

# Value Creation of Public Service Resources Based on Big Data Driven from the Perspective of Platform Integration

Ya Bi<sup>1,2,\*</sup>

<sup>1</sup>College of Business Administration, Hubei University of Economics, Wuhan, China

<sup>2</sup>Research Center of Hubei Logistics Development, Wuhan, China

\*Corresponding Author.

## Abstract

On the public service platform, resource integration and scheduling based on big data drive is the foundation and key of value creation of public service resources. This paper analyses the possibility and mechanism of value creation of superior resources on big data-driven public service platform, puts forward the path of value creation of public service resources, and deeply studies the resource intelligent allocation strategy based on public service platform in big data environment. In view of the unstructured characteristics of public service resources, this strategy introduces the concepts of connection depth and connection breadth of ontology tree, optimizes the calculation of ontology semantic distance and similarity function, and proposes a hierarchical intelligent public service resource allocation algorithm for the massive and substantial data and resources on public service platform. This strategy can not only realize rapid rent-seeking and accurate matching of resources on public service platform, but also integrates and intelligently allocates resources according to the needs and tasks, greatly reduces the generation of fragmented resources, reduces the difficulty and complexity of resource management by independent stakeholders, and expands the space of resource value creation.

**Keywords:** Public service resources, ontology semantic distance, value creation.

## 1. Introduction

The growth of big data is advancing at an astonishing rate, exerting a profound impact on society, economy, human life, and scientific research, becoming a defining characteristic of today's information society. From a management perspective, big data serves as a new paradigm and a driving force for innovation, offering societal interpretations with data footprints and transforming data from mere objects of processing into vital strategic information resources [1]. This not only aids in the quantitative research of social sciences but also fosters the emergence of computational social science, which holds significant strategic importance.

Public service platforms are the primary venues for governments and their related departments to optimize resource allocation, establish effective mechanisms for the supply of public products and services, and meet the basic demands of the populace for these offerings. They are not only the most extensive manifestations of the service functions of governments and related departments but also one of the main application scenarios for big data. The deep integration between the two can shift the focus of value creation from within enterprises to co-creation with external complementors, providing society with more accurate and effective public products and services. This reflects dynamic social sharing relationships and value and further gives rise to the economic, interactive, repeatable mining, and sticky characteristics of big data [2].

Firstly, public goods and public services possess the characteristics of "non-rivalry" in consumption and "non-excludability" in benefits, which have always been on the periphery of markets and governments. Relying solely

on government vertical management or market mechanisms, it is challenging to achieve compatibility between market interests and public interests [3]. Public service platforms, with their typical network externalities and channel characteristics, can integrate resources on demand, facilitate transactions, unify scheduling, and optimize allocation at a very low marginal cost under the drive of big data. This not only promotes collective action in public goods and services but also enriches and diversifies their forms and supply modes [4], enhancing the self-help capabilities of collective action [5].

Secondly, the transparency, openness, and ecological nature of public service platforms can not only break the boundaries of traditional enterprises and individual systems but also awaken the "sleeping data" [6] of stakeholders. Moreover, they can leverage their platform characteristics to "cleanse" big data [7], eliminating noise and significantly improving its usability [8]. Big data, through its knowledge feedback, can guide the practice of resource value creation on public service platforms, promoting interactive, repeatable, and supportive decision-making among the platform and various stakeholders.

Thirdly, public service platforms are characterized by platform flattening, coexistence of multiple modes, lack of unified rules, and complex structures and application types. Driven by big data, as carriers of resource transactions, they demonstrate advantages over traditional markets, such as being more transparent, having lower transaction difficulty, and easier resource management. That is, under the drive of big data, public service platforms can integrate and centrally dispatch dispersed social resources globally, significantly reducing market friction and the cost of resource transactions. This not only fully unleashes the natural attributes of decentralized decision-making in resource transactions, making them more compatible with flexible market mechanisms, but also, as a new model and means of resource management, the integration of big data and platform models directly opens up the value creation space for public service resources in production, transactions, and circulation.

Regrettably, there are still some theoretical gaps between the deep integration of public service platforms and big data and their positive mutual reinforcement, such as the incompatibility of big data with traditional resource management modes and data processes. Specifically, public goods and services are mainly provided through physical resources, which have many characteristics different from computing resources, such as non-replicability, non-instantaneous scheduling, and physical exclusivity. Therefore, when dealing with big data oriented towards physical public service resources, its acquisition, storage, description, processing, and mining processes are significantly different from traditional data models [9-10]. Secondly, the traditional centralized data processing framework is incompatible with the massive, distributed, and heterogeneous characteristics of big data, failing to discover and reflect the underlying knowledge of big data, resulting in the data obtained by the public service platform being merely "big" data, not necessarily valuable "good" data. Thirdly, the resources on the public service platform come from a vast number of entities with various forms, leading to non-uniform standards, uneven quality, and data silos between departments on the platform. Currently, the theoretical community is still exploring the processing, analysis, and algorithm design of big data, and the research on strategies for public service resource rent-seeking and matching driven by big data in platform situations is still shallow, limiting the in-depth expansion of the value creation space for public service resources. Fourthly, it is difficult to evaluate the effectiveness of value creation of public service resources driven by big data. Public service platforms find it hard to calculate the cost of obtaining big data and its contribution to specific businesses, making it difficult to manage and evaluate big data like tangible assets, resulting in the marginal benefits obtained by the public service platform through big data being hard to offset its marginal costs.

In summary, this paper aims to explore the integrated scheduling of resources through public service platforms under the drive of big data. The article focuses on analyzing the possibility and mechanism of value creation of superior resources on big data-driven public service platforms, and proposes innovative means of value creation and pathways for the reconstruction of value chains. The theoretical contributions of the paper are as follows: (1) It provides new perspectives and methods for the effective management and maximization of value of public service resources; (2) By employing intelligent configuration strategies driven by big data, it promotes the efficient use of public service resources and the improvement of public services, particularly in rural and remote

areas; (3) It advances the deep integration of public service platforms with big data technology, providing theoretical support and technical assistance for the formulation of relevant policies and practical operations.

## **2. Value Creation Pathways for Public Service Resources from a Platform Integration Perspective Driven by Big Data**

### **2.1 Reconstructing the resource optimization allocation model**

The personalization of demand has led to the diversification of public products and the shortening of their life cycles. This not only increases the complexity of managing public service resources but also raises the risks associated with their operation. Under traditional resource management models, resource allocation often takes place within a single enterprise or a few enterprises. This results in insufficient utilization rates, an inability to quickly meet user needs, poor supply chain collaboration, and under-realized resource value, highlighting the supply-demand conflict. In the era of big data, the integration of dispersed public service resources through platforms can break the constraints between ownership and management rights of these resources. Driven by big data, superior resources belonging to different stakeholders can be rapidly and transparently encapsulated and combined according to demand. That is, the public service platform aggregates advantageous resources on-demand during the resource allocation process, and this process is transparent to both the supply and demand sides [11]. This significantly improves the success rate of resource transactions, utilization rates, and customer satisfaction. It reduces not only the cost of the system's resource transaction matching but also the management difficulty for both parties involved in resource transactions. It provides a broad, personalized, and universal resource usage environment for all stakeholders [12], promoting the cross-integration of different public service resources. Moreover, it overcomes the profit-seeking behavior of resource owners based on bounded rationality and achieves coverage of public service resources in rural and remote areas, opening up space for the upward transformation and creation of social and economic value of public services.

### **2.2 Reconstructing products and markets**

Enterprises, leveraging the Internet and platforms for frequent interactions with users, generate massive amounts of data. Through big data user profiling analysis, businesses can establish a more precise user attribute tagging system, revealing the secretive, complex, dependent, and changeable needs of users. This brings the implicit consumer market to the fore, providing opportunities to capture product differentiation and repositioning, ultimately promoting product restructuring and the redefinition of market boundaries [13]. In the public service sector, when the utilization rate of public service resources is significantly improved under the new resource allocation model, not only can the public service needs of more citizens (especially those in rural and remote areas) be effectively met, but providers of public goods and services can also integrate societal demands into their entire production lifecycle driven by big data. This leads to the proposal of unique value propositions, obtaining sustainable core competitiveness, and creating more social public value.

### **2.3 Innovation in Value Creation Methods and Restructuring of Value Chains**

The integration of dispersed public service resources by platforms can address the "fragmentation of resources," while big data can uncover the operational trajectories behind these resources to reveal hidden patterns and knowledge. The combination of the two can solve bottleneck issues in key segments of the current public service domain [14]. For instance, it can aid in demand forecasting and defense against market uncertainty in the procurement phase; intelligent scheduling, resource planning, and process simplification in the production phase; user demand matching, inventory turnover rate improvement, and enhancement of product recommendation systems in the sales phase; and information dissemination and sharing, upstream and downstream enterprise collaboration, and "bullwhip effect" synergy in the operational management phase.

Moreover, by mining big data, the underlying patterns can be transformed into visual and actionable knowledge. This not only allows various participants on the public service platform to perceive the influx of knowledge and the resulting benefits but also reduces their management costs for their own resources and data information, making them less resistant to the spillover of data and knowledge [15]. Therefore, whether the relationships between various participants on the public service platform are horizontal competition or vertical supply, under

the drive of big data, their coupling relationships will be tighter. That is, the density between various participants on the public service platform will increase, the average path will be shortened, and the speed of collaborative innovation transmission and sharing on the public service platform will be enhanced [16]. The trust relationships and embedded intensity between various participants will continue to strengthen, and the cooperation of complementary resources between different participants will become more frequent and close. This will inevitably innovate the way public service resources create value and restructure the organizational form of their value chains.

From the above, it is evident that by leveraging the integration of globally dispersed resources on the public service platform and optimizing the dynamic allocation method of public service resources driven by big data, the boundaries of the public service market can be reconstructed, public goods and services can be innovated, and more value of public service resources can be created.

### 3. Dynamic Configuration Strategy for Public Service Resources Driven by Big Data

From a technical perspective, the essence of value creation for public service resources based on platform integration and big data drive is to innovate the way dispersed resources are configured on the public service platform under the drive of big data. Based on this, this paper takes into account the data characteristics of big data and the public attributes of the public service platform, and proposes a dynamic configuration strategy for public service resources driven by big data in a platform context. This strategy can be specifically described as follows:

Step 1: Design a formal description model optimized for semantic distance to describe the multi-source heterogeneous physical resources on the public service platform.

Step 2: Considering the volume of data on the public service platform and the time cost of resource rent-seeking and matching, use a coarse-grained filtering strategy to filter the status and type data of resources, thereby significantly reducing the matching time between the supply and demand sides of public service resources and improving the speed of matching.

Step 3: For public service resources that meet the requirements of Step 2, perform fine-grained filtering according to the capabilities and service quality of the resources to further meet the requirements of the demand tasks.

Step 4: Collect the resources screened in Step 3, and sort them comprehensively according to certain conditions to form a candidate resource pool that meets the matching conditions, providing a basis for the final configuration and transaction decision of public service resources.

#### 3.1 Formalized description rules for multi-source heterogeneous physical public service resources

The resources on the public service platform come from a wide range of sources and have typical characteristics of physicality, heterogeneity, and non-structured or semi-structured features. In order to support the public service platform in identifying, analyzing, comparing, and renting and matching a large number of resources, and to release the value that cannot be released in the traditional resource allocation model, it is necessary to fully capture the characteristic attributes of these resources and provide a structured description to eliminate or weaken the complexity of these resources in terms of underlying structure and type. The first step is to use a standardized and normalized formal description model to abstract the original form of these resources, providing a resource base for subsequent dynamic resource allocation and other content-level applications.

Definition: A 5-tuple formal description model is used to describe the physical resources on the public service platform as follows:

$$R^2 = \langle R_{basic}, R_{category}, R_{status}, R_{ability}, R_{QoS} \rangle \quad (1)$$

This 5-tuple description model can be specifically described as:

(1)  $R_{basic}$ : Mainly refers to the basic attributes and characteristics of public service resources, such as the name, category, traffic, carrier, ownership, and other descriptions of the natural and social attributes of the resources themselves.

(2)  $R_{category}$ : Mainly refers to the category attributes of public resources in fields such as science and technology, education, culture, and health that are oriented towards public services. When describing, it can be further subdivided according to industry standards. For example, the category attribute of emergency disaster relief transportation tools can be further subdivided into: freight tools - transport vehicles - box transport vehicles - cold chain box transport vehicles.

(3)  $R_{status}$ : Mainly refers to the state in which public service resources are when managed and scheduled centrally by the platform. Public service resources are mainly physical resources, which have many states different from completely virtualized computing resources, such as physical displacement, available state, usage time, and frequency, etc., and cannot be unlimitedly copied and instantly scheduled like computing resources.

(4)  $R_{ability}$ : Mainly refers to the ability of public service resources to provide services to the platform. Since the sources and forms of resources on the public service platform are diverse, the service capabilities of the resources vary. For example, two box trucks with the same basic service capabilities, one can provide GPS positioning and full traceability capabilities in addition to transportation; the other may be able to provide rapid automatic loading and unloading capabilities. These service capabilities are parameters that need to be considered when configuring the supply and demand of resources.

(5)  $R_{QoS}$ : The service quality of public service resources, mainly used to reflect the comprehensive service level of public service resources, is the last matching parameter in the intelligent configuration strategy of public service resources, mainly used to give priority to the candidate public service resources that have been screened to meet the demand tasks.

### 3.2 Reconstruction of ontology semantic distance and concept similarity

#### 3.2.1 Semantic distance between ontologies

Public service resources have many characteristics different from virtualized computing resources, such as unity, spatiotemporal exclusivity, and non-replicability. Therefore, it is necessary to extract key features of public service resources from the perspective of physical resources for hierarchical filtering [17], to control the integration of quantity and quality of big data from the source, to support semantic comparison on different contents of the public service platform, and application requirements at different levels.

Ontology is an abstraction of objective things. The semantic distance between two ontologies represents the degree of similarity between them, that is, the concept similarity. Using semantic distance and concept similarity functions can evaluate the mapping relationship between any ontologies [18], making multi-source heterogeneous data and resources consistent in expression and understanding. The existing traditional calculation method based on semantic distance of concept similarity only considers the connection distance between ontologies [19], that is,  $distance(x, y) = length(x, y) \times \sum_{i=1}^n w_i(x, y)$ . The recall rate and precision rate are not high. This indicates that the traditional semantic distance is not clear and accurate enough in describing the degree of similarity between ontologies, which will lead to a decrease in the accuracy of resource supply and demand matching and a waste of computing resources. Therefore, this paper intends to expand the connotation of the traditional ontology tree semantic distance, in addition to the connection distance in the traditional ontology semantic concept, the connection depth and connection breadth between ontologies are also considered, and the semantic distance of the ontology tree is redefined to optimize the calculation model of the ontology concept similarity.

The semantic distance of the concept node is redefined as follows:

$$\left\{ \begin{array}{l} \text{distance}(x, y) = 0, \text{ if identical concept} \\ \text{distance}(x, y) = \text{length}(x, y) \times \sum_{i=1}^n w_i(x, y) \times \frac{\sum_{i=1}^n N_i(x, y)}{T_{node}}, \text{ if inheritance relationship} \\ \text{distance}(x, y) = \infty, \text{ if not inheritance relationship} \end{array} \right. \quad (2)$$

Where:

$\text{distance}(x, y)$	represents the semantic distance between any two ontologies (Ontology A and Ontology B);
$\text{length}(x, y)$	represents the semantic distance between any two ontologies (Ontology A and Ontology B);
$\sum_{i=1}^n w_i(x, y) = \sum_{i=1}^n \frac{1}{2^{i-1}}$	represents the weight function of the connection distance between any two ontologies (Ontology A and Ontology B), which mainly reflects the connection depth between Ontology A and Ontology B;
$\frac{\sum_{i=1}^n N_i(x, y)}{T_{node}}$	represents the connection breadth between any two ontologies (Ontology A and Ontology B), which mainly reflects the ratio of the total number of nodes on the inheritance chain of Ontology A and Ontology B to the total number of nodes in the ontology tree.

### 3.2.2 Concept similarity function based on semantic distance

The meaning of concept similarity between ontologies is: the shorter the semantic distance between two ontologies, the higher the concept similarity, and the higher the degree of matching. Based on the optimization of the ontology semantic distance in the previous text, and considering the scale of the ontology tree, the traditional concept similarity function based on semantic distance is reconstructed.

The calculation method of concept similarity based on the new semantic distance is shown in formula (3):

$$\text{sim}(x, y) = \frac{1}{1+\gamma \times \text{distance}(x, y)}, \gamma \in [1,5] \quad (3)$$

Where:

$\text{sim}(x, y)$	is the concept similarity function between Ontology A and Ontology B;
$\gamma$	is the adjustment parameter of the ontology tree, mainly used to express the concept similarity numerically. That is, when the connection depth and breadth of the ontology tree are larger, a relatively larger value can be taken; otherwise, a smaller value is taken.

### 3.3 Intelligent configuration strategy for public service resources

The public service platform integrates a vast array of dispersed resources. In order to enable these resources to be rapidly and efficiently configured according to demand tasks, this paper designs a dynamic configuration strategy for public service resources driven by big data.

Step 1: On the public service platform, coarse-grained filtering of public service resources is conducted based on  $R_{basic}$  and  $R_{category}$ . Since  $R_{basic}$  and  $R_{category}$  contain fewer parameters, the computational complexity of resource matching is low. Therefore, initial screening is first conducted based on these two conditions, with the expectation of significantly narrowing the range of resource rent-seeking and improving the speed of resource configuration, where:

$D$	represents the set of task requirements proposed by the resource demander on the public service platform;
$S$	represents the set of resources provided by the resource supplier on the public service platform;
$i=(1, \dots, n)$	denotes a specific public service resource, indicated by subscripts;
$M()$	represents the set of resource matching threshold values proposed by the demander;
$U$	represents the set of resource matching results reached by both the resource demander and supplier.

$$U_1 = \emptyset; n = \text{Num}(S); i \subset S;$$

$$\text{for}(a^2 = 1; a^2 \leq n; a^2 ++)$$

$$\{\text{sim}_{i.category}(0) = \text{sim}(D_{category}(0), S_{i.category}(0));$$

/\*Calculate the concept similarity of  $R_{category}$  between the supply and

demand sides of public service resources.\* /

$$sim_{i.status}(0) = sim(D_{status}(0), S_{i.status}(0));$$

/\* Calculate the concept similarity of  $R_{status}$

between the supply and demand side of public service resources. \*/

$$if \left( (sim_{i.category}(0) \geq M.D_{category}(0)) \wedge (sim_{i.status}(0) \geq M.D_{status}(0)) \right) = 1;$$

/\*If the concept similarity between  $R_{category}$  and  $R_{status}$  matches\*/

$$\{U_1 = \{S_i\} \cup U_1\}$$

Step 2: According to the demand task, each parameter in  $R_{status}$  of the public service resource is screened one by one, that is, fine-grained filtering, and resources that meet the matching accuracy are placed into the candidate resource pool. In this step of the configuration strategy, the difficult problem to overcome is: due to the unstructured characteristics of resources, the description of resources by the demand task and the description of resources by the resource supplier do not match in terms of the number and type of parameters.

Let  $c$  be the parameter of the public service resource service capability; the public service capability required by the demand task is  $D_{ability} = D_{ability}(c_1, c_2, \dots, c_m)$ ; the service capability information of the public service resource supplier  $i$  is  $S_{i.ability} = S_{i.ability}(c_1, c_2, \dots, c_k)$ . Match each parameter in  $S_{i.ability}$  one by one.

$$n = Num(U_1); U_2 = \emptyset; i \in U_1;$$

for( $a = 1; a \leq n; a++$ )

$$\{if \left( (m \leq k) \wedge (content(S_{i.ability}) = content(D_{ability})) \right) = 1$$

/\*That is, the number of parameters required by the demand task for  $R_{ability}$

is the same as the number of parameters in the public service resource  $R_{ability}$ ,

and the content of the parameters is completely consistent\*/

$$\{c = 0;$$

for( $b = 1; b \leq m; b++$ )

$$\{sim_{j.ability}(c_j) = sim(D_{ability}(c_j), S_{i.ability}(c_j));$$

/\*Calculate the concept similarity for each parameter in  $R_{ability}$ \*/

$$if \left( sim_{j.ability}(0) \geq M.D_{ability}(c_j);$$

$$e^2 = -e^2 + 1;$$

/\*Let  $e$  be a loop counter\*/

if ( $e == m$ )

/\*If all parameters in the public service resource  $S_{ability}$

meet the concept similarity threshold requirements of the demand task\*/

$$sim_{i.ability} = \frac{1}{k} \left( \sum_{j=1}^m sim_{j.ability}(c_j) + k - m \right);$$

/\*If the number of parameters in the public service resource  $R_{ability}$

exceeds the number of parameters required by the demand task  $R_{ability}$ ,

then consider the excess part of the parameters as additional or higher quality service capabilities provided by the public service resource,

and default the concept similarity of this part of the excess parameters to 1.

At the same time, let the concept similarity of the public service resource  $R_{ability}$  that meets the matching requirements,

be the average of the sum of all parameter similarities\*/

Step 3: Based on the demand task parameters  $R_{QoS}$ , calculate the service quality of each public service resource in the candidate resource pool, and conduct a more in-depth and specific assessment of the resources that meet the matching requirements [20]. The challenge of the algorithm in this step lies in the fact that unlike the parameters represented in structured descriptive language in  $R_{basic}$ ,  $R_{catogry}$  and  $R_{ability}$ , the feature values in  $R_{QoS}$  are quantified, making it impossible to directly calculate their concept similarity using the semantic distance-based method. A redesign is necessary.

The basic approach is as follows: Establish a matrix  $A$ . Let the parameters of the demand task  $R_{QoS}$  be the column vectors of matrix  $A$ , where each column represents the evaluation indicators of the demand task for resources, with importance denoted by weights; let the  $R_{QoS}$  of each public service resource in the set  $U_2$  be the row vectors of matrix  $A$ ; let the optimal value of each column after normalization of matrix  $A$  be  $Y(y_1, y_2, y_3, y_4)$ , considering it as the optimal value for all resources  $R_{QoS}$  in the set  $U_2$ . Use the Euclidean distance between row vectors to assess the concept similarity of public service resources  $R_{QoS}$ , that is,  $sim_{i,QoS}(X_i[ ], Y) = 1 -$

$\sqrt{\sum_{j=1}^4 w_j(x_{ij} - y_j)^2}$ , where the shorter the vector distance, the higher the concept similarity of the public service resource  $R_{QoS}$ .

$$\text{Let } A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ \cdot & \cdot & \cdot & \cdot \\ a_{n1} & a_{n2} & a_{n3} & a_{n4} \end{bmatrix}, \text{ initialize it to obtain}$$

$$A' = \begin{bmatrix} \frac{a_{11}}{\sum_{x=1}^n a_{x1}} & \frac{a_{12}}{\sum_{x=1}^n a_{x2}} & \frac{a_{13}}{\sum_{x=1}^n a_{x3}} & \frac{a_{14}}{\sum_{x=1}^n a_{x4}} \\ \frac{a_{21}}{\sum_{x=1}^n a_{x1}} & \frac{a_{22}}{\sum_{x=1}^n a_{x2}} & \frac{a_{23}}{\sum_{x=1}^n a_{x3}} & \frac{a_{24}}{\sum_{x=1}^n a_{x4}} \\ \cdot & \cdot & \cdot & \cdot \\ \frac{a_{n1}}{\sum_{x=1}^n a_{x1}} & \frac{a_{n2}}{\sum_{x=1}^n a_{x2}} & \frac{a_{n3}}{\sum_{x=1}^n a_{x3}} & \frac{a_{n4}}{\sum_{x=1}^n a_{x4}} \end{bmatrix} = \begin{bmatrix} X_{11} & X_{12} & X_{13} & X_{14} \\ X_{21} & a_{22} & a_{23} & a_{24} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ X_{n1} & X_{n2} & X_{n3} & X_{n4} \end{bmatrix} = \begin{pmatrix} \cdot \\ \cdot \\ X_2[ ] \\ \cdot \\ \cdot \\ X_n[ ] \end{pmatrix}$$

Let  $M.D_{QoS}() = Y(y_1, y_2, y_3, y_4)$ . Within the confines of our analytical framework, we engage in the computation of Euclidean distances between the row vectors  $X_i[ ]$ , representing individual public service resources, and the column vectors  $M.D_{QoS}()$ , representing the parameters of demand tasks, within the matrix  $A'$ . This computational process is pivotal as it quantifies the degree of conceptual congruence between the resource's profile and the task's requirements, thereby facilitating an objective assessment of their alignment.

$$n = Num(U_2) ; \sum_{i=1}^4 w_i = 1;$$

for( $a = 1; a \leq n; a ++$ )

$$\left\{ \sin m_{i,QoS}(X_i[0], Y) = 1 - \sqrt{\sum_{j=1}^4 w_j (x_{ij} - y_j)^2} \right\};$$

In the concluding phase of our analysis, we determine the aggregate conceptual similarity among the candidate resources and proceed to rank them. This ranking is instrumental in offering accurate data-driven support for the ultimate decision-making process concerning public service resource transactions.

We conduct a weighted assessment of the conceptual similarities, assigning weights  $\alpha$  and  $\beta$  to  $\overline{sim_{i,ability}}$  and  $sim_{i,QoS}(X_i[ ], Y)$ , respectively. This approach is designed to realize incentive compatibility in resource allocation, thereby enhancing the accessibility of public goods and services to rural and remote regions through the cohesive scheduling mechanisms of the public service platform.

Subsequently, we perform a sorting of all public service resources within the set  $U_2$ , where  $U_3$  denotes the ensemble of resources ordered based on their aggregated conceptual similarity scores.

$$\begin{aligned} n &= Num(U_2); \\ U_3 &= \emptyset; \\ \alpha &\in (0,1); \beta \in (0,1); \\ \alpha + \beta &= 1; \\ \text{for}(a = 1; a \leq n; a ++ ) \\ \{ &SIM_{i.comprehensive}(0) = \\ &\alpha \times \overline{sim_{i,ability}} + \beta \times Sim_{i,QoS}(X_i[ ], Y); \\ &U_3 = rank(SIM_{i.comprehensive}(0)); \} \end{aligned}$$

#### 4. Results and Discussion

This paper addresses the issue of resource value creation within the context of a public service platform in the era of big data. Initially, we recognize the platform as the primary vehicle for the convergence, integration, and distribution of big data. Big data, in turn, enables the platform to process vast quantities of data more effectively, uncovering correlations and patterns that provide more precise data support and a basis for decision-making. Building on this foundation, we propose the notion that 'the integrated integration and allocation of resources by the public service platform, driven by big data, is an essential means of creating resource value.' Subsequently, we reveal the path of value creation for public service resources driven by big data from a platform integration perspective, namely, 'reconstruction of resource allocation models—reconstruction of public product and service markets---innovation in value creation methods, and restructuring of value chains. Finally, we design a dynamic configuration strategy for public service resources driven by big data in a platform context. Specifically, we first devise a quinary formal descriptive model for physical public service resources more suited to the platform environment, which mitigates the complexity of unstructured and semi-structured public service resources at the foundational structural and typological levels. Secondly, we introduce the concepts of connection depth and breadth between ontologies, optimizing semantic distance and concept similarity functions to enhance the precision of matches between public service resources. Lastly, we develop a multi-tiered filtering resource rent-seeking and matching algorithm based on different granularities, significantly narrowing the scope of rent-seeking for massive public service resources on the platform and improving the speed and accuracy of resource matching.

Based on the foregoing, the research conclusions drawn in this paper are as follows: (1) In the context of a big data environment, public service platforms can significantly enhance the success rate, utilization rate, and customer satisfaction of resource transactions through intelligent configuration strategies; (2) Such strategies enable the integrated and intelligent allocation of resources according to demand tasks, reducing the emergence of fragmented resources and diminishing the difficulty and complexity of resource management for independent

stakeholders; (3) By optimizing semantic distance and conceptual similarity functions, the matching between resources becomes more precise, laying a necessary foundation for the creation of value from public service resources.

Due to limitations in research capabilities and time, there are still some constraints in this study that warrant further in-depth investigation: First, considering the need to incline and cover rural and remote areas with public goods and services, it is necessary to incorporate incentive-compatible weights in the dynamic resource allocation strategy. If these weights are set too low, the coverage of public goods and services in rural and remote areas may be insufficient; conversely, it could lead to a prolonged divergence between the scheduling decisions of the public service platform and the stakeholders, potentially causing a mass exodus of stakeholders from the platform. Thus, the determination of these weights is a critical issue that requires focused research. Second, the dynamic resource allocation strategy proposed in this paper does not provide the final decision-making outcome for resource transactions on the public service platform but rather a collection of public service resources sorted by the precision of demand task matching. Third, due to the presence of network externalities, there are many unstable factors in the day-to-day operation of the public service platform. As more stakeholders join the platform and expand the utilization of resources, conflicts may arise between various goals such as information disclosure, privacy protection, and the socio-economic demands of multiple stakeholders. In this context, defining the boundaries of social resource integration by the public service platform, determining the optimal scale of resource integration, and preventing and overcoming the negative behaviors that result from opposition are all new challenges facing scientific researchers.

#### Acknowledgments

The project supported by the National Social Science Foundation, China (No. 21BGL230).

#### References

- [1] Yang shan-lin, Zhou kai-le. Management issues in Big Data: the resource-based view of big data. *Journal of management science in China*, 2015, 18 (5):1-8.
- [2] Alex Pazaitis, Primavera De Filippi, Vasilis Kostakis. Blockchain and value systems in the sharing economy: The illustrative case of Backfeed. *Technological Forecasting & Social Change*, 2017(125): 105-115.
- [3] Gammelgaard Britta, Andersen Christina B G., Figueroa Maria. Improving urban freight governance and stakeholder management: A social systems approach combined with relationship platforms and value co-creation. *Research in Transportation Business and Management*, 2017, 24: 17-25.
- [4] Carneiro Ricardo, Duque Brasil, Flavia de Paula, Almeida Silva Thaysa Sonale. Environment and collective actions: an analysis of urban environmental movements and their developments in Belo Horizonte in the recent context. *Praxis Sociologica*, n23, 2018: 233-253.
- [5] Gold Stefan, Muthuri Judy N., Reiner Gerald. Collective action for tackling "wicked" social problems: A system dynamics model for corporate community involvement. *Journal of Cleaner Production*, n179, 2018: 662-673.
- [6] Sun Ao-bing, Ji Tong-kai, Wu Xiao-qiang. Design and realization of big data open platform for smart city. *Journal of Computer Applications*, 2017, 37(S1): 340-343.
- [7] Mao cun-li, Yu zheng-tao, Shen tao. A kind of Nonferrous Metal Industry Entity Recognition Model based on Deep Neural Network Architecture, *Journal of Computer Research and Development*, 2015, 52(11): 2451-2459.
- [8] Meng Xiao-feng, Ci Xiang. Big Data Management: Concept, Techniques and Challenges. *Journal of Computer Research and Development*, 2013, 50(1): 146-169.
- [9] Xiao Ying-ying, Li Bo-hu, Cai Xu-dong. Research on the formalization description method of manufacturing capability service in cloud manufacturing. *Journal of System Stimulation*, 2015, 9(27): 2096-2107.
- [10] Li Xin, Dong Chao-yang. A Method of Intelligent Matching Technique of Cloud Manufacturing Resource and Processing Tasks based on Ontology Mapping. *Modular machine tool and automatic manufacturing technique*, 2015, 11:157-160.

- [11] Xu Xiao-lin, Li wei-dong. Research on the Public Service Mode Based on Cloud Computing. *Research of Administrative Science*, 2014, 1(2): 36-39.
- [12] Wang shi-long, Song wen-yan, Kang ling, Li qiang, Guo liang, Chen gui-song. A research of manufacturing resource allocation based on cloud manufacturing, *Computer Integrated Manufacturing Systems*, 2012, 18(07): 1396-1405.
- [13] Mittelstadt B, Allo P, Taddeo M, et al. The Ethics of Algorithms: Mapping the Debate. *Big Data and Society*, 2016, 3(2): 1-21.
- [14] Frederic P, Philipp K. Roger S M. Experience Co-creation in Financial Services: An Empirical Exploration. *Journal of Service Management*, 2015, 26(2): 295-320.
- [15] Etzioni A, Etzioni O. Designing AI Systems That Obey Our Laws and Values. *Communications of the ACM*, 2016, 59(9): 29-31.
- [16] Zeng jian-qiu. Big data drives the future, creates the share value, *Communications Information Bulletin*, 2016. 12. 28.
- [17] Ramirez-Gallego Sergio, Mourino-Talin Hector, Martinez-Rego David, Bolon-Canedo Veronica, Manuel Benitez Jose, Alonso-Betanzos Amparo, Herrera Francisco. An Information Theory-Based Feature Selection Framework for Big Data under Apache Spark. *IEEE Transaction on System Man Cybernetics-Systems*, 2018, 48(9): 1441-1453.
- [18] Naseriparsa Mehdi, Islam Md Saiful, Liu Chengfei, Moser Irene. No-but-semantic-match: computing semantically matched xml keyword search results. *World Wide Web-Internet and Web Information Systems*, 2018, 21(5): 1223-1257.
- [19] Bagherifard Karamollah, Rahmani Mohsen, Rafe Vahid, Nilashi Mehrbakhsh. A Recommendation Method Based on Semantic Similarity and Complementarity Using Weighted Taxonomy: A Case on Construction Materials Dataset. *Journal of Information and Knowledge Management*, 2018, 10.1142/S0219649218500107.
- [20] Bi ya, Yuan Hui-qun, Chu Ye-ping, Liu hui. Multilevel and intelligent rent-seeking and matching resource strategy and value creation of public service platform in big data environment, *Computer science*, 2019, 46(2): 42-49.