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Research on the Mechanism and Identification of Key Influencing Elements for Releasing the Value of Data Elements in Smart Cities

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Abstract: The development of new information technology makes more people and things connected to the network, expanding the scale of data elements in smart cities; it also makes data a new production factor to drive the development of smart cities, greatly increasing the potential value of smart city data elements. However, this does not mean that smart city data elements can directly provide better products and services. The key to making smart city data elements truly contribute to the efficient operation of smart cities is to release their value. Given this, this paper defined the concept of smart city data element value release, analyzed the mechanism of data element value release in smart cities combined with DPSIR theory, identified five dimensions and 47 influencing factors that affect the data element value release in smart cities, and used the fuzzy-DEMATEL method to further identify 11 key influencing factors from 47 influencing factors. This research helps clarify the mechanism for releasing the value of data elements in smart cities and identify the factors that play a key role in releasing the value of data elements in smart cities in order to maximize the value of data elements in smart cities.

Keywords: smart city; data element; value release; key influencing factor; mechanism

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1. Introduction

There are a large number of sensors in smart cities that can collect data generated by every citizen, infrastructure, etc., in the city in real time [1]. At the same time, the data collected during the operation of smart cities have their own self-growth characteristics such as being shareable, replicable, and infinitely suppliable [2]. Moreover, the trend of the assetization and capitalization of data is increasing. All these have profoundly changed how smart cities operate. Smart city data have become a new production factor to promote the development of smart cities [3], containing great value. According to Cisco's calculations, M2M connectivity will grow 2.4 times worldwide by 2023 compared to 2018 [4]; more data generated by citizens, infrastructure, and so on will be connected to IoT systems. The variety and number of smart city data elements will increase dramatically. However, the increase in smart city data elements does not mean that they can provide more value and services [5]. Along with the increase in the scale of smart city data elements, the value potential they contain is even richer, but the value that is truly beneficial to the operation of the smart city may be submerged in a large number of duplicated and erroneous smart city data elements and cannot be released. If effective measures are not taken, there may be consequences that affect the normal operation of the smart city. At the same time, the process of releasing the value of data elements in the smart city has also changed, generating more connections with concepts such as technology, society, and innovation,

which require that research should stand on a more comprehensive perspective. At present, from a comprehensive perspective, there is less research on the process of releasing the value of smart city data elements based on the current situation of smart city data elements, but in order to efficiently release the value generated based on the huge and messy smart city data elements, the first thing to do is to clarify the mechanism of releasing the value of smart city data elements.

In order to clarify the mechanism for releasing the value of data elements in smart cities, this paper will define the concept of the value release of data elements in smart cities based on a review of the existing related literature, then analyze the value release mechanism of data elements in smart cities combined with Driver-Pressure-State-Impact-Response (DPSIR) theory. On this basis, we will identify the dimension and the influencing factors under each dimension of the value release of data elements in smart cities from the five perspectives of driving force, pressure, state, impact, and response in DPSIR theory. After that, the combination of fuzzy set theory and Decision-making Trial and Evaluation Laboratory (DEMATEL) will be used to calculate the cause degree, center degree, influence degree, and influenced degree of each influencing factor for the value release of smart city data elements. Based on the results of the above "four degrees", the top-ranked factors will be selected as the key influencing factors for releasing the value of smart city data elements in order to provide specific direction for fully releasing the potential value of smart city data elements. Accordingly, this study addresses the following research questions:

Q1: What is the mechanism for releasing the value of data elements in smart cities?

Q2: What are the factors influencing the release of data element value in smart cities based on the mechanism?

Q3: Which factors are the most critical among all those influencing the release of data element value in smart cities?

In the second part, we will define the concept and analyze the mechanism of value of the release of data elements in smart cities, based on existing studies. Using DPSIR theory, we will identify dimensions and factors affecting this process. In the third part, we will apply the fuzzy-DEMATEL method to identify key influencing factors. The fourth part will analyze the attributes and interactions of these key influencing factors, highlighting their role in smart city operations. The fifth part will conclude with a summary, theoretical and practical implications, and future research directions.

2. Materials and Methods

2.1. Literature Review

From the literature review, it can be seen that the research on the value of data elements in smart cities mainly focuses on three aspects: the value creation of data elements in smart cities, the value release of data elements in smart cities, and the value assessment of data elements in smart cities.

In the study of the value creation of data elements in smart cities, Kühne and Heidel studied the classification of data-driven smart city supply chain items into 11 dimensions and analyzed the different characteristics and practical application value of each dimension [6]. This contributed to the effective exploitation of smart city data and releasing their potential value. Bencsik et al. proposed a three-dimensional framework including 12 business models based on a business model perspective of value creation and value capture by analyzing 130 smart city projects in Switzerland [7]. Lim et al. (2018) proposed that if the four principles of connection, collection, computation, and communication were satisfied, the different stakeholders of a smart city could collaborate and create value together [8]. Kim pointed out that the focus of smart cities has shifted from infrastructure development to the use of smart city data and information technology to provide sustainable and valuable services to citizens, which means that the key factors of smart city value creation have changed [9].

In the study of the value release of data elements in smart cities, some academic researchers have studied the act of seeking profits through the extraction, processing, and commercialization of smart city data from the perspective of platform capitalism, and this act could lead to the circulation of smart city data in the form of commercialization, which could release the financial value [10,11]. Rose et al. argued that citizens generate and share data through the use of smart city platform applications [12]. Two other forms of value were released in the flow of data; one was normative value, which means that smart city data were provided to promote public benefits such as health and education, the other one was interactive value, which was generated by users interacting with the data; the provision of smart city data would promote healthier and more sustainable citizen behavior to occur. Wang et al. constructed a framework based on DTs smart city traffic model, which could improve the accuracy of traffic scene recognition by calculating the collected smart city traffic data in real time and improving the algorithm to release the data value [13].

In the study of the value release of data elements in smart cities, Ianuale et al. summarized the characteristics and types of smart city data and suggested that once the data are linked, it will help to distinguish the strengths and weaknesses of the data types to assess their value and impact [14]. Karimi et al. summarized the techniques and systems involved in the value release assessment of data elements in smart cities and systematically analyzed the contents and shortcomings of each study [15]. Park proposed data as one of the components of smart cities and evaluated them in a way that transformed them into objective values, with the aim of identifying the most stable type of smart cities for citizens [16]. Zhao et al. proposed a homomorphic outsourcing computing toolkit for the privacy protection of data, which can be applied to protect the security of smart city data elements and ensure a successful evaluation of the value of data elements in smart cities [17]. Tufis introduced a data valuation process that integrates data context, quality, and utility, and explores how cities can benefit from it [18].

Through combing the above literature, we can see that, on the one hand, there are abundant studies on the value of smart city data elements, which can provide a solid theoretical foundation for this paper. On the other hand, in the study of releasing the value of smart city data elements, more studies analyze how to release the value of smart city data elements from the perspectives of smart city data collection, circulation, and processing, while there are fewer studies around the influencing factors of releasing the value of smart city data elements based on the analysis of the mechanism for releasing the value of data elements in smart cities. Research on the mechanism and key influencing factors for releasing the value of data elements in smart cities can help clarify the effective path to maximize the value of data elements in smart cities. In view of this, this paper will try to analyze the mechanism and influencing factors of the value release of data elements in smart cities based on the DPSIR theory after defining the concept of data element value release in smart cities; it will also identify the key influencing factors affecting the value release of data elements in smart cities by using the fuzzy-DEMATEL method in order to provide reference for maximizing the use of smart city data and fully utilizing the value of smart city data.

2.2. The Mechanism for Releasing the Value of Data Elements in Smart Cities

2.2.1. Defining the Release of Data Element Value in Smart Cities

Smart city data are the record or description of all objective things in the smart city [19], which is the original, unordered, and unprocessed material. The smart city data element refers to the data that are involved in the operation activities of the smart city, can bring economic benefits to the user or owner, and exist in electronic form [20], which are orderly data after a series of processing. Smart city data elements participate in and are affected by various activities such as production, distribution, circulation, and consumption in smart cities, containing great value [20]. But only by virtue of the smart city, data elements themselves cannot release their potential value. It is necessary to rely on the development of the social environment, the operation of the smart city, etc. The value of data elements

of smart cities is released in the process of the generation, flow, and application of data elements of smart cities. In order to better study the mechanism of the value release of data elements in smart cities and their influencing factors, we tried to define the concept of value release of data elements in smart cities. Releasing the value of data elements in smart cities refers to the process of using data processing technology to process the raw data generated during the operation of smart cities in a specific social environment context, and conducting data transaction under the guarantee of an institutional system, etc.; finally, externalizing the potential value contained in the raw data into data products or services that can be measured and exchanged, so as to optimize the social allocation. Releasing the value of data elements in smart cities can produce a multiplier effect on other production factors in smart cities and play its role as a new production element to promote the development of smart cities.

2.2.2. The Mechanism Based on DPSIR Theory

Introduced in 1993 by the Organization for Economic Cooperation and Development (OECD), DPSIR theory is a theoretical framework for sequentially modeling target areas to develop management responses consisting of five components, namely, driver (D), pressure (P), state (S), impact (I), and response (R) [21]. It is used in a variety of disciplines and fields such as the natural environment [17,22,23], regional sustainable development [24,25], and data management [26,27]. The theory provides a scientific analytical framework for systematically describing the causal process from the origin to the outcome of the target problem [28]. Within this framework, it is possible to simulate the context in which the target problem occurs and evolves, thereby finding ways to produce the desired results [28]. At the same time, DPSIR theory is able to simplify the structure of the target problem occurrence and evolution process, while maintaining enough complexity by integrating natural resources, the social environment, and human activities into the framework for comprehensiveness.

The value release of data elements in smart cities is a complex process, and the study of its mechanism needs to start from the causes that contribute to the occurrence of the value release of data elements in smart cities, analyze the multiple parts of the value release of data elements in smart cities under the action of multiple causes, and focus on the causal relationship between different parts. DPSIR theory fits this requirement by providing a systematic framework for the study of the mechanism for releasing the value of data elements in smart cities. Hence, this study will use DPSIR theory to analyze the role played by each part in the process of releasing the value of data elements in smart cities and the interactions between the parts, so as to analyze the mechanism for releasing the value of data elements in smart cities.

Under the DPSIR framework, the value release process of smart city data elements can be divided into five parts, namely, smart city data element value release driver (D), smart city data element value release pressure (P), smart city data element value release state (S), smart city data element value release impact (I), and smart city data element value release response (R) [29]. The smart city data element value release driver is the deepest reason affecting the value release of data elements in smart cities, driving the whole value release process to happen. The smart city data element value release pressure derived from the smart city data element value release driver can directly act on the smart city data element value release state, prompting the original value release state to change. The change in the state of the value release of data elements in smart cities will lead to the generation of different value release impacts, and different value release impacts of data elements in smart cities will prompt people in smart cities to take different initiatives or actions to respond. These response initiatives and actions will inevitably change the general environment for releasing the value of data elements in smart cities, bring about further optimization and improvement of the smart city data element value release driver, then change the whole process of releasing the value of data elements in smart cities. The value

of data elements in smart cities is released in this cyclic and complex process, and the release mechanism is shown in Figure 1.

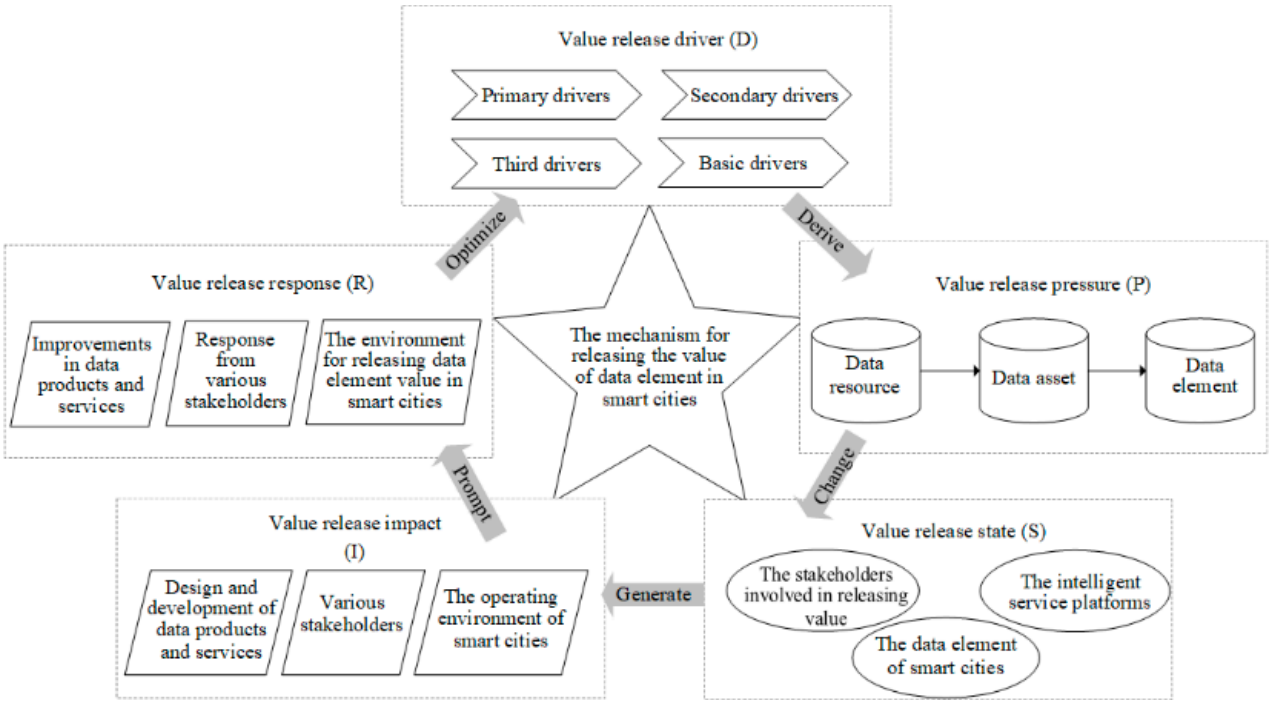


Figure 1. The mechanism of releasing the value of data elements in smart cities based on DPSIR theory.

As can be seen from Figure 1, value release drivers stem from macro social factors, such as socio-economic activities, natural environmental conditions, cultural ideologies, and urban demographics [30]. These elements create the foundational need for value release activities in smart city data, setting the stage for the entire release process. The resulting institutional, technical, and other artificially generated pressures drive the transformation of the original data collected during smart city operations into data resources, data assets, and ultimately data elements [31]. This is known as the value release pressure layer, where pressures arise from the demands of the value release driver layer. After undergoing this process, raw data is transformed into data elements, forming the basis for value release activities of data elements in smart cities. The value release pressure brings about changes in the value release state. When the data of smart cities undergo a morphological transformation, the status of the data elements of smart cities themselves, the stakeholders involved in releasing value, and the intelligent service platforms connecting the data elements and the stakeholders all change accordingly. Once the value release state of the data element in smart cities changes, it will have an impact on the design and development of data products and services, the satisfaction of the needs of various stakeholders, and even the operating environment of smart cities [32]. This constitutes the value release impacts layer, which arises directly from changes in the value release state. Faced with these impacts, people will respond with initiatives or actions that correspond to the generated effects, forming the value release response layer. These responses, in turn, adjust the social environment in which smart cities develop, including urban economic activities, natural environmental conditions, and cultural ideologies, thereby creating a more conducive environment for the value release activities of smart city data elements to initiate and progress.

2.3. Analysis of the Influencing Factors for Releasing the Value of Data Elements in Smart Cities

2.3.1. Dimensional Analysis

From the mechanism of releasing the value of data elements in smart cities, we can see that the process of releasing the value of data elements in smart cities goes through

five parts. These five parts can clearly present the multiple complex structures of data element value release in smart cities and cover the whole process of data element value release in smart cities. In view of this, these five parts can be determined as the dimensions for studying the value release of data elements in smart cities, that is, the driver of data element value release in smart cities (D), the pressure of data element value release in smart cities (P), the state of data element value release in smart cities (S), the influence of data element value release in smart cities (I), and the response of data element value release in smart cities (R).

2.3.2. Influencing Factor Under Each Dimension

After analyzing the 5 dimensions of the value release of data elements in smart cities, we adopted a literature research method to systematically review the existing literature on smart city data, smart city operation process, and value release of data elements. Combined with the release mechanism of data elements in smart cities analyzed in the DPSIR framework, we further analyzed the influencing factors of data element value release in smart cities under each dimension based on 5 dimensions, namely, the driver of data element value release in smart cities (D), the pressure of data element value release in smart cities (P), the state of data element value release in smart cities (S), the influence of data element value release in smart cities (I), and the response of data element value release in smart cities (R). The influencing factors for releasing the value of data elements in smart cities and their sources are shown in Table 1.

Table 1. The influencing factors for releasing the value of data elements in smart cities.

Dimension	Influencing Factor	Source
The driver of data element value release in smart cities (D)	Socio-economic level (D1)	Joshi et al. [33]
	Legal and policy formulation (D2)	
	Natural environmental condition (D3)	
	Socio-cultural level (D4)	Winters [34]
	Demographic change (D5)	Hansen [35]
	Infrastructure condition (D6)	Kim [9]
	Sustainable development (D7)	Joshi et al. [33]
The pressure of data element value release in smart cities (P)	Data acquisition technique (P1)	Lim et al. [8]
	Data storage technology (P2)	
	Data cleansing technology (P3)	
	Data computing technology (P4)	
	Data exchange technology (P5)	Joshi et al. [33]
	Data element identification (P6)	Yin et al. [32]
	Data transaction system (P7)	
	Data sharing system (P8)	Lee et al. [36]
	Data privacy protection (P9)	
	Data security technology (P10)	

Table 1. *Cont.*

Dimension	Influencing Factor	Source
The state of data element value release in smart cities (S)	Data element number (S1)	Demchenko et al. [37]
	Data element currentness (S2)	
	Data element type (S3)	
	Data element value potential (S4)	
	Data element authenticity (S5)	
	Smart city top-level design (S6)	IEC [38]
	Government sector regulatory structure (S7)	
	Financial budget (S8)	
	Corporate income system (S9)	
	Economic or policy support (S10)	
	Corporate finance model (S11)	
	End-user participation (S12)	Rodríguez-Labajos et al.; IEC [38,39]
	End-user burden cost (S13)	
	Expert engagement (S14)	IEC [38]
	Smart service platform availability (S15)	Alexopoulos et al. [40]
	Smart service platform ease-of-use (S16)	
	Collaborative stakeholder relationships (S17)	
The influence of data element value release in smart cities (I)	Design and provision of smart city data products and services (I1)	Lim et al.; Alexopoulos et al.; Gil-Garcia et al. [8,40,41]
	End-user satisfaction (I2)	
	Level of government governance (I3)	
	Smart city operating cost (I4)	Gil-Garcia et al.; Li et al. [1,41]
	Smart city operational efficiency (I5)	
	Smart city risk resilience (I6)	
The response of data element value release in smart cities (R)	Application of innovation results (R1)	IEC [38]
	Improvement of citizens' quality of life (R2)	
	Optimization of solutions for smart city problems (R3)	
	Uniform standard setting (R4)	IEC; Caporuscio [38,42]
	Development of cross-regional and cross-subject cooperation (R5)	
	Self-transformation of smart cities (R6)	
	Long-term maintenance of smart city infrastructure (R7)	

2.4. Identification of Key Influencing Factors for Data Element Value Release in Smart Cities Based on Fuzzy-Dematel Method

According to the mechanism and the analysis of all the influence factors on the value release of data elements in smart cities, there are several influence factors in the process of the value release of data elements in smart cities, but the influence degree on the value release of data elements in smart cities varies due to the different positions and roles of these influence factors. Identifying the influencing factors that play a key role in releasing the value of data elements in smart cities can provide concrete ideas for maximizing the value of data elements in smart cities. In view of this, we will use a combination of fuzzy set theory and DEMATEL method in this paper to identify the key influencing factors for the value release of data elements in smart cities.

The DEMATEL method calculates the center degree, cause degree, influence degree, and influenced degree of each element by calculating the direct influence matrix, so that

the position of each factor in the system can be determined. However, the limitation of this method is that expert scoring destroys the objectivity of the direct influence matrix. In order to break this limitation, some scholars have integrated and innovated the DEMATEL method, proposed to combine the DEMATEL method with fuzzy set theory, and used triangular fuzzy numbers to quantify the subjective scores of experts to ensure the objectivity of data.

In addition, we compare the fuzzy-DEMATEL method with a series of other baseline methods. There are few relevant studies on the identification of key influence factors for the value release of data elements in smart cities. So, we refer to the methods of identifying key influence factors in other fields. For example, Mashau et al. used a systematic literature review method [43]. They used ATLAS.ti to systematically analyze the available literature in order to identify key factors that can be used to assess the readiness of small and rural municipalities to implement smart cities. Yigitcanlar et al. identified key factors influencing the transformation of smart cities in Australia through multiple regression analysis using the overall LGA performance score as the dependent variable [44]. Chen et al. used a fuzzy large-scale group-DEMATEL method to identify the key impact elements of using blockchain technology in highways [45]. Chen et al. integrated fuzzy DEMATEL and ISM to evaluate safety factors in complex systems [46]. Suresh et al. combined fuzzy DEMATEL and ANFIS methods to assess and predict software project risks [47].

By comparing the above methods, we found that the DEMATEL method is able to classify the attribute of each influencing factor of smart city data element value release into two categories, cause and effect, and effectively show the interaction among the influencing factors, which is not possible by other decision-oriented methods [45]. Meanwhile, unlike predictive or nonlinear modeling methods, the DEMATEL approach allows for the direct classification of influencing factors into "cause" and "effect" categories and clearly demonstrates how these factors interact. This aligns with our study's goal of revealing key drivers and dependencies, rather than focusing on predictive modeling.

In addition, the use of fuzzy set theory can triangulate the experts' scoring, thus ensuring the objectivity of experts' scoring and making the subsequent identification of key influence factors more accurate. In summary, the fuzzy-DEMATEL method adopted in this paper can effectively identify the key influence factors of the value release of data elements in smart cities, clearly show the relationship between the influence factors, identify the attribute of each influence factor, and help the subsequent research to be carried out. Figure 2 is the analysis framework of this study.

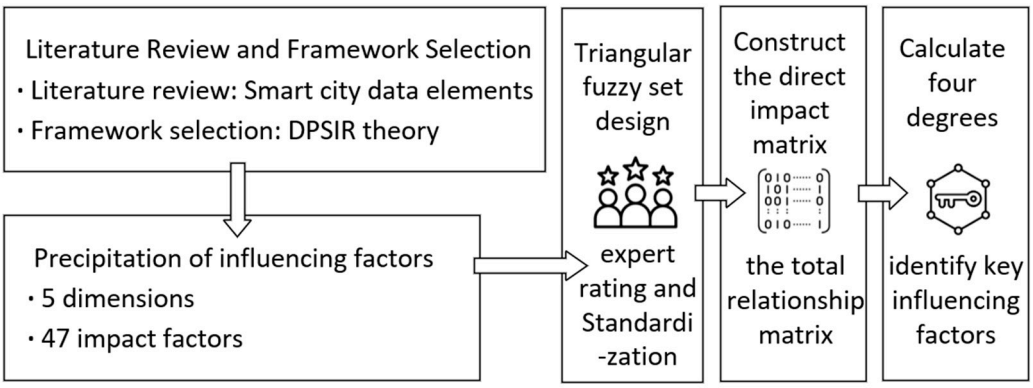


Figure 2. Analysis framework.

3. Results

3.1. Data Source

According to the requirements of the fuzzy-DEMATEL method, a total of 30 experts were invited to score each influence factor on the value release of data elements in smart cities according to a five-level Likert scale. The gender, education, region, and field of expertise of these thirty experts are shown in Table 2.

Table 2. Descriptive statistics for 30 experts.

Item	Classification	Proportion	Item	Classification	Proportion
The gender	Male	40%	**The education**	Junior college student	20%
	Female	60%		Bachelor	33%
The region	North China	60%		Master and above	47%
	East China	20%	**The field of expertise**	Smart city end-user	27%
	Northwest China	6%		Solution provider	30%
	Southwest China	10%		Enterprise personnel	23%
	South China	3%		Government staff	20%

In accordance with the requirements of the fuzzy-DEMATE method, we invited 30 experts with diverse backgrounds in the field of smart cities to evaluate the influence of various data elements. Table 2 provides an overview of these experts' demographics, including gender, education, region, and field of expertise. To ensure representativeness, experts were selected based on several criteria. First, regarding educational background, all participants were either current students or graduates from higher education institutions, with 33% holding bachelor's degrees, 47% holding master's degrees or higher, and 20% being junior college students. This distribution allowed us to gather perspectives across different educational levels concerning the value release of data in smart cities. Second, in terms of the field of expertise and work experience, the experts represented smart city end-users (27%), solution providers (30%), enterprise personnel (23%), and government staff (20%). Each participant possessed a minimum of two years of relevant experience, thereby providing well-rounded insights into the evaluation of data element influence factors in smart cities. Third, to minimize regional bias, experts were drawn from various parts of China, with 60% from North China, 20% from East China, and the remainder from Southwest, South, and Northwest China. This distribution reflects potential regional variations in perspectives on data usage within smart cities. Furthermore, all participants had foundational knowledge of data value assessments in the smart city domain, ensuring that they possessed the capability to provide informed and independent evaluations. We believe that the backgrounds and expertise of these 30 experts adequately represent the study's subject matter.

After the above experts' scoring of each influence factor on the value release of data elements in smart cities, the experts' scoring data were recovered and fuzzified. To ensure the objectivity of the scores of each influencing factor, this study transformed the experts' scores into triangular fuzzy numbers $Z^k_{mn} = (a_{mn}, b_{mn}, c_{mn})$, $1 \leq k \leq 30$. This formula represents the fuzzified value of any influencing factor m on influencing factor n. The specific calculation process is as follows.

3.2. Determine the Direct Impact Matrix

In order to obtain the direct impact matrix R of the influencing factor data for the value release of smart city data elements, we standardized the obtained expert scoring results according to the triangular fuzzy number principle, reduced the fuzzy number, and calculated the left and right standard values, the total standard value, and the overall standardized impact degree value [48,49].

(1) The triangular fuzzy number matrix is normalized and calculated as shown in Equations (1)–(3).

$$x^k_{mn1} = \frac{x^k_{mn1} - minx^k_{mn1}}{\Delta^{max}_{min}} \; 1 \leq k \leq 30 \tag{1}$$

$$x_{mn2}^{k} = \frac{x_{mn2}^{k} - minx_{mn1}^{k}}{\Delta_{min}^{max}} 1 \le k \le 30 \quad (2)$$

$$x_{mn3}^{k} = \frac{x_{mn3}^{k} - minx_{mn1}^{k}}{\Delta_{min}^{max}} \ 1 \le k \le 30 \quad (3)$$

(2) Reduce the fuzzy number and calculate the left and right standard values. The formula for calculating the left standard value is shown in Equation (4).

The formula for calculating the right standard value is shown in Equation (5).

$$ls_{mn}^{k} = \frac{x_{mn2}^{k}}{1 + x_{mn2}^{k} - x_{mn1}^{k}} \quad (4)$$

$$rs_{mn}^{k} = \frac{x_{mn3}^{k}}{1 + x_{mn3}^{k} - x_{mn2}^{k}} \quad (5)$$

(3) Calculate the total standard value with the formulas shown in Equations (6) and (7).

$$x_{mn}^{k} = \frac{ls_{mn}^{k}\left(1 - ls_{mn}^{k}\right) + rs_{mn}^{k} rs_{mn}^{k}}{1 - ls_{mn}^{k} + rs_{mn}^{k}} \quad (6)$$

$$w_{mn}^{k} = mina_{mn}^{k} + x_{mn}^{k}\Delta_{min}^{max} \ 1 \le k \le 30 \quad (7)$$

(4) Calculate the overall standardized impact degree value for each expert, and the formula is shown in Equation (8).

$$d_{mn} = \frac{\sum_{k=1}^{k} w_{mn}^{k}}{k} \quad (8)$$

The influence degree of each influencing factor for the value release of data elements in smart cities was calculated based on Equations (1)–(8). The direct impact matrix R of the influencing factors for the value release of data elements in smart cities was obtained, as shown in Table 3. Table 3 displays the direct impact matrix R of influencing factors in the value release of data elements in smart cities. Each cell value in the matrix represents the direct impact one factor exerts on another. Higher values indicate a stronger direct influence.

Table 3. The direct impact matrix R of the influencing factors for the value release of data elements in smart cities (partial).

	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**P1**	**P2**	**P3**	**P4**	**P5**
D1	0	0.3333	0.4333	0.3833	0.4333	0.3333	0.3250	0.3083	0.3500	0.3750	0.2833	0.3250
D2	0.1667	0	0.3583	0.3083	0.3583	0.2417	0.2583	0.2417	0.2750	0.3167	0.2083	0.2500
D3	0.0667	0.1417	0	0.2333	0.2750	0.1583	0.1417	0.1417	0.1750	0.2000	0.1167	0.1500
D4	0.1167	0.1917	0.2667	0	0.2833	0.1750	0.1833	0.1833	0.1917	0.2333	0.1417	0.1917
D5	0.2724	0.3454	0.2250	0.2167	0	0.1417	0.3374	0.3214	0.3454	0.2000	0.3073	0.1333
D6	0.1667	0.2583	0.3417	0.3250	0.3583	0	0.2500	0.2333	0.2667	0.3083	0.2083	0.2583
D7	0.1750	0.2417	0.3583	0.3167	0.3667	0.2500	0	0.2333	0.2750	0.3083	0.2083	0.2333
P1	0.1917	0.2583	0.3583	0.3167	0.3833	0.2667	0.2667	0	0.2917	0.3333	0.2250	0.2667
P2	0.1500	0.2250	0.3250	0.3083	0.3583	0.2333	0.2250	0.2083	0	0.2917	0.1833	0.2333
P3	0.1250	0.1833	0.3000	0.2667	0.3000	0.1917	0.1917	0.1667	0.2083	0	0.1333	0.1917
P4	0.2167	0.2917	0.3833	0.3583	0.4000	0.2917	0.2917	0.2750	0.3167	0.3667	0	0.2917
P5	0.1750	0.2500	0.3500	0.3083	0.3667	0.2417	0.2667	0.2333	0.2667	0.3083	0.2083	0

3.3. Standardized Processing

The direct influence matrix R of each influencing factor for the value release of smart city data elements was substituted into Equations (9) and (10) to obtain the total relationship matrix T of each influencing factor for the value release of smart city data elements.

(1) Calculate the standardized impact matrix S. The formula is shown in Equation (9).

$$S = \frac{1}{max\sum_{j=1}^{44} d_{mn}} R(1 \leq m \leq 47) \quad (9)$$

(2) Calculate the total relationship matrix T with the formula shown in Equation (10), and the results are shown in Table 4.

$$T = S(1-S)^{-1} \quad (10)$$

Table 4 shows the total relationship matrix T, incorporating both direct and indirect influences among factors. This matrix highlights the overall impact of each factor, allowing us to prioritize those with the most extensive influence across the network.

Table 4. Total relationship matrix T (partial) for each influencing factor of smart city data element value release.

	D1	D2	D3	D4	D5	D6	D7	P1	P2	P3	P4	P5
D1	0.0433	0.0817	0.1024	0.0949	0.1056	0.0750	0.0783	0.0757	0.0818	0.0955	0.0686	0.0791
D2	0.0433	0.0471	0.0799	0.0735	0.0823	0.0566	0.0605	0.0583	0.0630	0.0748	0.0520	0.0606
D3	0.0250	0.0383	0.0367	0.0486	0.0548	0.0360	0.0369	0.0361	0.0398	0.0472	0.0319	0.0377
D4	0.0324	0.0475	0.0606	0.0418	0.0634	0.0426	0.0454	0.0444	0.0470	0.0566	0.0387	0.0463
D5	0.0454	0.0621	0.0649	0.0613	0.0535	0.0456	0.0596	0.0576	0.0615	0.0612	0.0530	0.0482
D6	0.0434	0.0629	0.0791	0.0746	0.0826	0.0421	0.0602	0.0580	0.0626	0.0745	0.0521	0.0612
D7	0.0436	0.0616	0.0797	0.0737	0.0827	0.0569	0.0448	0.0576	0.0628	0.0742	0.0519	0.0595
P1	0.0501	0.0703	0.0892	0.0828	0.0936	0.0648	0.0681	0.0507	0.0713	0.0848	0.0593	0.0689
P2	0.0404	0.0581	0.0747	0.0704	0.0789	0.0537	0.0560	0.0539	0.0438	0.0702	0.0483	0.0570
P3	0.0333	0.0477	0.0633	0.0586	0.0652	0.0442	0.0465	0.0441	0.0486	0.0432	0.0387	0.0469
P4	0.0524	0.0735	0.0923	0.0867	0.0962	0.0674	0.0709	0.0685	0.0741	0.0882	0.0467	0.0716
P5	0.0437	0.0620	0.0792	0.0732	0.0826	0.0564	0.0609	0.0577	0.0623	0.0741	0.0519	0.0453

To calculate the influence degree, influenced degree, center degree, cause degree, and ranking of each influencing factor of smart city data element value release, we added up the members of each row of matrix T to obtain the influence degree E of each influencing factor, added up the members of each column to obtain the influenced degree F of each influencing factor, added up the influence degree of each influencing factor with the value of influenced degree (E + F) to obtain the center degree G of each influencing factor, and subtracted the influence degree of each influencing factor with the value of influenced degree (E − F) to obtain the cause degree H of each influencing factor. The results of the "four degrees" calculation are presented in Table 5, summarizing each influencing factor's influence degree, influenced degree, center degree, and cause degree. The four degrees and their rankings represent the overall impact of each factor, enabling the identification of the most influential factors—i.e., the key influencing factors.

Table 5. Influence degree, influenced degree, centrality degree, cause degree, and ranking of each influencing factor of smart city data element value release.

Influencing Factor	Influence Degree		Influenced Degree		Center Degree		Cause Degree	
	D	Rank	R	Rank	D + R	Rank	D − R	Rank
D1	3.8325	3	2.1053	47	5.9379	19	1.7272	1
D2	2.9310	30	2.9959	20	5.9269	22	−0.0649	30
D3	1.8472	46	3.7187	4	5.5659	44	−1.8715	46
D4	2.2340	44	3.4941	8	5.7280	34	−1.2601	42
D5	2.5640	38	3.8753	2	6.4393	6	−1.3113	44
D6	2.9404	29	2.6773	35	5.6177	39	0.2631	23
D7	2.9216	31	2.8573	25	5.7789	27	0.0643	26
P1	3.3966	9	2.7790	28	6.1756	9	0.6176	11
P2	2.7687	33	2.9539	22	5.7227	37	−0.1852	32
P3	2.2740	42	3.5493	7	5.8233	24	−1.2753	43
P4	3.4775	6	2.5024	41	5.9799	15	0.9751	3
P5	2.9210	32	2.8968	24	5.8178	25	0.0241	27
P6	2.9638	27	2.6031	38	5.5669	43	0.3608	19
P7	3.0524	21	3.6109	5	6.6633	5	−0.5586	36
P8	3.0788	19	2.4933	43	5.5721	40	0.5855	13
P9	3.9514	1	2.7203	31	6.6717	3	1.2312	2
P10	3.2931	13	2.4721	45	5.7652	30	0.8211	7
S1	2.0398	45	3.4728	9	5.5126	46	−1.4330	45
S2	2.7610	34	2.7392	30	5.5003	47	0.0218	28
S3	2.5404	39	3.2024	13	5.7428	32	−0.6620	38
S4	2.6920	37	3.0199	19	5.7119	38	−0.3279	33
S5	3.4304	7	2.4992	42	5.9295	21	0.9312	4
S6	3.4161	8	2.9840	21	6.4001	7	0.4322	18
S7	3.5289	5	2.6976	33	6.2265	8	0.8312	6
S8	3.3226	10	2.7538	29	6.0763	11	0.5688	14
S9	2.4354	41	3.3688	10	5.8042	26	−0.9334	40
S10	3.3103	11	2.6504	37	5.9608	18	0.6599	9
S11	1.7541	47	3.9719	1	5.7259	35	−2.2178	47
S12	3.2834	15	2.6507	36	5.9341	20	0.6327	10
S13	2.4731	40	3.0807	16	5.5538	45	−0.6076	37
S14	3.8580	2	3.5911	6	7.4492	1	0.2669	22
S15	3.0171	23	2.7082	32	5.7252	36	0.3089	20
S16	3.1317	17	2.5998	39	5.7315	33	0.5319	15
S17	3.5636	4	3.1004	15	6.6640	4	0.4631	16
I1	3.0357	22	3.0652	17	6.1008	10	−0.0295	29
I2	3.3098	12	2.4672	46	5.7770	28	0.8426	5
I3	2.7144	36	3.1472	14	5.8616	23	−0.4328	34
I4	2.7491	35	3.2720	12	6.0211	12	−0.5229	35
I5	3.0691	20	2.9436	23	6.0127	13	0.1254	25
I6	2.9527	28	2.8115	27	5.7641	31	0.1412	24
R1	3.0123	24	2.5548	40	5.5671	42	0.4574	17
R2	3.2768	16	2.4893	44	5.7661	29	0.7875	8
R3	2.9659	26	3.0320	18	5.9979	14	−0.0661	31
R4	3.1213	18	2.8458	26	5.9671	17	0.2754	21
R5	2.2551	43	3.3157	11	5.5708	41	−1.0606	41
R6	2.9977	25	3.7311	3	6.7288	2	−0.7334	39
R7	3.2891	14	2.6835	34	5.9726	16	0.6056	12

4. Discussion

4.1. Discussion of the Interrelationships Among the Influencing Factors for Releasing the Value of Data Elements in Smart Cities

The cause degree of each influencing factor reflects the causal relationship between that influencing factor and other influencing factors in the process of releasing the value of data elements in smart cities. If the cause degree >0, it means that this influencing factor is the cause factor, in other words, its ability to actively influence other influencing factors in

the process of releasing the value of smart city data elements is greater than the ability to be influenced. If the cause degree is <0, it means that this influencing factor is a result factor, and its ability to be influenced by other influencing factors in the process of releasing the value of smart city data elements is greater than its ability to actively influence. As can be seen from Table 4, there are 28 cause factors and 19 result factors in the process of releasing the value of data elements in smart cities. The relationship between the influencing factors in the process of releasing the value of smart city data elements is shown in Figure 3.

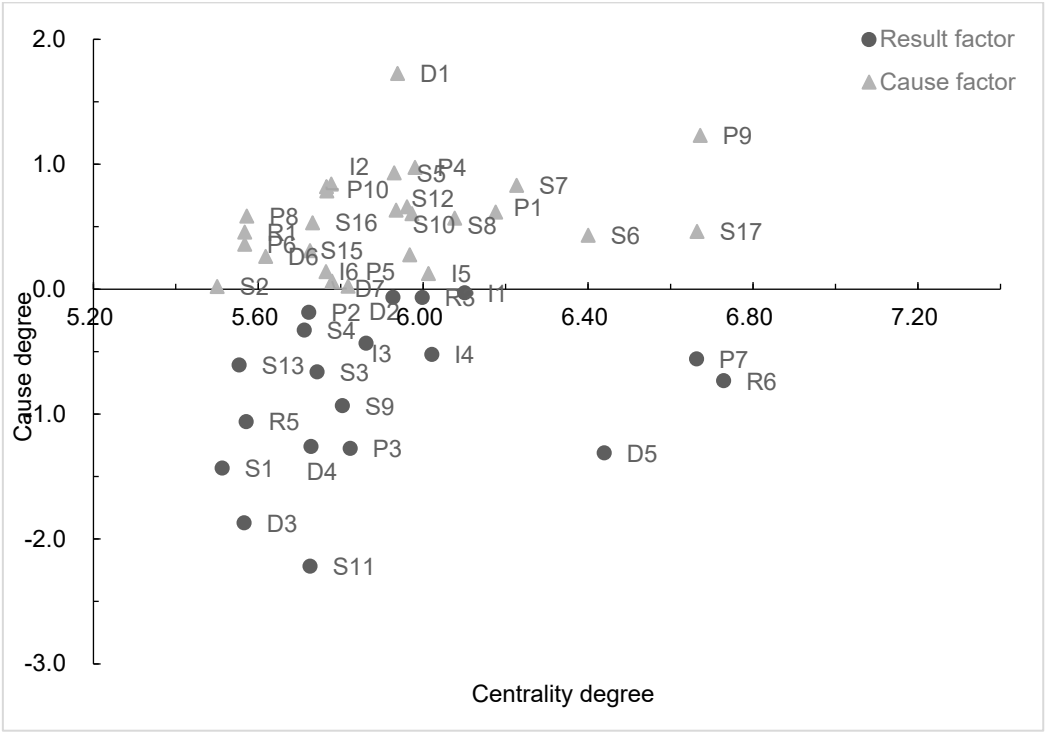


Figure 3. The relationship of influencing factors in the process of releasing the value of data elements in smart cities.

As shown in Figure 3, the influencing factors belonging to the cause factors in the process of data element value release in smart cities are D1, D6, D7, P1, P4, P5, P6, P8, P9, P10, S2, S5, S6, S7, S8, S10, S12, S14, S15, S16, S17, I2, I5, I6, R1, R2, R4, and R7. Among them, the socio-economic level (D1) ranks 1st in the degree of cause and 3rd in the degree of influence, while the degree of being influenced ranks at the bottom, indicating that this influencing factor has an extremely strong initiative and has a great possibility of affecting other influencing factors in the process of releasing the value of smart city data elements, but is not easily affected. Similarly, there are data privacy protection (P9), data computing technology (P4), and data element authenticity (S5), etc. The above-mentioned influencing factors are in the top of the list for both the degree of cause and the degree of influence, showing a strong initiative.

As shown in Figure 3, the influence factors belonging to the result factors in the process of releasing the value of smart city data elements are D2, D3, D4, D5, P2, P3, P7, S1, S3, S4, S9, S11, S13, I1, I3, I4, R3, R5, and R6. Among them, corporate finance model (S11) is ranked last in both the cause and effect degree, indicating that this influencing factor is highly susceptible to the influence of other influencing factors and is very closely linked to other influencing factors. Similar to it are the natural environmental condition (D3), demographic change (D5), and interregional and development of cross-regional and cross-subject cooperation (R5). The above influencing factors are ranked backward in terms of cause degree and influence degree; they are susceptible to other influencing factors in the process of releasing the value of smart city data elements.

4.2. Discussion of Identifying Key Influencing Factors for Releasing the Value of Data Elements in Smart Cities

In identifying the key influencing factors in the process of releasing the value of smart city data elements, the greater the center degree of an influencing factor, the more important the influencing factor is. In addition, the influence degree, influenced degree, and cause degree of the influencing factor also need to be considered comprehensively. From the results of the "four degrees" calculation of the influencing factors for releasing the value of smart city data elements, it can be seen that the center degree of expert participation (S14) is ranked number 1, and its influence degree and influenced degree are both at the top, which indicates that it is not only important but also closely related to other influencing factors. The process of releasing the value of smart city data elements involves a lot of professional knowledge and requires the participation of experts in related fields. In view of this, expert participation (S14) can be identified as a key influencing factor for the value release of smart city data elements.

The center degree of data privacy protection (P9), collaborative stakeholder relationship (S17), smart city top-level design (S6), and government sector regulatory structure (S7) are 3rd, 4th, 7th, and 8th, respectively, and they are all ranked at the top of the influence degree, indicating that these four influencing factors are prone to affect other influencing factors. Improvements in data privacy protection technology can increase the willingness of citizens to participate. The collaboration of stakeholders helps to improve the efficiency and cost savings in releasing the value of smart city data elements. Smart city top-level design and the regulatory structure of government sectors can determine the goal of releasing the value of smart city data elements from a more macro level and guarantee the smooth operation of the value release process. In view of this, data privacy protection (P9), collaborative stakeholder relationships (S17), smart city top-level design (S6), and government sector regulatory structure (S7) can be identified as key influencing factors for releasing the value of data elements in smart cities.

Data acquisition technology (P1) and data computing technology (P4) are ranked 9th and 15th in the center degree, and 9th and 6th in the impact degree, respectively. The collection of smart city data is the basis for releasing the value of smart city data elements. The improvement of data computing technology will help to better exploit the smart city data that has been collected and maximize the value contained in it. In view of this, data acquisition technology (P1) and data computing technology (P4) can be identified as key influencing factors for releasing the value of data elements in smart cities.

Data transaction system (P7), self-transformation of smart cities (R6), and the design and provision of smart city data products and services (I1) are ranked 5th, 2nd, and 10th in the center degree, respectively, and are all vulnerable to be affected. The smart city data trading system affects the process of the raw data of smart city from asset to factorization. Smart cities will eventually evolve into self-organizing forms after a series of changes. The design and provision of smart city data products and services is one of the expressions to externalize the value of smart city data elements. In view of this, data transaction system (P7), self-transformation of smart cities (R6), and the design and provision of smart city data products and services (I1) can be identified as key influencing factors for releasing the value of data elements in smart cities.

Although the center degree of socio-economic level (D1) is ranked 19th, its cause degree is ranked 1st and its influence degree is ranked 3rd, indicating that this influencing factor is extremely active and prone to affect the remaining influencing factors. The socio-economic level is the influencing factor throughout the process of releasing the value of data elements in smart cities, and affects each part of the process of releasing the value of data elements in smart cities, which can be identified as the key influencing factor of releasing the value of data elements in smart cities.

In summary, there are 11 key influencing factors for the value release of smart city data elements, which are the following: expert participation (S14), data privacy protection (P9), collaborative stakeholder relationship (S17), smart city top-level design (S6), government

sector regulatory structure (S7), data acquisition technology (P1), data computing technology (P4), data transaction system (P7), self-transformation of smart cities (R6), design and provision of smart city data products and services (I1), and socio-economic level (D1). The remaining influencing factors are ranked poorly in terms of the degree of center, cause, influence, and influenced, indicating that the importance, initiative, and synergistic relationship of these influencing factors are not obvious enough to be identified as key influencing factors for releasing the value of smart city data elements.

In the practical operation of smart cities, these 11 key influencing factors form a mutually supportive framework that is essential for enabling data value release. By optimizing the identified key influencing factors, the process of releasing the value of smart city data elements can be refined, enabling a more complete realization of their potential value.

Top-level design (S6) establishes an overall framework for smart city development, while government sector regulatory structure (S7) ensures an oversight of data security and compliance, aligning projects with a unified strategic direction. Expert participation (S14) brings technical expertise to decision-making, providing a scientific foundation for critical choices in planning and implementation. In practical execution, collaborative stakeholder relationships (S17) facilitate effective resource allocation and coordination among stakeholders, further enhancing efficiency and reducing operational costs.

At the data level in smart cities, data acquisition technology (P1) provides real-time, comprehensive foundational data support, while data computing technology (P4) enables efficient processing and analysis, ensuring robust support for precise management. Data privacy protection (P9) enhances citizen trust in data services by ensuring data security and compliance, thereby increasing citizen engagement. Additionally, the data transaction system (P7) facilitates effective data flow, transforming data resources into valuable assets and offering sustainable economic support for smart cities.

The self-transformation of smart cities (R6) enables cities to self-optimize and adapt to change, maintaining flexibility and innovation in a rapidly evolving environment. The design and provision of smart city data products and services (I1) allows for the externalization of data value, providing direct value-added services to citizens and businesses, thereby enhancing the economic and social benefits of smart cities. Lastly, the socio-economic level (D1) influences resource allocation, technological development, and data services, serving as a foundational pillar for smart city operations.

5. Conclusions

Data have emerged as a new production element, integrated into various aspects of smart city operations such as production, distribution, and social services, profoundly influencing the production and operational modes of smart cities. Given the increasing importance of data elements in smart cities, it is crucial to elucidate the mechanism of value release for these elements. Against this backdrop, this study investigates the mechanism and influencing factors of data element value release in smart cities, addressing three research questions and drawing the following conclusions.

First, in response to Q1 (What is the mechanism for releasing the value of data elements in smart cities?), a framework was constructed based on the DPSIR theory, systematically revealing the pathways and dynamic evolution logic of data element value release in smart cities. Second, addressing Q2 (What factors influence the release of data element value in smart cities based on the mechanism?), the study identified a comprehensive set of 47 influencing factors distributed across five dimensions derived from the established mechanism. Third, for Q3 (Which factors are the most critical among all those influencing the release of data element value in smart cities?), the fuzzy-DEMATEL method was employed to extract 11 critical factors from a pool of 47 identified factors. Furthermore, a "four-degree" analysis was conducted to classify the attributes of these factors and to examine the interactions among them. The contribution of this study is multifaceted.

5.1. Theoretical Implications

This research makes several significant theoretical contributions to the understanding of data element value release in smart cities. First, it demonstrates the potential of DPSIR theory as an analytical tool in this field, broadening the scope of DPSIR theory's application. By employing DPSIR, the process of data element value release in smart cities is systematically divided into five interrelated components: driver, pressure, state, impact, and response. This structured approach enhances understanding by embedding the value release process within the broader social context, rather than examining it in isolation.

Second, this research clarifies the mechanism of data element value release from a macroscopic perspective by taking into account social factors such as natural resources, technological conditions, and regulatory frameworks. This integration of social factors strengthens the connection between data element value release in smart cities and the surrounding environment.

Finally, from a microscopic perspective, this study contributes by identifying specific factors that influence data element value release. Through a literature review, we analyzed five dimensions and 47 influencing factors, followed by the application of the fuzzy-DEMATE method to identify 11 key factors. This analysis provides a granular understanding of the primary elements that drive value release in smart city data, supporting theoretical advancements in this domain.

5.2. Practical Implications

At the practical level, this study analyzes the mechanism of data element value release in smart cities and its key influencing factors, which helps to clarify the process of data element value release in smart cities; helps to visualize and analyze each influencing factor of data element value release in smart cities, which is hidden under multiple complex structures; and helps to precisely identify the factors that play a key influencing role on data element value release in smart cities. Focusing on the optimization of these key influence factors can help improve the efficiency of releasing the value of smart city data elements, promote smart city data elements to release the maximum value, make the smart city operation reach the best performance, improve the level of smart city services, and then improve the living standard of citizens, create a good business environment for enterprises, provide scientific and powerful decision-making basis for government departments, and finally, contribute to the sustainable development of the whole city.

5.3. Future Research

Future research can further analyze the interactions among each key influencing factor of smart city data element value release, as well as verify the correlation between the optimization degree of these key influencing factors and the release degree of smart city data element value through empirical research. In this way, the completeness of the research on the value release of smart city data elements can be continuously improved, and the degree of value release of smart city data elements can be increased.

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