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A REVIEW OF THE LITERATURE ON APPLICATIONS OF TEXT MINING IN POLICY MAKING

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ABSTRACT

Despite the increasing importance of using text mining and social media technologies in policy-making, an in-depth literature review on this area has yet to be conducted. In this paper, we develop a conceptual framework and review 55 articles related to the development of text mining applications for policy-making. The conceptual framework provides a concise illustration of the stages of policy-making involved in the applications, how applications support policy decision making and alleviate the bounded rationality of decision makers and who benefits from the applications.The literature review aims to facilitate knowledge accumulation concerning text mining applications for policy-making and serves as a guide for future research.

Keywords: Text Mining, e-Government, Policy Making, Literature Review, Conceptual Framework

1 INTRODUCTION

In recent years, a significant number of text mining applications have been developed for policy-making. Text mining applications for policy making have also become an emerging topic in a wide range of fields, including computer science, political science, public administration, as well as in various policy fields such as public health, homeland security, and financial regulations. This significant number is because both practitioners and scholars have realized that text mining applications can actually play an important role in policy making in number of aspects.

First, text mining applications help policy makers to process information and discover new knowledge at a low cost. These applications can replace the manual information processing and increase effectiveness and efficiency of the procedures. Aggarwal and Zhai (2012, p.2) reported that text mining involves "going beyond information access to further help users analyse and digest information and facilitate decision making" at a low cost. Based on the principle of adaptation, text mining applications save time in terms of data collection and information processing. Thus, decision makers can have more time to adapt to the actual problem environment and conduct better outcome estimations. For example, real-time text mining applications can detect earthquakes from texts on social media and issue early warning signals (Sakaki et al., 2013).

Second, text mining enhances policy deliberation among citizens, thereby expanding the democratic influence of citizens, because text-mining techniques enable policy makers to process tons of posts in the political forum or social media. In turn, citizens' voices can be heard by the policy makers. Several recent studies found that text mining applications can facilitate the collection of additional information for decision making through interaction with citizens on the Internet (Chun et al., 2010; Ahn and Bretschneider, 2011).

Finally, the incorporation of text mining applications into the policy making process alleviates the problem of bounded rationality, which is a long recognized problem for policy making (Simon, 1996) and is described as the underlying reason for incremental policy change (Lindblom, 1959; Wildavsky, 1984). Text mining applications can improve the rationality of policy makers during decision making and overall organisational capacity for processing information.

Given its importance, the present study aims to contribute to knowledge accumulation on text mining applications for policy-making by conducting a systematic literature review on this area. Since the emergence of the text mining applications as a research topic, the number of studies on the text mining application has grown exponentially. However, despite this growth, the trend and status of literature on text mining application remain unclear because researchers still encounter difficulties in distinguishing between studies on text mining applications for policy-making from those on other applications of text mining. A literature review is necessary to advance knowledge on text mining applications for policy making. Therefore, the objectives of this paper are as follows:

- To identify studies that investigate text mining applications for policy-making;
- To apply a conceptual framework as a taxonomy for summarising the identified studies;
- To provide research implications for researchers interested in investigate text mining applications for policy-making.

The rest of the paper will be organised as follows. Section 2 will briefly describe the research methodology of this literature review. In Section 3, the conceptual framework, which will be used to classify the identified research studies, will be introduced. Using the conceptual framework as the taxonomy, the identified studies will then be presented. In Section 4, conclusions will be drawn. Opportunities for future studies on text mining applications for policy-making will also be discussed

2 RESEARCH METHODOLOGY

The literature search will include journals published by various publishers, including Elsevier, Wiley, Sage, APSA, Emerald and Taylor and Francis. The literature search was based on the descriptors, "text mining" and "policy-making." The scope of this study is limited to the period from 1999 to 2015, as many scholars began exploring the potential of text mining in 1999 (Hearst, 1999). We also followed the structured approach for literature review recommended by Webster and Watson (2002). Articles citing or cited by relevant articles in the database were collected and reviewed to determine whether they were relevant to the review. Dissertations, textbooks, unpublished working papers and conference papers were excluded to ensure higher level of rigorousness. Journals have better representation of the most advanced studies in the eyes of academics and practitioners compared with other sources of academic knowledge (Nord and Nord, 1995). Although this extensive study represents a summary of modern text mining applications in policy making, the search for relevant journal articles was by no means exhaustive. The following sections describe a conceptual framework of applications of text mining in policy making, which will be used as the taxonomy for identified studies from the literature search.

3 DEVELOPMENT OF CONCEPTUAL FRAMEWORK

The framework offers a detailed structure that will enable the precise analysis of the usefulness of text mining applications to individual policy makers in policy decision making (Figure 1). The framework borrows the concepts of the policy making model in public administration. Although public policy has many approaches, the policy making model is a relatively common analytical tool in policy sciences (Zouridis and Thaens, 2003). From the perspective of individual decision making, discrete stages in the policy-making models assist in the identification of which decision makers benefit from the applications. Particularly, decision makers target goals with subtle differences throughout the policy making process. Discrete stages in the model contribute to the analysis of how decision makers use these applications to achieve their goals. Several versions of the policy making cycle have proposed (Dunn, 1994), but their differences are minor. Jann and Wegrich (2007) reported the policy making cycle to be divided conventionally into stages, namely, agenda setting, policy formulation and decision making, policy implementation and policy evaluation. Our framework adopts this convention.

The relevant articles were classified under the stages of the policy-making cycle. An article with overlapping categories is possible (e.g., Wandhöfer et al., 2012). For ambiguous articles that could not be classified under one category, a discussion between two independent researchers is arranged. A consensus among researchers is sought for a final decision. The differences between agenda setting and policy evaluation for classification are also worth mentioning. Policy evaluation compares policy outcomes with policy objectives. Popularity or public satisfaction is not normally the main objective of a policy program. Policy evaluation is focused more specifically towards a particular policy program, whereas agenda setting aims to discover previously unknown problems or issues in various policy areas. Applications for policy evaluation discover information related to a predefined criterion (i.e., objectives of policy programs), whereas applications for agenda setting provide decision makers with additional information that can aid them in deciding on whether particular policy areas require special attention.

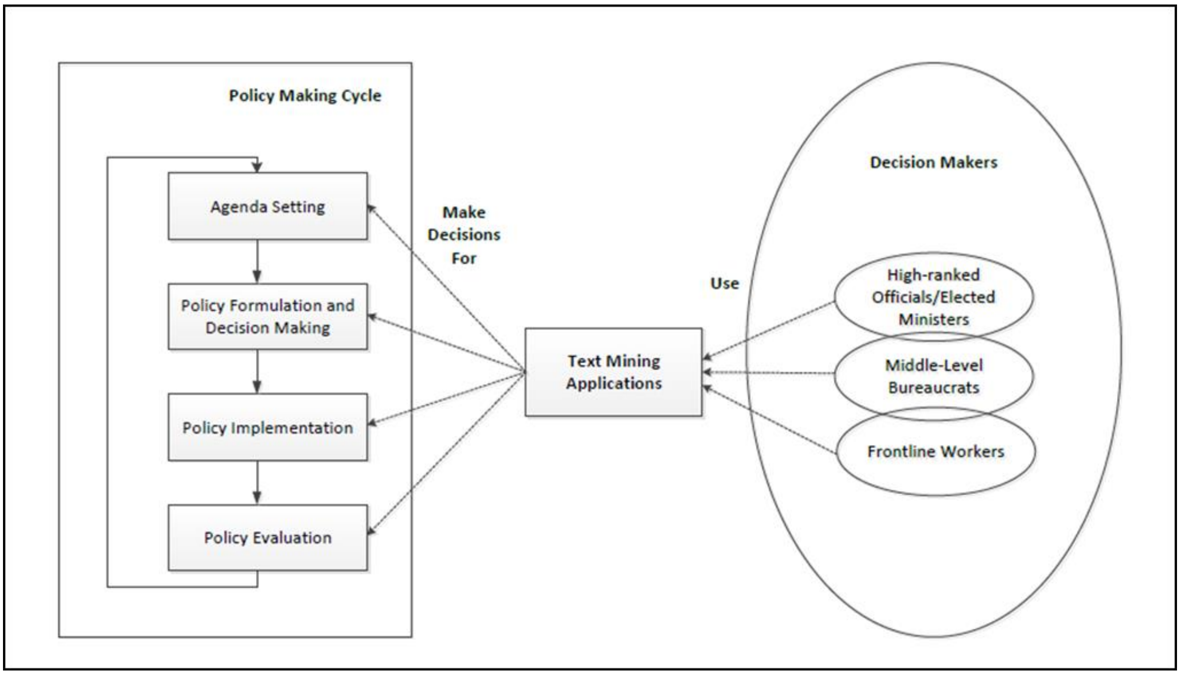

Figure 1. A Conceptual Framework of Applications of Text Mining in Policy Making

3.1 Stage 1: Agenda Setting

Agenda setting involves policy problem recognition, definition, and selection. Policy decision makers have to create a list of subjects and problems and pay serious attention in a given period of time because time and resources are limited. This list of subjects and problems is called the "policy agenda" (Kingdon, 1995). In liberal democracies, problem recognition and definition are largely conducted in the public, in the press, or in certain types of professional communities. However, the patterns of agenda setting vary with the composition of stakeholders and the role of the public (Jann and Kegrich, 2007). Knowing the attention and views of stakeholders and the public is conducive to policy decision making regardless of the variation. The high level of public attention and widespread media coverage are some of the main reasons why particular issues are included in the agenda (Kingdon, 1995). The definitions of an issue among the public, the press, or policy stakeholders are important. The definition of an issue or "policy image" shapes people's perception on whether the issue is a severe problem (Baumgartner and Jone 1993). Baumgartner and Jone (1993) proposed that issues that have been neglected for a long time are included in the agenda when their long-existing "policy image" changes.

Text-mining applications help policy makers gauge the attention and sentiment of policy stakeholders, including the public, the media, and interest groups. Information on the change of attention and sentiment is particularly important after natural disasters or events, which attract huge public attention and media coverage. Text-mining applications can also discover "policy images" in the eyes of various stakeholders. More than 10 years ago, Wormell (2000) indicated that text mining can help people track the evolution of a concept or an idea on academic publications, newspaper articles, and legislative documents. The author suggested that "issue tracking" through text mining can assist people to trace possible trends in the future or make forecasts.

3.2 Stage 2: Policy Formulation and Decision Making

Policy formulation refers to formulating details of policy programs for issues set in the agendas. Policy formulation aims to set the goals and priorities of the corresponding policy program with a well-defined problem or issue to list the available options to achieve these goals, to balance against costs and benefits of each option, and to find potential externalities, positives, or negatives associated with each option (Cochran and Malone, 1999, p. 46). However, the policy to be formulated is not necessarily what most people prefer. People vote candidates for a bundle of policy commitments that cannot be disentangled (Leib, 2004). A politician winning the election does not imply that a particular policy he proposed in the election is popular. A formulated policy may still fall short of public expectation even if government officials consult interest groups or legislative representatives of corresponding sectors. Wildavsky (1979, p. 252) succinctly pointed out that "whether interests groups close the gap between citizens and government depends on whether such groups speak for their own members rather than their bureaucrats, whether those who need representation get it, and whether the balance of power among all these contenders improves or worsens defects in the entire system." The system fails and policies deviate from public opinion when the interest groups or similar bodies cannot close the gap. The problem of "democratic deficit" occurs.

Many researchers have demonstrated the usefulness of text mining for policy formulation. Evangelopoulos and Visinescu (2012) used concept extraction techniques for the efficient interpretation of citizen feedback. They further summarized the voice of the people from the interpreted feedback. One case they presented is the extraction of articulated factors that represent the citizens' main suggestions with regard to the SAVE 2010 award for an efficient government. The technique helped policy makers obtain an efficient interpretation of citizen feedback. Kugo et al. (2005) clustered public comments on the proposed policy of high-level radioactive waste disposal. Correspondingly, the text-mining application helped policy makers analyze the public understanding of the policy and address their concerns before the legislation. Lourenço and Costa (2007) proposed a new model for e-participation. Consequently, local citizens were encouraged to contribute their views to the development of local policies. The authors utilized automatic text classification to identify related text and facilitate the collaborative writing process among citizens.

3.3 Stage 3: Policy Implementation

The present framework focuses on how text-mining applications are used as tools to help decision makers successfully complete their work of implementing policies. According to Jann and Kegrich (2007), an ideal policy implementation comprises three core elements (i.e., program detail specification, resource allocation, and decision-maker assignment). This study focuses on the element of resource allocation wherein decision makers receive text-mining tools as resources for their work. The text-mining applications perform particularly well in the field of homeland security, emergency management, and financial regulation. The decision makers in this stage of the policy-making cycle are usually frontline workers. Frontline workers are normally composed of policemen, crime investigators, health officers (e.g., doctors and nurses), and social workers.

3.3.1 Homeland Security

Text-mining applications employ several methods of facilitating crime investigation processes. First, police officers use text-mining applications to easily retrieve information from a textual database. This procedure reduces the cost of information for decision making. Accordingly, Chau et al. (2002) developed a text-mining system to extract entities (e.g., names, addresses, vehicles, narcotic drug, and personal property) from unstructured free-text police narrative reports. The information derived from these entities is useful for crime investigation.

3.3.2 Emergency Management

Many researchers have demonstrated the usefulness of text mining to detect and prevent emergencies. Torii et al. (2011) employed machine learning classifiers to investigate the computerized detection of online articles related to disease outbreaks. They proposed that the Naïve Bayes and support vector machine classifiers can together yield the optimal classification result on a large range of articles. Moreover, they demonstrated that irrelevant articles for disease spread detection need not be labeled, thus substantially reducing the time cost for manual labeling.

3.3.3 Financial Regulation

Text-mining applications process a large number of documents for the early detection of financial fraud and bankruptcy. Gupta and Gill (2012) argued that rosy language may camouflage indicators and present a fake perception to auditors. They proposed that text-mining techniques can be applied to texts in financial statements for the detection of potential financial statement frauds. Glancy and Yadav (2011) developed a fraud detection system for the automatic identification of management's discussion and analysis (MD&A) part with fraudulent content.

3.4 Stage 4: Policy Evaluation

Policy evaluation refers to the process of verifying whether a policy program meets the intended objectives. During an evaluation, policy makers compare the means and ends. Accordingly, technocrats may be more interested in numerical figures after the program is implemented. Elected ministers may also focus more attention on the satisfaction of voters and policy stakeholders. Thus, policy programs may not necessarily lead to the intended results and consequences.

Text mining applications are useful for the qualitative evaluation of policy effects. Stylios et al. (2010) applied opinion mining on user-generated posts on e-government issues to determine the views of the public on government decisions. They also predicted that the extent of the public views being discovered will affect future relevant decisions based on the results of the evaluation. These applications will aid decision makers in verifying whether the implemented policy programs meet the intended objectives. In most cases, these decision makers were middle-level bureaucrats. High-ranking officials/elected ministers may also use application-generated information when they want to revise the policy objectives. The applications reduce the costs for decision makers who seek additional information on public views and sentiment on existing policies.

Table 1 lists all the identified studies concerning text-mining applications for policy making from the literature.

Stage of Policy Making Cycle	References	Number of References
Agenda Setting	Wormell (2000); Lim (2002); Kugo et al. (2005); Thelwall et al. (2006); Grimmer (2009); Quinn et al. (2010); Suh et al. (2010); Park et al. (2011); Altaweel & Bone (2012); Fortuny et al. (2012); Schonhardt-bailey et al. (2012); Sobkowicz et al. (2012); Talamini et al. (2012); Talamini & Dewes (2012); Talamini et al. (2013); Wandhöfer et al. (2012); Young & Soroka (2012); Zirn & Stuckenschmidt (2013)	18
Policy Formulation and Decision Making	Lourenço and Costa (2007); Malouf & Mullen (2008); Scharl & Weichselbraun (2010); Velásquez & González (2010); Charalabidis & Loukis (2012); Evangelopoulos & Visinescu (2012); Kokkinakos et al. (2012); Walker et al. (2012); Wandhöfer et al. (2012); Gal-Tzur et al. (2014)	10
Policy Implementation	Homeland Security: Chau et al. (2002); Abbasi & Chen (2005); Iriberri et al. (2007); Elovici et al. (2010); L'Huillier et al. (2010); Al-Zaidy et al. (2012); Khalid et al. (2012); Tseng et al. (2012); Alruily et al. (2013); Rohn & Erez (2013) Emergency Management: Mykhalovskiy & Weir (2006); Herman Tolentino et al. (2007); Brownstein et al. (2008); Collier et al. (2008); Polgreen et al. (2008); Ginsburg et al. (2009); Hulth et al. (2009); Corley et al. (2010); Torii et al. (2011); Lee et al. (2012); Purohit et al. (2013); Sakaki et al. (2013); Van de Brug et al. (2014) Financial Regulation: Cecchini et al. (2010); Glancy & Yadav (2011); Gupta & Gill (2012); Lu et al. (2013)	25
Policy Evaluation	Stylios et al. (2010)	1

Table 1. Studies Concerning Text-mining Applications for Policy Making Identified

4 DISCUSSION AND CONCLUDING REMARKS

We surveyed the literature on text mining and policy-making and discovered an unbalanced development of text mining applications among the four stages of the policy-making cycle. Research initiatives on text mining applications clearly demonstrated path dependency. Researchers flock to topics that have emerged earlier. Zouridis and Thaens (2003) reported that e-government initiatives were mostly concerned with policy implementation, and a few initiatives focused on problem recognition and agenda setting. They did not mention any initiatives for policy formulation and decision making, as well as policy evaluation. Correspondingly, our findings indicated that text mining applications developed for policy implementation and agenda setting emerged significantly earlier than applications for policy formulation as well as decision making and policy evaluation. Most of the text mining applications were developed for policy implementation. Significantly more applications were developed for agenda setting compared with applications for policy formulation and decision making and policy evaluation.

The framework presented in this article can assist researchers in exploring the potential usefulness of text mining technology more objectively over the entire policy-making process. Researchers should investigate the procedures of decision makers at each discrete stage of policy-making, and subsequently explore how text mining applications can improve the decision-making involved in these procedures. The framework could assist researchers in thinking creatively away from prior studies, and thereby reduce the significance of path dependency. The framework also lessens subjectivity, enabling researchers to avoid blindly associating a technology with any policy-making process by intuition. Hence, a more balanced development of text mining applications among the four stages of the policy-making cycle can be achieved. Moreover, the framework is applicable not only to text mining, but also to other technologies that will emerge in future. The approach can be used to analyze the usefulness of mobile technologies or any other technologies in the future.

Focus should also be given to the dark side of the extensive use of text mining applications by the government.The automation of procedures has simply shifted this type of bounded rationality from the decision makers of original procedures to system designers, programmers, or people who can affect the decisions of the two previous groups. Therefore, extensive use of text mining applications or even e-government in general may cause a shift in the use of discretion for these people. Will these people manipulate the eventual policy outcomes if they possess discretion? If yes, how can we prevent them from doing so? A more cynical question would be whether governments will exceedingly collect user-generated data from social media and control the state. In other words, will governments become "big brothers"? We also need to ask ourselves how we should value the benefits of text mining applications versus preserving the privacy of citizens. Researchers have these conundrums to explore further in the future.

Despite the aforementioned contribution, this study has several limitations. First, this study includes only articles written in English, and therefore has a biased emphasis on journals in English. Second, the findings were based solely on academic research. The advancement and development direction of research in academia and the industry differ, but text mining applications developed in the industry for e-government are not presented in this study. Third, conference proceedings were excluded for quality control. However, we admit that high-quality conference proceedings exist, particularly in computer science. Although this extensive study can serve as a representative summary of modern text mining applications in policy-making, the search for relevant journal articles was by no means exhaustive. Relevant articles may also not have used the terms "text mining" and "policy-making," explicitly and they may not be cited by articles using these two terms. These articles could have inevitably been overlooked in this study.

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