# Structural Relationships among Factors Influencing Public Initial Acceptance Behavior of Government Open Data (Postprint)

**Authors:** Yaoqing Duan, meticulous, Shang Ting

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## Abstract

[Purpose/Significance] Clarifying the hierarchical relationships among factors influencing the public's initial acceptance behavior of government open data contributes to enhancing public acceptance and utilization efficiency of government open data, and provides theoretical support for the formulation and refinement of government open data policies in China. [Method/Process] Based on situational theory and expert survey methodology, 13 factors influencing the public's initial acceptance behavior of government open data were identified, and utilizing Interpretive Structural Modeling (ISM) to assist in modeling, a relational structural model of factors influencing the public's initial acceptance behavior of government open data was constructed. [Results/Conclusion] The results demonstrate that the relational structural model comprises five hierarchical levels, which can be categorized into three layers: the surface layer, middle layer, and root cause layer. The surface layer encompasses system resources, task urgency, and platform operation; the middle layer encompasses demand clarity, task subject, information awareness, information knowledge, and information capability; the root cause layer encompasses education level, age, policies and regulations, social influence, and platform design.

## Full Text

### Research on the Structural Relationship of Influencing Factors of Public Initial Acceptance Behavior of Government Open Data

**Duan Yaoqing**[1,2], **Zhou Mi**[1], **Shang Ting**[1] [1]School of Information Management, Central China Normal University, Wuhan 430079 [2]Hubei Data Governance and Intelligent Decision Research Center, Wuhan 430079

**Abstract:**
[**Purpose/Significance**] Clarifying the hierarchical relationships among factors influencing public initial acceptance behavior of government open data helps improve public acceptance and use efficiency of government open data, providing theoretical support for the formulation and improvement of relevant policies in China. [**Method/Process**] Based on situational theory and expert survey methods, 13 factors influencing public initial acceptance behavior of government open data were identified. Using the Interpretive Structural Model (ISM) to assist modeling, a relational structure model of these influencing factors was constructed. [**Result/Conclusion**] The results show that the relational structure model comprises five hierarchical levels, which can be divided into three layers: the presentation layer, intermediate layer, and fundamental layer. The presentation layer includes system resources, task urgency, and platform operation; the intermediate layer includes requirement clarity, task topic, information awareness, information knowledge, and information capability; the fundamental layer includes education level, age, policies and regulations, social influence, and platform design.

**Keywords:** government open data; public initial acceptance behavior; interpretive structural model; situational theory

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Open government construction has become a crucial topic in democratic society development, aiming to enhance government transparency, citizen trust, and public participation [1]. Government open data, as an essential component of open government construction, has also become a research hotspot in government, industry, and academia. In September 2015, the State Council promulgated the "Action Outline for Promoting Government Open Data Development," explicitly stating the need to build a unified national government open data platform. Research on government open data shows certain differences: foreign studies primarily focus on related technologies, influencing factor analysis, and application research, with factor studies mainly exploring legal policies, organizational environments, and technical factors [2]; domestic research concentrates on status surveys [3-4], policy studies [5-6], platform construction [7-8], data evaluation [9-10], and comparative foreign studies [11-12]. Regarding user behavior research on government open data, current studies are relatively limited, particularly regarding in-depth investigation of public initial acceptance behavior. The value of government open data can only be realized when used by the public [19], and initial acceptance behavior is a prerequisite for continued use. Numerous factors influence this behavior, with complex interrelationships. Although existing research has examined how various factors affect public initial acceptance, it has not fully revealed the interaction mechanisms among these factors. This study identifies influencing factors based on situational theory and expert surveys, employs ISM to construct a relational structure model, and analyzes the hierarchical relationships and their impacts, aiming to provide references for promoting government open data acceptance and utilization and for improving relevant policies and regulations.

## 1. Identification of Influencing Factors of Public Initial Acceptance Behavior of Government Open Data

Public acceptance behavior of government open data refers to data users' recognition, use, and adoption of government open data, comprising both initial acceptance and continuous usage behaviors with significantly different influencing factors. Initial acceptance is a prerequisite for continuous usage, and different perspectives can identify different factors. This study first reviewed literature to preliminarily identify factors based on government open data influencing factors and situational theory factor selection. Then, through expert surveys, final factors were determined by synthesizing expert opinions.

Situational theory posits that context refers to the circumstances, conditions, or immediate environment in which events develop or individual behaviors occur at a particular time [20]. The essence of studying context resembles that of organizational behavior, which explores how individuals, groups, and organizational structures affect organizational behavior patterns and relationships with the social environment within specific organizational contexts. For government open data users in different contexts, varying impacts on initial acceptance behavior occur, making situational difference analysis highly applicable. Based on situational classification frameworks, contextual factors can be divided into four categories: user, task, system, and environment [21]. As immediate conditions for individual behavior, context represents the unity of subjective and objective conditions, characterized by continuity, ecology, and uncertainty [22]. Current context-based factor research primarily follows two approaches: (1) decomposing context into system, task, user, environment, and IT factors for empirical studies on acceptance and usage intention [23-25]; (2) introducing context as exogenous environmental variables to examine its impact alongside other factors [26-28]. Situational theory emphasizes individual-environment interaction forming a dynamic whole, including individuals, psychological activities, and environment [29]. Treating context as merely exogenous can cause conceptual overlap and hinder deep exploration of context-subject relationships. Therefore, this study adopts the contextual factor decomposition perspective, identifying factors across user, task, system, and environmental dimensions.

Decomposed user and task factors remain underexplored in other government open data studies. User factors include age, gender, knowledge, experience, profession, physical condition, and education level, while task factors refer to user purposes when interacting with systems to fulfill information needs [24]. Fu Rong [30] argues that public information literacy is the primary external driver of government data openness. Li Jian et al. [31] propose that information literacy comprises information awareness, knowledge, capability, and ethics. Li Mei et al. [32] suggest that public information demand drives countries to provide one-stop government data access services. Qiu Minghui et al. [24] identify task factors including task source, topic, stage, requirement changes, clarity, complexity, and urgency. Combining these with the specific characteristics of government open data initial acceptance, this study establishes seven user-based factors (age, gender, education, information awareness, information knowledge, information capability, information ethics) and three task-based factors (task topic, requirement clarity, task urgency).

System and environmental factors, decomposed from contextual factors, are frequently examined in government open data research. Liang Yikai et al. [15] found that timeliness and comment ratings significantly positively affect government open data utilization. Jiang Hongbo et al. [18] discovered that platform design and operation significantly positively influence acceptance. Mo Zuying [2] reviewed studies identifying legal policies, organizational environment, and technical support as key factors. Tan Le et al. [26] identified technical, organizational, and environmental factors as obstacles. Zhu Hongcan et al. [8] argued that government data open platforms are indispensable tools where data accessibility and interaction methods directly affect user experience. Accordingly, this study establishes three system-based factors (system resources, platform operation, platform design) and two environmental factors (policies and regulations, social influence).

Based on literature review, influencing factors were extracted and a questionnaire was distributed to 15 government open data experts. Statistical results synthesizing expert opinions are shown in Table 1 .

**Table 1** Expert Agreement Count on Different Influence Levels of Various Factors on Public Initial Acceptance Behavior of Government Open Data (Unit: persons)

[Table content would be here]

As shown in Table 1, except for gender (which most experts considered to have minimal impact), the vast majority rated each factor's influence as moderate or above. This yielded 13 final influencing factors based on situational theory, presented in Table 2 . Factor codes use Xi, where X1-X5 represent public intrinsic factors and X6-X13 represent other factors.

**Table 2** Influencing Factors of Public Initial Acceptance Behavior of Government Open Data Based on Situational Theory

| Code | Factor | Description |
|---|---|---|
| X1 | Age | Data user's age |
| X2 | Education level | Data user's education (illiterate, semi-literate, primary, junior high, technical secondary, high school, university, master's, doctoral) |

| Code | Factor | Description |
|---|---|---|
| X3 | Information awareness | Data user's cognition, attitude, value orientation, and needs regarding information in information activities |
| X4 | Information knowledge | Knowledge of IT required to obtain and use information (communication technology, computer technology, network technology, database technology, multimedia technology, etc.) |
| X5 | Information capability | Ability to effectively utilize information awareness and knowledge to acquire, process, and create new information |
| X6 | Task topic | Topic of data user's task to obtain government open data (daily life, research work, comprehensive tasks) |
| X7 | Requirement clarity | Clarity of data user's needs for government open data |
| X8 | Task urgency | Urgency of tasks requiring government open data |
| X9 | System resources | Open data resources on government platforms (quantity, quality, timeliness, coverage) |
| X10 | Platform operation | Ease of operation of government data open platform functions |
| X11 | Platform design | Aesthetic and rational design of government data open platform interface |
| X12 | Policies and regulations | National strategies, laws, regulations, and local supporting policies for government open data |
| X13 | Social influence | Environmental support for government open data services, including mass media and interpersonal influence |

## 2. Construction of the Interpretive Structural Model of Influencing Factors

The basic idea of ISM is to use graph theory to represent ambiguous ideas and relationships in a system as matrices, then apply matrix operations and decomposition to process elements and their relationships, forming a clear multi-level hierarchical structure model that reveals inter-element relationships and identifies surface and root causes [33]. Since objectively and scientifically quantifying influencing factors of public acceptance behavior is difficult, this study adopts ISM, which can simply and clearly construct relationship structures without requiring specific quantitative indicators.

ISM construction steps include: (1) identifying factors, determining binary relationships, and obtaining adjacency matrix A; (2) calculating reachability matrix M through matrix operations; (3) simplifying M to M , calculating reachability sets R(Xi), antecedent sets A(Xj), and common sets C(Xij) for hierarchical extraction; (4) establishing the interpretive structural model based on hierarchical decomposition and rearranged reachability matrix M  [17].

### 2.1 Constructing Adjacency Matrix A and Reachability Matrix M

Adjacency matrix A represents basic binary relationships between system elements. A binary relationship refers to the relationship between two elements (row element Xi, column element Xj) with transitivity [34]. If row element directly influences column element, it is marked 1; otherwise 0 [35], expressed as:

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1, if Xi has a binary relationship with Xj
0, if Xi has no binary relationship with Xj
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A matrix questionnaire was distributed to 10 domain experts, adopting majority rule for logical relationship judgments [33]. For relationships with 50% expert support (e.g., information capability's effect on information knowledge), expert panel discussion decided the outcome. This yielded adjacency matrix A shown in Figure 1 [Figure 1: see original paper].

Reachability matrix M represents transitive binary relationships between elements through any number of steps. Through matrix power operations on (A + I), when (A + I)^(k-1) ≠ (A + I)^k = (A + I)^(k+1), reachability matrix M = (A + I)^k is obtained, where k is iteration count.

The reachability matrix $M = (A + I)^3$ is shown in Figure 2 [Figure 2: see original paper].

In matrix M, rows and columns for X3 and X4 have identical elements, indicating strong connections that can be merged. X3 was retained while X4's row and column were deleted for matrix reduction. Similarly, X12 was retained while X13 was removed.

This yielded simplified reachability matrix M  shown in Figure 3 [Figure 3: see original paper].

### 2.2 Decomposing Factor Hierarchical Relationships

Hierarchical decomposition uses the reachability matrix to partition system elements into different levels according to specific rules, extracting relationships to build the interpretive structural model. From simplified reachability matrix M , reachability sets R(Xi), antecedent sets A(Xj), and common sets C(Xij) = R(Xi)   A(Xj) were calculated [30].

If A(Xj) = C(Xij), the element belongs to the bottom-level factor set; if R(Xi) = C(Xij), it belongs to the top-level factor set. After identifying top-level factors, their rows and columns are removed from the matrix for the next iteration [35].

The first-level partitioning results are shown in Table 3 .

**Table 3** First Reachability Matrix Partitioning of Reachability and Antecedent Sets

[Table content showing X1, X11, X12 as bottom-level factors and X8, X9, X10 as top-level factors]

After removing X1, X8, X9, X10, X11, X12, the second partitioning yielded Table 4 , identifying X2 as a lower-level factor and X7 as an upper-level factor.

**Table 4** Second Reachability Matrix Partitioning

[Table content]

After removing X2 and X7, Table 5 identified X3, X5, X6 as same-level intermediate factors.

**Table 5** Third Reachability Matrix Partitioning

[Table content]

Finally, merging previously combined factors (X3/X4 and X12/X13) back yielded the complete hierarchical decomposition table (Table 6 ).

**Table 6** Hierarchical Decomposition of Influencing Factors

| Level | Factors |
|---|---|
| Level 1 (Top) | X8, X9, X10 |
| Level 2 | X7 |
| Level 3 | X3, X4, X5, X6 |
| Level 4 | X2 |
| Level 5 (Bottom) | X1, X11, X12, X13 |

### 2.3 Establishing the Interpretive Structural Model

According to ISM hierarchical theory, the structure can be divided into three layers: presentation, intermediate, and fundamental [36].

- **Level 5 factors** (policies/regulations, social influence, age, platform design) provide safeguards and normative constraints, forming fundamental factors.
- **Level 4 factor** (education level) is a user characteristic forming the basis of initial acceptance behavior.
- **Level 3 factors** (information awareness, information knowledge, information capability, task topic) constitute required information literacy and needs, influenced by fundamental factors while affecting presentation layer factors.
- **Level 2 factor** (requirement clarity) directly influences task urgency.
- **Level 1 factors** (system resources, task urgency, platform operation) have the most direct impact.

Rearranging simplified reachability matrix M according to Table 5's hierarchical partitioning yielded rearranged matrix M shown in Figure 4 [Figure 4: see original paper].

After removing reflexive (self-influence) and transitive relationships from Figure 4 and restoring merged factors, the final interpretive structural model was obtained, shown in Figure 5 [Figure 5: see original paper].

## 3. Hierarchical Analysis of the Influencing Factors

The interpretive structural model contains five levels, further summarized into three hierarchical layers.

### 3.1 Presentation Layer Factors

System resources, task urgency, and platform operation constitute the presentation layer—the most direct influences on initial acceptance behavior.

**System resources** affect users' value perception of government open data. High-quality data with quantity, timeliness, and broad coverage promotes development and utilization, maximizing social value. Rich resources enable deep mining for specific needs, enhancing value perception.

**Task urgency** influences the immediacy of data acquisition. As authoritative, reliable, and economical primary data, government open data is easily accessible. When tasks are urgent, users lack time for alternative sources and prefer primary government data, increasing acceptance and promoting understanding and utilization.

**Platform operation** affects operational convenience. Ease of use directly influences perceived usability, allowing novice users to browse and download data without training, lowering the barrier to utilization.

### 3.2 Intermediate Layer Factors

Requirement clarity, task topic, information awareness, information knowledge, and information capability form the intermediate layer.

**Requirement clarity** directly affects task urgency. These factors interact: higher clarity enables better understanding of task urgency, while urgent tasks demand rapid clarification of requirements.

**Task topic, information awareness, information knowledge, and information capability** affect requirement clarity. Task topic determines required data types; familiar topics yield clearer requirements. Information awareness, knowledge, and capability collectively form information literacy. Higher literacy increases information sensitivity, knowledge of acquisition channels, accurate evaluation, and creative utilization, leading to deeper self-understanding of needs. Studies show task topic and information capability also influence information awareness and knowledge. Different task topics require different knowledge backgrounds, prompting users to learn new information knowledge while strengthening awareness. Stronger information capability enhances collection and processing abilities, increasing sensitivity and enriching knowledge and awareness.

### 3.3 Fundamental Layer Factors

Education level, age, policies/regulations, social influence, and platform design are fundamental, foundational factors that directly or indirectly affect intermediate or presentation layer factors.

**Education level** (Level 4) affects task topic and information capability. Higher education correlates with different task topics and stronger learning abilities, enabling users to understand more channels and methods for information acquisition and utilization while fostering innovation.

**Age, policies/regulations, social influence, and platform design** (Level 5) are the deepest influences:

- **Age** directly affects education level during specific periods, thereby influencing task topic and information capability. During compulsory education, age increases correlate with higher education levels. Most users cease formal education in middle age, making age's direct impact limited to specific periods.
- **Policies/regulations** directly affect system resources, information awareness, and knowledge, thereby influencing requirement clarity. National strategies, laws, and policies have mandatory and binding force, ensuring system resource quantity, quality, and coverage. For example, the 2017 "Opinions on Promoting Public Information Resource Opening" mandated data "integrity, accuracy, originality, machine readability, non-

discrimination, and timeliness." Policy promulgation enhances public attention and cognition, improving information knowledge and awareness.

- **Social influence** directly affects system resources, information awareness, and knowledge. Social recognition of open data encourages governments to increase openness, enriching platform resources. Interpersonal communication promotes information knowledge dissemination and strengthens awareness.
- **Platform design** directly affects platform operation. Aesthetic interfaces with reasonable information classification and subject indexing facilitate browsing, querying, and utilization, providing better user experiences.

# 4. Conclusions and Discussion

## 4.1 Research Conclusions

Based on situational theory, this study identified 13 influencing factors through expert surveys and constructed a relational structure model using ISM. Results show the model comprises five levels summarized into three layers: system resources, task urgency, and platform operation (presentation layer); requirement clarity, task topic, information awareness, information knowledge, and information capability (intermediate layer); and education level, age, policies/regulations, social influence, and platform design (fundamental layer). These conclusions are reasonable and innovative, revealing overall influence mechanisms and factor interactions to provide theoretical guidance for promoting government open data acceptance and utilization.

## 4.2 Policy Implications

This research offers policy insights for advancing China's government open data work from three aspects:

### 4.2.1 Strengthen Government Data Open Platform Construction and Improve System Resource Utilization

Current government organizations insufficiently focus on dataset, resource, and metadata management on open data portals [37]. Governments should strengthen data processing, storage, and management, clearly specifying procedures, data types, access, publication formats, metadata standards, and interoperability [38]. Platforms should provide multiple query channels and regularly solicit user feedback to embody a "public demand-oriented" philosophy, improving system resource utilization.

### 4.2.2 Improve Government Open Data Laws and Regulations to Ensure Orderly Development

China's government open data policy system remains incomplete, lacking normative and operational specifics [39]. Governments should promptly improve laws and regulations, clarifying scope, content, and ownership of open data under new circumstances [21], addressing fundamental issues. Drawing on international experiences while considering domestic realities can create suitable legal frameworks, fostering a favorable social environment.

#### 4.2.3 Strengthen Publicity to Expand Social Influence and Raise Public Awareness

China's government open data platforms started relatively late with low 普及率 (popularization rates), and users lack understanding. Relevant departments should intensify promotion through multiple channels to help users recognize open data value, leveraging group effects to expand publicity scope, increase public awareness, and improve initial user understanding and utilization.

### 4.3 Limitations and Future Directions

This study has three limitations: (1) ISM only hierarchically categorizes factors without measuring importance degrees; (2) It only analyzes initial acceptance factors, not continuous usage; (3) The survey sample was small, limited to dozens of government open data research experts.

Future research should: (1) Consider assigning values to quantify factor importance; (2) Investigate factors influencing continuous usage behavior, combining both models for more comprehensive analysis; (3) Expand survey scope to include government staff or other domain experts familiar with government open data for factor selection and relationship determination.

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## Author Contributions

Duan Yaoqing: Provided research ideas and revised the paper.
Zhou Mi: Designed questionnaires, collected data, and wrote the paper.
Shang Ting: Collected data and wrote the paper.

*Note: Figure translations are in progress. See original paper for figures.*