischemic Stroke

Knowledge graph embedding, also known as knowledge graph modeling, centers on mapping the *head* and *tail* entity nodes within each triplet, along with their relation, into a continuous low-dimensional vector space. This preserves the semantic structural information between triplets and represents entities as vectors. Models like TransE and TransD process this semantic structure to compute entity similarity. This paper employs the TransE and TransD models, which are currently widely used in knowledge representation.

The TransE model is one of the most representative translation models. For a given triplet, the *relation* is interpreted as a translation vector from *head* to *tail*. That is, when the triplet <*head*, *relation*, *tail*> holds true, *head* + *relation* ≈ *tail*. Otherwise, the tail node should not be linked to the other end of the head entity node and relation. The specific function formula is shown in Equation (2):

$$f_r(h,t) = \|h + r - t\|_{L_1/L_2} \tag{2}$$

Here, $L1/L2$ denotes whether the distance from $L1$ or $L2$ is used in computation. Due to its sparse parameters and low computational complexity, the TransE model excels at handling one-to-one relationships but exhibits insufficient performance when processing one-to-many or many-to-many relationships. Therefore, this paper will also employ the TransD model and the TransR model—an extension of TransE—to process knowledge representation for triples in the medical knowledge graph of acute ischemic stroke.

The TransD model overcomes the limitations of TransE by distinguishing the semantic representation of head entity nodes, tail entity nodes, and the relationship connecting them within a triple, projecting vectors into a dimensional space specific to the relationship. Specifically, it employs mapping matrices Mh to map head entity nodes to a specific relation space and Mt to map tail entity nodes to another specific relation space. Each relation's mapping matrix is decomposed into the product of two vectors, as shown in Equation (3):

$$f_r(h,t) = \|M_h h = r - M_t t\|_{L_1/L_2} \tag{3}$$

The head entity node vector Mh and tail entity node vector Mt are both related to the entity and relationship, where $M_h = r_p h_p + I, M_t = r_p t_p + I, I$ is the identity matrix. The goal of improving computational efficiency is achieved through vector transformation.

2.3 Service QoS Utility Function

QoS, or quality of service, does not refer to any generic concept of quality of service in the context of strokes, but it is actually a technical set of metrics used to measure and improve the operation of important services like medical information systems and emergency response processes. Its objective is to ensure patients receive high-quality, reliable medical care within the shortest possible timeframe, playing a pivotal role especially during the “golden treatment window.” Applying the utility function (UF) from economics to QoS-based service or resource selection enables the measurement of service or resource availability. Introducing a utility function into QoS-based service or resource selection allows for the normalization of various QoS attributes to determine service or resource availability. The utility function's domain ranges from [0.0, 1.0]. A lower function value indicates reduced availability of the service or resource, thereby diminishing the likelihood of successful acute ischemic stroke treatment.

2.3.1 Definition of Hospital Selection Criteria

Reliability of hospital services (*re*): Represents the probability of a hospital successfully treating patients. The calculation formula is as follows:

$$re(X) = \frac{t}{n} \tag{4}$$

In the formula, t represents the number of successful service implementations;

n represents the total number of service implementations;

Hospital service price (C): The cost required for this hospital to treat patients.

Capacity level (lev) of the hospital's service: Expressed as a probability, where higher values indicate a higher level. Hospital classification: Level I, II, and III hospitals, each further subdivided into Class A, B, and C tiers, with Level III hospitals additionally featuring a Special Class.

Service response time t: This refers to the waiting time for service, composed of two parts: 1) Time to reach the hospital $T'_{est} = \frac{S}{V_{\text{Real time}}}$; 2) Waiting time in the queue after arriving at the hospital.

2.3.2 Calculation of Hospital Selection Indicators

The hospital selection criteria prioritize shortest response time, high capacity level, and high reliability. Therefore, when calculating using utility functions, QoS parameters must first be categorized according to their inverse proportional relationship with availability. Among hospital selection indicators, resource availability decreases as service price, time, and saturation increase, while it increases with higher reliability and capacity levels. The calculation methods for the utility functions of the aforementioned QoS indicators are described below.

1) As price increases, service suitability decreases, represented by a linear decreasing function. Therefore, the utility function for price is defined as follows:

$$U_c = \frac{c_{\max} - c}{c_{\max} - c_{\min}} \tag{5}$$

c represents the price of hospital emergency care, where $c_{\max}$ and $c_{\min}$ denote the maximum and minimum prices offered by hospitals, respectively.

2) As service waiting time increases, service availability decreases. Waiting time for emergency care is the most critical factor. Therefore, the time utility function is calculated as follows:

$$U_t = \frac{\ln t_{\max} - \ln t}{\ln t_{\max} - \ln t_{\min}} \tag{6}$$

where t represents the waiting time for hospital services, and $t_{\max}$ and $t_{\min}$ denote the maximum and minimum waiting times for services within the hospital.

3) The service capacity level of a resource indicates the quality of care it provides. Patients select hospitals with appropriate treatment levels based on their medical needs. As capacity levels increase, service availability improves. Therefore, the utility function for capacity can be defined as follows:

$$U_{lev} = \frac{lev - lev_{\min}}{lev_{\max} - lev_{\min}} \tag{7}$$

where lev represents the emergency service capacity provided by the target hospital, with $lev_{\max}$ and $lev_{\min}$ denoting the maximum and minimum service capacities respectively.

4) Reliability indicates the probability that a resource's service can be successfully invoked. Therefore, its utility function is calculated as follows:

$$U_{re} = \frac{e^{re} - e^{re_{\min}}}{e^{re_{\max}} - e^{re_{\min}}} \tag{8}$$

where re represents the reliability information of the hospital's service provision, $re_{\max}$ and $re_{\min}$ denote the maximum and minimum reliability values of the hospital's emergency service provision, respectively.

The hospital's QoS evaluation employs a multi-objective utility function, calculated by weighting the utility functions of individual QoS parameters. The calculation formula is as follows:

$$U(c,t,lev,re) = \frac{w_c \times U_c + w_t \times U_t + w_{lev} \times U_{lev} + w_{re} \times U_{re}}{w_c + w_t + w_X + w_{lev} + w_{re}}, r_i \in R \tag{9}$$

Here, w_i represents the weight of the corresponding attribute.

Select a hospital resource r_i such that equation (9) achieves its maximum value, i.e., $\mathrm{Max}(U(c,t,lev,re))$.

2.3.3 Multi-Objective Utility Function for QoS

For the integrated digital platform for acute ischemic stroke prevention and emergency services, a service combination must be selected to maximize the utility value of the system's overall QoS requirements. Formally defined as:

$$\left(cs_1', cs_2', \ldots, cs_n'\right) = \underset{(x_1, x_2, \ldots, x_n) \in (cs_1, s_2, s_3)}{\operatorname{argmax}} \ utility\left(cs_1, cs_2, \ldots, cs_n, st_1, st_2, \ldots, st_m, x_1, x_2, \ldots, x_n\right)$$

Among these, $cs_1, cs_2, \ldots, cs_n$ — parameters required for evaluating the effectiveness of stroke prevention and emergency services; $st_1, st_2, \ldots, st_m$ — constant parameters within the system; $x_1, x_2, \ldots, x_n$ — parameters requiring selection. The optimization objective function is expressed as:

$$utility\left(cs_1, cs_2, \ldots, cs_n, st_1, st_2, \ldots, st_m, x_1, x_2, \ldots, x_n\right) = \sum_{i=1}^{r} w_i objective_i \tag{10}$$

where w_i represents the weight. By selecting the set of services with the maximum utility values, this serves as the outcome of the service selection.

2.4 Service Selection Algorithm Based on QoS Analysis

2.4.1 Problem Description

Within the integrated digital platform providing acute ischemic stroke medical services, multiple service providers utilize their resources to deliver the same emergency care. The primary challenge addressed in this chapter is how to select an optimal set of prevention and emergency services from multiple options to enhance service reliability and timeliness. Service selection within the prevention and emergency service system must satisfy specific constraints while accounting for dependencies between services. The choice of data analysis services, prevention services, and emergency services must consider the Quality of Service (QoS) metrics of each service to select those meeting user requirements.

2.4.2 Algorithm Description

Algorithm Input:

1) $r = \{r_1, r_2, r_3, \ldots\}$ is a set of service resources (hospitals)

where r_i — represents a specific service resource, defined as $r_i = \{name_i, c_i, t_i, lev_i, re_i\}$

$name_i$ — denotes the hospital's name;

c_i — Cost required to use the services provided by this hospital;

t_i — Waiting time required to use the treatment services provided by this hospital;

lev_i — Capacity of the services provided by this hospital;

re_i — Reliability of the services provided by this hospital.

2) QoS analysis results list datadictionary;

3) User requirement list RList

$$RList = \{R_0, R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8, R_9\} \tag{11}$$

Algorithm Output:

Service Selection Result List: *result*

The optimization objective of this problem is to select a service combination $result = \{s_1, s_2, .., s_i\}$ such that

$$Max\left(utility = \sum_{i=0}^{3} w_i objective_i\right) \tag{12}$$

Among these, w_i represents the weighting coefficient, with $\sum_{i=0}^{3} w_i = 1.0$;

$$objective_0 = -\sum_{i=0}^{8} R_i \tag{13}$$

$$objective_1 = -\sum_{i=1}^{3} \sum_{x=1}^{s_i} c_i^x \tag{14}$$

$$objective_2 = resource \tag{15}$$

$$objective_3 = R_9 \tag{16}$$

$$w_0 = w_2 = w_3 = 1000s, w_1 = 1.0 \tag{17}$$

Figure 2 depicts the service selection algorithm workflow. The steps of the service selection algorithm are as follows:

Input: List of hospital information r, list of user requirements RList, list of QoS analysis results datadictionary; Output: Service selection result result.

1) Calculate the utility function for QoS metrics of services provided by hospitals;

2) Select the hospital with the highest utility value from multiple hospitals based on Equation (9);

3) Calculate the row value corresponding to each key in the data dictionary using Equation (10);

4) Select the service combination with the highest utility value that maximizes the optimization objective function as the specific service to be invoked.

5) If this solution fails to meet user QoS requirements, modify the user SLA agreement—i.e., adjust user QoS demands—to approximate user needs as closely as possible. Re-execute analysis and selection.

6) Output results.

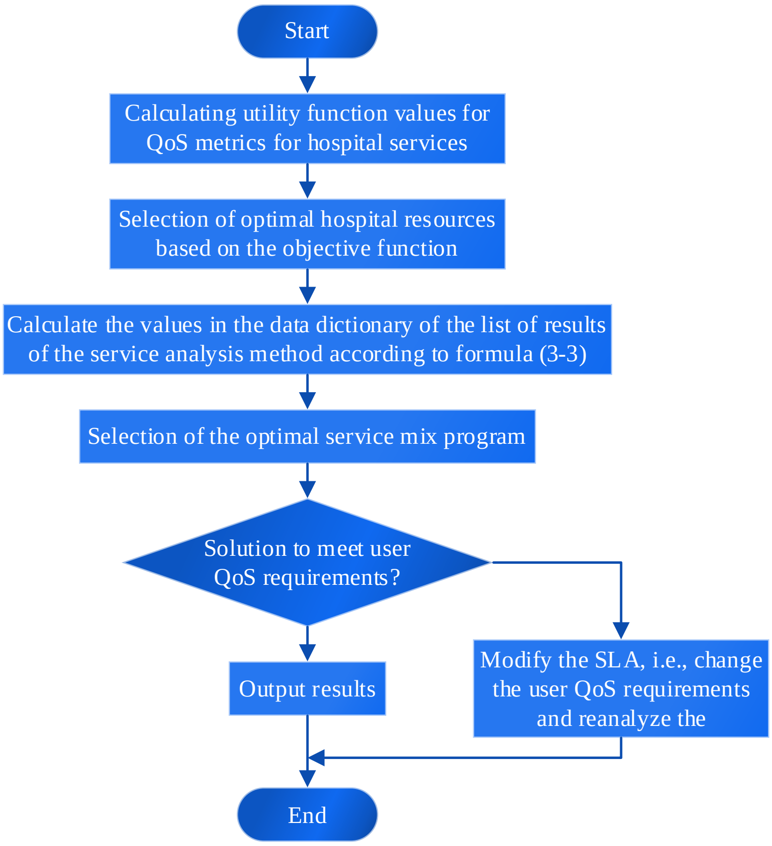


Figure 2: Flowchart of Service Selection Algorithm

3 Application of an Integrated Digital Platform in Stroke Emergency Care

3.1 Analysis of the Knowledge Graph Construction Process for Stroke Based on the MCDE Method

3.1.1 Entity Statistics for Stroke Medical Dataset

To demonstrate that selecting MCDE as a deep learning-based entity relation extraction and completion method can deeply mine knowledge related to acute ischemic stroke, thereby enhancing the coverage and accuracy of knowledge graphs, this section analyzes the stroke knowledge graph construction process based on MCDE. The stroke related properties and relational information, such as the symptoms, therapies, medication, and first aid, is preprocessed. After tokenization and part-of-speech tagging, Table 1 displays statistical findings on the entity segmentation in the acute ischemic stroke medical dataset. The medical entities that are extracted by the stroke are grouped into eight types of attributes which include examination items, departments visited, diseases, medications, foods, symptoms, patient demographics, and lifestyle habits. It is consistent with the somewhat small amount of entities present in medical datasets. The number of entities varied between 371 and 2372 entries, which is quite a wide range of content. To improve the entity relation extraction and completion performance of MCDE, the entity data was randomly partitioned into training, validation, and test sets.

Table 1: Entity statistics of medical data set for acute ischemic stroke

Entity type	Number of entities	Training set	Validation set	Test set
Check items	1317	715	301	301
Department of visit	371	141	115	115
Disease	1236	662	287	287
Medicine	2372	1344	514	514
Food	1138	602	268	268
Symptoms	1234	656	289	289
Crowd	791	397	197	197
Living habits	1110	702	204	204

3.1.2 Recognition Performance for Different Entity Types

When MCDE training was finished, its recognition of different entities was measured with respect to entity data of the test set. The following table (Table 2) presents the recognition results of MCDE on the different types of entities on the test set. In the medical dataset, MCDE was used to find entities in the integrated digital platform. The findings reveal that the greatest measures of precision, recall, and F1 were obtained by the entities that are known as the Department Visited and Population Group. The entity recognition of the department visited had a precision of 0.9875, a recall of 0.9931 and a F1 score of 0.9718. The performance of identifying patient group entities obtained a result of 0.9905 in terms of accuracy, 0.9769 in terms of recall and 0.9653 in terms of F1 score. It is inferred that it could be due to the fact that there are relatively few names of these two types of entities, they are inherently distinctive, and the standard forms of expressions can be effectively learned through deep learning.

Table 2: Recognition effect of MCDE on different entity types on the test set

Entity type	Accuracy rate	Recall rate	F1 value
Check items	0.9741	0.9696	0.9531
Department of visit	**0.9875**	**0.9931**	**0.9718**
Disease	0.9782	0.9582	0.9497
Medicine	0.9446	0.9331	0.9207
Food	0.9731	0.9671	0.9516
Symptoms	0.9342	0.9257	0.9116
Crowd	**0.9905**	**0.9769**	**0.9653**
Living habits	0.9077	0.9034	0.9019

3.1.3 Knowledge Graph Embedding Example

Upon completing the processes of medical entity knowledge, such as the definition of entity relationships, entity characteristics, knowledge extraction, knowledge fusion, entity linking, and knowledge merging, medical knowledge concerning acute ischemic stroke is eventually put into the knowledge graph in the form of triples. The knowledge graph will be further incorporated into the integrated digital platform of stroke care, which will enable its use at the emergency response stage. Figure 3 is a picture of some part of the stroke knowledge graph. This segment illustrates entities and relationships associated with acute ischemic stroke. The eight entities correspond to: liver function tests, neurology department, muscle weakness, aspirin, hawthorn, facial asymmetry, diabetic patients, and high-fat/high-salt diet. When a diabetic patient experiences acute ischemic stroke symptoms like muscle weakness, the integrated digital platform's knowledge graph enables rapid identification of potential patient conditions. Combined with a service selection algorithm based on QoS analysis, this facilitates determination of optimal emergency interventions.

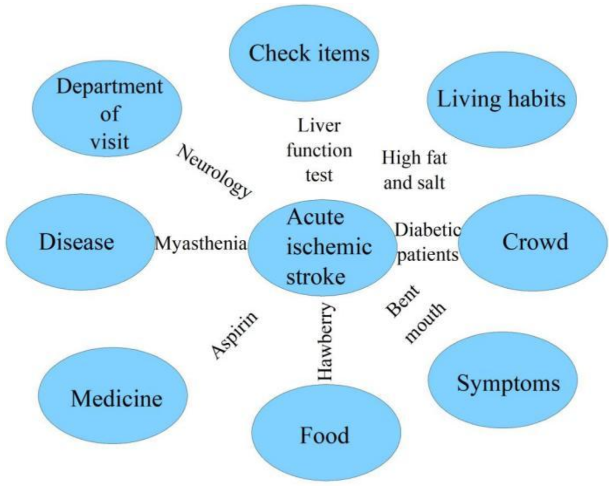


Figure 3: Example of partial knowledge graph of stroke

3.2 Performance Evaluation of Service Selection Algorithms Based on QoS Analysis

3.2.1 Scalability Analysis

In acute ischemic stroke emergency care, a single patient may require multiple services, or multiple patients may require the same service. Therefore, scalability in solving uncertain emergency medical service combination problems is a key criterion for evaluating the quality of service (QoS)-based service selection algorithms. To assess the scalability of QoS-based service selection algorithms, the BHUC algorithm is selected as the comparison algorithm. Subsequently, the quantities of uncertain and certain emergency medical services within the integrated digital platform's resource repository—such as dynamically adjusted knowledge graphs—were varied. The response time for solving an uncertain emergency medical service combination problem under these conditions was then measured to test algorithmic scalability. This section divided the 30,000 emergency medical services in the service repository into three groups, each containing different numbers of uncertain services (5, 6, 7). Within each group, as the number of emergency medical services increases from 1,000 to 4,000, the response time results for the two algorithms are obtained as shown in Figure 4.

When the number of uncertain emergency medical services is 5, the response time for the QoS-based service selection algorithm is 2.428–5.032 seconds; when the number is 6, the response time is 11.475–13.155 seconds; When the number was 7, the response time was 31.985–34.844 s. For numbers 5, 6, and 7, the corresponding response times for the BHUC algorithm were: [2.754, 5.637] s, [12.418, 14.294] s, and [52.738, 55.792] s. When emergency medical service tasks under uncertainty are consistent, the QoS-based service selection algorithm consistently achieves shorter solution response times than the comparison algorithms. Thus, applying the QoS-based service selection algorithm within an integrated digital platform enables faster response to emergency demands and identification of combined service solutions that fully satisfy all healthcare personnel requirements.

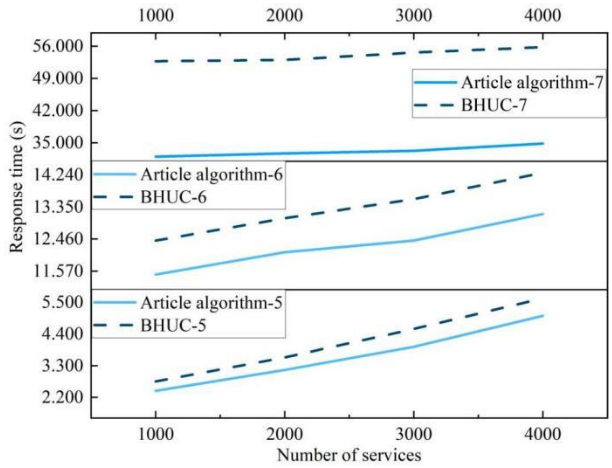


Figure 4: Time required for 2 algorithms to solve problems of different groups

3.2.2 Reliability Analysis

The solution process for five combinations of uncertain emergency medical service problems is illustrated. By analyzing uncertain QoS call records of emergency medical services, the reliability of service selection algorithms based on QoS analysis is evaluated. Table 3 presents the QoS call record results when the number of uncertain emergency medical services is five. The five uncertain emergency medical service problems were sequentially decomposed into two parts for simultaneous solution with millisecond-level time precision. The solution result availability ranged from 0.781 to 0.925, with the highest exceeding 0.900. Moreover, the delay in the simultaneous solution process did not exceed 0.010 ms, with the minimum being only 0.004 ms and the maximum delay being just 0.009 ms. The simultaneous resolution of multiple uncertain emergency medical service problems using a QoS-based service selection algorithm yields highly reliable results that meet the correctness requirements for emergency scenarios.

Table 3: QoS call records for emergency medical services with 5 uncertainty level

Task Node	Service Library	Service	Response time (s)	Usability	Delay (ms)
T_1	R_1	Rm_1	2.428	0.781	0.004
		Rm_2	2.441	0.785	0.005
T_2	R_2	Rm_3	3.154	0.802	0.003
		Rm_4	3.209	0.813	0.004
T_3	R_3	Rm_5	3.957	0.845	0.006
		Rm_6	4.014	0.871	0.005
T_4	R_4	Rm_7	4.582	0.894	0.007
		Rm_8	4.736	0.898	0.007
T_5	R_5	Rm_9	5.002	0.910	0.009
		Rm_{10}	5.032	0.925	0.009

3.2.3 Service Quality Analysis

When medical personnel assess a patient's condition during acute ischemic stroke emergency care and specify different QoS preferences on an integrated digital platform, the QoS-based service selection algorithm can generate varying numbers of interval Pareto-optimal service combinations. These solutions minimize response time and latency while maximizing availability for combined emergency medical services. Specifically, when medical personnel provide no QoS preferences, the uncertainty-aware QoS-aware emergency medical service combination problem yields 32 interval Pareto optimal solutions. These encompass all other combination service solutions with preference constraints. Moreover, within the set of combination service solutions, no two combination services exhibit mutually dominant QoS values. To visually represent the distribution characteristics of QoS quality in the combined service solutions, the upper and lower bounds of each QoS interval dimension were selected. Figure 5 illustrates the combined distribution characteristics of QoS values in three-dimensional space for combined service solutions when medical personnel did not specify QoS preference constraints. The availability of the 32 Pareto-optimal solutions ranges from a maximum of 95.283% to a minimum of 77.112%, with most exceeding 80%. Even without healthcare personnel specifying QoS preferences, the service quality maintained by the QoS-based service selection algorithm remains at a high level. When healthcare personnel provide explicit QoS preferences, the resulting solutions become more precise.

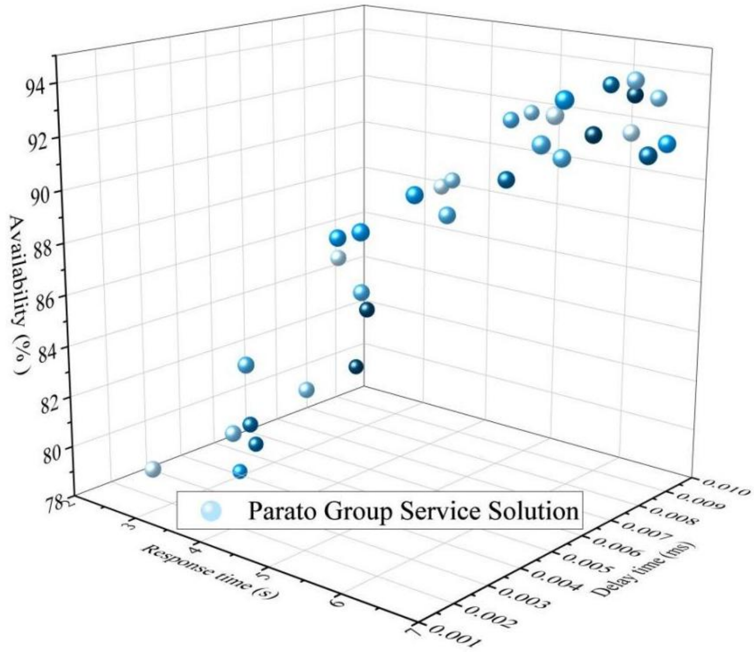
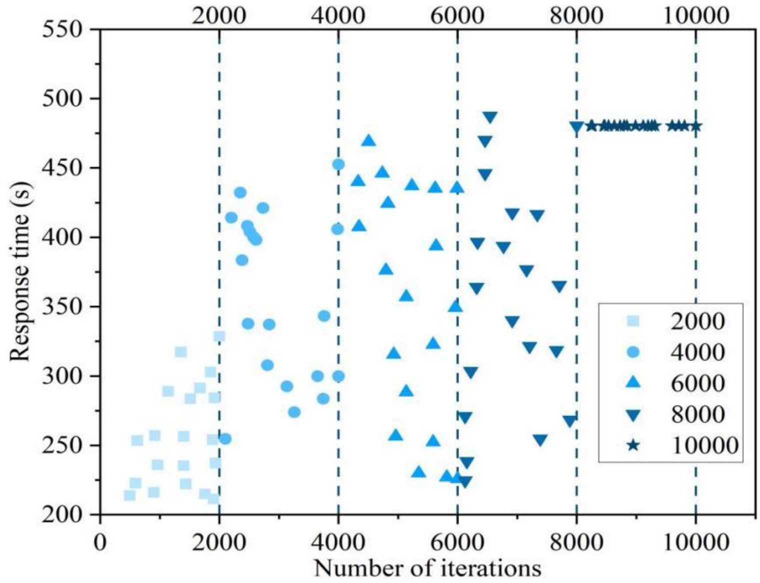


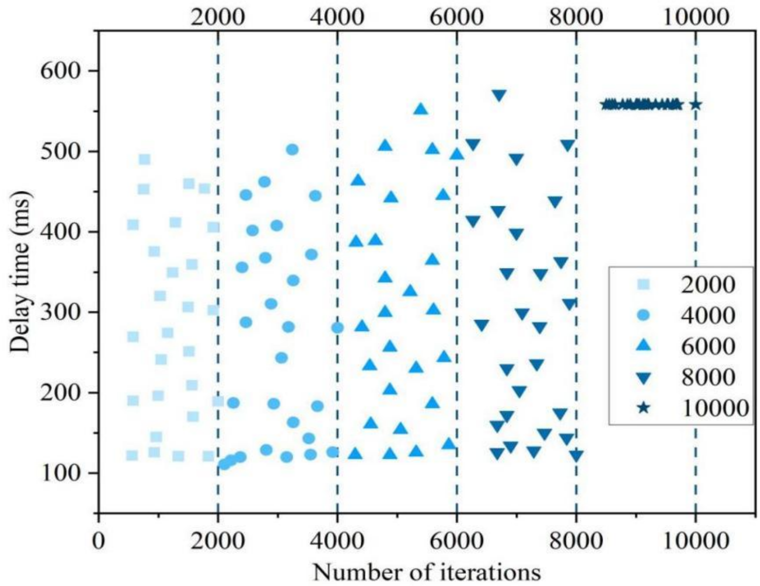
Figure 5: QoS spatial distribution of emergency medical team services

3.2.4 Convergence Analysis

To further validate the convergence of the QoS-based service selection algorithm when addressing multiple uncertain emergency medical service problems, we analyze how the optimal QoS values for combined services change with increasing iteration counts. Figure 6 displays how the response time and delay time values of the combined service QoS change with the number of iterations. Both the optimal response time and delay time of the combined emergency medical service continue to vary before 8,000 iterations, with both having unstable values. Following 8,000 iterations, the best emergency medical combined service QoS response time and delay time are constant, and tend towards stability. It shows that the algorithm of selecting a service by means of QoS analysis has good convergence properties, which can bring the solution to the uncertain QoS-related problem of combining emergency medical services to a set of constants.



(a) Change in the QoS response time of the combined service



(b) Change in the QoS delay time of the combined service

Figure 6: Change in optimal QoS value when the number of iterations changes

3.3 Emergency Application and Effectiveness Analysis

3.3.1 Comparison of Emergency Response Efficiency Between the Two Patient Groups

Following the conclusion of building the integrated digital platform and testing the performance of its knowledge graph and QoS-based service selection algorithm, the platform was used on acute ischemic stroke emergency response tasks. In order to make sure that the platform would be effective, there were two groups created, including an observation group and a control group, each with 100 acute ischemic stroke patients to perform simulated emergency response experiments. The experimental group did emergency tasks through the integrated digital platform whereas the observation group applied conventional emergency measures. Another control group was also set up whereby no emergency management was done. The comparison between the emergency efficiency and results of three groups was made to determine whether the integrated digital platform can be used in acute ischemic stroke emergency response.

The figure 7 illustrates the comparison of the efficiency of emergency response between these three groups. In contrast with the control group where the emergency treatment was not given, the experimental and observation groups showed a significantly greater effectiveness of the emergency response. Three emergency efficiency indicators, i.e., DTP, DTT, and DNT, the efficiencies obtained by the experimental group were 6.29±1.03, 20.48±3.74, and 17.35±5.12, respectively, which are higher than the values of the observation group of 3.91±1.37, 13.27±4.92, and 10.65±5.81. All three groups had P-values of 0.001 (significant differences) in their emergency response efficiency. Implementation of an integrated digital platform allows providing acute ischemic stroke patients with quicker access to critical emergency information and ensures the highest possible quality of emergency care.

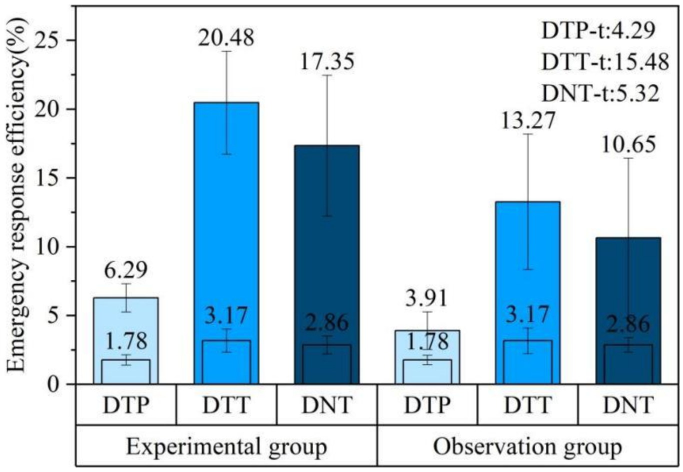


Figure 7: Emergency response efficiency of the two groups of patients

3.3.2 Comparison of Emergency Treatment Outcomes Between the Two Patient Groups

Figure 8 compares the emergency treatment outcomes across three patient groups. After utilizing an integrated digital platform to assist emergency care, the experimental group achieved a thrombolysis success rate of 91.86% in acute ischemic stroke patients, with a NIHSS score of 7.79 (out of 10) 24 hours post-thrombolysis. The control group, which did not receive emergency measures, achieved a thrombolysis success rate of only 20.57% and a NIHSS score of 0.93. The P-value for all three groups was 0.001, indicating a statistically significant difference at the 0.01 level. The use of an integrated digital platform for emergency care resulted in superior emergency treatment outcomes.

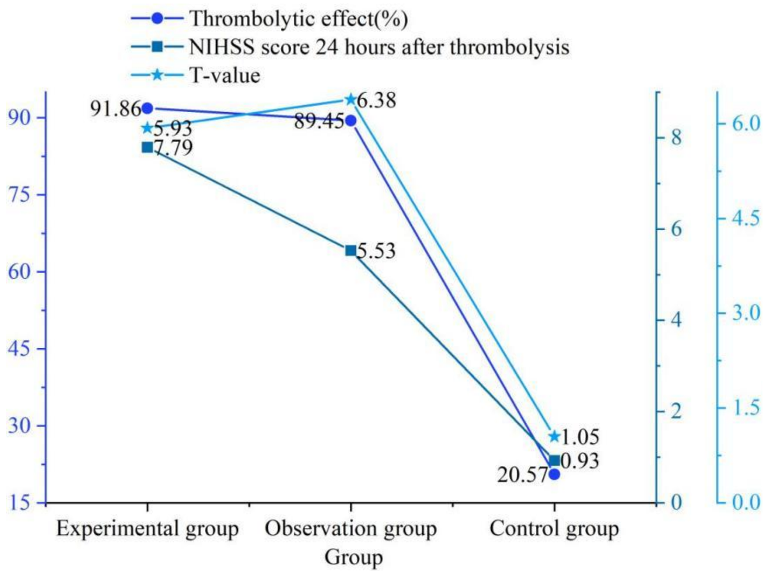


Figure 8: Emergency treatment effects of the three groups of patients

4 Conclusion

This paper designs and constructs an integrated digital platform to enhance the speed and quality of stroke emergency care. In knowledge graph construction using the MCDE method, medical knowledge data was categorized into 8 entity types, with the highest recognition accuracy achieved for the two entity types: outpatient departments and patient demographics. The algorithm of service selection that was built upon the analysis of QoS demonstrated the ability to respond rapidly to uncertain emergency medical tasks at levels 5, 6, and 7. The results of solutions were highly usable, reaching a peak of 0.925, and synchronous solution delays are kept under 0.010 ms which makes them extremely fast. Three emergency care evaluation metrics have been met by the integrated digital platform: 6.29±1.03%, 20.48±3.74% and 17.35±5.12%. The highest efficacy of thrombolysis was found to be 91.86 percent, and the NIHSS score after 24 hours of thrombolysis was 7.79, which is much higher than the effectiveness of traditional emergency procedures and non-intervention.

About the Authors

Xiaolin Hou (1977-7), male, Han nationality, Yinchuan, Ningxia, master's degree, director, research interests include cerebrovascular disease and neurointervention.

Huarui Zhang (1999-10), female, Han Chinese, Zhongwei, Ningxia, Undergraduate master's degree, research direction cerebrovascular disease.

Juan Yang (1985-06), female, Han ethnicity, Ningxia Tongxin, doctoral candidate, associate chief physician, research interests include cerebrovascular disease, neuroimmunology, etc.

Li Zhao (1981-10), female, Han ethnicity, Alxa Left Banner, Inner Mongolia, Postgraduate student, associate chief physician, research interests include cerebrovascular disease, neuroimmunology, etc.

Xiaoyu Wu (2002-1), female, Han ethnicity, Inner Mongolia, Xilingol League, undergraduate, graduate student, research direction cerebrovascular disease.

Xiaoping Tu (1969-10), male, Han nationality, Yinchuan, Ningxia, Undergraduate, associate chief physician, research interests include cerebrovascular disease, neurointerventional medicine, etc.

Yi Zhao (1999-1), male, Han nationality, Guyuan, Ningxia, he is an undergraduate and a graduate student. His research interest is cerebrovascular disease.

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