Research on the Impact of the Knowledge Graph on Public Service Quality

Yingjing Wang(✉)

Xiamen University Malaysia, Jalan Sunsuria, 43900 Bandar Sunsuria, Sepang, Selangor, Malaysia
Wangyingjing70@gmail.com

Abstract. The improvement of public service quality is an inevitable requirement for promoting national well-being, safeguarding public interests, and promoting social progress. At present, artificial intelligence technology characterized by permeability, synergy, substitution, and innovation is defined as the prime mover to the development in various industries. Artificial intelligence technology represented by the knowledge graph will complete the transformation of the public service system from automation to intelligence. Based on the existing problems of public service and the technical logic of the knowledge graph, this article attempts to explore the possibility of the knowledge graph to improve the quality of public services. By discussing the technical characteristics and creation process of the knowledge graph, a feasible application scheme in grassroots service is proposed.

Keywords: Artificial intelligence · Knowledge graph · Public services · Quality improvement

1 Introduction

Whether it is an intangible labor product or an institutional arrangement for government empowerment, public service itself contains core values such as efficiency and fairness. Public service is the main function of government, and citizen supremacy is one of the basic principles for the government to perform its obligations (Sanchez-Ramos, 2018). Unfortunately, it is quite challenging for the government to truly implement these concepts in the process of providing public services.

All actions of the government will generate a large amount of service data. Challenges abound in analyzing big data because of its diversity, timeliness, uncertainty, and so on (Kitchin, 2014). Thanks to the development of the information age, science has been bringing changes to the field of public service over the past few decades. In 2012, Google proposed the concept of the knowledge graph which was used to improve the efficiency of search engines and enhance the user experience (P. WANG, 2021). However, as a relational organization technology, the knowledge graph can describe entities, attributes, and their relationships in real society as well. This enables the intelligent response service system driven by the knowledge graph to respond more efficiently, optimize solutions, and improve service satisfaction.

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The public service encompasses a wide range of activities, the service span is vast, and the cases involving complex interpersonal relationships emerge endlessly, which leads to the inefficient output of public service efficiency and the difficulty of unified service quality. At present, researchers normally apply the knowledge graph to the fields of financial technology, e-commerce, libraries, and medical care, but ignore that public service has always been one of the best places for this technology implementation.

2 Construction Background

2.1 The Urgency of Improving the Quality of Public Service

Digital governance is the foundation of modern governance and an effective guarantee to promote the transformation of public service mechanisms to modernization. It is challenging to break through the bottleneck of the existing service quality by the traditional service demand model. Therefore, technological innovation and reconstruction of the governance structure have become necessary.

First, the contradiction between the digital technology of information exchange and the bureaucratic system with a distinct hierarchy has gradually become prominent (Weng, 2023). The openness of big data can increase the transparency operations and eliminate regulatory blind spots. (Lindstedt & Naurin, 2010) Compared with the hierarchical bureaucracy, the addition of big data has encouraged the social public and media to participate in service supervision (Naz, 2009).

In addition, the repeatability of government work will be reduced by data connectivity, exchange, and sharing (Troisi et al., 2018). Compared with the traditional service model that is prone to data fragmentation and data barriers, artificial intelligence technology can improve the reuse value of data resources scattered in various departments.

Decision unfairness and unreasonable prediction are other dimensions of bad situations (Rissi et al., 2015). We can accurately predict demand by building a big data platform with an evidence-based decision-making mechanism. With the assistance of intelligent algorithms, resources are rationally allocated for the diverse needs of the people (Kim et al., 2014). At the same time, it will alleviate the dependence of traditional decision-making methods on subjective cognition and empirical judgment.

The public service sector is an important position for big data-driven change and currently moving towards an intelligent model based on algorithms and data. Big data will be used to correct and reconstruct the public service form of the government in the information age (Naz, 2009).

2.2 The Correlation Between the Knowledge Graph and Public Service

The integration of the knowledge graph can improve the scientificity of public service decision-making, which mainly makes up for the lack of information in a manual system. Data-based intelligent algorithms can address the unreasonable decision-making of service personnel relying on experience and feeling. By crawling the existing data in the database, the scientific scheme generated by the knowledge graph can better convince users to solve the deviation caused by individual values.

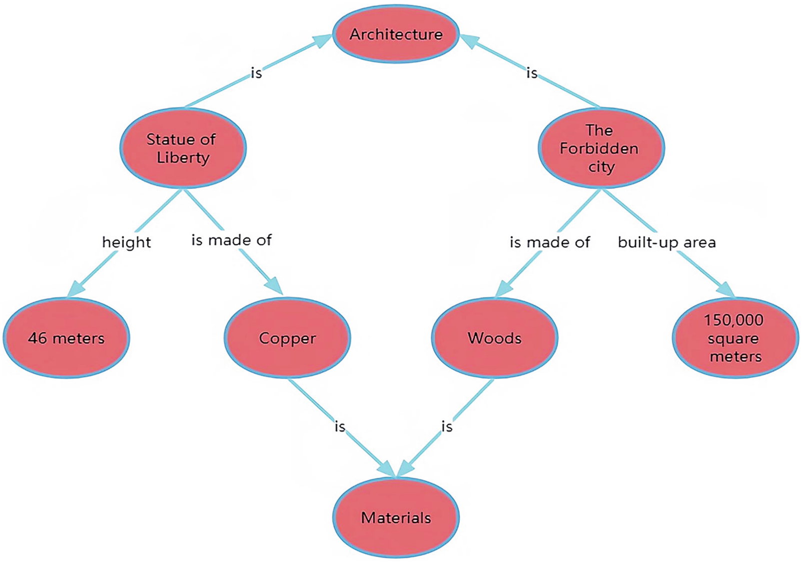

Fig. 1. Example conceptual diagram

In addition, with the support of artificial intelligence technology, the knowledge graph has been combined with many fields related to public services (H. WANG, 2021). The knowledge graph can be applied to Question Answering (QA) in the field of public services as well. Compared with ordinary search engines, the knowledge graph can dig out the answer that best meets the user's intention and improve satisfaction. Based on the rich amount of data, it improves the standardization of public services, which means that the objects of public services can be more extensive. This undoubtedly expanded the service communication channels. Diversified big data platforms enable citizens to choose the way to interact with the government (Sanchez-Ramos, 2018).

3 Construction of the Knowledge Graph

3.1 Overview of the Knowledge Graph

The essence of the knowledge graph is a semantic network. Nodes and edges are the main components of the knowledge graph. The entities of the objective world are the nodes in the knowledge graph. Among them, entities are divided into physical entities and conceptual entities. The edge is composed of attributes and relations. The knowledge graph is a multi-relational graph generated by linking nodes and edges, which contains a variety of different types of nodes and edges (Fig. 1).

3.2 The Construction Logic of the Knowledge Graph

The knowledge graph can be logically divided into two levels: the pattern layer and the data layer. The pattern layer is above the data layer and is the core of the knowledge graph

(YUAN et al., 2022). The pattern layer has two forms: entity-attribute-attribute value and entity-relation-entity (D. ZHAO et al., 2020). The data layer is mainly composed of a series of facts.

The knowledge graph mainly has two construction methods: top-down and bottom-up. The top-down construction method needs to define a data template for the knowledge graph before adding entities. The source of these entities relies on structured data in high-quality databases. The bottom-up construction method requires us to extract entities from public external data (Su et al., 2016). The ontology model can be constructed after selecting the part with higher credibility and adding the database.

This research uses a combination of two methods to construct a public service knowledge graph to improve data credibility and coverage. The construction process is shown in Fig. 2.

Pattern Design

We need to determine what type of knowledge graph is constructed, including the definition of class relations, class domains, and class attributes (Su et al., 2016). Class relation contains the active and passive relationship between two entities. They can be defined as unidirectional or bidirectional. The definition of class attributes is divided into two categories: public attributes and private attributes. Among them, public attributes represent the common characteristics of basic things such as name and time. Private attributes have different definitions according to different areas, such as built-up areas of architecture. Pattern design determines the key nodes of knowledge extraction and is the basic framework for the automatic construction of the knowledge graph (Sun et al., 2021).

Knowledge Extraction

Knowledge extraction is a process of identifying, extracting, and formatting semi-structured data and unstructured data. We need to extract entities to show the potential

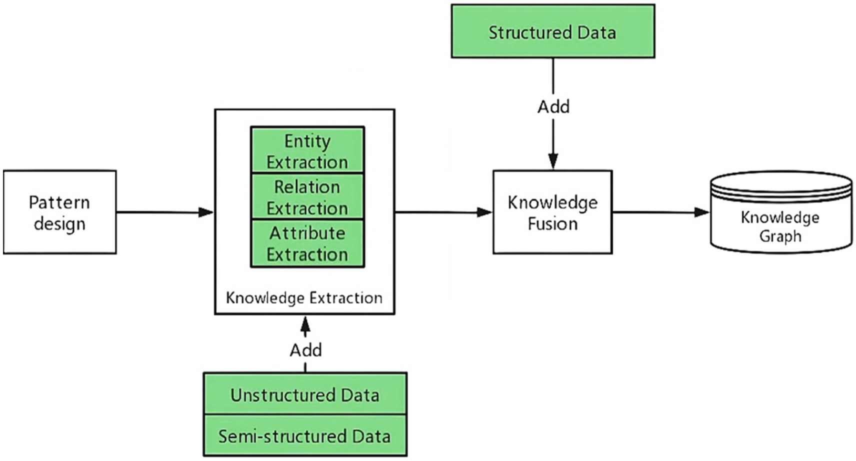

Fig. 2. Flow chart of knowledge graph construction

relationship between them. Knowledge extraction is a necessary operation before data enters the database. Entity extraction is the identification of defined public attributes such as names and locations. The primary purpose of relation extraction is to identify the relationship of each entity in the statement and construct the identified data into triples. Attribute extraction further enriches the dimension of the knowledge graph by extracting private attributes and attribute values of entities (H. ZHAO, 2020).

Knowledge Fusion

Knowledge fusion is a process of data cleaning and data integration of the knowledge graph after adding structured data. Its significance is to eliminate the heterogeneity of knowledge graphs and clean up the overlapping data between different knowledge graphs. Knowledge fusion is generally divided into two steps: ontology alignment and entity matching. Due to different data sources, knowledge fusion technology faces challenges in data quality and data size (Pan & Zhang, 2016).

4 Ontology Construction of Public Service System

This research modifies the ontology construction of the public service system based on the Seven-step Method to make it more in line with the current situation. The modified construction process is roughly divided into defining domain, information acquisition, determining ontology attributes and labels, digging out entity relationships, and instance construction.

4.1 Defining Domain

We need to identify the domain of the ontology based on the information type and application requirements. The focus of the research is the field of public service. Based on this logic, we frame the domain of ontology construction within the issue of citizen life services. The problem of life service mainly involves education problems, safety problems, medical security problems, traffic problems, and so on.

4.2 Information Acquisition

One of the prerequisites for the construction of the knowledge graph is to collect and integrate data from different data sources. First of all, we can obtain data from the records of previous government services and crawl data through existing databases. These two methods are the embodiment of the reusing and transformation of existing ontology (Su et al., 2016). Another broader and commonly used way is to crawl semi-structured data or unstructured data on society and the Internet.

4.3 Determining Ontology Attributes and Labels

First of all, according to the progression of events, we can divide the knowledge graph entities into three categories: related people or departments, causes, and results. The relevant public service departments must cover all aspects of citizens ’ daily life such

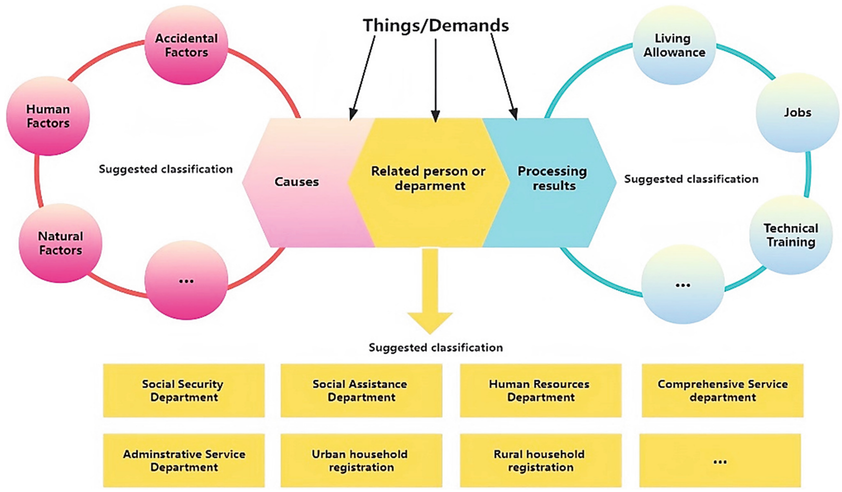

Fig. 3. Suggested classification

as the Social Security Department, Social Assistance Department. Furthermore, the classification of citizens can be divided into rural and urban areas according to the type of household registration. As long as the classification can cover all citizens are considered reasonable. The cause can be divided into human factors, natural factors, and so on according to the properties of the event. After that, the final processing results can be expressed as the benefits obtained by citizens (Fig. 3).

4.4 Digging Out Entity Relationships

The tasks of relation extraction mainly include named entity recognition, relation extraction, entity resolution, and coreference resolution (Culotta & Sorensen, 2004). We need to dig out entities and label them first. The entity resolution requires us to merge and identify different names of objects as the same entity fusion. For the pronouns appearing in the sentence, we will perform coreference resolution and merge the same entity (Deng, 2021).

4.5 Instance Construction

Any created instance will be stored in the database as an individual of the class. Just like we put new data into the table, the database needs to be constantly incorporated into new examples to improve and upgrade. Some examples of construction are shown in Fig. 2. (Example: The resident holds a rural household registration, and the accidental factors caused his disability. The Social Assistance Department provided him with a living allowance, and the Human Resources Department provided him with a job) (Figs. 4 and 5).

4.6 Accuracy Evaluation of the Knowledge Graph

After establishing a new knowledge graph, we need to evaluate the accuracy rate (AR) and recall rate (RR) of the knowledge graph regularly. In this research, TP (true false)

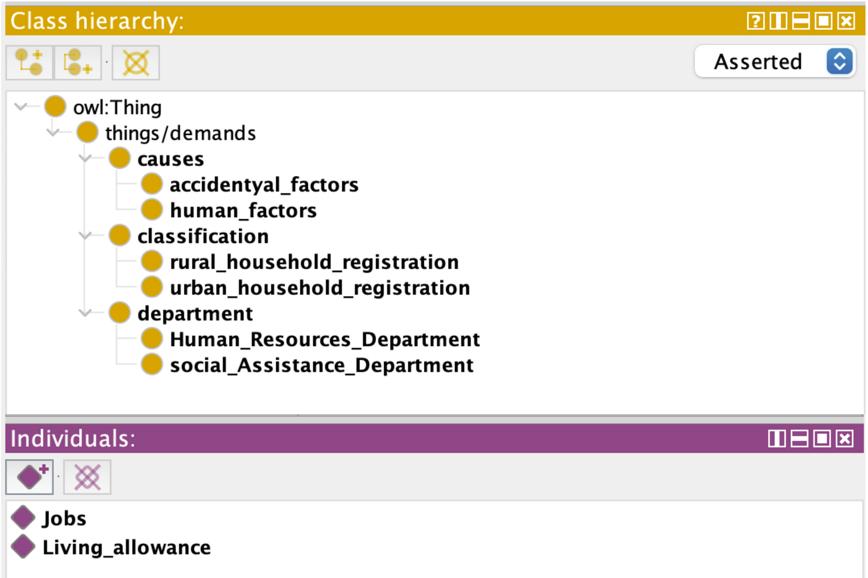

Fig. 4. Ontology construction diagram

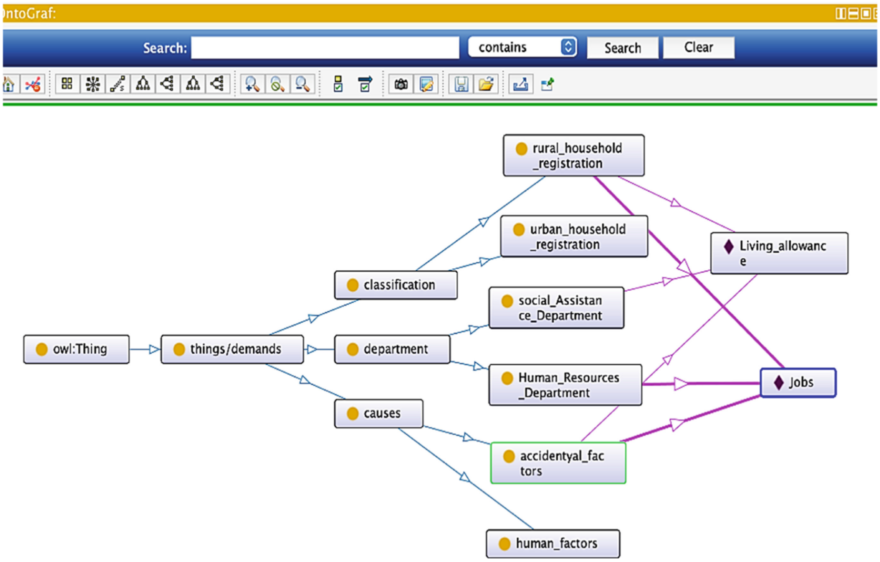

Fig. 5. Partial result presentation

refers to correct recognition and correct prediction, FP (false positive) refers to correct recognition but wrong prediction, TN (true negative) refers to wrong recognition but correct prediction, and FN (false negative) refers to wrong recognition and wrong prediction. (Qin, 2021) The formulas of accuracy rate (AR) and recall rate (RR) are shown in (1) and (2). The F1 value is to consider the comprehensive effect of the two, and the formula is shown in (3).

$$AR = \frac{TP}{TP + FP} \tag{1}$$

$$RR = \frac{TP}{TP + FN} \tag{2}$$

$$F1 = \frac{2 * AR * RR}{AR + RR} \tag{3}$$

The method with the highest success rate for the above detection is manual detection, but it is not suitable for the large-scale whole. Therefore, this study takes accuracy rate (AR) as an example and adopts the method of sample evaluation. The statistical significance involved is unbiased and confidence interval, the latter is the embodiment of the accuracy of the knowledge graph.

We assume that the sample ratio $\overline{p}$ is a point estimator of the overall ratio p, , and its formula is shown in (4). x represents the number of questions answered accurately, and n represents the sample size of the sample. The mathematical expectation of $\overline{p}$ can be obtained by the mean of all $\overline{p}$, which is equal to the overall ratio p. Therefore, we have $E(\overline{p}) = p$, that is, $\overline{p}$ is an unbiased estimator of p.

$$\overline{p} = \frac{x}{n} \tag{4}$$

According to the central limit theorem, when the capacity n of any sample is large enough, that is, $np \geq 5\, and\, n(1-p) \geq 5$, its sampling distribution can approximately conform to the normal distribution. Since we do not know the overall probability$p$, we use the probability $\overline{p}$ of the sample to estimate and replace$p$. We first calculate the standard deviation of$\overline{p}$. In this research, the default population is limited and recorded as N. According to the rule of thumb if we have ${}^{n}/_{N} \leq 0.05$, then we will use the formula (5) to calculate. On the contrary, it is necessary to adopt a finite overall correction coefficient, the specific formula is shown in (6).

$$\sigma_{\overline{p}} = \sqrt{\frac{p(1-p)}{n}} \tag{5}$$

$$\sigma_{\overline{p}} = \sqrt{\frac{N-n}{N-1}}\sqrt{\frac{p(1-p)}{n}} \tag{6}$$

The margin of error is $z_{\alpha/2}\sigma_{\overline{p}}$ and we have the possibility of $100(1-\alpha)\%$ to contain the overall true value in the final confidence interval. The specific calculation formula of the confidence interval is shown in (7). Where $1-\alpha$ is the confidence coefficient, $z_{\alpha/2}$ is the z value when the upper side area is $\alpha/2$ under the standard normal distribution.

$$(\overline{p} - z_{\alpha/2}\sqrt{\frac{\overline{p}(1-\overline{p})}{n}}, \overline{p} + z_{\alpha/2}\sqrt{\frac{\overline{p}(1-\overline{p})}{n}}) \tag{7}$$

If expressed as a percentage, the accuracy of the overall knowledge graph is between $100\left(\overline{p} - z_{\alpha/2}\sqrt{\frac{\overline{p}(1-\overline{p})}{n}}\right)\%$ and $100\left(\overline{p} + z_{\alpha/2}\sqrt{\frac{\overline{p}(1-\overline{p})}{n}}\right)\%$ at the confidence level of $100(1-\alpha)\%$.

5 Evaluation of the Use Area

We need to apply knowledge graph technology to areas with low service satisfaction. This study evaluates the service quality of a region based on the SERVQUAL model. According to the five dimensions, namely, Assurance, Empathy, Reliability, Responsiveness, and Tangibility, a questionnaire survey was conducted. We must first analyze the reliability and validity of the questionnaire results to calculate the satisfaction of the region based on the SERVQUAL model. Reliability is the credibility of the measurement results and the consistency of multiple measurement results. Validity represents the true level of measurement (Fig. 6).

5.1 Reliability Analysis

In this research, the most common Cronbach's Alpha coefficient is used for reliability analysis. Usually, the value of Cronbach's Alpha coefficient is between 0 and 1. If the coefficient value is less than 0.6, we believe that the internal consistency is insufficient. The reliability between 0.7 and 0.9 is acceptable. A coefficient greater than 0.9 represents excellent reliability.

The calculation formula is shown in (8). In this formula, k represents the number of items to be measured, ${S_i}^2$ is the variance of the measured value of the item score, and ${S_x}^2$ is the variance of the total score. When calculating ${S_x}^2$, we need to calculate the total score of all rows and form a new data set. By calculating the mean and variance of the data set, ${S_x}^2$ can be obtained.

$$alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k} {S_i}^2}{{S_x}^2}\right) \tag{8}$$

$$var(x_1, x_2, \cdots, x_n) = \frac{(x_1 - \overline{x})^2 + (x_2 - \overline{x})^2 + \cdots + (x_n - \overline{x})^2}{n-1} \tag{9}$$

5.2 Validity Analysis

This research uses the KMO test to measure validity. Validity is measured by comparing the relative size of the simple correlation coefficient and the bias correlation coefficient

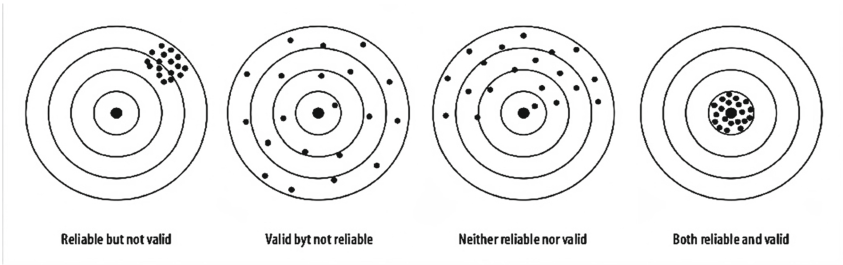

Fig. 6. Display of the reliability and validity

between the original variables. When the sum of squares of the latter value is much smaller than the sum of squares of the former value, we say that the correlation coefficient between variables is very small and the KMO value is close to 1. Its calculation formula is expressed as (10).

Here r_{ij} represents the simple correlation coefficient. $\alpha_{ij.1,2,3,\cdots k}$ denotes the partial correlation coefficient, that is, when the variable x_n(n = 1, 2, 3, $\cdots$,k) is fixed, the partial correlation coefficient of the two variables x_i andx_j. It refers to the linear correlation coefficient of two specific variables in n variables when the remaining (n-2) variables are fixed.

To obtain the KMO value, we must perform two summations. For example, for variables i and j, our sum objective function is F (i, j). We first need to find the sum of the F (i, j) values when i changes. Then we get the sum of F (i, j) values when j changes. When $\alpha_{ij.1,2,3,\cdots k} \approx 0$, we have KMO $\approx$ 1. When $\alpha_{ij.1,2,3,\cdots k} \approx 1$, we have KMO $\approx$ 0.

$$KMO = \frac{\sum\sum_{i\neq j} {r_{ij}}^2}{\sum\sum_{i\neq j} {r_{ij}}^2 + \sum\sum_{i\neq j} {\alpha_{ij.1,2,3,\cdots k}}^2} \quad (10)$$

Next, setting the confidence level to 95%, we use the Bartlett spherical test to make assumptions: H_0: the correlation coefficient matrix is the unit matrix, H_a: the correlation coefficient matrix is not the unit matrix. We use SPSS output to test chi-square statistics, degrees of freedom, and significance values. If p-value $\leq$ 0.05, we reject the null hypothesis that the correlation coefficient matrix is not a unit matrix and the variables are correlated.

5.3 Service Quality Analysis

The calculation formula of the SERVQUAL model is shown in (11). Where SQ is the calculated value of service quality, n is the number of questionnaire questions, P_i is the actual score of the residents of the ith project, and E_i is the expected score of the residents of the ith project.

$$sq = \Sigma_{i=1}^{n}(P_i - E_i) \quad (11)$$

To reflect the bias of residents toward different service indicators, we use the objective weighting method to determine the weight of the five dimensions of SERVQUAL and different questionnaire questions. (Wu, Li, et al., n.d.)The specific calculation formula is shown in (12), where w_i is the weight of factor i and B_i is the variance contribution rate. In this research, n in the formula (12) can be equal to 5 (five dimensions) or the number of questions in the questionnaire survey.

$$w_i = \frac{B_i}{\sum_{i=1}^{n} B_i} \quad (12)$$

$$B_i = \frac{\sigma_i}{\sum_{k=1}^{p} \sigma_k}(i = 1, 2, \cdots, p) \quad (13)$$

After merging (11) and (12), we get (14), where n represents the number of questions in the questionnaire, w_j is the weight of the jth dimension, and w_i is the weight of the ith question (j = 1, 2, 3, 4, 5, i = 1, 2, 3,$\cdots$, n).

$$\widetilde{sq} = \sum\nolimits_{j=1}^{5} w_j \sum\nolimits_{i=1}^{n} w_i\left(\overline{P_i} - \overline{E_i}\right) \tag{14}$$

If $\tilde{sq} < 0$, that is, $\overline{P_i}$ is less than $\overline{E_i}$, then we can say the quality of service does not meet the expectations of residents. On the contrary, the region does not need to improve the quality of service to save resources.

6 Service System After Introducing the Knowledge Graph

We generally divide the service process supported by the knowledge graph into four steps, which can be modified and improved according to the real situation.

Step 1. When residents encounter life problems or generate demands, they need to briefly describe their problems and input them into the knowledge graph system.

After the user inputs the question, we need to segment the problem and measure the similarity by calculating the word frequency. This study uses the cosine similarity calculation method based on TF-IDF. Compared with the ordinary counting method, this method increases the weight to reflect the importance of different words. We need to reduce the weight of common words to achieve the purpose of accurate identification. Then we will get an eigenvector.TF represents word frequency. Represents the frequency of a word in a document, and the formula is shown in (15). Where d_j represents a specific document, and n_{ij} represents the number of times a word appears in document d. The IDF calculation formula of a word is shown in (16). Where $|D|$ denotes the number of all documents and $\left|\left\{j : t_i \epsilon d_j\right\}\right|$ denotes the number of documents in which the word is located (P. WANG, 2021). The value of TF-IDF is the product of the above two, and its formula is expressed as (17).

$$tf_{ij} = \frac{n_{ij}}{\sum_k n_{k,j}} \tag{15}$$

$$idf_i = \log \frac{|D|}{\left|\left\{j : t_i \epsilon d_j\right\}\right|} \tag{16}$$

$$tf - idf_{i,j} = tf_{i,j} \times idf_i \tag{17}$$

In a multidimensional space with N dimensions, we assume that there are two objects X and Y, X = $(x_1, x_2, x_3, \cdots, x_n)$, Y = $(y_1, y_2, y_3, \cdots, y_n)$. The cosine similarity calculation formula of x and y is shown in formula (18).

$$\cos\theta = \frac{\sum_{i=1}^{n}(x_i \times y_i)}{\sqrt{\sum_{i=1}^{n}(x_i)^2} \times \sqrt{\sum_{i=1}^{n}(y_i)^2}} \tag{18}$$

After counting the words in the question and the database, we use the formula (15), (16), and (17) to calculate their tf-idf values as vectors. The fitting results are obtained by calculating the cosine similarity of the two vectors. The smaller the similarity, the greater the distance. The greater the similarity, the smaller the distance.

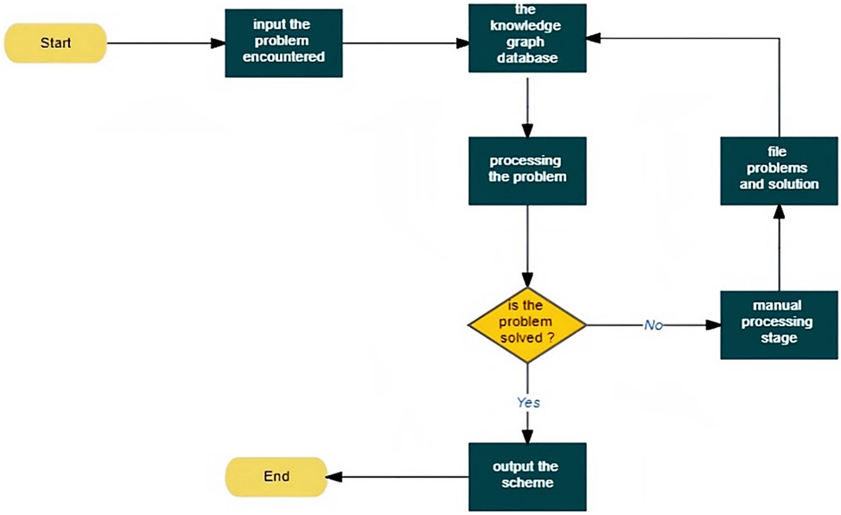

Fig. 7. Flow chart of service process

Step 2. The knowledge graph outputs the corresponding scheme according to the residents ' situation. At this time, residents should judge if they can solve the problems according to the guidance provided by the knowledge graph. If so, the service stops and the scheme is output. If not, the event will be transferred to the manual processing stage.

Step 3 (possibly). Employees will hold analysis meetings on this part of the problem that cannot be solved or has not yet appeared. The analysis meeting needs to address the problems encountered by residents and have feedback to residents through the platform on time.

Step 4 (possibly). Employees should file quality problems and solutions to the database after the meeting. The newly added data will be used to continuously improve the knowledge graph and serve as a basis for subsequent traceability (Fig. 7).

7 Conclusion

With the overall development of the economy, the traditional public service system at this stage is difficult to match the rapidly increasing quality of life standards. The information age has created a digital opportunity for the public service industry and forced the addition of artificial intelligence technology to be inevitable. This research explored the feasibility of the knowledge graph and made suggestions for the transformation of service system. For the public service field, the application of the knowledge graph is mostly in the research stage. The inability to carry out large-scale applications is being hindered by the difficulty of constructing and the acceptability of the public. The essence of public service quality improvement lies in the matching degree between the supply side and the demand side (Weng, 2023). How to use the evolving intelligent technology to complete the two-end matching in the information age is the focus of our continuous exploration.

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