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Critical Factors in Central Government Information and Data Governance - Empirical Study

Chuan-Chun WU[1], Hsin-Chung CHU[2]

Abstract

Along with the development of information and communications technology being popular, types of data become rich and multiple, the analysis scope changes from structured data to non-structured data without sorting context, and the data volume becomes huge and is continuously growing. When data application cases and value benefit are gradually noticed in past years, government agencies realize that data could develop the value through cross-boundary collaboration, rather than simple relying on internal processing and analyses, and the collaboration process allows the government cultivating to apply data with added-value and establish evidence-based governance. Aiming at employees in public sectors in the central government of Taiwan, total 320 copies of questionnaire are distributed and 247 valid copies are retrieved, with the retrieval rate 77% . The research results are summarized as below: (1) Regarding the curiosity and expectation of data analysis of the government, either directors of agencies or key case officers, with the expectation of applying the possessed data with added value, do not simply regard data as dead records, but attempt to apply data to solve specific public issues; (2) In addition to inducing the curiosity about data application in the internal organization, success cases of other agencies could facilitate the action of an organization participating in the project for expanding to central and local levels or cross-units inducing the agencies with similar businesses engaging in the project as well as accelerate project influence through experience sharing and reinforce the confidence of other units in information and data governance; (3) Information and data governance could benefit the government shaping positive image to interpret outcomes through data for the reference of future policies, strengthen the industrial and academic research energy of the business, as well as enhance public trust and agency transparency through cooperation with experts. According to the results to propose suggestions, it is expected to provide related

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policy suggestions for the government examining the internal organization from management to execution about the preparation for data governance and the reference for top decision-makers planning data application strategies, applying data to public-private collaboration, and improving existing data governance structure.

Keywords: central government, government information, data governance, critical factors, social problem, evidence-based governance.

Introduction

Along with the development of information and communications technology being popular, types of data become rich and multiple, the analysis scope change from structured data to non-structured data without sorting context, and the data volume becomes huge and continuously grows. Both the government and enterprises try hard to explore the deep value and innovative service application of data and establish the dominance in the competitive environment, with which enterprises make business profits while the government takes internal decision assistance and promotion of public interests by solving public issues into account. Data are regarded as the new petrol to control the future development of the world. Governments in various nations gradually emphasize the data policy. In the promotion of digital transformation agenda in 2010, European Union regarded big data as a key development and announced official document of "Moving towards a booming data-driven economic era" in 2014, stressing on data as the key in controlling future development. The Obama government promoted big data research and development plans in 2012 and largely invested in capitals and research dynamics, expecting to enhance the development and boom with data economics. Asian countries, such as South Korea, Singapore, and Japan, presented no less performance. Japan regarded the combination of the government with big data as the key mission in 2020. Open data, big data, and crowdsourcing were taken as the policy focus domestically to assist the government in applying technological tools to have the people sense the governance. Apparently, the value created by data in either international trend or domestic policies is emphasized.

The government introduces policy service through information and communications technology to show the benefits of saving time and expanding service coverage and content diversity for external public. In terms of internal organization, it allows faster data delivery among departments to promote government service effectiveness and high quality; the organization managers then have better reference for making decisions. Although data result in operation benefits for the government, the challenge to data governance has not been stopped. The huge data volume is not affordable with existing technologies and manpower and could hardly be coped with existing management mechanisms; without processing, data would not present the value. The government has never been in the dilemma of lacking data, but, as a matter of fact, encounters information overload and most data being seldom applied. Apparently, agencies, with negative attitudes towards data, used to keep hard copy documents, but did not develop the value of data. Data application cases and value benefits are gradually noticed in past years. Government agencies realize that data could better develop the value through cross-boundary collaboration, rather than simply relying on internal processing and analyses; besides, the collaboration process allows the government cultivating the bases for added-value data application and the establishment of evidence-based governance. Nonetheless, data do not simply create economic value, but could be used for solving social problems and facilitating organizations promoting decision effectiveness. After all, decision management makes judgment with reference; the government has to promote public interests with sustainable perspectives. Regardless the cooperation method between government sectors and private sectors, it is worth of discussion to clarify the challenge encountered in the cooperation between internal public servants and external experts, understand the factors in the ideas and evaluation of government agencies and internal public servants, comb critical factors in the success of collaborative projects, and discuss the effect of collaboration results on the internal organization of the government or participating colleagues. Critical factors in central government information and data governance are therefore discussed in this study, expecting to provide related policy suggestions for the government examining the internal organization from management to execution about the preparation for data governance and the reference for top decision-makers planning data application strategies, applying data to public-private collaboration, and improving existing data governance structure.

Literature review

Data and application

Ghani *et al.* (2019) regarded the characteristics of data as being able to re-form and re-interpret. Data were original records without being sorted, and the classification was mainly discriminated with structure, namely structured data, semi-structured data, and non-structured data. Data with fixed column, format, and sequence were structured data; semi-structured data, for convenient exchange, showed fixed column but could not guarantee the data consistency; non-structured data, which could be regarded as information assets with potential value, contained texts, films, images, and even audio records without being sorted and contextualized. Susha *et al.* (2019) mentioned that the promotion of data processing techniques resulted in the popularity and fast transmission of data collection devices to form big data, in which the growth of non-structured data was astonishing. Chakkol *et* *al.* (2018) pointed out the importance of data mining. How to transform data into useful information and develop the benefits? The knowledge discovery in database stage proposed by Fayyed *et al.* in 1996 was the most famous. It stressed on the process transforming messy data into apparent, unknown, and possibly useful knowledge and described the cyclic process of data being integrated, processed, modeled, analyzed, and interpreted. Enterprises first used it for seeking business opportunities; and, it was also applied to social welfare. The model was explained as below: (1) Selection: Aiming at specific target to select correspondent data; (2) Preprocessing: Aiming at errors in target data for cleaning; (3) Transform: Cleaned data should be transformed into analytic and format structure. (4) Data mining: Applying technology to analyze data; (5) Interpretation/evaluation: Explaining and interpreting the meaning of data analysis result and evaluating the need for correction in the process.

Data science, as the aggregate of interdisciplinary knowledge, includes mathematics, statistics, and information science. Abraham *et al.* (2019) reputed data science as the fourth science paradigm, after theoretical science, experimental science, and computational science. It referred to transforming original unsorted data into contextual knowledge complex with action meaning. It could be regarded as the dynamic process from collection, analysis, to application; and the derived position, data scientists, were capable of data mining, data analysis, and dataset management in the front part and even the back part of data visualization (Altayar, 2018).

Data governance

Safarov (2019) defined data governance as the model process involving in data related affairs, including decision making and process distribution of power and responsibilities. In other words, the process would explain a person or an organization, under specific situations, applying certain information to specific actions. Alhassan *et al.* (2019) defined data governance as the discussion of who to make decisions of data assets and be responsible in the decision making process. Gascó-Hernándeza *et al.* (2018) regarded data governance as the process to promote data value, involving in policies and programs for development, execution, monitoring, and control to make decisions and control data assets. Al-Ruithe *et al.* (2018) defined data management as the process to handle a series of data quality related problems.

Green (2019) proposed the goal of data governance, covering 1.enhancing decision quality, 2.reducing conflict on execution and operation, 3.taking care of data stakeholders' needs, 4.having top managers and entry-level employees adopt same measures to data issues, 5.establishing standards and repeatable process, 6.coordianting to reduce costs and enhance effectiveness, and 7.ensuring process transparency. Apparently, data presented benefits on organization, process, and manpower; however, basic principles should be taken care of in the data application process. Clausen *et al.* (2019) pointed out the data governance principles, including: (1) *integrity*: establishing trust through interaction process; (2) *transparency*: each action participant clearly understanding relevant decisions and application process; (3) *accountability*: process and risk being traceable and controllable; (4) *stewardship*: data management not simply the responsibility of data managers, but including application executors; (5) *check and balances*: definitely regulating data application process and personnel duties; (6) *standardization*: supporting data standardization of organization, and (7) change management: concerning about active adaptation and passive effects of various levels in the data application process.

The data governance scope would determine the problems faced by decision makers. Zhao & Fan (2018) proposed 10 major governance elements for data governance structure, containing: mission, focus area, data rule and definitions, decision right, accountability, control mechanisms, data stakeholders, data governance office (DGO), data stewards, and data governance processes. Marchildon *et al.* (2018) comprehended with 4W1H to clarify data stakeholders and managers & executors (who), reasons (e.g. solving problems, completing business work) (why), and situations (when) aiming at specific data (what) for processing (how) in data governance structure.

After clarifying the key roles of data governance, participants would further discriminate influential decisions. Hong *et al.* (2018) considered that data governance involved in five decision areas, namely 1.data principle, 2.data quality, 3.metadata, 4.data access, and 5.data lifecycle, and discussed such 5 major decisions in detail. For instance, participants had to clarify the principles of data use, goal, and communication mechanism, made selections for data quality, e.g. timeliness and reliability, process and interpret data, set and discuss data application authority, and have definitely data definition, generation, and analysis process.

Critical success factor

Leong *et al.* (2017) explained that critical success factor was proposed by the economist, Commons, J. R., in 1943, who applied the idea of "limiting factor" to management and negotiation. Danial, D. W., in the writing "Management Information Crisis" in 1961, proposed that most industries presented 3-6 critical success factors. Critical success factor was then broadly applied to various research fields. Liu (2016) stated that the most important competitiveness or competitive asset required for an enterprise facing competitors was industrial critical success factors; unsuccessful enterprises generally lacked certain or some critical success factors to develop the competitive advantage. Samuel *et al.* (2017) considered that, in specific industries, it was the skill or asset required for successfully competing with other competitors. The competitiveness of an enterprise could be judged by analyzing the match between advantage and critical success factors. When the advantage performed on the industrial critical success factor, the enterprise could acquire competitive advantage. Morgan (2017) proposed to check the resource conditions of the organization and, with the unique resource conditions as the niche, to design competition strategies which could not be easily imitated by competitors. Hosseini & Keshavarz (2017) considered that critical success factors were dynamic, would change with an enterprise changing the business goal, and were essential for the success business of an enterprise.

Methodology

Fuzzy Delphi Method

Lee & Kim (2019) pointed out four common methods to confirm critical success factors, including (1) Regression Analysis, (2)Factor Analysis, (3)Delphi Method, and (4)Analytical Hierarchy Process (AHP). Noh *et al.* (2018) proposed the use of Analytical Hierarchy Process for collecting opinions of scholars, experts, and participants through group discussion, simplifying complicated problems into a hierarchical evaluation system with simple elements, and then calculating the contribution or priority of components in various hierarchies corresponding to the elements on the upper hierarchy. By objectively interview department supervisors, Ho *et al.* (2018) proposed that the goal and mission were first confirm according to management procedure and individual critical success factors were then proposed according to individual practical experience and needs; critical success factors to achieve the goal were then organized through analyses and selections and further sequenced to effectively allocate resources, and indicators were eventually established for measuring practice effectiveness.

Expert questionnaire survey is preceded in this study. In consideration of mean, decision-attribute related, and inaccurate group decision in traditional Delphi Method, Fuzzy Delphi Method (FDM) and Analytical Hierarchy Process (AHP) are applied to analyze data in this study, in order to definitely select critical factors in central government information and data governance.

1) Fuzzy Delphi Method (FDM): Murry *et al.* first integrated fuzzy theory into traditional Delphi Method in 1985. The value of correspondent variables was used for the expression. For instance, sematic weights, in human natural language, could be regarded as language variables, with the value of “extremely low”, “low”, “medium”, “high”, and “extremely high”, or other words with various levels, which were given different weights for the estimation. Murry *et al.* proposed such fuzzy semantic variables for evaluation, aiming to solve the fuzziness problem in traditional Delphi Method; however, more specific calculation was not proposed. Successive researchers therefore proposed solutions, such as range, fuzzy integral, triangular fuzzy number, and double triangular fuzzy number.

2) Analytical Hierarchy Process: After integrating experts' opinions, the complicated decision system was constructed a hierarchical system to clarify questions according to hierarchical development. Various dual appraisals were further completed with pair comparison to evaluate the importance of factors.

Establishment of indicator

Fuzzy Delphi Method (FDM) is applied in this study to select primary and secondary criteria for expert questionnaire survey and thresholds. Expert questionnaire survey in Fuzzy Delphi Method (FDM) could shorten times of questionnaire survey and time for calculation to enhance the correction and allow experts' group decisions and opinion consensus being more flexible and efficient. In terms of fuzzy semantic expression, fuzzy semantic variable chart is used as the reference in this study, and the factors in expert questionnaire survey are displayed with 9-point scale. Regarding the integration and calculation of experts' group decision consensus, mean and geometric mean in general model are utilized in this study. The criteria and research structure (Figure 1), after being modified with Delphi Method, are listed as below.

1) Organization: data as assets, understanding benefits to organization, precedence, execution or supervision, organizational culture, collaborative interaction.
2) Knowledge: relevant knowledge, skills & experience, training & communication mechanisms, quality & acquisition, trust & commitment.
3) System & environment: related policy, role & responsibility, cross-functional integration, continuity, legal norms, costs.

Research subjects

Aiming at employees in public sectors of the central government, R.O.C., total 320 copies of questionnaire are distributed, and 247 valid copies are retrieved, with the retrieval rate 77%.

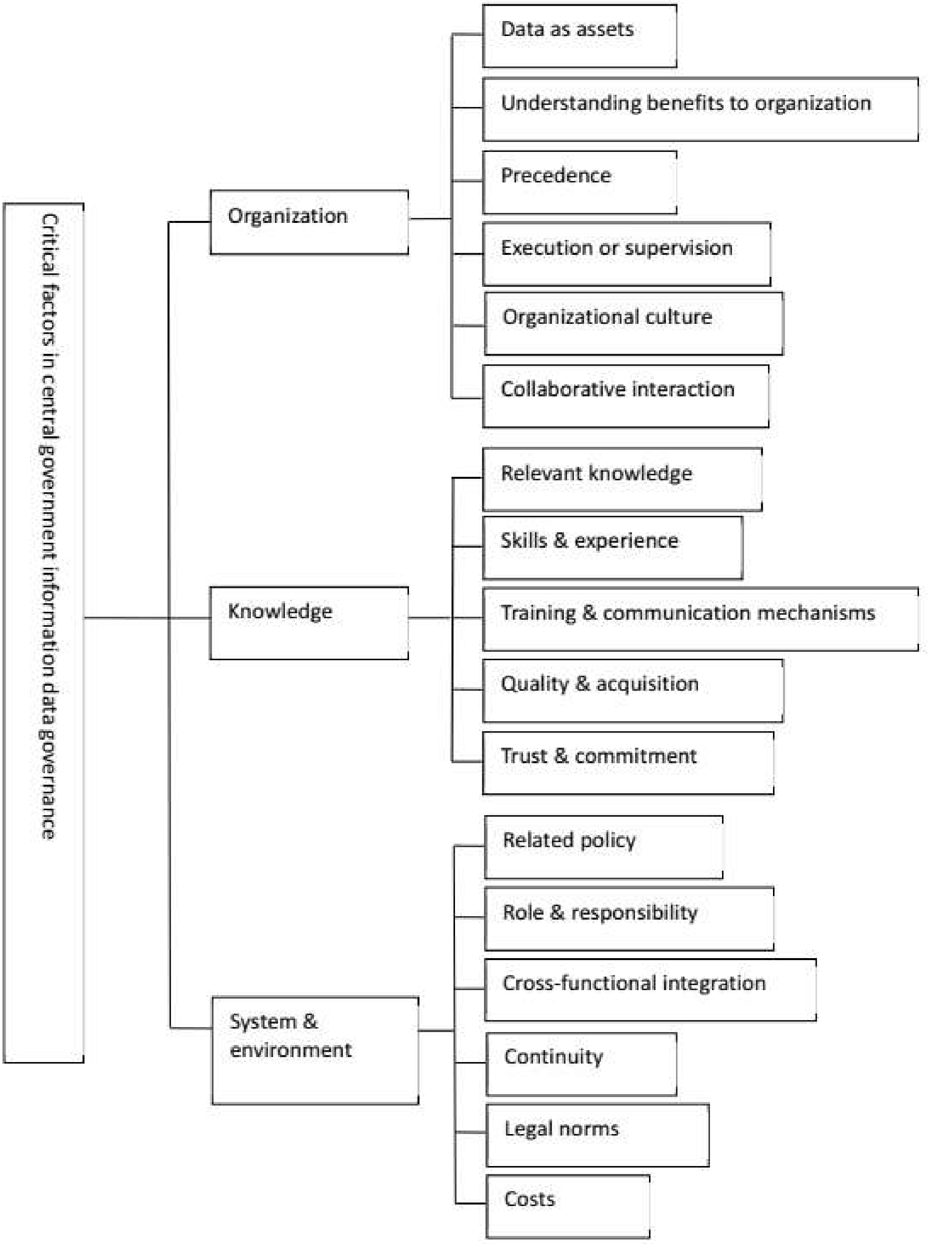

Figure 1. Research framework

Discussion

Organization of central government information and data governance Hierarchy 2

After completing the weights in Hierarchy 2, the allocation is preceded according to the relative importance of indicators in Hierarchy 2 to reveal the importance of such indicators in the entire hierarchy as well as to generate the overall weight of factors in central government information and data governance. The data are organized in *Table 1*.

Table 1. Organization of central government information and data governance Hierarchy 2

Hierarchy 2		
dimension	dominance weight	order
organization	0.364	1
knowledge	0.309	3
system & environment	0.327	2

Organization of central government information and data governance

After completing the weight in all hierarchies, the allocation is preceded according to the relative importance of indicators in various hierarchies to show the importance of such indicators in the entire evaluation system as well as to generate the overall weight of critical factors in central government information and data governance. The data are organized in *Table 2*.

Table 2. Overall weights of central government information and data governance

Hierarchy 2 dimension	Hierarchy 3 (H2×H3)		
	indicator	overall weight	overall order
organization	data as assets	0.103	1
	understanding benefits to organization	0.073	4
	precedence	0.045	11
	execution or supervision	0.054	9
	organizational culture	0.043	12
	collaborative interaction	0.063	7

knowledge	relevant knowledge	0.085	3
	skills & experience	0.035	14
	training & communication mechanisms	0.066	6
	quality & acquisition	0.057	8
	trust & commitment	0.038	13
system & environment	related policy	0.070	5
	role & responsibility	0.032	15
	cross-functional integration	0.094	2
	continuity	0.051	10
	legal norms	0.026	16
	costs	0.022	17

Conclusion

The questionnaire survey analyses are organized in *Table 1*, from which the following results are acquired. Among dimensions in Hierarchy 2, “organization”, weighted 0.364 and about 36.4% of overall weight, is the most emphasized dimension, followed by “system & environment” (weighted 0.327) and “knowledge” (weighted 0.309). The results show that organization is the most emphasized dimension among critical factors in central government information and data governance.

Among the indicators in Hierarchy 3, the weights are sequenced as below:

1) Indicators in organization are sequenced data as assets, understanding benefits to organization, precedence, execution or supervision, organizational culture, and collaborative interaction.
2) Indicators in knowledge are sequenced relevant knowledge, skills & experience, training & communication mechanisms, quality & acquisition, and trust & commitment.
3) Indicators in system & environment are sequenced related policy, role & responsibility, cross-functional integration, continuity, legal norms, and costs.

From the overall weight of indicators for critical factors in central government information and data governance, top five indicators, among 17, are sequenced (1) data as assets, about 0.103 of overall weight, (2) cross-functional integration, about 0.094 of overall weight, (3) relevant knowledge, about 0.085 of overall weight, (4) understanding benefits to organization, about 0.073 of overall weight, and (5)related policy, about 0.070 of overall weight.

Discussion

Cutting in from the viewpoint of data governance, how the government drives governance decision with data is discussed in this study, which focuses on difficulties and challenges encountered when government agencies precede the government data project, and clarifies critical factors in data management. Difficulties encountered in central government information and data governance are discussed and critical factors in information and data governance are clarified in this study; therefore, the clarification of difficulties and success factors are worth of considering for the smooth execution of government information and data governance in the future. First, regarding the curiosity and expectation of data analysis of the government, either directors of agencies or key case officers, with the expectation of applying the possessed data with added value, do not simple regard data as dead records, but attempt to apply data to solve specific public issues. Second, in addition to inducing the curiosity about data application in the internal organization, success cases of other agencies could facilitate the action of an organization participating in the project. Success cases could help persuade agencies adopting actions, and the influence is not merely in the same organization, but would be expanded to central and local levels or cross-units to induce the agencies with similar businesses engaging in the project as well as accelerate project influence through experience sharing and reinforce the confidence of other units in information and data governance. Third, information and data governance could benefit the government shaping positive image to interpret outcomes through data for the reference of future policies, strengthen the industrial and academic research energy of the business, as well as enhance public trust and agency transparency through cooperation with experts. Finally, the more practical motivation is that agencies could rely on the specialty of private sectors to overcome inadequate data science talents and techniques.

Recommendations

Above analysis results of critical factors in central government information and data governance could provide reference for relevant units.

1) Central government has to comprehend data value and interpretation possibility that active measures should be practiced to apply data to advance public decision quality, e.g. persuading agencies adopting actions through more success cases, strengthening the benefit of central government driving governance with data, inducing critical innovators, such as starting from internal business colleagues or executives making prospective decision directions, rather than passively making central government data become the burden to increase businesses.
2) Central government, when preceding information and data governance, is suggested to inspect data quality for the smooth promotion of government

data project. Data quality would be affected by business property and execution fact in agencies. For instance, social welfare data are mostly text records collected by grass-root social workers that the business context should be grasped before data application. Through the opportunity of data project, external experts and agency colleagues should inspect whether existing data management and application process need improvement and adjustment, and the emphasis of the government on data governance should be promoted.

3) Common government data projects highly depend on external experts' project execution ability, e.g. private or academic research. Hackathon simply provides government data for external experts stimulating creativity, but could hardly solve problems in the businesses. Self-study of central government colleagues could not feedback the businesses, and few would automatically start data analyses. Returning to the system after the project should be emphasized, i.e. whether central government colleagues could transfer knowledge in the project process and implement data science techniques and knowledge in the businesses or the organization. After all, a project should not be simply invested in fixed costs without feedback, but expecting mutual benefit of agencies and external experts in the project collaboration process and data project outcomes.
4) It is suggested that key persons for successive promotion should be introduced in the central government information and data governance project process, rather than merely calling colleagues with interests, to deepen the data science related knowledge and competence and strengthen the promotion of future data project. Furthermore, standard operating procedures for establishing data project, after information and data governance project should be systemized to reduce colleagues' risk awareness of collaboration model and enhance colleagues' participation in collaboration and successive promotion.

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