Towards Data-Driven Decision-Making in Government: Identifying Opportunities and Challenges for Data Use and Analytics

Yongjin Choi
University at Albany, State University of New York
ychoi2@albany.edu

J. Ramon Gil-Garcia
University at Albany, State University of New York &
Universidad de las Americas Puebla
jgil-garcia@ctg.albany.edu

G. Brian Burke
University at Albany, State University of New York
bburke@ctg.albany.edu

Jim Costello
University at Albany, State University of New York
jcostello@ctg.albany.edu

Derek Werthmuller
University at Albany, State University of New York
dwerthmuller@ctg.albany.edu

Oguz Aranay
University at Albany, State University of New York &
University of Kirkuk, Iraq
oaranay@albany.edu

Abstract

Despite the growing body of literature on data-driven decision-making (DDDM) and, more recently, big data, empirical analyses on processes and strategies of government agencies toward DDDM are still scarce. To mitigate this gap in the literature, this study identifies and explains opportunities and challenges of data use and analytics found in a case of a U.S. state-government agency that is in charge of water quality management and has started to implement Evidence-Based Policy Making (EBPM). By drawing on four dimensions, data, technology, organization, and institutions, the results show how the organization's DDDM practices are enabled or constrained by nine types of determinants: data quality/coverage, compatibility/interoperability, external data, information technologies/software, analytical techniques, cooperation, culture, privacy/confidentiality, and public procurement. Overall, the findings imply that either quality data or advanced analytic techniques alone do not guarantee effective DDDM; organizational and institutional support is also needed for successful implementation.

1. Introduction

Remarkable advances in data processing and analytic technologies with the emergence of big data have led to a renewed call for data-driven decision-making (DDDM) in the public and private sectors [1]. Recent claims of DDDM advise that big data together with emergent technologies will help improve decisions and accountability in many fields, such as education and environmental management [2], [3].

Given that digitalizing government involves social and structural transformations in organizations [4], [5], it is not surprising that there has been a growing body of literature discussing DDDM from organizational culture and implementation perspectives. They describe transitioning to DDDM as an organizational and cultural reform leading to an expert-oriented organization that requires cultural/institutional supports for analysts, participation from organizational members, and analytic capabilities of individual decision-makers, as well as the extensive use of advanced information technologies (ITs) [6], [7].

This paper adds a piece of evidence that elaborates on opportunities and constraints that promote or hamper the organization that is attempting to transition to DDDM by conducting a case study of a state agency in the U.S. Even though it is encouraging that many studies have provided guidelines to achieve DDDM by drawing on management and organization theories, many of these attempts lack empirical analysis and evidence. Therefore, the research question guiding this paper is: what are the main opportunities and constraints when transitioning to DDDM? Without empirical examinations, the call for transitioning to DDDM might fall into an abstract claim that lacks practicality. To fill this gap in the literature, we explore a case, based on in-depth interviews, where a state agency attempted to implement DDDM.

In discussing the case, this paper also draws on the discussion on evidence from the literature on Evidence-Based Policy (EBP). The spread of EBP sheds light on a new opportunity not being sufficiently analyzed by previous studies on the implementation of DDDM. EBP and DDDM share the utilitarian philosophy in that both of them advocate a result-based approach in decision-making, however, different from

URI: https://hdl.handle.net/10125/70881
978-0-9981331-4-0

DDDM, discussion in EBP includes specific scientific standards for producing good evidence [8], [9]. Such a discussion from EBP describes the nature of knowledge that organizations need to pursue through the utilization of data (big and small), suggesting a direction for the discussion about DDDM in the public sector to move forward.

The empirical part of this paper highlights opportunities and challenges observed in a case where a state-department in the U.S. attempts to promote DDDM in water quality (WQ) management. In response to a state-wide environmental problem, the agency has launched a project for enhancing the analytic capabilities by drawing on state-of-the-art technologies and analytical techniques and extensive use of external datasets as well as the organization's legacy systems that contain water sampling results. In this process, evidence principles from EBP contributed to identifying the direction where the project should be heading, which datasets and analytic techniques are necessary, and, ultimately, what are opportunities and challenges posed in the transitioning process toward DDDM. By documenting this process based on a set of in-depth interviews with practitioners, this study would contribute to unpack and better understand the transitioning process to DDDM in practice.

The paper is organized into six sections, including the foregoing introduction. Section two briefly presents the results of our review of existing literature, with a focus on data-driven decision making and evidence-based policymaking. Section three introduces the background of the case investigated in this paper. Section four briefly describes our research design and methods. This study is based on semi-structured interviews and the analysis of official documents. Section five elaborates on specific opportunities and challenges found through the qualitative analysis of the interviews. This section presents our main findings based on four dimensions: data, technology, organization, and institutions. Finally, section six discusses the implications of the findings and provides some concluding remarks.

2. Literature Review

DDDM and EBP share the idea of substituting/complementing individual intuition and experience in decision-making with knowledge and evidence from analytic findings pulled out from systematically gathered data. However, their discussion diverges in terms of good evidence for decision-making, since it is assumed to come from different origins and backgrounds. DDDM today tends to set an ambiguous evidentiary boundary than that of EBP due to its background from emerging big data and advanced analytics technologies, while the EBP literature includes lots of debates on the boundary of evidence and tend to privilege evidence produced by rigorous scientific methods and theories appropriate for the specific policy area. We argue that the emphasis on the scientific standard in producing evidence can significantly contribute to the DDDM literature when facing a problem where the knowledge gap poses a significant challenge.

2.1. Data-Driven Decision Making as a Strategy for Government Reform

Digital government has been one of the most influential paradigms of government reform that triggered enormous changes in the public sector throughout the past several decades [10]–[12]. The broader definition of digital government embraces a variety of transformative actions that help governments address social problems and provide services by using information technologies, as well as a set of emergent technologies that can be applied to the public sector [13]. Advanced ITs have promoted governments to work more closely with data in a variety of areas such as communications, performance management, and data management [14]–[16].

This movement has recently met a new turn where DDDM, which refers to a style of decision-making that relies on data analysis than intuition [1], is increasingly emphasized with the emergence of big data. Over the past decades, governments and businesses have begun to recognize the value of data and started to pay attention to how to better accumulate and utilize data. Recent data storage technologies, such as Hadoop, MapReduce, and Docker, provide a foundation on which organizations can process enormous amounts of data from various sources. Meanwhile, the explosive growth in analytic technologies, such as machine learning and data mining, has helped extract novel and practical insights from such huge amounts of data, thereby there has been an expectation recently grown that decision-making that heavily relies on data analysis may outweigh, or even substitute, decisions that depend on individual intuition and experience.

Based on these advances in technologies, people who advocate DDDM argue that increasingly more data should be used in government decision making. DDDM generally refers to the practice of a style of decision-making that heavily relies on the knowledge extracted from data analysis rather than individual intuitions and professional experience [1]. In recent years, there has been an increasing number of cases in the public sector where DDDM is put into practice, with the growth of the field of data science coming along with relevant data processing and analytic technologies and the emergence of the concept of big data [3]. This approach grounds on a belief that knowledge generated by data systematically measured and analyzed leads to more reliable decision-making. Studies emphasize that recent advances in data availability and analytic technologies allow new insights with less uncertainty as benefits from DDDM. For example, in practice, a teacher can use a pre-defined set of metrics with performance data for adopting a novel educational tool rather than rely on intuition and experience that are based on heuristics and vulnerable cognitive biases [17].

Scholars have urged organizational transformations towards DDDM by claiming that DDDM can create new opportunities by giving best practices. As described in the digital government literature, the transition to DDDM is more likely to involve social and structural transformations triggered by advanced ITs than a simple application of specific technologies [4], [5]. Moreover, such a process can be constrained or expedited by existing organizational characteristics and institutional arrangements [18]. Likewise, many studies describe transitioning to DDDM as an organizational reform that requires social and cultural transformations [19], [20]. It involves various organizational-level efforts, such as cultural/institutional supports for analysts, participation from organizational members, and analytic capabilities of individual decision-makers, as well as the extensive use of advanced ITs [6], [7].

However, practicality of such claims might be somewhat limited in that much of their discussion largely lack empirical evidence. There have been only a few studies that described the transitioning process to DDDM in detail, particularly in the public sector. It may be encouraging that the literature has started recognizing the organizational changes embedded in the process toward DDDM, however, without unpacking the process with empirical descriptions and systematic analysis, its academic advice might misguide practitioners.

2.2. Evidence-Based Policy Making

EBP, which refers to the idea that policymaking should be based on scientific evidence by decoupling from politics and other threats to rationality, is another recent movement of government reform that originated from the field of medicine [9]. Similar to DDDM, EBP tries to complement or replace individual intuition and experience with research evidence and emphasizes result-based policymaking from the utilitarian point of view [21]. But it is noteworthy that discussion in EBP includes specific standards for good evidence. As EBP has transferred evidence-based principles to the policy area [22], EBP began in an attempt from the field of public health to promote inputs from science in policymaking practice in response to the complexity of social problems that governments face [23]. Lots of studies in this area have attempted to establish rigorous scientific standards for making sound evidence for policymaking [9]. As such attempts have swept several fields, especially public health, education, and corrections, there have been a number of cases reported that governments expanded the use of research evidence in practice [24], [25].

A rigorous approach in EBP emphasizes two conditions for good evidence: systematic investigation and theoretical approach [8], [9]. First, a piece of good evidence should be based on a systematic investigation that includes a sufficient number of observations balanced across different groups and classes in the study population (e.g., randomized controlled trials). This allows a research finding to be a piece of evidence that can be generalizable across time and space. Second, policy evidence should be derived from empirical findings discussed from a theoretical standpoint. Theories help a researcher avoid arbitrary judgments in research design, analysis, and interpretation of the finding. For example, an analyst can carefully select variables by reviewing prior studies rather than relying on intuition when running a regression analysis. A comprehensive literature review that synthesizes existing research findings can also be an important methodological tool for building up good evidence that is theoretically grounded.

This approach tends to narrowly define the boundary of what is evidence by advocating that evidence should be made based on the scientific process which requires systematic observations, e.g., randomized trials, and theory-based analysis, e.g., controlling variables and synthesizing previous findings [9], [26]. The key assumption shared by studies from this perspective is that there are universal criteria in the quality of evidence. On the other hand, there is another approach that provides a broader definition of evidence by emphasizing the contexts of the social problem when understanding evidence. In other words, this perspective tends to embrace all the available information relevant to the given problem because it denies the idea that science can provide an optimal and timely solution [27]–[29].

We argue that the discussion of EBP that explicitly suggests the scientific standard as the most important characteristic of good evidence provides practical implications for implementing DDDM. The current claims that advocate DDDM clearly highlight opportunities from big data and suggest the direction public organizations should pursue in terms of policymaking. However, they are limited in providing specific conditions for data to replace the intuition and experience of individual decision-makers. In the absence of the conditions for moving toward the implementation of DDDM, opportunities and challenges that may eventually emerge in the process of public service reform induced by advanced ITs cannot be identified either.

To fill this gap in the literature, this paper describes opportunities and challenges in transitioning to DDDM in a case where a state-department in the U.S. attempts to promote DDDM in WQ management by drawing on the EBP perspective. This organization, which deals with environmental issues in a state in the U.S., launched a project to improve the organization's data analytic capabilities as one of the measures to address a state-wide problem of WQ in lakes and rivers. In this process, the scientific standards from EBP became a guide to help the department identify the conditions required to promote DDDM successfully. We believe that unpacking opportunities and challenges found in this process can contribute to theorizing the transition process toward DDDM in government.

3. Case: A State Department that Manages Water Quality in the United States

This study explores a Division of Water (DOW) in a state government in the U.S. that monitor water resources. This organization consists of five bureaus that oversee WQ monitoring/assessment, water permit/compliance, and flood protection.

In recent years, DOW has been struggling to address state-wide environmental problems such as Harmful Algal Blooms (HABs) and high chloride concentrations, which are critical to public health and recreational activities. In response to the environmental challenges, the state government launched a state-wide initiative and has invested hundreds of thousands of dollars to develop clean water infrastructure and combat HABs and chloride concentrations, among other important issues. The countermeasures include improving monitoring systems and analytic capabilities of DOW by adopting advanced ITs and sophisticated techniques as well as implementing action plans for cleaning impaired water bodies and enhancing volunteer-based monitoring programs.

This study draws on a prototype project, launched as part of this initiative, where DOW attempted to improve its analytic capabilities by adopting advanced ITs in partnership with the Department of Health (DOH) and Center for Technology in Government (CTG) from the University at Albany, SUNY. This project aimed to develop efficient data management practices, suggest governance models, and identify analytic techniques potentially beneficial to addressing HABs and chloride related problems.

This case provides a conducive opportunity to observe data use and analytic practices in implementing DDDM in the public sector in that DOW attempted to move beyond typical data production and analysis through the project. As an organization oversees WQ monitoring/assessment and water-related compliance, DOW has collected water chemistry and water permit data and developed several databases to manage the datasets. Moreover, DOW's routine decisions (e.g., determining impaired water or discharge allowance for certain facilities) and long-term planning heavily rely on some data analysis already. However, up against the recent complicated environmental crisis, decision-makers and analysts of DOW found that the legacy systems and current analytical practices were quite limited in providing evidence with confidence for policymaking. Over the last 30 years, the major issues in the state have largely moved toward eutrophication and overloading of nutrients into water bodies that cause excessive algae growth and chlorination in water. However, the primary cause of the problems still remains a big puzzle. The primary goal of the project was to help DOW implement DDDM in understanding and addressing the HABs and chloride problems.

4. Research Design and Methods

This case study uses transcripts from twelve in-depth interviews to document opportunities and challenges in implementing DDDM. The interviews were conducted with practitioners working at DOW, as a part of a project for developing a data analytics prototype. The interviewees included five managers and seven research scientists, as shown in Table 1. Even though their job titles differ, they play similar roles as decision-makers and also more traditional policy analysts who inform top decision-makers. Even though their analytical results often produce evidence for planning and designing environmental interventions, the data primarily becomes a source of information for routine decisions, such as determining sampling sites and discharge allowance for facilities across the state.

Table 1. Characteristics of Interviewees

Job Title	Number of Interviewees
Manager	5
Research Scientist	7
Total	12

The interview questions were related to their use of data and data analytics for the daily work as well as challenges and results (e.g., *How do you use data in your current job?; Can you give examples of data standards that your organization uses?*). The coding process focuses on identifying opportunities and challenges from the transcripts. The process consists of two stages of qualitative coding: initial coding and focused coding [30]. The first stage identified emergent themes related to opportunities and challenges in implementing DDDM. In the second stage, we revisit the data after developing nine factors from the themes. The result section describes the nine factors based on four deductive categories developed for conducting the interviews, *data, technology, organization, and institutions.*

5. Opportunities and Challenges in Implementing Data-Driven Decision-Making in Government

5.1. Data determinants

Decisions in DOW heavily rely on in-house data produced by water sampling/assessment and water-related permits. DOW has implemented a quality assurance (Q.A.) process that has been successful in creating reliable data to some extent by reflecting scientific standards and methods required by the respective federal agencies (e.g., EPA). However, significant limitations are found in other issues: manual sampling, data coverage, missing values, compatibility, and interoperability.

5.1.1. Data quality and coverage. DOW produces various home-grown datasets, as the staff members describe them, coming from water monitoring programs and permit-related requirements on facilities that discharge wastewater in the state. These outputs primarily become inputs for answering questions from top decision-makers, such as commissioners and the governor, mandatory reporting to the federal agencies, such as the Environmental Protection Agency (EPA), and informing the public and researchers upon requests.

DOW's data have some desirable characteristics for analysts. The first advantage is reliability. DOW has mechanisms that help produce reliable WQ data. The EPA has required states to identify impaired waters through reports of section 303(d) starting from 1992 and 305(b) from 2002 under the Clean Water Act and provided detailed guidance for assessing WQ based on scientific standards [31]. The guidance includes protocols for how to identify the effects of pollutants and trends over time, characterize waterbodies, and report WQ conditions. DOW set up an internal Q.A. process to follow the guideline through which DOW sends water samples to external laboratories to be processed to identify chemicals or certain species in water. DOW receives the electronic output, typically a comma-separated values (CSV) file, once the process of about 24 to 48 hours is done.

Given the EPA requirements that DOW follows, it is fair to say that DOW's in-house data has been reliable in that the staff members have had no serious problems in the quality of the samples. This provides two clear opportunities to implement DDDM. First, it helps save time and effort for validating when processing and cleaning data. Second, the reliability also allows to compare the quality of water with nearby states. As the samples are collected based on the same methods guided by the federal agencies and stored to a shared repository, such as WQX of the EPA and Water Quality Portal (WQP) of the United States Geological Survey (USGS), they become a source of data for state-level analyses usually required when developing vision documents and long-term plans.

However, one of the significant challenges to the data comes from the manual sampling method. DOW's water sampling has been conducted through fieldwork of staff members and consultants hired by DOW. Even though DOW has a Q.A. process that makes sure the quality of the samples and protocols for standardizing the sampling method, human errors can always occur when sampling water in the field.

Another quality-related challenge is data coverage. One of the chronic problems in DOW has been the balance between sampling frequency and its cost. It is evident that many statistical techniques, especially regression analyses, require systematic observations based on repetitive sampling with lots of water bodies to be not biased. However, collecting more samples, on the other hand, simply requires enormous amounts of time and labor costs, as most of the samples are collected through fieldwork by the staff members and consultants and go through scientific laboratories to be processed. This is the reason why it takes a long time for analysts to explore new parameters, even when they are asked about emerging contaminants. One of the analysts who respond to the Total Maximum Daily Loads (TMDLs) reporting said: "*I think that's probably like the biggest challenge… is weighing how much is enough to make decision ... We have to move forward. But we don't want to move forward without feeling pretty confident about the amount of data in that is definitely something that we are working through ... And, that's something that is difficult, in general, having a feeling confident that you have sufficient amount of data to actually make a good decision. And we struggle with that with our TMDLs.*" Correctly assessing characteristics of waterbodies demands a certain level of frequency. However, water sampling takes a lot of time to collect and process data. Moreover, DOW covers thousands of water bodies in the state with a limited number of staff members. For this reason, DOW's monitoring programs usually have monthly, seasonal, or yearly intervals; even some of them are conducted under five years rotations which are insufficient in characterizing waterbodies when considering that the characteristics of water change every moment, limiting the organization's capability in improving the data coverage.

5.1.2. Compatibility and interoperability. DOW has a number of staff members who are involved in data production or data analysis and whose roles are interrelated. Given that sampling is one of the primary methods of monitoring watersheds, different teams respectively record observations for different types of water, such as lakes and streams. The bureau that is in charge of regulatory surveillance also has its own repository for storing permit and compliance data. Interchanges and compiling of data frequently occur across individual analysts, teams, and bureaus.

Having a high number of data producers and analysts provides an opportunity for DOW because it allows for the environment where the staff members can cooperate, as will be explained later, however, it can also pose some challenges in managing consistent data. There are a couple of reasons for a dataset to be incompatible among different systems or individuals. First, data producers and analysts in DOW have different versions of files. The Filemaker that DOW has used for file management does not lock down fields, allowing multiple users to manipulate the original data, which might be risky in terms of data integrity. Moreover, levels of observation might be incompatible between different systems. For example, one of the analysts said: "*We have been working on trying to crosswalk the data, like so we can look at it all at the same sort of scale. Because like permits is at a facility specific location, but yet it's discharging to a specific water body, I want it to connect to that water body, but the way that they report their data is like it's as a receiving water body but they're receiving water body doesn't necessarily match with our assessment unit and that's like, oh my god.*"

The interoperability of data is also another issue that provides challenges, usually time-consuming, in producing evidence. First, data format depends on what kind of model it is and what the model is about; different models can have different formatting input requirements. Sometimes analysts need to spend extensive amounts of time preparing data, getting it ready to go into the model. Second, various tools can have different formatting requirements, and such a difference poses challenges in converting and cleaning data. For example, shapefiles usually used for running ArcGIS are not easily readable in Excel and some statistical tools, such as SAS and STATA.

5.1.3. External data. DOW staff members often take advantage of using external datasets when answering relatively complicated and tricky questions. Responding to the regulatory requirements to the federal agencies does not necessarily require the extensive use of external datasets; however, some environmental and social issues set more complex challenges and questions that cannot be addressed only with the home-grown data sources. The analysts then can look for other data sources like geospatial information, land use or impervious surface cover, or pull out information about geologic formations, or surficial and bedrock geology under layers.

Vision documents that typically contain long-term visions and missions provide an excellent example of using external data. Developing vision documents require to communicate with top decision-makers and sometimes to the public at large, who are not likely to have expertise in water-related sciences. In such cases, the analysts can provide charts and maps by combining water chemistry data with geographical data of water bodies to visualize data effectively.

On the other hand, using external data can bring about challenges in producing evidence for DOW's decision-making. One of the difficulties comes from the quality of the sources. As external data providers are not likely to be under DOW's control, it is difficult for DOW's analysts to guarantee the quality of those external datasets. Even when data is available, external datasets are, in general, collected for different purposes; thereby, they are likely to make problems in the level of analysis. For example, analysts in DOW often want to differentiate the effects of certain types of discharges, such as corn or soybean meal farms, on waterbodies. Still, land-cover data from USGS, which is publicly available, does not provide that specificity because it gives only one category of farmlands.

5.2. Technological determinants

Analysts of DOW produce evidence for supporting decision-making by combining data with various database management and analytical techniques. The use of advanced technologies often provides benefits in answering complex questions, however, the rapid advances in technology give challenges as well as opportunities in implementing DDDM.

5.2.1. Information systems and software. Advanced analytics technologies and database management systems have provided lots of advantages to DOW. Notably, the recent advances in R and Python as analytic tools provide lots of new opportunities. One of the most apparent advantages is replicability. Before using script-based analysis, DOW staff members had to rely on tacit knowledge that can cause human errors, especially in processing and cleaning data. Another problem was that it was difficult for other analysts to get a sense of how the data is processed and analyzed. However, with the growth in staff who can use R and Python, the script environment allows the analysts to conveniently make the analytic process transparent and replicate the procedures done by other analysts by sharing scripts. Moreover, R and Python are open source software programing languages, thereby they are free and include lots of packages developed by other developers. Another opportunity is the open environments of these programming languages and their relevant packages. Many online communities help R and Python users communicate with each other, such as GitHub. GitHub provides a web-based code hosting interface and repository for projects by which users can collaborate and share code.

However, existing systems and tools become obsolete, as new technologies emerge, and sometimes constrain the adoption of new technologies. For example, DOW has developed its water chemistry database based on a Filemaker system, which was adopted around the 1980s. Filemaker provides basic functions for managing relational tables, however, with a lot of users who produce or use the data in it, the Filemaker database has been exposed to a critical limitation that it does not guarantee data integrity due to the absence of functions for locking down fields or version control. DOW has attempted to be less dependent on Filemaker by bringing other information systems, however, such attempts have not been totally successful, as one of the analysts said: "*I think four or five years ago and we are trying to potentially move away from the use of FileMaker but we haven't succeeded yet.*" This was mainly because of the nature of data analysis and evidence in DOW's decision-making that requires to analyze long-term trends and effects. Consequently, the more datasets have already been stored on the platform, the more difficult it is for the users to move away from it. There has not been a project large enough to replace the existing system entirely, leaving the analysts to keep relying on the old Filemaker system more and more.

5.2.2. Analytical techniques. In addition to advanced ITs and software, DOW's decisions heavily rely on statistical analyses. Mandatory reporting, such as TMDLs, may not require sphisticated analysis. However, analysts in DOW attempt to answer complex questions by using statistical methods and modeling. For example, in response to the recent problems of HABs and chloride concentration, DOW's analysts have struggled to identify the causes and effective countermeasures by analyzing water chemistry data in combination with statistical analysis and modeling. The analytical techniques range from t-test and ANOVA to regression and time-series analysis, as well as descriptive statistics. Sometimes, their data analyses are often related to characterizing the overall condition of water bodies and assessing impacts of discharges and pollutants on aquatic life, human health, or recreation opportunities.

Advanced academic degrees of the analysts have provided primary sources of knowledge for bringing statistical techniques into DOW. DOW staff members include many research scientists from diverse academic backgrounds in relevant sciences, such as environmental science and biology. The section chiefs and program coordinators usually hold a doctoral degree and lead other research scientists in conducting in-house research on water-related issues. They guide or run statistical models, while other research scientists, who also hold a master's degree, are in charge of administering data production and reporting.

Even though the use of sophisticated analytical techniques has helped the analysts support the organization's decision-making with scientifically rigorous evidence, it also poses a challenge in that such techniques are often hard to understand and time-consuming. One of the analysts mentioned that: "*We had to develop a specific monitoring plan to track down what those potential sources were we actually went out and collected the data. We analyze the data, and we had to do that like in two weeks or less, I think I do not remember what it was, but we had to have our everything done within like 24 hours. That was the timeline.*" This quote shows the difference in viewpoint between analysts and high-level decision-makers in approaching the use of evidence in decision-making. Many of the analysts in DOW are willing to draw on rigorous methods from science and produce evidence with which they are confident enough, however, decisions do not necessarily wait for such attempts.

5.3. Organizational determinants

The discussion in this section highlights that data production and analysis in DOW are an organizational process rather than an individual activity. As an organization staffed by analysts with diverse technical capabilities and knowledge about different data productions, DOW implements DDDM.

5.3.1. Cooperation. As explained earlier, data production and analysis in DOW are conducted based on organizational cooperation among multiple staff members. DOW has several home-grown databases for water chemistry and compliance and also receive water data from private data providers and local agencies. Water monitoring and assessment programs involve lots of sampling activities that cover the state based on fieldwork by the staff members and consultants, thereby collecting data and quality control is inherently a labor-intensive activity that requires cooperative efforts of many staff members.

Using techniques for producing evidence is also an organizational activity that involves different tools ranging from SAS to R and Python. In DOW, the type of expertise varies across staff members. Some analysts are heavy users of R and Python; they help perform extensive analyses that draw on large datasets and sophisticated statistical techniques. Other staff members, especially long-serving technicians, are likely to be familiar with DOW's legacy systems and the Filemaker database and help other analysts struggling with querying and manipulating data. Geographical analysis is another area that demands professional experience and expertise, given the need for knowledge about the use of specific tools, such as ArcGIS. Combining geographic information with WQ data is one of the frequently used tasks required in DOW's analytic flow, but only a limited number of members have that expertise. Therefore, for those who do not have knowledge in ArcGIS, working with somebody familiar with the tool is essential .

5.3.2. Culture. Even though DOW is a government organization that provides public services, there have been changes toward a research-oriented culture by increasingly hiring more employees with academic backgrounds. An engineer described in an interview that: "*One of the changes in culture, and the people who engender that culture is that they are using research scientists, for researchers. And it's clear to the researchers coming in your researchers, you are expected to do data analytics, you are expected to generate manuscripts, you are expected to do more than we used to do. That's a change in culture. And it's a change in a bit even those of us who aren't researchers strongly support something we should have been doing a long time ago, that for many reasons, some good some way they are you just fell out of that.*" As more research scientists come into the organization, cultural support and opennes to new tools and techniques have been essential for staff members to bring new datasets and technologies into DOW. Managers in DOW have been quite open to extra training for learning new methods and adopting advanced technologies. Involvement in academic research is also highly encouraged in DOW; analysts in DOW can freely conduct analysis for academic purposes and publish the results in scientific journals. One of the research scientists mentioned that interacting with academia prevents them from being isolated as researchers: "*So there is no formal process. It is not like analysis for submission. The goal with our bureau is to present it at regional and national conferences and to publish it in journals but within the department, we do not have to do that to communicate with the managers about what we are finding. I personally like the mechanism of publishing in a peer review because it makes me feel less like in an island.*"

Part of this change has come from the flexibility of research scientist as a job title. It endorses analysts in DOW to take advantage of academic experience and skills by getting rid of exam-related burdens, as an engineer interviewed mentioned that: "*Well, I'm an engineer, but the rest of them are largely research scientists, for many years. Without going into a lot of details. Research Scientist is what is considered a non-competitive title, meaning there is no civil service list and exam associated with it. There's a fair amount of flexibility for us to find researchers. And it doesn't mean we have to pick a biologist who got a 95 on the exam, which is the constraints we have with a competitive title*."

5.4. Institutional determinants

Working as a public organization, DOW's activities and use of data and technologies frequently face strict rules and specific legal requirements. As an agency of a state government in the U.S., DOW enjoys the support of several federal agencies and collaborate with other state agencies. However, there are some rules and laws that impose constraints for the use of data and information technologies for decision-making.

5.4.1. Privacy and confidentiality. Even though DOW deals with environmental data, which is not likely to include personal information, public perception greatly influences the data that it collects. For example, the HABs problem has become one of the most sensitive environmental issues in the state in recent years. People are worried about living close to impaired waterbodies. "*You do not want to make people freak out. You also do not want to like hide anything. ... Like what does point one mean, and 10 if the scale is one to 100, and it is just like putting that into perspective, like you want to be informative, but you do not want to cause alarm, panic about something either. So that is it, I think that is a challenge. It is the way that the data is interpreted and having confidence and getting no like a feeling that we can make a really informed decision about what that data means.*"

Sometimes, the privacy issue constrains DDDM by limiting the use of data sources potentially beneficial to DOW's analysis. This is especially important if the dataset includes information that might affect one's property rights. "*It is kind of a confidentiality agreement between Soil and Water Conservation Districts and private landowners that they do not share the landowner information because as soon as information comes to us, it becomes public. So we do not receive that information directly. I know that is something that has been frustrating sometimes to folks here because it would be really nice if we knew where the project actually went in within the watershed.*"

5.4.2. Public procurement. Another area regulated by state laws and other rules is procurement and investment. Even though supervisors in DOW have been quite supportive of getting the analysts trained, there are important organizational challenges. For example, they do not automatically have the ability to buy a newly developed package or join a training program. This needs to get approved through the state's procurement rules and is successful, most of the time. However, such a process causes a delay in adopting new tools and technologies.

This kind of issue also happens when accessing free online tools and communities, which also need to be approved before being able to use them and this is now always allowed. Many of the analysts in DOW believe that this constraint causes critical limitations in capability building in the new environment where online communities and platforms, such as GitHub and Trello, take a large part of learning and collaboration. Moreover, a large part of innovations in developing analytic tools and packages are shared through those online platforms, however, the DOW's environment partly isolated from the outside poses a significant challenge to analysts in DOW, as a section chief in an interview said: "*That has been a hindrance right now. The other one has for us has been this like sensitivity to GitHub and other tools that the rest of the world is using? Like, I mean, there is the rest of the world is using these sharing platforms, these collaborative working platforms, like Trello and GitHub and Bitbucket, right. You know, there is like this sensitivity to using them and so, I had to go and get permission from operations folks to be able to have access to them, you know, like on a case by case basis. So, there are definitely those, those hindrances we have, overcome them. But it is just a matter of time when one of them shows up and, we cannot overcome it.*"

6. Discussion and Conclusion

Insofar, we have described opportunities and challenges in transitioning to DDDM by studying a state agency struggling to address emerging issues. The organization has been implementing DDDM previously to some extent in that its decisions have been heavily relying on data use and data analysis, but the existing tools and techniques could not provide enough evidence in light of the new complicated problems of HABs and high chloride concentrations. This gap has become a motivation for the organization to revisit and attempt to improve its analytic capabilities to the extent of being able to produce more appropriate evidence for decision-making.

The nine determinants in the process of innovation highlight the nature of implementing DDDM, which could involve or even require significant organizational and institutional transformations. Not only data and technologies, but also organizational and institutional factors provided pivotal opportunities and challenges to DOW in producing sound evidence for decision-making. These determinants reveal practical issues that public organizations can face when attempting to adopt or implement DDDM. Data use and data analysis in decision-making have become quite common today. However, as DOW's struggles with producing evidence in light of the environmental issues show, conducting data analysis does not necessarily lead to the full potential of DDDM. Rather, a meticulous organizational strategy that maximizes opportunities while minimizing challenges that might emerge in walking toward DDDM would be necessary to implement it successfully. We believe that the nine determinants can provide beneficial insights that can help government agencies and policymakers get off to a running start.

The description of the case demonstrated that knowledge from the EBP literature could contribute to the discussion on DDDM as well. The previous studies on DDDM have paid insufficient attention to instances where organizations are incapable of producing good evidence even with advanced ITs and a huge amount of data and how to overcome such impasses. By drawing on the discussion about EBP, we were able to demonstrate how an organization's capabilities can be limited in implementing DDDM despite established data use and adequate analytical practices. Specifically, the lens focused on the capability of producing evidence highlighted the aspect that being able to use data and data analysis was not enough to drive all the decisions in the case. We argue that research questions asking essential conditions for good evidence would be beneficial to the DDDM literature to move forward.

References

[1] F. Provost and T. Fawcett, “Data Science and its Relationship to Big Data and Data-Driven Decision Making,” Big Data, vol. 1, no. 1, pp. 51–59, 2013, doi: 10.1089/big.2013.1508.

[2] H. G. Han, H. J. Zhang, Z. Liu, and J. F. Qiao, “Data-Driven Decision-Making for Wastewater Treatment Process,” Control Eng. Pract., vol. 96, 2020, doi: 10.1016/j.conengprac.2020.104305.

[3] E. B. Mandinach, “A Perfect Time for Data Use: Using Data-Driven Decision Making to Inform Practice,” Educ. Psychol., vol. 47, no. 2, pp. 71–85, 2012, doi: 10.1080/00461520.2012.667064.

[4] R. Kling, “Computerization and Social Transformations,” Sci. Technol. Human Values, vol. 16, no. 3, pp. 342–367, 1991.

[5] P. M. Blau, C. M. Falbe, W. McKinley, and P. K. Tracy, “Technology and Organization in Manufacturing,” Adm. Sci. Q., vol. 21, no. 1, p. 20, 1976, doi: 10.2307/2391876.

[6] J. C. Wayman, “Involving Teachers in Data-Driven Decision Making: Using Computer Data Systems to Support Teacher Inquiry and Reflection,” J. Educ. Students Placed Risk, vol. 10, no. 3, pp. 295–308, 2005, doi: 10.1207/s15327671espr1003_5.

[7] P. Wohlstetter, A. Datnow, and V. Park, “Creating a System for Data-Driven Decision-Making: Applying the Principal-Agent Framework,” Sch. Eff. Sch. Improv., vol. 19, no. 3, pp. 239–259, 2008, doi: 10.1080/09243450802246376.

[8] S. Nutley, A. Powell, and H. Davies, “What Counts as Good Evidence?,” London, UK, 2013. [Online]. Available: http://www.alliance4usefulevidence.org/assets/What-Counts-as-Good-Evidence-WEB.pdf.

[9] H. T. Davies, S. M. Nutley, and P. C. Smith, What Works? Evidence-Based Policy and Practice in Public Services. Briston, U.K.: The Policy Press, 2000.

[10] T. A. Ho, “Reinventing Local Governments and the E-Government Initiative,” Public Adm. Rev., vol. 62, no. 4, 2002.

[11] R. Sandoval-Almazan, L. F. Luna-Reyes, D. E. Luna-Reyes, J. Ramon Gil-Garcia, G. Puron-Cid, and S. Picazo-Vela, “Developing a Digital Government Strategy for Public Value Creation,” in Building Digital Government Strategies: Principles and Practices, vol. 16, New York, NY: Springer, 2017, pp. 7–20.

[12] P. Dunleavy, H. Margetts, S. Bastow, and J. Tinkler, “New Public Management Is Dead—Long Live Digital-Era Government,” J. Public Adm. Res. Theory, vol. 16, no. 3, pp. 467–494, 2006, doi: https://doi.org/10.1093/jopart/mui057.

[13] M. J. Moon, “The Evolution of E-Government among Municipalities: Rhetoric or Reality?,” Public Adm. Rev., vol. 62, no. 4, pp. 424–433, 2002, doi: 10.1111/0033-3352.00196.

[14] J. Layne, Karen; Lee, “Developing Fully Functional E-Government: A Four Stage Model,” Proc. ASME Turbo Expo 2014 Turbine Tech. Conf. Expo., vol. 18, p. 122–136, 2014, doi: 10.1016/j.comnet.2009.08.011.

[15] K. V. Andersen and H. Z. Henriksen, “E-Government Maturity Models: Extension of the Layne and Lee Model,” Gov. Inf. Q., vol. 23, no. 2, pp. 236–248, 2006, doi: 10.1016/j.giq.2005.11.008.

[16] X. Papadomichelaki and G. Mentzas, “E-GovQual: A Multiple-Item Scale for Assessing e-Government Service Quality,” Gov. Inf. Q., vol. 29, no. 1, pp. 98–109, 2012, doi: 10.1016/j.giq.2011.08.011.

[17] E. Kurilovas, “On Data-Driven Decision-Making for Quality Education,” Comput. Human Behav., vol. 107, 2020, doi: 10.1016/j.chb.2018.11.003.

[18] M. Ku and J. Ramon Gil-Garcia, “Ready for data analytics?: data collection and creation in local governments,” 2018.

[19] C. S. Mayo, J. O. Deasy, B. S. Chera, J. Freymann, J. S. Kirby, and P. H. Hardenberg, “How Can We Effect Culture Change Toward Data-Driven Medicine?,” Int. J. Radiat. Oncol. Biol. Phys., vol. 95, no. 3, pp. 916–921, 2016, doi: 10.1016/j.ijrobp.2015.12.355.

[20] A. S. Krishen and M. Petrescu, “Data-Driven Decision Making: Implementing Analytics to Transform Academic Culture,” J. Mark. Anal., vol. 7, no. 2, pp. 51–53, 2019, doi: 10.1057/s41270-019-00056-5.

[21] M. J. Roberts and M. R. Reich, “Ethical Analysis in Public Health,” vol. 359, no. 9311, pp. 1055–1059, 2002.

[22] M. Howlett, “Policy Analytical Capacity and Evidence-Based Policy-Making: Lessons from Canada,” Can. Public Adm., vol. 52, no. 2, pp. 153–175, 2009, doi: 10.1111/j.1754-7121.2009.00070_1.x.

[23] B. W. Head, “Wicked Problems in Public Policy,” Public Policy, vol. 3, no. 2, p. 101, 2008.

[24] Pew-MacArthur Results First Initiative, “How States Engage in Evidence-Based Policymaking: A National Assessment,” 2017.

[25] U.K. Cabinet Office, “Modernising Government,” 1999.

[26] G. H. Guyatt and J. W. Busse, “The Philosophy of Evidence-Based Medicine,” in Evidence-based Endocrinology, V. M. Montori, Ed. Totowa, NJ: Humana Press, 2006, pp. 25–33.

[27] J. Parkhurst, The Politics of Evidence: From Evidence-Based Policy to the Good Governance of Evidence. London, UK: Routledge, 2017.

[28] J. Parkhurst and S. Abeysinghe, “What Constitutes ‘Good’ Evidence for Public Health and Social Policy-making? From Hierarchies to Appropriateness,” Soc. Epistemol., vol. 30, no. 5–6, pp. 665–679, 2016, doi: 10.1080/02691728.2016.1172365.

[29] N. Shulock, “The Paradox of Policy Analysis: If It Is Not Used, Why Do We Produce So Much of It?,” J. Policy Anal. Manag., vol. 18, no. 2, pp. 226–244, 1999, doi: 10.1002/(SICI)1520-6688(199921)18:2<226::AID-PAM2>3.0. C.O.;2-J.

[30] R. K. Yin, Case study research and applications: Design and methods, 3rd ed. Thousand Oaks, CA: Sage Publications, Inc., 2003.

[31] Environmental Protection Agency, “Guidance for 2006 Assessment, Listing and Reporting Requirements Pursuant to Sections 303(d), 305(b) and 314 of the Clean Water Act,” Washington, DC, 2005.