Recovery Timing Strategies for Government Open Data Service Failures Based on User Sensitivity: A Postprint Study

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Date: 2023-04-01T00:00:00+00:00

Abstract

[Purpose/Significance] As the government open data movement gains momentum worldwide, "government open data" has emerged as a focal point of multidisciplinary research; however, few studies have investigated service failure issues following government data opening, which impacts the efficacy of government open data initiatives. [Method/Process] This paper focuses on service failure recovery in government open data services, examines types of service failures from a data quality perspective, constructs a timing strategy model for failure recovery based on user sensitivity, and employs the Lagrange multiplier method to solve the model. [Results/Conclusion] The results from model solution and numerical example analysis demonstrate that recovery timing, user sensitivity to open data, and user sensitivity to failure recovery exert significant influence on the timing strategy for government open data service failure recovery. Government agencies should attach paramount importance to user sensitivity, select appropriate recovery timing, and conduct timely failure recovery.

Full Text

Preamble

Volume 64, Issue 2, January 2020

Research on the Recovery Timing Strategy of Government Open Data Service Failure Based on User Sensitivity

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Abstract: [Purpose/Significance] With the rise of the government open data movement globally, "government open data" has become a multidisciplinary research hotspot. However, few studies have examined service failures after government data opening, which affects the effectiveness of government open data initiatives. [Method/Process] This paper focuses on the recovery of government open data service failures, explores failure types from a data quality perspective, constructs a recovery timing strategy model based on user sensitivity, and solves the model using the Lagrange multiplier method. [Result/Conclusion] Model solutions and example analysis demonstrate that recovery timing, user sensitivity to open data, and user sensitivity to failure recovery significantly influence government open data service failure recovery strategies. Government agencies should attach full importance to user sensitivity, select appropriate recovery timing, and implement timely failure recovery.

Keywords: Government open data; Data quality; Failure recovery; User sensitivity
Classification Number: G203
DOI: 10.13266/j.issn.0252-3116.2020.02.004

With the advent of the big data era, users have placed higher demands on government open data services, and related issues have increasingly attracted attention from both government and academia. In December 2007, 30 open government advocates proposed eight fundamental principles for open government data in California: completeness, primary source, timeliness, accessibility, machine processability, non-discrimination, non-proprietary format, and license-free usage[1]. In June 2013, G8 leaders signed the G8 Open Data Charter in Northern Ireland, establishing principles for accessing, publishing, and reusing data: open by default, quality and quantity, accessible to all, improving governance through data release, and encouraging innovation through data release[2]. Over the past decade, governments worldwide have competed to provide data opening services, marking a new trend in government data resource sharing. Some domestic cities (such as Beijing, Shanghai, and Wuhan) have pioneered public data opening initiatives. The entire process of government open data is dynamically evolving, requiring coordinated efforts from data providers, managers, and users to build a sound data ecosystem, with potential failures at every stage. From a data quality perspective, collection, cleaning, publication, fusion, and utilization all impact data quality and can cause service failures. From a user perspective, user sensitivity also influences perceptions of government open data services and failure recovery—when perceived quality falls short of expected quality, failure occurs. This study focuses on user sensitivity to investigate timing strategies for government open data service failure recovery.

2 Research Status

2.1 Government Open Data Research Status

Following the proposal of national big data strategies, research on government open data has proliferated[4], becoming a hotspot in information science, public management, computer science, and data science. Current domestic research primarily adopts perspectives from information science and public management, gradually shifting from conceptual to management and technical levels. Research focuses on: elaborating concepts, significance, and necessity; exploring methods to improve data quality, usability, and privacy; and comparing Chinese and foreign government open data practices to provide recommendations[5]. Studies emphasize data "opening" but pay less attention to data "utilization" and its effectiveness, with particularly scarce research on transforming open data into public value-enhancing services[6]. Xia Yichun et al.[7] proposed that as providers of open data, government departments should manage and optimize data collection, publication, and utilization processes, though they did not specifically address post-opening service failures or their impact on data quality.

Regarding government open data service quality, scholars have primarily studied it from an information science perspective. Ma Haiqun et al.[8] constructed a structural equation model for government open data website service quality using variables such as website accessibility, data usability, webpage usability, service comfort, user satisfaction, and user trust to measure and evaluate service quality. As government open data activities expand, with dramatically increased data volumes and increasingly complex sources and structures, Chao Lemen[9] argued that basic technical research in data management should combine with high-level theoretical research to leverage interdisciplinary advantages in solving common problems. The difficulty and risk of government open data have increased accordingly, prompting scholars to examine barriers, causes, risks, and prevention measures. Cai Shijie and Xia Yichun[10] proposed that data opening risks negatively impact the process, management order, ecosystem, and costs of government open data, recommending that countries establish risk identification and response mechanisms. However, they did not address how to respond to risks or how government should implement timely recovery after service failures. Moreover, domestic research on government open data risks remains largely normative, 停留在 theoretical discussion and logical reasoning stages, lacking algorithmic and model support and empirical analysis.

Foreign research on government open data began earlier, with interdisciplinary and cross-regional characteristics. Research perspectives have focused on technical aspects, gradually moving toward algorithmic approaches with more specific content such as urbanization, climate change, and public health[5]. Foreign scholars have paid more attention to barriers to government open data, including public interest in using data, costs of opening data, data ownership risks, legality, and privacy issues[11–13]. Beyond benefits and challenges, foreign scholars have studied open data usage. K. Braunschweig et al.[14] found that how people access and use open data is heavily influenced by publication methods. P. Conradie et al.[15] proposed that internal government processes, such as how agencies store, access, and use data, are crucial for open data publication. S. Sadiq et al.[16] argued that quality matters more than quantity for government open data, requiring interdisciplinary research to establish knowledge systems for effective utilization. V. Weerakkody et al.[17] built models from a user perspective to analyze UK government open data websites, finding a disconnect between potential and actual impacts of usable open data on citizens. Overall, foreign scholars focus on how government departments, as data providers, should manage and optimize data collection, publication, and utilization processes, but lack research on post-opening service failures and their impact on data quality.

Through reviewing domestic and foreign literature, most studies focus on the significance, obstacles, management, risk assessment, and effectiveness evaluation of open data, lacking targeted and systematic research on main processes and stages, particularly scientific research on failure recovery.

2.2 Government Service Failure Recovery Research Status

Research on service failure recovery began in the 1980s, primarily examining concepts, processes, and recovery strategies from perspectives of fairness, satisfaction, and loyalty. Despite extensive research, existing literature focuses on traditional service industries, e-commerce, crisis public relations, and public opinion control, with limited attention to government open data service failure recovery. Li Xin and Yu Bo[18] proposed implementing service recovery strategies based on customer-perceived service quality. Tang Xiaofei et al.[19] introduced the concept of "delayed recovery" —recovery conducted after leaving the scene but within an effective time period—and studied the impact of recovery timing and personality traits on recovery performance. With the rise of internet services, online service failure recovery has attracted academic attention. B.C.F. Choi et al.[20] studied how corporate recovery actions after privacy breaches affect online customer behavior. Jian Zhaoquan et al.[21] noted that most online service failure research either ignores failure types or broadly categorizes them as process or outcome failures, overlooking the particularities of online service failures. Domestic and foreign scholars have concentrated research on service failure recovery and subsequent customer behavioral intentions on satisfaction, loyalty, and perceived fairness, with less research on recovery satisfaction and its impact on subsequent behavioral intentions[22]. Zhu et al.[23] argued that future service failure and recovery research should expand to more complex and broader domains.

After introducing service failure recovery and customer satisfaction to the public service domain, researchers have constructed multiple public service satisfaction models. Due to the special characteristics of public services provided by government— "indivisibility," "non-excludability," and "non-selectivity" [24]—research on service failure recovery in the public service domain is scarcer than in traditional service industries, with more literature focusing on emergencies, emergency management, and public opinion dissemination and control. While scholars have conducted extensive research on emergency event monitoring and identification, most focus on specific stages or methods from information science or systems theory perspectives, failing to fully recognize the importance of recovery strategies. Li Gang et al.[25] argued that emergency identification primarily provides methodological support for various stages of the warning process, with the difficulty lying in information integration and fusion—namely, developing technologies for collecting and integrating multi-source, heterogeneous information. Lei Zhimei et al.[26] studied information gaps in emergency decision-making processes, constructing an information flow model and categorizing causes of information gaps into subjective and objective reasons: subjective reasons refer to decision-makers' limited awareness, cognitive abilities, and differences (different decision-makers facing the same emergency problem may have different knowledge structures and experiences, leading some to know what information they truly need while others do not); objective reasons refer to time pressure, environmental complexity, uncertainty, and destructiveness. From a public opinion control perspective, Zhang Fei et al.[24] studied the impact of service recovery on mass word-of-mouth dissemination willingness during the incubation period of public opinion when government public services fail, conducting empirical research that found proactive recovery is always more effective than reactive recovery, and recovery effects in outcome failures are significantly higher than in process failures. This research demonstrates that government-provided public services should also attach importance to service failure recovery and user service experiences.

In summary, although academia has begun to focus on service recovery in government public services and risk prevention and quality assurance in government open data, specific response strategies have not been proposed. Despite rich research achievements on government open data, public service failures, crisis management, and public opinion control, during the government open data process, different users have different sensitivities to data, perceive failures differently, and user sensitivity to failure recovery and government-selected recovery timing affect recovery strategy effectiveness. Moreover, as a type of public service, government open data services provide data to users through network platforms, combining characteristics of both public and network services. Its failure types differ significantly from traditional services, and recovery effectiveness uncertainty increases substantially. However, as a public data asset provided by government, open data is a double-edged sword that can bring enormous value to government and society while also carrying risks, making post-failure recovery measures essential. To ensure optimal effectiveness of government open data service failure recovery timing strategies, determining user sensitivity and selecting appropriate recovery timing is particularly important. Therefore, researching recovery timing strategies for government open data service failures has important theoretical and practical significance.

3 Problem Description and Model Construction

3.1 Causes and Types of Government Open Data Service Failures

Government open data service failures are unavoidable. The main causes are threefold: outdated government open data platform technology and low service quality[27]; data quality issues during collection, processing, publication, fusion, and utilization[28]; users finding data fails to meet expectations during search and use[29]. Although governments recognize these problems and implement preventive measures, decision-making remains based on legal requirements rather than user satisfaction with data quality. S. Laura[30] proposed that data quality is defined by two related factors: the degree to which it meets consumer expectations, and the degree to which it represents the objects, events, and concepts it was created to represent. The latter—representational accuracy—is quantifiable quality, considered objective data quality. The degree to which data meets user expectations depends on both quantifiable quality and user sensitivity, considered subjective data quality. Therefore, causes of government open data service failures can be divided into objective and subjective reasons. For government data publishers, failures can be categorized from an objective quality perspective as accuracy failures, usability failures, security failures, and timeliness failures. For government data users, failures can be categorized from a subjective quality perspective as perceived service failures and perceived recovery failures. The failure types, meanings, and corresponding government open data principles are shown in Table 1 .

3.2 Conceptual Model and Parameter Setting

As discussed, failure recovery should consider both objective and subjective causes of government open data service failures. The conceptual model aims to study influencing factors and their relationships when government departments formulate recovery timing strategies, narrowing the gap between user perception and expectation by improving objective data quality to develop successful recovery timing strategies. Service failure and recovery have been systematically studied domestically and internationally. Since 1991, scholars have defined service failure as situations where services fail to meet customers' acceptable minimum levels, cannot satisfy customer requirements and expectations, and cause dissatisfaction[31]. According to the "expectation-disconfirmation" paradigm of customer satisfaction theory, when user perception falls below expectation, users become dissatisfied, leading to service failure. Value-oriented service failure and recovery mathematical models provide new approaches for failure recovery research, studying recovery effectiveness from a perceived value perspective and arguing that future research should expand to more complex and broader domains[23]. Additionally, even facing the same service, different users have different expectations and perceptions. Therefore, failure recovery research should consider user differences. Drawing on the definition of "consumer sensitivity to personal information" [32], this paper proposes that "user data sensitivity" refers to the degree to which users perceive data quality, influenced by context, individual characteristics, and users' ability to acquire and utilize data. In the government open data domain, before failure occurs, users have different perceptions of government open data quality—i.e., different sensitivities to open data. After failure occurs, users also have different perceptions of improved data quality from government recovery actions—i.e., different sensitivities to failure recovery. Therefore, user data sensitivity affects user perception of data quality, influences user satisfaction, and consequently impacts the effectiveness of government open data service failure and recovery. According to Tang Xiaofei et al.[19], recovery timing also affects recovery effectiveness, and government departments should select appropriate recovery timing and formulate different recovery timing strategies based on different user sensitivities.

Based on the above analysis, this paper uses objective data quality before and after government open data failure recovery as a baseline, combines subjective data quality of user expectation and perception, introduces recovery timing and data sensitivity variables to study government recovery timing strategies, and proposes a conceptual model for government open data service failure recovery timing strategies as shown in Figure 1 [Figure 1: see original paper].

The model divides into pre-recovery and post-recovery stages, focusing on how user sensitivity to open data and user sensitivity to failure recovery affect total perceived data quality, and how recovery timing affects perceived recovery data quality. When perceived data quality is less than expected data quality, government open data service failure occurs. After failure occurs, user sensitivity to failure recovery changes, affecting perceived recovery data quality. Government selects appropriate recovery timing to implement recovery measures, making perceived recovery data quality exceed expected recovery data quality, thus achieving successful government open data service failure recovery timing strategy. Key variables and relationships in the conceptual model are: when perceived data quality G is less than expected data quality Y, service failure occurs; expected recovery data quality Y equals the difference between expected data quality Y and perceived data quality G; perceived recovery data quality G exceeds expected recovery data quality Y , indicating successful recovery timing strategy. Parameter assumptions and meanings are shown in Table 2 .

3.3 Mathematical Model and Solution

Based on the conceptual model and parameter assumptions, this section transforms the conceptual model into a mathematical model and solves it using the Lagrange multiplier method. As shown in Figure 2, the optimal strategy for government open data service failure recovery is to minimize the data quality improvement required during recovery while ensuring user satisfaction—i.e., the objective is minimizing recovery data quality (X).

Construct the objective function:

$$\text{Min } X' = X'(\beta, T, G') = \frac{G'}{\beta \cdot (1-T)}$$

Construct the constraint function:

$$G' \geq Y'$$

From the objective function (1) and constraint function (2), construct the Lagrangian function:

$$\Phi = \Phi(\beta, T, G, \lambda) = \frac{G'}{\beta \cdot (1-T)} + \lambda(G - Y') = \frac{G'}{\beta \cdot (1-T)} + \lambda(G - Y + \theta \cdot X)$$

Taking first-order partial derivatives of function (3) with respect to each variable and setting them to zero yields:

$$\frac{\partial \Phi}{\partial \beta} = -\frac{G'}{\beta^2 \cdot (1-T)} = 0$$

$$\frac{\partial \Phi}{\partial T} = \frac{G'}{\beta \cdot (1-T)^2} = 0$$

$$\frac{\partial \Phi}{\partial G} = \lambda = 0$$

$$\frac{\partial \Phi}{\partial \lambda} = G - Y + \theta \cdot X = 0$$

Solving the system of equations (4)-(7) yields the optimal solution:

$$T = 1 - \beta \quad (9)$$

$$G' = Y' \quad (10)$$

The optimal solution for government open data service failure recovery timing strategy indicates: government recovery timing is negatively correlated with user sensitivity to failure recovery, and their sum equals 1—i.e., the higher the user sensitivity to failure recovery, the earlier the government should implement recovery measures. When perceived recovery data quality equals expected recovery data quality, the government open data service failure recovery timing strategy achieves optimal effectiveness. The optimal recovery timing strategy depends not only on user sensitivity to failure recovery but also on user sensitivity to open data. Government should select optimal recovery timing and formulate recovery timing strategies based on different user sensitivities to open data and failure recovery. The following section discusses through example analysis how user sensitivity and recovery timing affect government recovery data quality and their interrelationships.

4 Example Analysis

To enhance generalizability, assume a certain type of government open data on W City data opening platform has quality values: $X_1 = 10$, $X_2 = 8$, $X_3 = 7$, $X_4 = 6$ (range 0-10). Assume this data type emphasizes usability and accuracy over security and timeliness, with weight coefficients $r_1 = 0.3$, $r_2 = 0.4$, $r_3 = 0.2$, $r_4 = 0.1$, then: $X = \Sigma(r\_i \cdot X\_i) = 8.2$. Set expected user data quality Y at 9, indicating government open data service failure. Assume user sensitivity to open data is positively correlated with user sensitivity to failure recovery β, where $0 \leq \beta \leq 1$, $0 \leq T \leq 1$.

Using the optimal solution from Section 3, we can calculate how government recovery data quality X changes as parameter T varies from 0 to 1. When the correlation curves between and β differ, the impact of recovery timing T changes (from 0 to 1) on government recovery data quality X is shown in Figure 3 [Figure 3: see original paper].

In Figure 3(a)-(f), each subfigure contains 10 curves showing the relationship between recovery timing T and recovery quality X when user sensitivity to open data ranges from 0.1 to 1. Subfigures (a)-(f) show curves with different correlation coefficients between parameters and β. Example analysis results indicate: The more user sensitivity to failure recovery β increases relative to user sensitivity to open data (flatter curves), the less data quality improvement X government recovery measures require; User sensitivity to open data is negatively correlated with recovery data quality: more sensitive users (higher values) require less data quality improvement X from government recovery; Except for Figure 3(a) (where user sensitivity to failure recovery shows basically no change relative to user sensitivity to open data), Figures 3(b)-(f) all show that as recovery timing T increases (delayed recovery), required government data quality improvement X increases accordingly; All Figures 3(a)-(f) show that when recovery timing T 0.8, required government data quality improvement X begins to increase sharply, indicating a threshold for recovery timing T at approximately 0.8. When recovery timing T exceeds this threshold, required government data quality improvement X increases dramatically.

Example analysis demonstrates that user sensitivity significantly affects government open data service failure recovery effectiveness. Government should prioritize user sensitivity during the open data process, select appropriate recovery timing based on different user sensitivities, and formulate government open data service failure recovery timing strategies. Additionally, recovery timing should be selected before the threshold; otherwise, achieving optimal recovery timing strategy effectiveness becomes difficult.

Conclusion

This study examines government open data services, summarizes causes and types of service failures, investigates recovery strategy issues, and determines how different user data sensitivities affect recovery timing strategy selection.

By constructing a government open data service failure recovery timing strategy model using variables such as user data sensitivity, recovery timing, and user perception versus expected quality, and solving it with the Lagrange multiplier method, this paper discusses through example analysis the relationships among recovery timing, user sensitivity, and government recovery data quality at optimal solutions. The study finds that user sensitivity significantly affects optimal failure recovery timing, and changing user sensitivity can alter government open data service failure recovery effectiveness. Results indicate that after government open data service failures, agencies should formulate recovery timing strategies based on user data sensitivity while avoiding overly delayed recovery. This points toward a "user-centered" direction for government open data services. Government departments should develop deeper understanding of service processes, reconsider roles, service process management, and failure recovery, and examine interactions among service process components from the perspective of building a government open data ecosystem to ultimately achieve sustainable development of government open data.

This study' s innovations include three aspects: Introducing failure recovery concepts into government open data research, addressing the lack of attention to post-opening failure recovery; Systematically categorizing causes and types of government open data failures; Constructing and solving a mathematical model for government open data service failure recovery timing strategies based on user sensitivity, exploring how changes in user data sensitivity affect recovery quality under different timing scenarios. Future research should further investigate how user sensitivity affects recovery effectiveness based on different types of government open data service failures.

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Author Contributions: Jiang Hui: mathematical model construction and solution, paper writing; Duan Yaoqing: research idea proposal, conceptual model construction, paper revision.

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