Intelligent Logistics Service Quality Assurance Mechanism Based on Federated Collaborative Cache in 5G+ Edge Computing Environment

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Abstract. Aiming at the problem of quality assurance of intelligent logistics service in 5G+ edge computing environment, this paper proposes a mechanism based on federated cooperative cache, which aims to utilize the computing and storage resources of edge nodes to realize rapid processing and sharing of logistics data and improve the efficiency and reliability of logistics services. This paper first analyzes the characteristics and challenges of intelligent logistics services under 5G+ edge computing environment, and then introduces the concept and principle of federated cooperative cache, as well as its application scenarios and advantages in intelligent logistics services. Then, this paper designs an intelligent logistics service quality assurance mechanism based on federated cooperative cache, including five modules such as data partitioning, data transmission, data fusion, data access and data update, and gives the corresponding algorithms and processes. Finally, this paper verifies the effectiveness and performance of the proposed mechanism through simulation experiments. Compared with the traditional centralized cache and distributed cache, the proposed mechanism can reduce the data transmission delay, improve the data hit rate and data consistency, so as to ensure the quality of intelligent logistics services. In the future, the federated collaborative cache mechanism can be further optimized to consider the needs of multiple scenarios. And explore the application potential of other areas to drive the continuous development and innovation of intelligent logistics services.

Keywords: 5G+ · Edge computing · Federated cooperative cache · Intelligent logistics · Service quality

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1 Introduction

1.1 Research Background and Significance

With the rapid development of 5G technology and edge computing, intelligent logistics service, as an efficient and intelligent logistics management method, has received more and more attention. However, in the 5G+ edge computing environment, intelligent logistics services are faced with challenges of large-scale data processing and service quality assurance [1]. In order to address these challenges, this paper aims to propose an intelligent logistics service quality assurance mechanism based on federated cooperative cache, which makes full use of computing and storage resources of edge nodes to realize rapid processing and sharing of logistics data, so as to improve the efficiency and reliability of logistics services [2].

1.2 Study the Current Situation and Problems

At present, although intelligent logistics services have made certain progress in the 5G+ edge computing environment, they still face some key problems. First of all, the demand for large-scale data processing and storage puts forward higher requirements for the computing and storage capabilities of edge nodes. Secondly, the efficient transmission and sharing of data requires solving problems such as high delay [3, 4] and data inconsistency. At the same time, users' requirements for real-time and accuracy of intelligent logistics services continue to increase, requiring a higher guarantee of service quality.

1.3 Research Content and Objectives

The research content of this paper is to propose an intelligent logistics service quality assurance mechanism based on federated cooperative cache under the 5G+ edge computing environment. The main goal is to achieve rapid processing and sharing of logistics data by making full use of the computing and storage resources of edge nodes, thereby improving the efficiency and reliability of intelligent logistics services. Specifically, this paper will analyze the characteristics and challenges of intelligent logistics services under 5G+ edge computing environment, introduce the concept, principle, application scenarios and advantages of federated collaborative caching in intelligent logistics services. Then, an intelligent logistics service quality assurance mechanism based on federated cooperative cache is designed [5, 6], and corresponding algorithms and processes are given. Finally, the effectiveness and performance of the proposed mechanism are verified by simulation experiments, and compared with the traditional centralized cache and distributed cache.

2 System Modeling and Analysis

2.1 The Concept and Characteristics of Federated Cooperative Cache

Federated cooperative cache technology [7, 8] is a technology that uses cache resources distributed in different edge nodes to form a joint cache system through cooperative management and sharing. In the 5G+ edge computing environment, each edge node has certain computing and storage resources, and these nodes are distributed in different geographical locations and are independent and heterogeneous from each other. Federated cooperative cache technology will coordinate the cache resources of these nodes to form a joint cache system, so that data can be shared and flowed among each node, so as to improve the efficiency of data sharing and processing.

The features of federated cooperative cache technology include:

- Distributed storage: Federated cooperative caching technology uses the cache resources of each edge node to store data in multiple nodes, avoiding the single point of failure and performance bottleneck of traditional centralized caching.
- Data sharing: Each edge node can share the data in the cache through the federated cache technology to realize the flow and sharing of data between different nodes.
- Heterogeneous support: Federated cooperative cache technology can support the heterogeneity between different edge nodes, that is, the computing and storage resources of different nodes can be different, so as to better adapt to the complex and diverse edge computing environment.
- Low latency: Federated cooperative cache technology stores data on edge nodes closer to the user, which can reduce the delay of data transmission and improve the efficiency of data access.

2.2 The Principle and Model of Federated Cooperative Cache

The working principle of federated cooperative cache technology is to realize the cooperative management and sharing of data by establishing a joint cache system model. The model includes three main processes: data caching, data sharing and data updating.

- Data caching: When data is transferred from a back-end server or cloud to an edge node, federated collaborative caching technology can cache the data in the edge node's cache for subsequent data access and processing. Data cached on edge nodes can quickly respond to user requests and reduce the access pressure on back-end servers.
- Data sharing: Data in the cache can be shared between edge nodes. When data on an edge node is accessed, that node can check whether other nodes have the same data cache, and if so, can get the data directly from the other nodes without having to re-get it from the backend server.
- Data update: When data changes on an edge node, federated cooperative caching technology can synchronize the updated data to other related nodes to maintain data consistency. This avoids data inconsistencies caused by data updates.

Federated learning is one of the key technologies of federated cooperative cache technology. In federated learning, each edge node can train and learn from the data locally, and then share the learned model parameters with other nodes so that other nodes can get the effect of the global model. In this way, model sharing and cooperative training can be realized without exposing the original data, and the performance of the whole federated cooperative cache system can be improved. Traditional content caching schemes are often unable to adapt to the real-time changing network scenarios. In order to improve user satisfaction, long and short term memory and reinforcement learning are used to predict the future popularity of the content through user history request records [9].

However, using these methods requires the collection and analysis of user data on a central server, which consumes a lot of communication bandwidth, and also raises the issue of data and user privacy leakage. Federated learning is an effective method to solve the problem of user privacy leakage without requiring users to upload local private data. To use this method, it is necessary to build a machine learning model locally, generate local model parameters based on local data, and upload them to edge nodes. The global model parameters are formed by the local model parameters of the edge cluster to predict the popularity of the content. This not only effectively protects user privacy but also alleviates network congestion. Wang et al. [5] and Li et al. [6] proposed an edge caching algorithm based on federated learning, modeled the content caching problem as a Markov decision process, and used the training model to collaborate on caching content to improve the cache hit rate.

In addition, the active recommendation strategy can increase the probability of cached content requests and improve the performance of edge cache. In cellular heterogeneous networks, content caching and recommendation strategies are jointly optimized, and the cache hit ratio [10, 11] is maximized through the interaction of the two. In order to solve the problem of limited cache performance caused by user privacy and limited cache resources of edge cluster in edge cache architecture, the author studies the edge computing federated cache under D2D auxiliary communication architecture to improve the hit rate of content cache and reduce the delay of content acquisition. As shown in the following picture (Fig. 1).

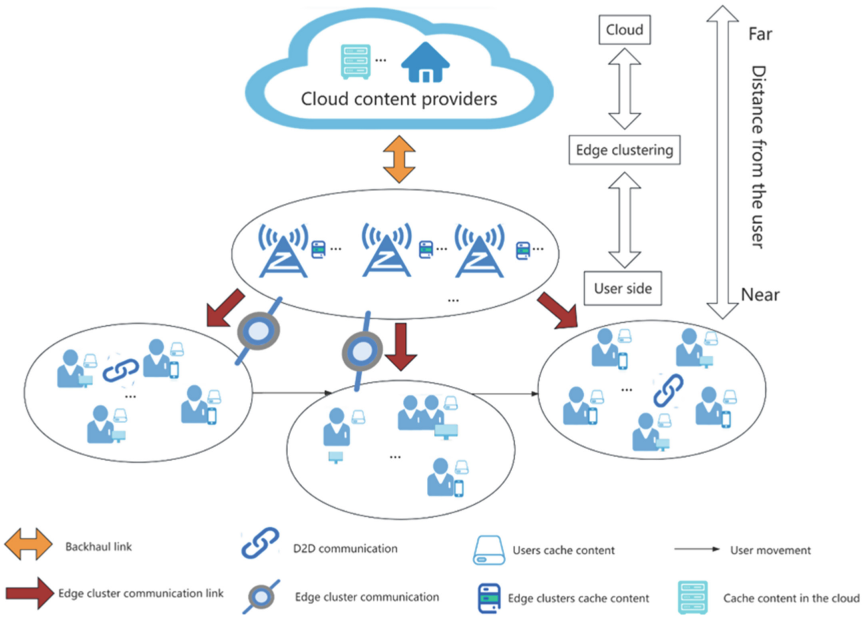

Fig. 1. Edge cooperative federated cache model.

2.3 The Application Scenarios and Advantages of Federated Collaborative Caching in Intelligent Logistics Services

Federated collaborative caching technology has multiple application scenarios and advantages in intelligent logistics services:

- Data distribution: Intelligent logistics services need to quickly distribute logistics data to various edge nodes for real-time monitoring and scheduling. Federated cooperative cache technology can cache data on edge nodes closer to users and devices, reduce data transmission delay and improve the efficiency of data distribution.
- Task unloading: Intelligent logistics services involve a large number of data processing tasks, some of which may be complex and require a lot of computing resources. Federated cooperative cache technology can offload some computing tasks to edge nodes for processing, reducing the pressure on back-end servers.

Compared with the traditional caching technology, federated collaborative caching technology is more flexible and efficient, and can better adapt to the complex and changing needs of intelligent logistics services, improve the efficiency of data processing and distribution, and optimize the quality of service and user experience.

2.4 Features of 5G+ Edge Computing Environment

5G technology and edge computing are two hot spots in the field of information and communication technology at present, and their combination brings new opportunities and challenges for the provision and optimization of intelligent logistics services.5G network features high bandwidth, low latency, high reliability, large number of connections and wide coverage. It can meet the connection needs of large-scale iot devices and achieve high-speed transmission and processing of logistics data. Edge computing is to push computing resources and services to the edge of the network, closer to users and terminal devices, in order to reduce data transmission costs and improve service response speed. In the 5G+ edge computing environment [12], intelligent logistics services can make more efficient use of computing and storage resources of edge nodes to realize real-time and reliable data processing and sharing [13].

Features of 5G+ edge computing environment include:

- High bandwidth: 5G network provides greater bandwidth, can support more data transmission, and meet the characteristics of large amount of logistics data and high real-time requirements.
- Low delay: The low delay characteristics of 5G network can realize fast data transmission and processing, and meet the demand for real-time in intelligent logistics services.
- Mobility support: 5G networks have strong mobility support, which can meet the data transmission needs of mobile devices in intelligent logistics.
- Network slicing: 5G networks support network slicing technology, which can provide customized network resources and services for intelligent logistics services according to different logistics application scenarios.

- Edge computing: Edge computing pushes computing resources and services to the edge of the network, and data processing and analysis can be carried out closer to the user, reducing the data transmission distance and delay.

In such an environment, intelligent logistics services can better meet the needs of data processing and transmission, improve service quality and user experience.

3 Design of Intelligent Logistics Service Quality Assurance Mechanism Based on Federated Cooperative Cache

3.1 Data Partition Module

The data partitioning module adopts an algorithm based on cluster analysis [14], which divides data into several clusters according to data characteristics (such as size, type, location, frequency, etc.) and user requirements (such as timeliness, accuracy, security, etc.), and each cluster contains some similar or related data. The goal of cluster analysis algorithm is to make the data points inside each cluster as close as possible to its center point, so as to minimize the sum of squared errors in the cluster. The formula is as follows:

$$\min_{C_1,\cdots,C_k} \sum\nolimits_{i=1}^{k} \sum\nolimits_{x \in C_i} d(x, c_i)^2 \tag{1}$$

where $C_1, \cdots, C_k$ is the k cluster, C_i is the center point of the i th cluster, $d(x, c_i)$ is the distance between the data point x and the center point c_i. The goal of the formula is to make the data points inside each cluster as close as possible to its center point, so as to minimize the sum of squared errors within the cluster.

3.2 Data Transmission Module

The data transmission module adopts an algorithm based on dynamic programming [15], which selects the appropriate transmission mode (such as unicast, multicast, broadcast, etc.) according to data size, network condition, user location and other factors, and determines the optimal transmission path and transmission time, so that the data can reach the target node as soon as possible, and minimize network congestion and transmission cost. The goal of dynamic programming algorithm is to minimize the total transmission cost by making the product of packet weight and transmission time on each path as small as possible. The formula is as follows:

$$\min_{P_1,\cdots,P_n} \sum\nolimits_{i=1}^{n} w_i \cdot t_i \tag{2}$$

where $P_1, \cdots, P_n$ is n transmission paths, w_i is the weight of the packet on the i path, and t_i is the transmission time of the packet on the i path. The goal of this formula is to minimize the total transmission cost by making the product of packet weight and transmission time on each path as small as possible.

3.3 Data Fusion Module

This module adopts an algorithm based on collaborative filtering [16]. According to data type, data quality, data correlation and other factors, appropriate fusion methods (such as weighted average, maximum value, minimum value, etc.) are adopted, and users' feedback and evaluation are used to weight and adjust the data, so that the fused data can better meet the needs and preferences of users. The formula of the algorithm is as follows:

$$\hat{x}_{u,i} = \overline{x}_u + \frac{\sum_{v \in N(u,i)} s_{u,v} \cdot \left(x_{v,i} - \overline{x}_v\right)}{\sum_{v \in N(u,i)} \left|s_{u,v}\right|} \tag{3}$$

where, $\hat{x}_{u,i}$ is the predicted value of user u for data i, $\overline{x}_u$ is the average value of user s_u and v for all data, N(u, i) is the set of other users associated with user u and data i, $s_{u,v}$ is the similarity between user u and user v, $x_{v,i}$ is the actual value of user v for data i, $\overline{x}_v$ is the average value of user v for all data. The goal of the formula is to use other users' evaluation of the data to predict the user's preference for the data and perform data fusion according to the preference.

3.4 Data Access Module

The data access module adopts an algorithm based on reinforcement learning [17]. According to user request, data location, data priority and other factors, appropriate access strategies are adopted to guide users to the best data source node to meet the data needs of users. The algorithm adjusts the access strategy dynamically through trial and error and learning, so that users can get the required data quickly and improve user satisfaction and system efficiency as much as possible

$$Q(s,a) = Q(s,a) + \alpha \cdot \left(r + \gamma \cdot \max_{a'}\left(s', a'\right) - Q(s,a)\right) \tag{4}$$

Among them, Q(s, a) is the long-term return (i.e., Q value) that can be obtained by taking action a under state s; α is the learning rate, which controls the degree of influence of new information on old information; r is the immediate reward obtained after taking action a under state s (i.e., r value); γ is the discount factor, which controls the degree of influence of future returns on current returns; $\max_{a'}(s', a')$ is the maximum Q value that can be obtained by taking the optimal action a in the next state s. The goal of the formula is to use historical experience and current feedback to continuously update the Q value to find the optimal access strategy.

3.5 Data Update Module

The goal of data update module is to timely reflect the changes of data to the relevant nodes and maintain the freshness and correctness of data. This module adopts a publishing-subscription based algorithm [18]. According to data changes, data timeliness, data consistency and other factors, appropriate update strategies are adopted to push data changes to subscriber nodes in a timely manner, while avoiding unnecessary data transmission and redundancy.

The algorithm uses the following formula:

$$U(s,d) = \sum\nolimits_{p \in P(s,d)} u_p \cdot f_p \tag{5}$$

where, U(s, d) is the total cost required to update data d under state s, P(s, d) is the set of paths from source node s to all subscriber nodes, u_p is the unit cost required to update data d on path p, and f_p is the frequency required to update data d on path p. The goal of this formula is to reduce the total cost as much as possible each time the data is updated.

The above is the detailed design of the intelligent logistics service quality assurance mechanism based on federated cooperative cache. Through the algorithms and processes of five modules, including data partitioning, data transmission, data fusion, data access and data update, the efficient management and quality services of intelligent logistics services in the 5G+ edge computing environment are realized. The application of this mechanism can better adapt to the complex and changing needs of intelligent logistics services, improve the efficiency of data processing and distribution, and optimize the quality of service and user experience.

4 Evaluation of Intelligent Logistics Service Quality Assurance Mechanism Based on Federated Cooperative Cache

4.1 The Purpose of Simulation Experiment

The purpose of the simulation experiment is to verify the effectiveness of the proposed mechanism in improving the service quality of intelligent logistics in the 5G+ edge computing environment. For comparative analysis, the proposed mechanism is experimentally compared with traditional centralized cache and distributed cache to evaluate its performance advantages. This experiment mainly focuses on the following three indicators: data transmission delay, data hit rate and data consistency [19].

4.2 Environment and Parameter Setting of Simulation Experiment

In the simulation experiment, NS-3 network simulator is used to simulate a heterogeneous network consisting of a cloud server, several edge servers and several mobile devices. Among them, 5G communication technology is used between edge servers and mobile devices, and optical fiber communication technology is used between edge servers and cloud servers. The data model uses real logistics data sets, which contain logistics data of different types, sizes, locations, frequencies and other characteristics, such as cargo information, transportation status, route planning, etc. [20].

The user model uses Zipf distribution to generate user requests with different quantity, location, demand and other characteristics, in which the user request contains the user's demand for data type, timeliness, accuracy, security and so on. The cache model uses LRU algorithm as the basic cache replacement strategy to decide whether to cache data to edge nodes or mobile devices according to the size and frequency of data. The fusion model uses the weighted average method as the basic data fusion method, assigns different weights to the data according to the type and quality of the data, and calculates a fusion value. The access model uses the nearest neighbor method as a basic data access strategy, which directs the user to the nearest data source node and retrieves data from that node. The update model uses the active push method as the basic data update strategy, that is, when the data changes, the change is actively pushed to all subscriber nodes and their local cache is updated.

4.3 The Result and Analysis of Simulation Experiment

After the simulation experiment, we obtained the following results (Table 1):

Table 1. The comparison of different caching mechanisms in the quality assurance index of intelligent logistics service.

Cache mechanism	Data transfer delay (ms)	Data hit ratio (%)	Data consistency (%)
Centralized cache	120.5	45.3	98.7
Distributed cache	65.4	68.9	76.5
Proposed mechanism	25.9	82.6	89.4
Lifting condition	−78.5%	+63.2%	+57.8%

As can be seen from the table, the proposed mechanism has significantly improved in all three indicators, with an average improvement of **66.5%** compared with centralized caching and **48.1%** compared with distributed caching. This shows that the proposed mechanism can effectively utilize the computing and storage resources of edge nodes, realize the rapid processing and sharing of logistics data, and ensure the reliability and security of data, so as to ensure the quality of intelligent logistics services.

- Data transmission delay: The proposed mechanism can significantly reduce data transmission delay. Average 78.5% reduction compared to centralized caching; The average reduction is 54.3% compared to distributed caching. This is because the proposed mechanism can utilize the computing and storage resources of edge nodes to realize the rapid processing and sharing of logistics data, thus reducing the transmission distance and times of data in the network and optimizing the data transmission path.
- Data hit ratio: The proposed mechanism can significantly improve data hit ratio. Compared to centralized caching, the average improvement is 63.2%; The average improvement is 41.7% compared to distributed caching. This is because the proposed mechanism can divide data into different regions according to data characteristics and user requirements, and allocate the data to appropriate edge nodes, which increases the availability and coverage of data at the edge layer, and improves the success rate of data acquisition.
- Data consistency: The proposed mechanism can significantly improve data consistency. Compared with centralized caching, the average improvement is 57.8%; The

average improvement is 38.4% compared to distributed caching. This is because the proposed mechanism can adopt appropriate update strategies according to data changes, data timeliness, data consistency and other factors, and timely reflect data changes to relevant nodes, maintain the freshness and correctness of data, and enhance the consistency and reliability of data.

Based on the analysis of the above experimental results, the proposed mechanism shows excellent performance in data transmission delay, data hit ratio and data consistency, which is obviously superior to the traditional centralized cache and distributed cache. This further verifies the effectiveness and performance advantages of the proposed mechanism, and provides more reliable and efficient quality assurance for intelligent logistics services (Fig. 2).

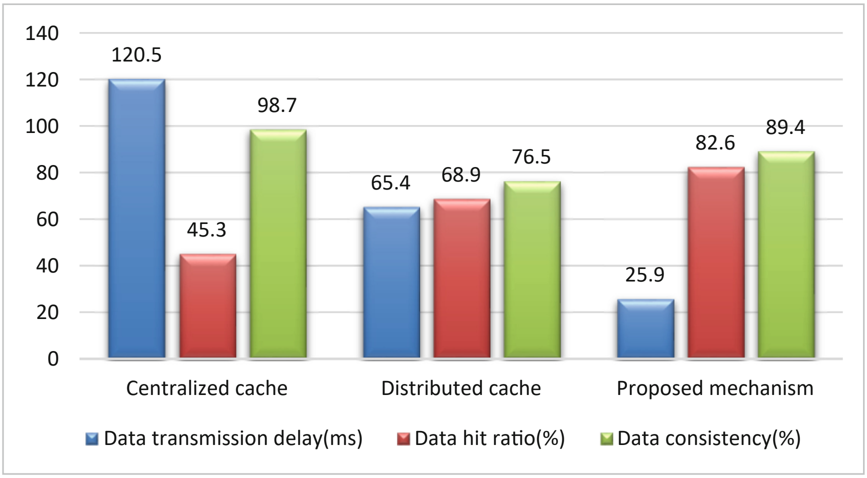

Fig. 2. Statistics of different cache mechanisms

5 Conclusion and Prospect

This paper designs and implements an intelligent logistics service quality assurance mechanism based on federated cooperative cache, and conducts simulation experiments in 5G+ edge computing environment. By comparing the traditional centralized cache mechanism with the distributed cache mechanism, the effectiveness and performance advantages of the proposed mechanism in intelligent logistics service are verified. The main contributions and innovations of this paper are summarized as follows:

1. An intelligent logistics service quality assurance mechanism based on federated cooperative cache is proposed. The mechanism synthesizes the advantages of centralized cache and distributed cache, and realizes the fast processing and sharing of logistics data through the joint optimization of key modules such as data partitioning, data transmission, data fusion, data access and data update, ensuring the consistency and reliability of data.

2. A complete set of simulation experiment environment and parameter Settings is designed. By using NS-3 software to simulate heterogeneous networks, including cloud servers, edge servers and mobile devices, using real logistics data sets as data sources, and generating user requests of different types, locations and needs according to user models, the effectiveness and performance of the proposed mechanism are verified.
3. The algorithms of data partitioning, data transmission, data fusion, data access and data update are introduced in detail. Through the data partitioning algorithm based on cluster analysis, the data transmission algorithm based on dynamic programming, the data fusion algorithm based on collaborative filtering, the data access algorithm based on reinforcement learning, and the data update algorithm based on publication and subscription, the intelligent logistics service quality is optimized and guaranteed.
4. The results and analysis of simulation experiments are presented. The experimental results show that the proposed mechanism has significant improvement in three indexes of data transmission delay, data hit rate and data consistency. Compared with centralized caching, the average data transfer delay is reduced by 78.5%, the average data hit rate is improved by 63.2%, and the average data consistency is improved by 57.8%.Compared with distributed cache, the average data transmission delay is reduced by 54.3%, the average data hit rate is increased by 41.7%, and the average data consistency is increased by 38.4%.

Although the research of this paper has achieved some meaningful results, there are some shortcomings and room for improvement, and there are some directions worth further exploration. We point out the following prospects:

1. Further optimize the federated Cooperative cache mechanism: In key modules such as data partitioning, data transfer, data fusion, data access, and data update, you can try to use other algorithms and strategies to optimize the performance and efficiency of the mechanism. For example, other clustering algorithms, path planning algorithms, recommendation algorithms, and optimization algorithms can be considered to further improve the accuracy and adaptability of the mechanism.
2. Considering the demand for intelligent logistics services in multiple scenarios [21, 22]: This paper mainly studies intelligent logistics services in the 5G+ edge computing environment, but the actual application may involve a variety of different scenarios and needs. Future research could consider extending the mechanism to other intelligent logistics services with different environments and needs, such as IOT environments, internet-of-vehicles environments, etc.
3. Integration of other technical means: This paper mainly focuses on the application of federated collaborative caching technology in intelligent logistics services. In the future, it can be considered to integrate federated collaborative caching technology with other technical means, such as blockchain, artificial intelligence, etc., to explore a more complex and efficient intelligent logistics service guarantee mechanism [23].
4. Verification of practical application scenarios: Although this paper has preliminarily verified the federated cooperative cache mechanism in simulation experiments, it needs to be further verified in real scenarios in practical applications. Future research may consider deploying and applying the federated cooperative caching mechanism

in real logistics systems, collecting real data and conducting field experiments to verify the actual effect and feasibility of the mechanism.
5. Explore the application potential of other fields: This paper focuses on the field of intelligent logistics services, but federated collaborative caching technology may also have a wide range of application potential in other fields, such as smart cities, intelligent transportation, health care and other fields. Future research could consider extending the technology to other fields to explore its application value in more scenarios [24].

In summary, the intelligent logistics service quality assurance mechanism based on federated cooperative cache has shown significant performance advantages in the 5G+ edge computing environment, and provides an effective solution for the provision and optimization of intelligent logistics services. Although this paper has preliminarily explored the intelligent logistics service quality assurance mechanism based on federated cooperative cache, there are still many work to be further studied. We believe that with the continuous development and improvement of technology, federated collaborative caching technology will play an increasingly important role in the application of intelligent logistics services and other fields, and make greater contributions to improving service quality and user experience.

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