BIG SOCIAL DATA ANALYTICS:

A MODEL FOR THE PUBLIC SECTOR

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Big Social Data Analytics:

A Model for the Public Sector

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Abstract

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Big Social Data Analytics: A Model for the Public Sector

Keywords: Big Social Data, Public Sector, Social Network Theory, Social Network Analysis, Content Analysis, Sentiment Analysis, Local Government.

The influence of Information and Communication Technologies (ICTs) particularly internet technology has had a fundamental impact on the way government is administered, provides services and interacts with citizens. Currently, the use of social media is no longer limited to informal environments but is an increasingly important medium of communication between citizens and governments. The extensive and increasing use of social media will continue to generate huge amounts of user-generated content known as Big Social Data (BSD). The growing body of BSD presents innumerable opportunities as well as challenges for local government planning, management and delivery of public services to citizens. However, the governments have not yet utilised the potential of BSD for better understanding the public and gaining new insights from this new way of interactions. Some of the reasons are lacking in the mechanism and guidance to analyse this new format of data. Thus, the aim of this study is to evaluate how the body of BSD can be mined, analysed and applied in the context of local government in the UK. The objective is to develop a Big Social Data Analytics (BSDA) model that can be applied in the case of local government. Data generated from social media over a year were collected, collated and analysed using a range of social media analytics and network analysis tools and techniques. The final BSDA model was applied to a local council case to evaluate its impact in real practice. This study allows to better understand the methods of analysing the BSD in the public sector and extend the literature related to e-government, social media, and social network theory.

Declaration

I hereby declare that this thesis has been genuinely carried out by myself and has not been used in any previous application for a degree. Any valuable participation of others in this thesis has been acknowledged where appropriate.

Mohamed Ali Bin Saip

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Workshop

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List of Abbreviations

API	Application Programming Interface
BSD	Big Social Data
BSDA	Big Social Data Analytics
CAP	Crime and Punishment
DOI	Diffusion of Innovations
DS	Decision Strump
FA	Factor Analysis
ICTs	Information and Communication Technologies
IS	Information Systems
IT	Information Technology
KNIME	Konstanz Information Miner
LDA	Latent Dirichlet Allocation
LG	Local Government
MDS	Multidimensional Scaling
Naïve	Naïve Bayes
NHS	National Health Services
NRCC	National Research Council Canada
NT	Network Theory
SH	Structural Holes
SLR	Systematic Literature Review
SM	Social Media
SMA	Social Media Analytics
SNA	Social Network Analysis
SNT	Social Network Theory
SWT	Strength of Weak Ties
TAM	Technology Acceptance Model
TATS	The Adventures of Tom Sawyer
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UK	United Kingdom
UTAUT	Unified Theory of Acceptance and Use of Technology
VFI	Voting Features Intervals

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CHAPTER 1: INTRODUCTION

1.1 Background

Over the last decade, the use of Information and Communication Technologies (ICTs) in government administration around the globe is getting established. The ICTs is no longer limited to just transforming government administrative duties but has become an increasingly important medium for government to deliver public services and interact with citizens. Many government agencies such as Public Health Services, Department for Transport, and Local Government (LG) are utilising the ICTs to support communication between government and citizens.

In recent years, electronic government (e-government) utilises various social media platforms to enable the government-citizen interactions for better engagement with the public. Social media is an internet-based application that facilitates interaction among internet users in exchanging respective content (Kaplan and Haenlein 2010; Kavanaugh et al. 2012) without barriers of time, place and bureaucracy. A direct, two-way and unfiltered communications between government and citizens through social media promote better transparency and increase citizens engagement in the government decision-making processes (Haro-de-Rosario et al. 2018; Bertot, Jaeger and Hansen 2012).

The main social media platforms used in e-government are Facebook, Twitter and YouTube (Gao and Lee 2017; Ellison and Hardey 2014). Twitter is the most widely used in the United Kingdom (UK), whereby 89 per cent of its LGs are actively adopting the platform as compared to Facebook of 68 per cent (Ellison and Hardey 2014). As of July 2018, on the average, Facebook has more than two billion daily active users (Statista 2018) whilst everyday internet users around the globe post 500 million tweets on Twitter, upload 50 million photos on Instagram and view 4 billion videos on YouTube (InternetliveStats 2018). These statistics are increasing over the years which indicate the importance of digital interaction.

The extensive and increasing use of social media will continue to generate huge amounts of user-generated content known as big social data (BSD) (Chun et al. 2012; Stieglitz, Mirbabaie, et al. 2018). The BSD refers to large volumes of data related to social interaction including texts, links to webpages, images and videos in structured and unstructured format (Olshannikova et al. 2017; Mukkamala et al. 2014b). This study defines BSD as a collection of user-generated data comprises of comments, feedback and suggestions from the government-citizen interactions through various social media platforms.

Recently, it is extremely interesting to see that the use of social media has been encouraging in e-government. This is evidenced in the government websites where links to several social media platforms such as Facebook, Twitter and YouTube are commonly included in their main page. Social media technology has the ability to create efficient engagement tools in two-way communication between government and citizens (Ong 2014). Increased demand from the community to interact with government through social media has encouraged the implementation of the technology by a number of public sectors including LG. In addition, the adoption of technology is due to its enormous potential benefits (Sharif et al. 2015).

Governments that adopted social media have enormous amounts of BSD which contain valuable insights to enhance their understanding of citizens' need and expectations. Thus, it is critical for a government to analyse the BSD in order to improve its public services. Currently, there are a few guidance in the literature on how to analyse the BSD. Appropriate analytics techniques of analysing BSD can transform information into insights and actions. Having such insights, government decision-makers may improve their decisions pertaining to planning, managing and policy-making (Henninger 2013; Cecilia Fredriksson et al. 2017). Moreover, the adoption of information and analytics approaches offers great values to organisations specifically the LGs (Lavalle et al. 2011).

Thus, this study aims to explore the potential use of BSD in a LG and propose a Big Social Data Analytics (BSDA) model to guide the government in analysing the data generated from social media interaction between citizens and governments particularly in the United Kingdom (UK). The study focuses on developing and validating an applied model using only data from Twitter in the context of LG.

The following section explains in detail about the research problem. The remaining of this chapter will be organised as follows. Section 1.2 discusses the problem statement, section 1.3 highlights the rationale of this study, section 1.4 explains the research objectives, section 1.5 underlines the research questions, and section 1.6 describes the organisation of this thesis.

1.2 Research Problem

Evidence in the literature shows that ICTs have drastically influenced the way government administers its public services which have not only impacted on the method of delivering, but also on the citizen's engagement with the government (Sivarajah et al. 2015; Ellison and Hardey 2014; Bryer 2013). The internet technology in particular social media has transformed the means of interaction between a government and its citizens. Advocates point out that the use of social media in the public sphere can encourage citizen engagement, improve interaction, increase integrity and trust of public agencies, and contribute towards a more democratic and transparent government (Guillamón et al. 2016; Bertot, Jaeger, Grimes, et al. 2012; Bonsón et al. 2012; Picazo-Vela et al. 2012; Haro-de-Rosario et al. 2018).

Furthermore, a number of studies have asserted that citizen engagement and confidence in government social media channel can be enhanced through proper management by the respective public agencies in terms of the level of online transparency, types of social media activities and offered interactivity (Bertot, Jaeger, Grimes, et al. 2012; Bonsón et al. 2012). For example, social media such as Facebook has been used in LG to promote public agencies where the local authority launched a marketing campaign using a wide range of communication channel including social media to educate citizens on their recycling behaviours (Reddick et al. 2017).

However, despite the positive indicators of the high rate of government adoption of social media, researchers highlight that governments are not yet utilising the social media technology towards achieving a better understanding of their citizens. At the moment, most governments use social media as a channel to disseminate information in one way communication without trying to understand the citizen's needs and expectations (Haro-de-Rosario et al. 2018; Reddick et al. 2017).

Recent studies suggested that decision-making team in the government can be better informed about the citizen need and expectation by utilising the enormous volumes of existing data including BSD using various data analytics techniques and methods (Liu et al. 2018; Chang et al. 2014; Philip Chen and Zhang 2014). In the meantime, e-government researchers work collaboratively with data scientist in exploring the innovative methods to process BSD in order to support the decision-making teams (Liu et al. 2018).

The growing number of governments that adopt social media towards citizen-centric governance indicate that there is a critical need for more implementation of smart tools and techniques to mine and analyse the BSD. This is important in utilizing new insights concerning publics' behaviour, feelings, and interaction in the social media network (Olshannikova et al. 2017). However, the mechanism of analysing BSD in a LG context is still lacking (Lee 2017; Shahsavarani 2014; Chun et al. 2012). Therefore, this research intends to fill this gap by developing a BSD analytics model as a recommendation for LG decision-makers in analysing their BSD. Although the research focuses on one particular LG, the findings can be generalised to other public sectors with similar circumstances.

1.3 Rationale for Study

The rapid growth of internet users in the last few decades offers enormous opportunities and challenges to the private and public sectors. Based on the Internet World Stats recorded until 30 June 2018, the total number of Internet users has reached 4,208,571,287 (WorldStats 2018). The same web site reports that social media is one of the preferred internet applications by internet users. For instance, Facebook received more than 2.1 billion subscribers in 2017 (WorldStats 2018). This statistical data signifies that internet technology particularly social media is an important platform for the digital community to interact and share information.

The extensive and increasing use of social media will continue to generate enormous amounts of user-generated content called BSD. The user-generated contents are publicly accessible, comprise of creative works and creations without commercial market purposes (Vickery and Wunsch-Vincent 2007). The BSD is a subset of big data which includes structured and unstructured data in large volumes.

Big data plays important role in the fourth industrial revolution (Industry 4.0). The Gartner's hype cycle analysis in advanced analytics and data science predicted that big data research will remain relevant at least for another five years (Linden 2015). In the current Gartner's report, text analytics technology is positioned at the fourth phase which indicates that the technology has achieved a matured level and intense benefits are clearly understood by the enterprise (Krensky and Hare 2017; Jackie et al. 2017). Researchers also urged that study on big data applications in the public sector is insufficient and future research should concentrate on this topic (Cecilia Fredriksson et al. 2017).

Government agencies that have implemented e-government employed social media as a medium of communication to interact with citizens particularly in the local levels (Bonsón et al. 2012; Haro-de-Rosario et al. 2018). The extensive government-citizen interaction through social media offers publicly available BSD that can be analysed to gain new insights into understanding citizens. At the time of conducting this study, LG had not fully engaged in utilising BSD. This is evidenced by the dearth of literature on BSD in LG (Liu et al. 2018; Lee 2017). Thus, it is important to explore various analytical methods of utilising BSD to guide the public authorities in processing this available data.

1.4 Research Objectives

The aim of this study is to evaluate how the body of BSD can be mined, analysed and applied in the context of local government in the United Kingdom. The specific objectives are as follows:

OB1 Identifying the current and potential use of BSD in local government.

- **OB1a** Conduct a comprehensive study of literature on social media and government to highlight the current and potential use of BSD in local government planning, management and future policy-making.
- **OB1b** Conduct interviews with internal stakeholders of the local government.

OB2 Filling the knowledge gap on the model to provide guidance for decision-makers using BSD in the public sector, especially in local government in the United Kingdom, by:

- **OB2a** Exploring the tools and techniques that can be used to analyse BSD in local government.

OB2b Developing an integrated model based on OB2a in providing guidance to decision-makers to facilitate in local government in planning, managing and delivering of services to citizens.

OB2c Empirically testing the integrated model to measure the impact on planning, managing and delivering services in the context of local government.

OB2d Verifying the integrated model with experts from the local government.

1.5 Research Questions

In order to fill up the research gap, the following research questions are proposed:

RQ1 How can the local government decision-makers use BSD for planning, managing and delivering services to citizens?

RQ2 What are the BSD tools and techniques that can be used in the context of local government?

RQ2a How can the identified tools and techniques be applied towards better understanding of the social network users engaging with local government?

RQ2b How can the identified tools and techniques be used by decision-makers in the local government?

RQ2c How can the roles of social network users engaging with local government be identified?

RQ3 How does the social network theory (SNT) been applied in the BSDA model in the context of the public sector?

1.6 Measures of Success

The success of the research presented in this study is measured in terms of the following criteria:

- Firstly, the research questions and sub questions listed in section 1.5 must be answered.
- Secondly, an investigation illustrating whether the proposed BSDA model can be implemented in the real world, and thus be used commercially.
- Finally, the findings from the validation process has to be verified by the experts from LG.

1.7 Thesis Structure

This thesis presents a research project that explores the potential use of BSD in LG and proposes a BSDA model to guide the government in analysing the data generated from social media interaction between citizens and governments particularly in the United Kingdom (UK).

The structure of this thesis is organised as shown in Figure 1.1. Chapter One provides the introduction and background of the thesis including problem statement, rationale for conducting the study, research objectives, research questions, and thesis structure. Chapter Two reviews the previous studies related to e-government, social media, BSD, and BSDA. Chapter Three explains the underpinning theories of this study including social network theory and theories related to it. The online social media network structure is also discussed, and the metrics and measurement used in this study are described. The chapter also explains the implication of online social media network structure. Chapter Four provides a detailed discussion of the research methodology. The chapter begins with a discussion on the research design process followed with the explanation and justification for all decisions taken in each phase of the research process. Next, are the descriptions on the data sources used in this study, choice of mixed methods, and data collection techniques. Chapter Five describes the case study of the selected LG in the UK. The qualitative data from the interviews were analysed using thematic analysis and the findings were presented in this chapter. Chapter Six explains the development of the conceptual model based on the literature review and case study. Chapter Seven explains the operationalisation of the model using empirical data. The chapter also discusses the development and implementation of tools related to content and network analyses techniques. Next, the elaboration on the feedback from the expert's review and presentation of the revised version of the model. Chapter Eight outlines the reflection on the research questions and discusses the theoretical and practical contributions followed by limitation and possible areas for future research.

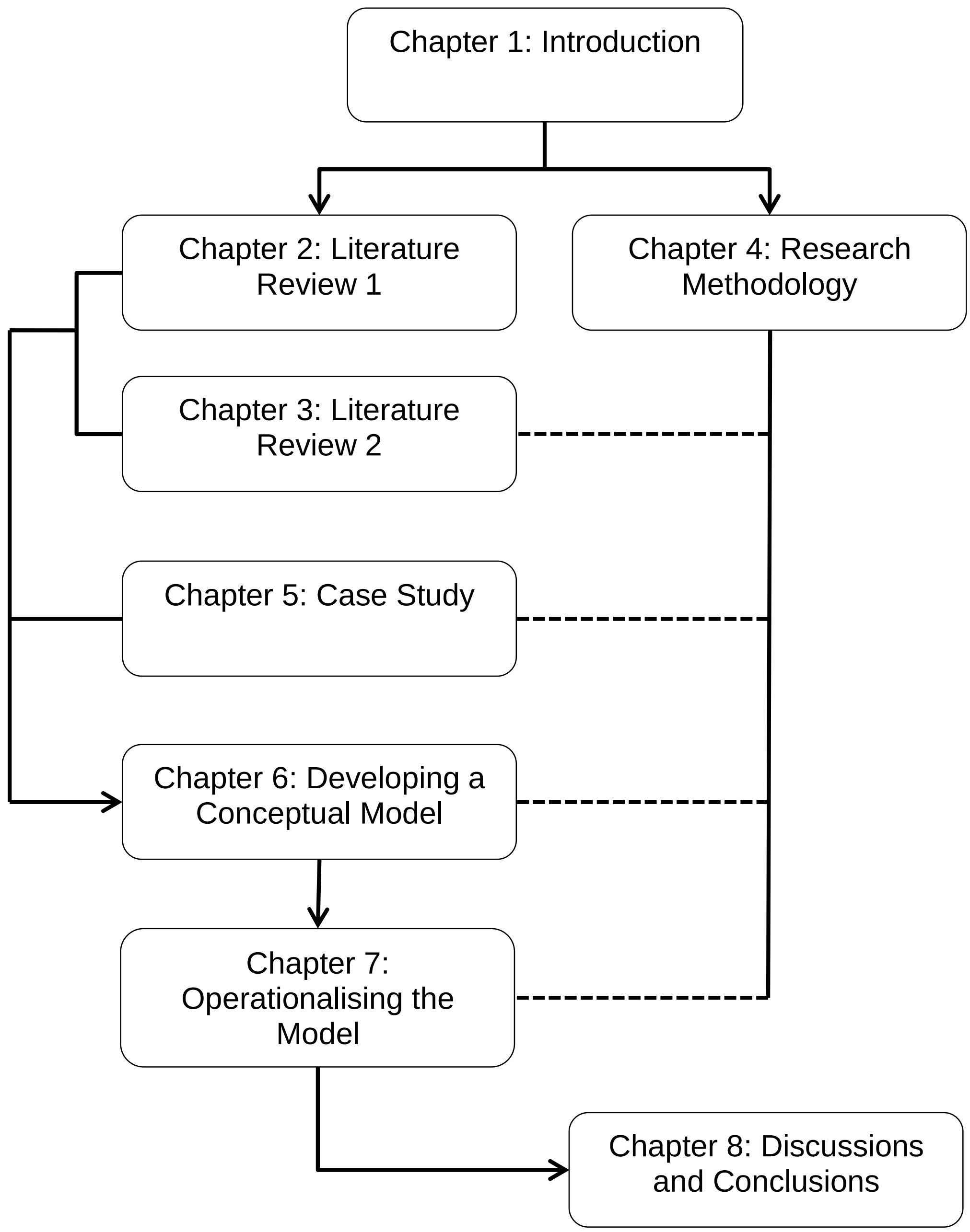

Figure 1.1: Thesis Organisation

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CHAPTER 2: LITERATURE REVIEW I (ELECTRONIC GOVERNMENT)

2.1 Introduction

This chapter presents an overview of e-government research and development. The section begins by introducing the general concept and evolvement of e-government, its definition, and benefits of adopting the concept from the administrative and political perspectives. The second section discusses the research trends in e-government followed by the explanation on the current research topics. Finally, the topic of BSDA is discussed to clarify the term and determine the potential use in the public sectors.

2.2 Electronic Government

An exciting concept of electronic government (e-government) was introduced in the late 1990s to utilise ICTs in public services (Heeks and Bailur 2007). At the earlier stage of the e-government implementation, the aims were to increase efficiency and effectiveness of delivering government information and services to citizens (Ronaghan 2002; Jaeger 2003; Carter and Belanger 2005) by reducing the documentation processing cost (Montagna 2005), increasing business processes efficiency and procurement processes effectiveness (Moon 2002).

After two decades of implementation, e-government is no longer limited to only delivering government information but also becoming an important channel of communication between government and citizens. Thus, the current e-government infrastructures have to facilitate engagement and participation activities in order to involve citizens in the government's decision-making processes (UNPAN 2014).

Traditionally, there is no consensus definition of e-government among researchers or practitioners (Halchin 2004; Yildiz 2007; Al-Sobhi et al. 2010). Hence, the researchers have offered different definitions depending on the study interests and perspectives (Al-Sobhi et al. 2010). In general, e-government is defined as "*the use of information and communications technologies (ICTs), and particularly the Internet, as a tool to achieve better government*" (OECD 2003, p.3). This definition views e-government as a platform that has the potential to improve the quality of public services through internet technology including web site applications and social media.

Throughout this thesis, the term e-government is used to refer to government effort in utilising information technologies applications to transform the public administration for providing better public services delivery, improving government-citizen interactions through multiple channels of communications, and promoting citizens' engagement in the government decision-making processes. A detailed discussion of the e-government evolvement and benefits is explained in Appendix A.

2.2.1 Research on e-government

After two decades of e-government implementation globally, there is an increasing number of studies and reviews being published in related academic journals which indicates that it is growing towards maturity. This growing body of literature recognises the importance of the e-government concept and this is attracting researchers from different disciplines to engage in exploring new strategies, theories, techniques, methods and applications to advance the field of e-government research (Lean et al. 2009).

The e-government research area is wide and multidiscipline which invites diverse research projects within the field to explore different perspectives of government including management, operation, planning, citizen interaction, trust, and policy-making. In order to understand the current trend of e-government research, a preliminary study was conducted using Bibliometrics and Social Network Analysis (SNA) methods. Bibliometrics was used to examine scholarly publication while SNA was utilised to analyse prominent articles and authors in the research area. The study extracted articles related to e-government research from the Scopus database spanning from 2000 to 2013. The findings were then categorised into three clusters, namely: (1) e-government development model, (2) adoption and acceptance of e-government, and (3) e-government using social media. A detailed description of the study is explained in Appendix B.

2.2.2 E-government using Social Media

The explosion of social media led the e-government research to focus on the use of this technology in the public sectors. Although the research activities on e-government and social media are in the early stage, researchers in this discipline have explored many issues related to transparency, corruption, citizen interaction and engagement, collaboration, and e-participation.

Previous studies have reported that adoption of social media in government has the ability to create transparency culture and reduce corruption in the public administration (Bertot et al. 2010; Jaeger and Bertot 2010). This is important as a transparent government can promote citizen engagement and increase e-participation with government activities through social media (Bonsón et al. 2012; Haro-de-Rosario et al. 2018). Moreover, studies found that there is a positive relationship between social media use and citizen engagement (Skoric et al. 2016). This indicates that government services have to consider the adoption of social media in promoting public participation in the decision-making process.

Furthermore, social media technology creates new atmospheres for government and citizen interaction in various democratic meanings. Scholars argue that a citizen-government interaction through social media has great potentials to enhance collaboration and improve communication in the LG level in order to promote transparency and offer better services (Picazo-Vela et al. 2012; Bertot, Jaeger and Hansen 2012; Sandoval-Almazan and Gil-Garcia 2012; Norris and Reddick 2013). The distributed nature of this culture, and their capacity of anti-corruption, meant that social media could be used for promoting citizen engagement and participation about government activities (Bonsón et al. 2012; Haro-de-Rosario et al. 2018), for collaboration and to generally perform communication functions (Picazo-Vela et al. 2012; Bertot, Jaeger and Hansen 2012; Sandoval-Almazan and Gil-Garcia 2012; Norris and Reddick 2013).

The wide use of social media in government services has increased opportunities for e-democracy including citizen engagement and collaboration in the government decision-making process (Liu et al. 2018). These activities can advance democratisation and trust of citizens in government (Kuzma 2010). Additionally, citizen engagement through social media can be recorded for future references and analysis to explore new insights. The advantages of e-government using social media are summarised in Table 2.1.

Table 2.1: Advantages of e-government using social media

Advantages	**Authors**
Increase transparency and anti-corruption	(Bertot et al. 2010) (Jaeger and Bertot 2010) (Picazo-Vela et al. 2012) (Bertot, Jaeger and Hansen 2012) (Sandoval-Almazan and Gil-Garcia 2012) (Norris and Reddick 2013) (Kapoor et al. 2018)
Promote citizen participation and engagement	(Chu et al. 2008) (Bertot et al. 2010) (Bonsón et al. 2012) (Picazo-Vela et al. 2012)

	(Warren et al. 2014) (Shahsavarani 2014) (Ong 2014) (Bonsón et al. 2015) (Skoric et al. 2016) (Haro-de-Rosario et al. 2018) (Kapoor et al. 2018)
Create democratic environment	(Kuzma 2010) (Liu et al. 2018)
Facilitate co-production of materials between governments and citizen	(Bertot et al. 2010) (Picazo-Vela et al. 2012)
Encourage collaboration, crowdsourcing solutions and innovations	(Bertot et al. 2010) (Shahsavarani 2014)
Increase citizen satisfaction	(Carter and Belanger 2005) (Kamal et al. 2009) (Teo et al. 2009) (Alawneh et al. 2013)
Advance government information dissemination and government-citizen communication	(Carter and Belanger 2005) (Kamal et al. 2009) (Teo et al. 2009) (Paris and Wan 2011) (Picazo-Vela et al. 2012) (Hofmann et al. 2013) (Alawneh et al. 2013) (Shahsavarani 2014) (Meijer and Torenvlied 2014) (Ellison and Hardey 2014) (Williams et al. 2015)
Better public services	(Picazo-Vela et al. 2012) (Bertot, Jaeger and Hansen 2012) (Sandoval-Almazan and Gil-Garcia 2012) (Norris and Reddick 2013)

Other than the advantages of using social media for e-government, the most important challenge is how the governments, especially at the local level, are utilising data generated from government-citizen interactions through social media or known as BSD. In the private sector, BSDA is well established to collect and analyse consumers' feedback for marketing and other purposes (Lee 2017; Holsapple et al. 2018) whilst the use of BSDA in public sectors are still in a new phase. Accordingly, the BSDA is essential to assist governments in analysing the social media data in order to have a better understanding of citizens and gain new insights in improving public services. The following section discusses this issue.

2.3 Big Social Data

Researchers define social media in many ways depending on their research interest. For example, Kaplan and Haenlein (2010, p.61) defined social media as:

> *"A group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and allow the creation and exchange of user-generated content''.*

This definition highlights that social media does facilitate interaction among participants in a social network in expressing their opinions, feelings and point of views, and enabling information sharing process in an online community. In the context of the public sector, social media can be seen as a tool to promote public engagement with government and enhance citizen participation in the public agencies decision-making process for better public services (Criado et al. 2013; Reddick et al. 2017).

Recently, scholars listed three basic characteristics of social media applications include facilitating human network communications, allowing two-way interaction, and enabling multiple types of content and interaction formats (Landsbergen 2010). On the one hand, Davies and Mintz (2009) classified social media applications into four groups according to the characteristics as listed below:

- User-generated social content: A set of web applications that allow users to submit content that others can access.
- Social networking such as Facebook and Myspace that allows users to interact and share information.
- Collaboration: Users become involved in conversations, co-creation of content, collaborative filtering, and collective action.
- Cross-platform data sharing: Sharing content by transferring data across sites.

In contrast, Ishikawa (2015) categorised the social media applications according to the service contents including blogging, micro-blogging, social network service, sharing service, video communication, social search, social news, social gaming, crowdsourcing and collaboration. Even though the debate on the categorisation of the social media applications still continue, the most important point is the creation of enormous amount of user-generated data called BSD which has the potential to gain new insights to the public or private organisations. Researches showed that the decision-making process can be improved with supporting information from a large volume of structured or unstructured data analysing using big data analytical techniques (Delibašić et al. 2015; Elgendy and Elragal 2016; Albeshri and Thayananthan 2018).

Over the past few years, there has been considerable attention on big data from both the academia and practitioners. This attention is driven by the fact that data are generated continuously in enormous volumes from autonomous sources with a variety of formats. This type of data is known as big data (Cecilia Fredriksson et al. 2017; Ishikawa 2015; Kitchin 2013). Scholars argued that big data varies from normal data with three characteristics of the 3Vs (volume, variety, and velocity) (Ishikawa 2015; Kitchin and Lauriault 2015). The big data involves extraordinary volumes, variety in formats which expanded into semi-structured and unstructured data. In addition, the velocity or speed of data, which are generated is extremely high in or near real-time. These features are extended with another 'V' called veracity which means vary in credibility and reliability of data sources (Abbasi et al. 2016). While many others added big data features with more 'V's, scholars agreed that the huge amount of data represented is the basic constructions to be considered (Cecilia Fredriksson et al. 2017; Akter and Wamba 2016; White 2012; Wu et al. 2014). Additionally, Bertot et al. (2014) argued that big data could come from the accumulation of small data sets which have been developed and manipulated to become big data sets.

Accordingly, BSD, highly user-generated content, are generally a subset of big data with similar characteristics (Ishikawa 2015; Olshannikova et al. 2017). Bello-Orgaz et al. (2016) referred to BSD as a blended of social media and big data due to the social media data that originated from many sources with high volume and multiple formats. For example, BSD has been proved in 2012, when Twitter reported that more than 10 million tweets generated within two hours during a debate between President Barack Obama and Governor Mitt Romney (Twitter Blog 2012). The BSD has the potential to be mined, collected, collated and analysed to extract actionable patterns for a better understanding of the interactions content among different entities such as individual users, groups or organisations (Tundjungsari 2013). In term of data collection, BSD offers better techniques with less cost, saves time and spreads to wider geographical areas compared to the traditional survey method (Bright et al. 2015).

Researchers classified BSD into three categories namely digital self-representation, technology-mediated communication, and digital relationships data (Olshannikova et al. 2017). The first category relates to the profiles data of users, which describe the user background and identity depiction such as name, address, country, education and birthday. The second category represents the types of data generated from the user interaction through two-way communication in order to share an idea, thought and feeling which created collaborative knowledge in a digital environment. Finally, the third category of data reveals the relationships patterns explicitly such as followers' relationships or implicit ties including retweets relationships. These categories of data can bring large value to the organisations when the appropriate analysis is executed.

Research topics related to BSD have become entrenched and involved an important set of questions in the research community (Halavais 2015). Straton et al. (2017) examined a BSD generated from user engagement in the healthcare services. They applied both supervised and unsupervised learning techniques to determine appropriate contents and the strategic time to post in social media in order to utilise users' engagement and promote preventive healthcare. Jussila et al. (2017) investigated the BSD research community to identify the prominent authors in this field and research topics that have been discovered to enhance the knowledge and potential for future research exploration. In a more recent study, Alaoui et al. (2018) analysed BSD from Twitter that is related to the 2016 United State election in identifying popular candidates. Sentiment analysis was applied to predict voters' opinion polarity and it was proved that the technique was effective in measuring public opinions.

More recent researches indicated that government agencies, especially at the local level, have not utilised their BSD for a better understanding of citizens' needs and expectations (Liu et al. 2018; Reddick et al. 2017) due to the lack of proper guidance on analysing and processing data (Liu et al. 2018). Whilst many social media facilities can be employed to advance government-citizen interactions, the LGs only used social media platforms to disseminate information in a one-way direction (Reddick et al. 2017; Ellison and Hardey 2014). Thus, a study on how government agencies could process their BSD for better facilitation in the decision-making processes becomes essential to improve public services.

2.4 The Potential Use of BSD in the Public Sector

Since the rise of social media usage in the public sector, researchers and practitioners in e-government have been searching for various ways to generate visible benefits of BSD. Previous studies indicated that BSD utilisation by governments provides enormous advantages in understanding their citizens (Haro-de-Rosario et al. 2018; Su et al. 2017; Mohammad 2015; Moss et al. 2015; Zavattaro et al. 2015). This understanding significantly contributes in improving the management of public service operations, communications, and policy-making processes (Haro-de-Rosario et al. 2018; Liu et al. 2018; Moss et al. 2015).

In managing public services operations, BSD utilisation can support governments in understanding citizens' needs and expectations. By analysing citizens' postings on social media, the government can extract discussion topics and predict citizens' opinion on related issues. Analytical techniques such as topic modelling, term frequency, and prediction analysis can be applied in the extraction processes that provide an indication of public awareness and opinion regarding government services (Haro-de-Rosario et al. 2018). Moreover, the BSD is valuable in providing a signal of public experience and detecting complaints on public services which could involve overwhelming negative publicity (Eom et al. 2018; Bright et al. 2015).

Additionally, the government that utilised BSD can be more responsive to any query or comment from the citizens particularly at the local level (Eom et al. 2018).

The government agencies also can utilise BSD to monitor citizens' feeling on their services. Sentiment analysis has been proved as an effective method in analysing and forecasting public feelings (Alaoui et al. 2018). Thus, by applying sentiment analysis on government's social media site can facilitate government agencies in monitoring citizens feeling in real time and taking immediate necessary action (Su et al. 2017; Zavattaro et al. 2015; Kwon et al. 2013; Williamson and Ruming 2016). The term frequency and topic modelling can be employed to proceed with further investigation on identifying reasons behind the citizens' sentiment. Knowing the term frequency, discussion topics and citizens' sentiment help in providing better input for the government decision-making teams in prioritising public issues (Chang 2018; Haro-de-Rosario et al. 2018).

Public agencies have adopted social media for various purposes such as to overcome barriers in government-citizen interaction (Haro-de-Rosario et al. 2018). Government authorities that are utilising BSD can enhance communication with the public. For instance, Williamson and Parolin (2013) examined Twitter messages posted in Australian LG to explore communication patterns on government-related information through social media. The study also suggested that the dissemination of such information through social media has a positive impact on the public understanding of government planning. Another study by Zavattaro (2015) that applied sentiment analysis on the LG in the United State (US) concluded that online participation can be encouraged through positive sentiment.

In practice, the analytical techniques such as social network analysis (SNA) can be applied on government's BSD to identify influential people in the social media network. This prominent figure can act as strategic alliances to broadcast government-related information and receive feedbacks from the public. This strategy can enhance government-citizen interaction, increase public relations and promote the council's good reputation (Moss et al. 2015). Those researchers who applied SNA to study social role in LG social media network found that the mayor of the city serves a significant role as a connecting centre in the social platform (Eom et al. 2018).

Another potential used of BSD in public agencies is related to policy-making. For example, BSD can be analysed to measure the public's awareness and reaction towards new policies implementation or changes of the current rules (Cecilia Fredriksson et al. 2017; Bright et al. 2015). The results obtained from the BSD analysis can ascertain governments with the public's response and attention to specific policies.

Moreover, prediction analysis on future events information that will be held around the district such as entities involved, time, and location of events can be identified through the analysis of BSD. Researchers have applied various algorithms and techniques for event (Petrovic et al. 2010; Becker and Gravano 2011; Wang 2013; Vavliakis et al. 2013; Vieweg et al. 2014; Alsaedi et al. 2017; Hasan et al. 2018; Yılmaz and Hero 2018; Kursuncu et al. 2018) and locations detections (Chi et al. 2016; Inkpen et al. 2017). For instance, an algorithm called Latent Dirichlet Allocation (LDA) was employed on BSD in several event detection systems (Panagiotou et al. 2016; Vieweg et al. 2014; Vavliakis et al. 2013). Gerber (2014a) analysed Twitter messages to predict potential crime based on the discussion topics between social media users. The study, which applied specific linguistic analysis and topic modelling to detect potential crimes, concluded that crime prediction performance is improved with increasing number of Twitter messages.

In the nutshell, with the opening and availability of data in social media, there is now a great opportunity for governments to understand citizens' needs and expectations as well as to predict future policies of public services through proper BSD utilisation. Table 2.2 summarises the potential benefits of using BSD in public agencies. This study focused on the use of social media data to help decision-makers in the local government to improve planning, managing and delivering of services to citizens.

Table 2.2: The Potential use of BSD in the Public sector

The potential use of BSD	**Authors**
Analysing term frequency and discussion topics related to public issues	(Gerber 2014b) (Zafarani et al. 2014) (Bright et al. 2015)

	(Wang et al. 2015) (Khan et al. 2017)
Determining citizens' sentiment	(Williamson and Parolin 2013) (Kwon et al. 2013) (Hasan et al. 2014) (Mohammad 2015) (Zavattaro et al. 2015) (Williamson and Ruming 2016) (Su et al. 2017) (Haro-de-Rosario et al. 2018) (Alaoui et al. 2018)
Measuring customer services and public relations	(Moss et al. 2015)
Public consultation and engagement	(Moss et al. 2015)
Identifying key people in the social media network	(Benton and Fernández Fernández 2014) (Dubois and Gaffney 2014) (Stieglitz, Mirbabaie, et al. 2018)
Improve communications	(Moss et al. 2015) (Haro-de-Rosario et al. 2018)
Increase responsiveness	(Eom et al. 2018)
Crisis Communication and management	(Vieweg et al. 2014) (Steiger et al. 2015) (Wang and Ye 2017)
Forecasting policy demands and citizens opinion	(Cecilia Fredriksson et al. 2017)
Support participatory decision and policymaking	(Grubmüller et al. 2013) (Bright et al. 2015) (Liu et al. 2018)
Provide indications of public reactions to specific policies	(Bright et al. 2015)
Predict depression via Twitter in Healthcare	Prediction (Gerber 2014a)
Prediction Events	(Petrovic et al. 2010) (Becker and Gravano 2011) (Wang 2013) (Vavliakis et al. 2013) (Vieweg et al. 2014) (Alsaedi et al. 2017) (Hasan et al. 2018) (Yılmaz and Hero 2018) (Kursuncu et al. 2018)
Predict Locations	(Chi et al. 2016) (Inkpen et al. 2017)

2.5 Big Social Data Analytics

The literature has emphasised that data from social media can be analysed using a set of techniques called social media analytics (SMA) (Batrinca and Treleaven 2015; Stieglitz et al. 2014; Fan and Gordon 2014).

SMA is a method of collecting, storing, monitoring, analysing, and reporting semi-structured and unstructured data from social media to extract pattern and valuable hidden insights for decision-making process facilitation (Khan 2015; Fan and Gordon 2014). This method is considered as a new emerging research ground that uses computational methods to analyse a big collection of data (Hobbs 2014).

Recently, SMA involves an enormous amount of user-generated data from social media interactions which consist of data with similar characteristics of big data such as large in volumes, variety formats, and high velocity in the form of historical archives (Cecilia Fredriksson et al. 2017; Ishikawa 2015). These types of data sets require advanced methods and techniques to collect, store, analyse and represent. This method is known as BSDA (Ghani et al. 2018; Mukkamala et al. 2014a). The impact and value of BSDA have been explored in numerous societies to determine remarkable benefits. The utilisation of big data analytics in private sectors has enhanced operations performance and facilitated better-informed decision-making in manufacturing firms (Mikalef et al. 2019; Popovič et al. 2016).

Several scholars recommended various analytical methods to analyse BSD. Lee (2017) reviewed social media analytics methods and stated that sentiment analysis, social network analysis, and statistical methods are the most widely used to gain new insight from BSD. Sentiment analysis, also called opinion mining, classifies texts into positive, negative, or neutral based on the analysis of words from a text (Tunggawan and Soelistio 2016; Bravo-Marquez et al. 2014; Pak and Paroubek 2010; Pang and Lee 2008). Social network analysis studies a network structure to identify relationships between actors and positions of actors in the network to relate with social roles (Borgatti and Halgin 2011), whilst statistical method can be applied in many types of data including BSD to determine patterns and trends.

Other researchers proposed a framework to analyse BSD (Stieglitz et al. 2014; Stieglitz and Dang-Xuan 2013b). The framework listed a combination of several analytical methods namely statistical, social network, sentiment, content and trend analyses that can be applied to transform BSD into meaningful insights. Although the framework was tested with empirical data from a political discussion on social media, it can be utilised by other organisations to derive substantial values and gain new insights.

Researchers in e-governments explored various analysis methods on the BSD to test and create values from the available data. BSD of government agencies from Facebook and Twitter was studied using several analysis methods such as content analysis (DePaula et al. 2018; Guillamón et al. 2016; Williamson and Ruming 2016; Bonsón et al. 2015), sentiment analysis (Stieglitz, Bunker, et al. 2018; Williamson and Ruming 2016), text mining (Reddick et al. 2017), descriptive analysis (Haro-de-Rosario et al. 2018; Mergel 2016), and social network analysis (Eom et al. 2018; Stieglitz, Bunker, et al. 2018; Stieglitz, Mirbabaie, et al. 2018). For example, Bonsón et al. (2015)

analysed Facebook postings from the selected largest cities in the European Union (EU) countries using content analysis to measure the use of social media in LG. The study found that citizens are more interested to interact with LG when the discussion topics related to their everyday issues.

Another study by DePaula et al. (2018) applied content analysis method on the Facebook postings of LGs in the U.S. to identify communication patterns. The study found that many information related to government operations, policies and events can be extracted from the Facebook postings. This evidence show that content analysis methods including topic modelling, term frequency, keyword extraction are able to analyse texts from social media posts.

Even though the aforementioned literature attracted the attention of public administration scholars and practitioners regarding the potential and challenges of social media as a tool to expand the beneficial effects in the public sector, this study believes that LG decision-maker teams urgently need a guidance on BSD utilisation. Such guide has not been sufficiently dealt with both theoretical and empirical BSD explorations on the beneficial effects to citizens in the public sector.

Current research activities have explored various methods of analysing BSD, but there is still an insufficient number of studies that focus directly on the use of social network analysis (SNA) on the LGs’ BSD. SNA is an appropriate method to analyse BSD since the volume of user-generated data in social media keeps on increasing on the daily basis. Research related to SNA in the public sector is still inadequate, particularly in LG. Therefore, an investigation on how LG can utilise the SNA for a better understanding of citizens in a social media network is crucial. Previous studies showed that the use of social media in LG is becoming a new trend and increasingly widespread. However, questions related to the real use of BSD and SNA to largely reform government operation and redefine government-citizen relationships remain to be answered. Table 2.3 summarises techniques used to analyse BSD in the previous studies and compared with the techniques applied to develop a proposed BSDA model in this study.

Table 2.3: Comparison of BSD Analysis Techniques

Author		Content Analysis			Network Analysis	Predictive	Theory	Domain	Platform
	Text Analysis	Term Frequency	Topic Modelling	Sentiment Analysis	Social Network Analysis	Statistical Analysis			
(DePaula et al. 2018)	√						Not identified	LG	Facebook
(Eom et al. 2018)					√		Social Network	LG	Twitter
(Stieglitz, Bunker, et al. 2018)				√	√	√	Not identified	FG	Twitter
(Reddick et al. 2017)	√		√				Double-loop learning	LG	Facebook
(Panagiotopoulos et al. 2017)	√						Not identified	FG	Twitter
(Guillamón et al. 2016)	√						Agency theory	LG	Facebook
(Williamson and Ruming 2016)	√			√			Not identified	LG	Twitter
(Bonsón et al. 2015)	√						Institutional Theory	LG	Facebook
(Stieglitz et al. 2014)			√	√	√	√	Not identified	Political	
A Proposed BSDA model	√	√	√	√	√	√	The Strength of Weak Ties, Structural Holes, Social Role	LG	Twitter

*LG: Local Government, FG: Federal Government

2.6 Chapter Summary

This chapter discusses e-government research evolvement, benefits, and related concepts to provide a fundamental overview of this area. The chapter deliberates on the current state of e-government research based on the preliminary study by categorising it into three stages; e-government development model, adoption and diffusion of e-government, and e-government using social media. The BSD term, which is the main focuses of this study, is also discussed in this chapter followed by the potential use of BSD in the public sectors.

BSDA, an analysis method of BSD, is described in this chapter together with the potential techniques that can be used to analyse BSD. The chapter highlights that social network analysis (SNA), one of the BSDA techniques, is still not widely used in the field of e-government particularly in the context of LG. Therefore, this study attempts to fill this gap in the existing literature. The chapter then concludes that research in e-government and social media has big potential to be explored in different areas in order to utilise the BSD and gain insights to the benefits of the public sectors and citizens in general.

3

CHAPTER 3: LITERATURE REVIEW II (SOCIAL NETWORK)

3.1 Introduction

This chapter discusses the underpinning theories used in this study. The chapter begins by introducing the social network theory and related concepts. Three related social network theories are explained in detail followed by a discussion on online social media network and measurement used to identify social roles in the network structure.

3.2 Social Network Theory

Network Theory (NT) views the interaction of a set of components and processes as working together to achieve certain objectives individually or collectively (Borgatti and Halgin 2011). The network contains nodes and edges. The nodes are also known as vertices, actors or network elements, while the other names for edges are ties, links, or connections. There are many types of network in the real world such as a computer, traffic, blood vessels, and molecular networks.

The real-world networks can be categorised into four loose groups (Newman 2010; Newman 2003) such as social, information or knowledge, technological, and biological. The first category, social network, relates to human interaction such as family and business relationship networks. Most of the times, the link in a network is in the form of mutual relationship (undirected) but in some cases, it can be a one-way relationship (directed). The second category, information or knowledge network, represents the interconnection between information such as the networks of web pages and co-citation. The third category, technological network, can be explained through some examples such as the electric grid, air traffic system, and computer networks which are purposely designed to distribute resources. In the computer networks, nodes represent computers, servers, hubs, or switches while edges are network cables or wireless connections. The nodes interact with each other through edges by sending or receiving resources such as package data. Researchers argue that technological networks are inherent connections from social networks (Wellman 2001; Denning 2004). Finally, the fourth category, biological network, refers to a human body system such as neural networks, nerves, and immune systems. Another example of a biological network is a food web which represents the interconnection of food chains. Even though it is one of the categories listed, the social network is still as broad as the current technology of computing makes it more complex and difficult to be specified as either social or information network.

Most of the networks in the social science study are related to social, which contains a set of actors linked by a set of ties (Kadushin 2012). The actors represent people or groups of people, whilst the ties are relationships between people through interactions or communication (Newman 2003). The actors also can represent objects, events, ideas, or other things such as organisations, journal articles, and Twitter users' accounts. In sequence, the ties are connections or pipes of flow between actors that contain resources such as digital information as in the case of the social media networks.

In order to differentiate the relationship between actors, Borgatti and Halgin(2011) divided the ties into two types called states and events. The states-type tie is continuous relationship such as kinship, cognitive, affective and other role-based ties. This type of ties can be measured in terms of strength, intensity, and duration. Even though it is not continuous and necessarily repeated, the other type of tie, events-tie, can be counted over periods of time. Examples of the events-tie include giving advice, retweeting message, and making a sale.

The social network research focuses more on the social relationships to investigate the consequences of the ties rather than the attributes of the actor itself without denying the contribution of the attributes in developing the actor profiles. The social structure scientists view the behaviour of actors as not only subject to the characteristics of the actors but also as being established from the interaction and relationships with other actors in their network structure (Borgatti et al. 2014; Freeman 2004; Tichy et al. 1979)

Researchers have also introduced five principles of NT (Wellman 1988). Firstly, the relationships among actors in the network structure constructed the actors' behaviour rather than the characteristics of the individual actor. Secondly, the relations between units are the centre of analysis, instead of the units themselves. Thirdly, analytic methods deal with the pattern of relations based on the population or sample. The units of analysis are interdependence. Fourthly, the pattern of relations between actors in a network structure is the main concern in characterizing the actor behaviour. The resources flow is not only in dyadic ties but also with other actors in the network. Finally, some network structures have multiple subgroups which are not necessarily discrete clusters but rather overlapping networks. An actor is possible to lay in multiple clusters.

Degenne and Forse (1999) recommend three basic inferences regarding the actors embedded in a social structure that is applied in social network research. The first inference, social network structure, contains resources such as digital information (e.g., tweets) that flow between actors in the social network through interactions such as messages forwarded between Twitter users. Second, are the actors in the social network structure that are interdependent and supporting each other. Third, are the social networks that offer opportunities as well as constraints on actors in the network structure. These characteristics are getting the attention of advanced research in social network and interesting to be explored in order to recognise the implication to the organisations, culture and behaviour.

Based on the abovementioned descriptions, the key objective of studying a social network that is being proposed by scholars is to understand the relationships among social actors which generates patterns of relations.

The patterns can be examined to advanced our knowledge in terms of the implications of these relationships and how the patterns of relations allocate resources in a social network structure (Wellman 1988; de Nooy et al. 2011; Wasserman and Faust 1994). Moreover, the patterns of relations can also determine the characteristics and behaviours of the actors or roles. Knowing the roles in a network structure can accelerate related opportunities, limitations, and threats (Mislove et al. 2007).

The network analysts also study the pattern of ties to understand the impact on the actors' behaviours. For example, a study has been conducted to identify the influence of social network ties in identifying voting preferences (Watts 2014). The study investigated the type of relationships among the participants that can influence the individual decision in voting rather than the attributes of the participants such as gender or age. The researcher argued that people are more likely to interact with each other if they shared a common interest. In addition, the study proved that the type of relationships in a social network will influence the behaviour of the participants particularly their voting decision.

3.2.1 Understanding the social network

Scholars have suggested three steps in understanding a social network (Mrvar and Batagelj 2016; Thelwall 2014; Borgatti and Halgin 2011). The first step is to identify the network structure and its components. The network structure contains ties between actors, positions of the actors and resources flow. The ties can be seen not only based on the types but also on the patterns of the connections. A certain pattern of ties can give a specific meaning to the network structure. The positions of the actors also contribute to certain behaviour and the role of actors in the network. After the network structure has been clearly recognised, the second step is to investigate the ties between actors and the position of the actors in the network. At this stage, mathematical and computational methods can be applied to measure the ties and actors' position. However, the issue here is how to select the type of ties to be measured. The simple answer pertaining to this issue falls back to the purpose of the study. Different research has a different objective to be achieved. For example, if the objective is to identify the key people who are responsible in disseminating information through the social media such as Twitter, the relation type of tie can be used to investigate the pattern of followers sharing the information. Finally, the finding from the second step can be analysed to understand the consequences of the network structure in the real social world. The position of actors and ties between actors represents the social roles and relationships between people in their networks. The theories related to the social network are discussed in the next subsection.

3.2.2 The Strength of Weak Ties Theory

Many fundamental network theories and concepts have contributed to the development of Social Network theory. One of the seminal theory in a social network is called the Strength of Weak Ties (SWT) theory (Granovetter 1973; Granovetter 1983). In this theory, there are two main arguments. Firstly, the theory argues that ties between two actors can be measured based on the level of strength and weakness. The strong ties between actors represent close relationships such as kinship or best friend while the weak ties represent a loose relationship or acquaintances. When two people have strong ties, they are more likely to share similar resources such as job opportunities, breaking news, and the latest twitter messages. Such strong tie may trigger the potential of sharing redundant resources among the actors in their network structure. The theory claims that when two persons have a strong relationship between them, they will at least have a weak relationship with the other persons who have strong relationships with their neighbours. Based on the example in Figure 3.1, if the tie between X and Y is strong, and the tie between Y and Z is also strong, X and Z are most likely to have at least a weak tie.

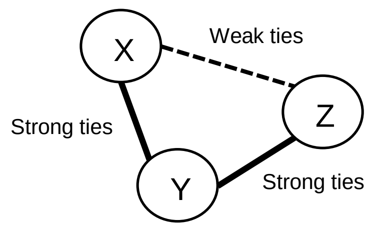

Figure 3.1: Strong and weak ties

Secondly, the theory states that a bridge is a strategic position of actors in the social network structure which linked between two subgroups or clusters. The actors connected through a bridge tie are more likely to receive new resources from the other cluster and spread the resources to the members in their cluster. For example, in Figure 3.2, an actor X is the only node from cluster A that is connected to the other node in cluster B. In this case, the relationship between actor X and Y represents a bridge tie. The bridge offers opportunities for actor X to receive resources circulating in cluster B through actor Y which will transform actor X to be a focal point of resources for cluster A.

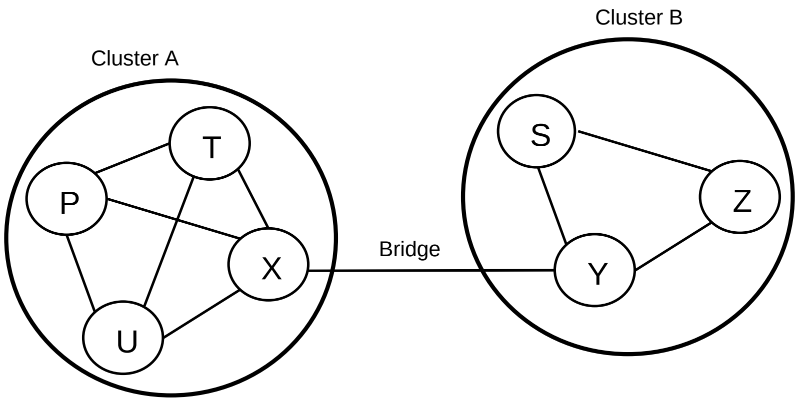

Figure 3.2: The bridge in a Social Network

Based on the two stated arguments, Granovetter (1983) frames the SWT theory with a suggestion that weak ties have the potential to become a bridge rather than the strong ties because when the ties become stronger, the connected actors will become known to each other and it is more likely for them to share the same resources in the network. In contrast, the actors who are connected in weak ties do not know much about each other. Thus, the actors have the potential to receive and provide access to new resources (Gupta et al. 2016). In summary, the weak ties assist in the integration of the social systems by bridging the flow of resources within various clusters in the network.

3.2.3 Structural Holes Theory

A complete network is a network with all actors linked to each other. In the real world, complete networks are sometimes impossible to exist particularly when an individual actor in the network cannot connect to the other actors due to certain circumstances. For instance, in a small classroom with ten students, it is highly likely for all of them to know each other by their first name. However, in a large lecture hall with an outsized number of students, it is unlikely for each student to know each other by their first name. Thus, an incomplete network will be generated when a network of students in the large lecture hall is constructed to represent who know each other by their first name. The incomplete network will have a structure hole that exists when a direct connection between two actors in the network structure is absent. Alternatively, another actor known as a broker will take the role to link these actors. This concept is explained in the Structural Holes (SH) theory introduced by Ronald Burt in 1992 (Burt 1992). The theory argues that when two actors in the same cluster are connected, it is more likely that they share redundant resources. However, the law is not applied to the actor in the broker position since the broker received many links from different clusters. Thus, the broker is more likely to receive non-redundant resources and has the potential to control the resources flows between clusters in the network. The non-redundant resources and power of resources flow control are value-potential of the structural holes (Burt et al. 2013). The network structure in Figure 3.3 shows a structural hole between actors B and C which are bridged by broker Z. The broker Z has the potential to receive different resources from actors B, C, and D. Thus, the broker Z has the power to control the resources flows between actors B and C or between actors B and D.

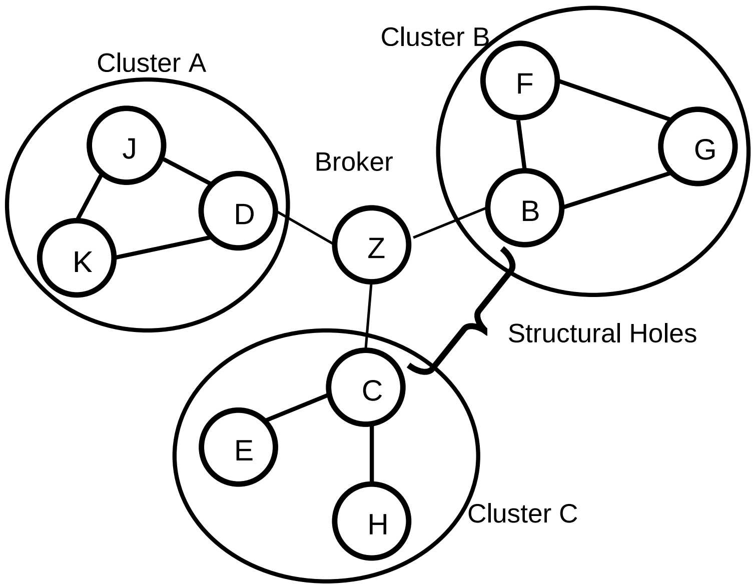

Figure 3.3: A network structure with structural holes

Burt (2004) classifies the brokerage into four types depending on the value of the generated functions. The first type is a simple brokerage which basically updates the clusters with new resources. The second has an advanced function which transfers the best practice between clusters to add values for both parties. The third is capable of transferring resources with similar features of the other clusters in order to solve problems or enhance opportunities. Finally, the last type of brokerage has the ability to integrate and synthesise the behaviours from both clusters to generate new solutions for creating competitive advantages.

3.2.4 Social Role Theory

Discussion about the social role concept among sociologists and social psychologists began in the early 20th century where the first article was published in the 1930s. The main concern of the social role theory is to define various roles based on human daily activities in forming characteristics behaviour patterns or social roles. The theory views each person as a social actor, member of social positions, and as acts per their social roles (Biddle 1986). The social role is a set of expected standards of responsibilities and obligations, conduct and behaviours that each person should meet and accomplish. For example, a football player is expected to act and behave depending on the situation and the player's position on the field. The goalkeeper and striker have different roles and need to act accordingly.

The structural role theory, one of the prominent social role theories, explains a role from the perspective of social structure that performs the social role and focuses less on the social actor characteristics. The social structure is an interconnection between persons, positions and tasks. The position of a person specifies the behaviours and way that the person interacts with other persons (Forestier et al. 2012). In the case of a football game, the player's position is more important in defining the behaviours of each player compared to the characteristics of an individual player such as name, age, or gender.

Grounded from the structural role theory, a social role in the social network can be determined by the interaction between actors which generate relationship patterns. The actors with similar behaviour and relationship patterns share an equal position in the social network structure (Forestier et al. 2012; Junquero-Trabado and Dominguez-Sal 2012). Thus, in the social media network, the social roles and positions are identified through the analysis of the social media users' behaviour and interaction patterns in the social media environment. For instance, the interaction patterns in the Twitter network among its users could be analysed in order to identify the social roles that can be used by an organisation to enhance the understanding of its customers.

3.3 The Online Social Media Network Structure

Network analysts study network structures to understand the phenomena of a social network. The network structure is an organisation and representation of the actors in a network (Kadushin 2012). An understanding of the network structure is crucial in advancing our knowledge of attributes to be measured and examined in the networks. Thus, the impact of the network structure on the actors' behaviours and organisations can be identified. Additionally, the network structure can inform the level of network complexity by applying adequate algorithms to measure the number of dependency relations within the network (Morzy et al. 2017; Kim et al. 2011). This thesis views the online social media network structure based on the position of the social media users and types of ties between them. The understanding help to define the behaviours and roles of social media users in the online social media networks.

In the network structure, relations are one of the main concepts to be considered when analysing the networks. The actors and relations between actors are the key elements to be described in the networks (Borgatti et al. 2014; Carpenter et al. 2012). Therefore, these two elements should be clearly defined in order to understand the network structure. The ties between actors represent relationships, whilst the pattern of relations play an important role in locating an individual actor at a certain position. An actor can have many relations with other actors in the network structure. In contrast, an actor also can have few relations or no relation with any other actors in the network. Typically, the actors with more relations are more likely to get exposure with various information from numerous sources. Subsequently, the highly-connected actors will have the potential to be more influential in the network structure.

Scholars developed an outline to understand the network structure which can be divided into two levels of networks called actor-level (monadic) and tie-level (dyadic) (Khan and Wood 2016; Katz et al. 2004; Borgatti and Foster 2003).

At the actor-level, the position of actors represents the social roles in the network. The position of actors refers to the location of the actors in the network structure which includes the connection and distance of each actor from other actors in the network. From the lens of the social role theory, the position of actors and the pattern of relations can influence the behaviour of the actors and define their roles. Moreover, the position of actors represents the types and amount of resources available to be accessed in the network. The actors in the strategic positions have greater control on the resources flow as well as more potential to influence than those at the other positions (Borgatti et al. 2014; Borgatti 2005; Wasserman and Faust 1994; Burt 2002; Brass 1984). For instance, an actor in the central position has more power to control the resources compared to the one in the peripheral of the network structure.

In the actor-level, the number of relations that each actor has is called a degree. The degree represents the actors' activities of either sending or receiving resources with other actors in the network. The number of degrees for each actor can be measured and examined using mathematical or computational methods such as centrality measures, which can be applied to locate the position of actors in the network structures (Borgatti et al. 2013; Freeman 1979). In this case, Freeman (1979) had introduced three basic centralities to measure relationships between actors and identify the actors' positions in the network structure known as a degree, closeness, and betweenness. For example, the betweenness centrality is used to identify potential actors to take a role as a bridge between clusters in the networks. The bridge has the advantage of receiving non-redundant resources from various clusters to gain the power of control on the resources flows in the networks.

Burt (1992) argued that the actor's position is not an individual or group privilege, but a collective engagement between actors that connect them in the network. Thus, an investigation about ties is relatively important to understand the relations between actors. At the tie-level, understanding can be based on the tie types such as direct or indirect connection, and the level of strength or weakness. For example, the direct or indirect ties can be used to confirm the connections between actors either reciprocal or one-way interaction as debated by researchers regarding the ties that are able to give benefits to organisations in terms of knowledge sharing, complementarity, and scale (Ahuja 2000).

Borgatti et al. (2009) classified the ties into four types called similarities, social relations, interactions, and flows. The first type, similarities, can be formed into three types; location, membership, or attribute. For instance, the ties can be formed based on the same type of gender, a club of membership or city of location. The second type, social relations, is classified into four subgroups called kinships such as mother of, other roles such as a friend of, affective such as likes or hates, and cognitive such as knows about. The third type is the interactions between actors, for example, by using Twitter users can follow other users. The final type of ties can be based on the resources flow in the network such as a message on Twitter (tweet) from one user being forwarded (retweet) by another user and further forwarded by the third user who read the tweet and retweets it. When this process continued with many users, a network can be developed based on the flow of the tweet distribution.

Furthermore, the level of relationships among actors in the network can be measured using the strength and weakness ties (Granovetter 1983; Wasserman and Faust 1994). The strong relationship among actors represents a cohesive network. If the network represents the interactions among the people in a community, the strong ties between the people in the community are translated as a cohesive community. The strong ties can be measured based on the number of ties connected between the people in the community (de Nooy et al. 2011).

Based on the abovementioned discussion, the analyses of the structure level and metrics can give implication on the social roles and the main function of the ties. By applying the structure metrics at the actor level enables a network analyst to identify the position of actors in the network known as social roles. In contrast, by applying the structure metrics at the tie level helps to understand the flow and power of resources. This discussion is based on the three theories explained at the beginning of this chapter namely the social role, strength of weak ties and structural holes. Table 3.1 illustrates this concept in a framework to understand the network structure.

Table 3.1: A Framework to understand the Network Structure

Structure Level	Structure Metrics	Implication	Theory
Actor level (Monadic)	Position of nodes Network Centrality Degree (indegree/ outdegree) Closeness Betweenness Eigenvector	To identify social roles: Opinion Leader Influencer Brokerage Isolate Etc.	Social Role The Strength of Weak Ties Structural Holes
Tie level (Dyadic)	Ties between nodes Types of ties Direct/Indirect Strong/Weak Ties	The implication of ties: The flow of resources. Power	

3.3.1 Measurement

The social roles can be discovered by studying the social network structure. Researchers have proposed many measurements to identify social roles from the network structures such as degree, closeness, betweenness, and harmonic centralities (Rochat 2009; Everett and Borgatti 2005; Costa et al. 2007; Wasserman 1994; Faust 1997; Freeman 1979). Zygmunt (2014) classified four main methods to identify social roles from the social network structure. The first method is based on the structural equivalence initially proposed by Wasserman and Faust (1994). The second method is by separating nodes in the network structure into two groups; core and periphery. This concept was introduced by Borgatti and Everett (1999). The third method is based on the analysis of basic social network analysis measures. The features of the actor's position in the network structure such as the number of connections with other actors and distance from their neighbours are considered. Finally, the fourth method is by clustering feature vectors where a vector with relevant attributes of behaviour and relationships are used to represent each actor in the network structure. The clustering process is based on these types of vectors. Thus, this study follows the third method to identify the social roles from the social network structures.

Selection of measurement for the appropriate type of networks is critical to ensure that the measurement accurately tested relevant indicators for the research questions. Each network measurement such as a degree or betweenness centralities were designed for a specific type of network and might not be accurate to measure other types of network (Borgatti 2005). For example, betweenness centrality is designed to measure the amount of traffic that flows through a node while closeness centrality is to measure the shortest time a node can reach all other nodes in a network. In this case, researchers proposed parameters to reduce the risk of misuse of the social network measurement. For instance, Borgatti (2005) proposed a typology of flow processes for researchers and practitioners to apply the pertinent centrality measures based on the type of social network investigated in their studies.

The measurement concept of centrality, grounded from the graph theory, was introduced by Freeman (1979) to identify the actors' position in social network structure particularly those in the central positions. Although the concept has evolved and advanced in many ways such as centrality of network flows (Freeman et al. 1991), immediate effects centrality and mediative effects centrality (Friedkin 1991), faster algorithm for betweenness centrality (Brandes 2001), ego betweenness (Everett and Borgatti 2005), complex degree centrality for bibliometric and webometric data (Kretschmer and Kretschmer 2007), trust centrality (Barbian 2011), control centrality (Liu et al. 2012), diffusion centrality (Kang et al. 2012), game centrality (Simko and Csermely 2013), C-Betweenness and L-Betweenness (Abnar et al. 2015), duality of closeness and betweenness (Brandes et al. 2016), the key notion of centrality is the central actor in the network structure which generally equivalence to power (Chiu et al. 2017; Sozen 2012; Lamertz and Aquino 2004), prestige (Andrews et al. 2017; Zhao et al. 2015; Russo and Koesten 2005), influence (Kayes et al. 2012) or new resources (Burt 2015).

Researchers in various disciplines examined the centrality concept to identify actors' roles such as opinion leaders, influencers, followers, and isolators in various types of social network structures. For example, Everett and Borgatti (2005) applied the correlation between ego and network betweenness in a traditional social network to identify the central actors. They suggested that the ego-betweenness can give a better measurement of the conditions when the betweenness scores of all actors are extreme either hardly differentiated or highly differentiated.

Another study by Kayes, Qian, Skvoretz and Iamnitchi (2012) investigated the blogger community network to detect the influential users among bloggers. The study applied six centrality measures that include degree, betweenness, closeness, eigenvector, communicability and hub. The correlation between these centralities was compared to get the best results. Form the results, it was concluded that all the six centrality measurements were highly correlated in identifying the influential bloggers in the blogger community network structure.

Another study by Shafiq, Ilyas, Liu and Radha (2013) had applied six social network analysis measures into two online social media networks called Everthing2 and Facebook without considering the text content. The degree centrality, several triangles, clustering coefficient, eigenvector centrality, PageRank and average shortest path length were tested to classify four actors' roles as either introvert or extrovert leaders, followers or neutrals. The results showed that their proposed model that was based on the six social network analysis measures can be used to determine four different patterns of actors' behaviour.

Xu et al (2014) examined political social network in order to identify opinion leaders. They used the betweenness centrality measure to investigate user relations. Xu et al (2014) referred to opinion leader as the power to control resources flow including the capability to generate new resources and drive other users to disseminate the resources.

The more recent research proposed a structural social role mining framework (SSRM) in order to identify four roles in emails exchanged social network (Abnar et al. 2015). They extended the betweenness centrality with two new centralities called C-Betweenness and L-Betweenness. Both centralities were used to measure the shortest path. The former centrality is for measuring the path between different communities while the latter is for a path between leaders of different communities. They tested the framework with emails exchanged network structure and successfully identified four roles named as outsiders, outermost, mediators, and leaders.

Other studies that used social network analysis focused on the online social media networks such as Twitter (Stieglitz, Mirbabaie, et al. 2018; Soares et al. 2018; Xu et al. 2014; Cha et al. 2010) and Facebook (Revelle et al. 2016; Shafiq et al. 2013) to identify social roles in the political discussion (Soares et al. 2018; Dubois and Gaffney 2014; Xu et al. 2014), LG (Haro-de-Rosario et al. 2018), and emergency situation (Sadri et al. 2017; Remy et al. 2013). The summary of the measurement used related to the online social network in investigating social roles are listed in Table 3.2.

Table 3.2: Measurement used in the online Social Network

Authors	**Network**	**Measurement**	**Social Roles**
(Russo and Koesten 2005)	Online Class	Centrality Prestige	Influencer Isolate
(Kayes et al. 2012)	BlogCatalog network	Correlation Of Centralities: Degree Betweenness Closeness Eigenvector Hub Communicability Centrality	Influential Bloggers

(Cha et al. 2010)	Twitter	Indegree Retweets Mentions	Influential Users
(Shafiq et al. 2013)	Everything2 Facebook	Degree Number of Triangles Clustering Coefficient Eigenvector Centrality Pagerank Average Shortest Pathlength	Introvert Leaders Extrovert Leaders Followers Neutrals
(Huang et al. 2014)		Degree Ego Betweenness Centrality Eigenvector Centrality	Core (Leader, A Star, A Hub Etc.) Bridge
(Dubois and Gaffney 2014)	Twitter	Indegree Centrality Eigenvector Centrality The Local Clustering Coefficient of Nodes Knowledge Interaction	Politicians Journalist Activists Bloggers Average Users
(Xu et al. 2014)	Twitter	Betweenness Centrality User's Geographic Proximity	The Predictors of Opinion Leadership
(Abnar et al. 2015)	Email exchange network	Betweenness C-Betweenness L-Betweenness	Outsiders Outermost Mediators Leaders
(Kratzer et al. 2016)	2 offline networks 1 online network	Betweenness	Bridges
(Revelle et al. 2016)	Facebook and Scratch	In-Degree Betweenness Centrality PageRank	Popular Friendly Explorer Reciprocated Community Member An Active Community Member
(Soares et al. 2018)	Twitter	Indegree Outdegree Modularity	Opinion Leaders Informational Influencers Activists

3.3.2 Measurement Used in This Study

Centrality, a concept applied in the analytics network measure, illustrates the central actors in a network structure that control the information flow through the ties (Wasserman and Faust 1994). In addition, the concept is an important way to measure actors in a network (Newman 2010). The three basic analytic network measurement are degree, betweenness and closeness centralities (Freeman 1979).

The degree or also known as local centrality measures the number of direct links between actors. In a directed network, the degree centrality is divided into indegree and outdegree centralities to show input coming to and demonstrate the resources going out from the actor, respectively. An actor with high degree centrality number indicates the central position of an actor in the network.

The second measurement, betweenness centrality, identifies the actor's position which stands in the middle between other actors. The betweenness centrality measures the extent to which an actor acts as an agent to the other actors in the social network (Scott 2000). The actor with high betweenness centrality represents an important position in the network because other actors will depend on it to be connected with the rests of the actors. Moreover, the actor with high betweenness centrality likely to manage the resources flow in the network.

Finally, the closeness centrality denotes how quick an actor can reach other actors in the social network. The lowest average of step to reach each other actor in the network is considered high-closeness centrality which will be perceived as a leader to disseminate resources in the network (Freeman 1979) and most efficiently to make contact with other actors (Scott 2000). Closeness centrality does not apply for an unconnected network (de Nooy et al. 2011). Alternatively, harmonic centrality can be used in such network and it is identical to closeness centrality (Boldi and Vigna 2013; Rochat 2009). Table 3.3 summarises the measurement used in this study.

Table 3.3: Measurement used in this study

Measurement	Description
Degree centrality	Immediate influencers where direct contacts to another actor held by an actor.
Indegree centrality	The total number of direct ties of an actor to the others - incoming links.
Outdegree centrality	The total number of ties from the focal actor to the other - outgoing links.
Closeness centrality	How fast can this person reach everyone in the network?
Betweenness centrality	The degree of mediator or brokerage position of an actor between two other actors.

3.4 The Implication of Online Social Media Network Structure

The impacts of the network structure on the actors' behaviour can be seen based on the role that each actor performs in the network. This study identifies nine social roles based on the pattern of relations in the online social media network structure, which include brokerage, opinion leader, influencer, sink, isolate, transmitter, carrier, ordinary, and communicator.

The first social role, a brokerage, is to link between one cluster to another. The link is critical because if it is broken, some clusters might be disconnected from the main network. This position is not only crucial but also valuable because the brokerage has access to different resources from different actors outside his or her cluster. Additionally, the brokerage has the power to control the flow of the resources within clusters. There are two ways of measuring this position either by using betweenness centrality (Freeman

1979) or network constraint (Burt 2006). The actors with high betweenness centrality have the potential to be an important brokerage.

The second social role, an opinion leader, is the actor who has the ability to be sources of reference for other actors in the social network by generating new resources such as breaking news, ideas, and new jobs information. The opinion leader also has the capability to disseminate resources in order to influence other actors in the social network. The metric can be used to identify the position of the opinion leader as indegree centrality or proximity prestige.

The third social role, an influencer, is a central position as the focal point that has the ability to spread resources in order to influence the decision of other actors in the social network. The influencer is highly connected and able to access other actors in the shortest distance in the social network structure. This indicates that the influencer is close to the other actors and potentially can be good disseminators. The closeness centrality measure (Freeman 1979) can be used to identify the influencer.

The fourth social role is known as sink or receiver who can only receive many resources but do not send anything to any actor. Even though it recognised as having the power of resources, the sink can be overloaded because all the received resources are being kept to itself. The metrics used to identify the sink are indegree and outdegree centralities. The actor is identified as having the sink position when it only receives many incoming links but fails to send out any link. The fifth social role, an isolated, is an actor that is not connected to the network. The isolated is present in the network structure but is not connected to any other actors in the network structure. This actor can be detected when indegree and outdegree centralities are equal to zero.

The sixth social role, a transmitter, is an actor who sends many resources to other actors in the network but does not receive anything from them. The transmitter can be measured using the indegree and outdegree centralities. The seventh social role is called a carrier, which represents the actor that only receives and sends one resource. The eighth social role, an ordinary, is an actor who receives and sends more than one resources in the network. This social role can be played by most of the actors since the ordinary is a normal actor in a network structure. This ordinary actor can be measured by applying the indegree and outdegree centralities.

The final social role is the communicator that acts as an actor who receives and sends many resources in the network. Although it is not as critical as the brokerage, opinion leader or influencer, the communicator position contributes to the dissemination of resources in the network. The metrics used to measure communicator are indegree and outdegree centralities. The typology of the online social media network structure is summarised in Table 3.4.

Table 3.4: Typology of social roles in an online social media network

Social Roles	**Descriptions**	**Measurement**
Brokerage	An actor who link between two or more clusters and has the potential to receive non-redundant resources from different clusters.	Betweenness centrality
Opinion leader	An actor who has the ability to generate resources (information, ideas etc.), and disseminate the resources to influence other actors in the social network.	Indegree centrality
Disseminator	An actor who is capable of spreading resources in order to influence the decision of other actors in the social network. Central position.	Closeness centrality (strongly connected network) Harmonic centrality (unconnected network)
Sink / Receiver	An actor who receives many resources but sends none. The power of resources but has the potential to be overloaded with resources.	Indegree > 0 Outdegree = 0
Isolate	An actor who is disconnected from the network. Receive none and send none.	Indegree = 0 Outdegree = 0
Transmitter	An actor who sends more resources but receives none.	Indegree = 0 Outdegree > 0
Carrier	An actor who receives and sends only one resource.	Indegree = 1 Outdegree = 1
Ordinary	A normal actor who receives and sends more than one resources in the network.	Indegree > 1 Outdegree > 1
Communicator	An actor who receives and sends many resources.	High in-degree High out-degree

3.5 Summary

This chapter discusses the underpinning theory of this study namely the social network theory (SNT). Three theories related to SNT were selected to be discussed in this chapter. The social role is important to be identified in the social network structure. The chapter explains possible social roles to be identified and metrics to be used in measuring the position of actors in the online social media network. Finally, the implication of the online social media network in identifying the nine social roles using selected metrics is discussed.

Based on a review of the literature to date, there was no approach similar to the approach developed for this study. The three techniques applied in this context are underpinned by SNT to operationalise the novel BSDA model developed in this research.

4

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Introduction

This chapter describes the research methodology adopted in this study to realise the research aim and objectives by resolving issues related to utilising the BSD in the public sector. Research is a step by step procedure to be undertaken in order to extract and analyse data related to a certain topic (Creswell 2014). Therefore, key assumptions of research paradigms, approaches, strategies and methods to collect the data are identified carefully in order to answer the research questions and achieve the research objectives as stated in Chapter One.

4.2 Research Design Process

Research design represents the overall strategy of the selected component of a study in a logical order. There are four basic stages used in the research design including selection of a research paradigm, approach, strategy and method that establish the outline for the collection and analysis of data (Creswell 2014; Saunders et al. 2009). Having these four stages, it is ensuring to address the research problem. This study adopted the same stages of research design as follows: 1) determining the research paradigm, 2) determining the research approach, 3) identifying the research strategy, and 4) determining the methods and techniques for collecting and analysing data.

Figure 4.1 illustrates the research design process whilst detailed descriptions are presented in the following sections.

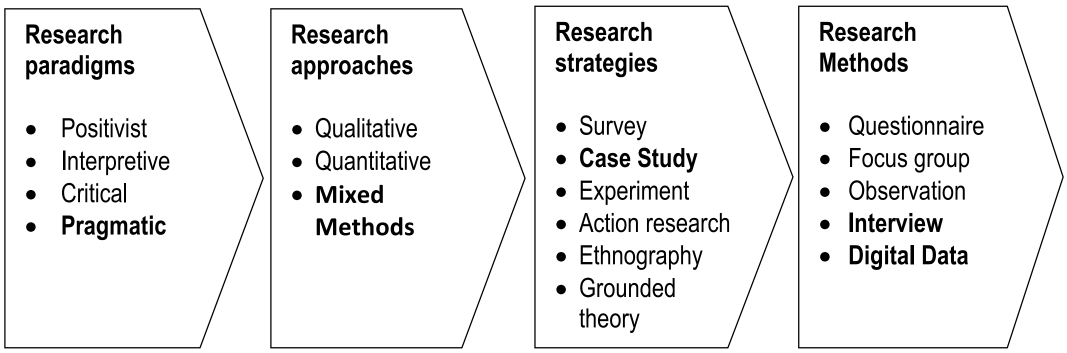

Figure 4.1: Research design process

4.3 Research Paradigms

Among the crucial step in the research design process is determining an appropriate research paradigm (Walsham 1995). A paradigm is the way of thought or worldview that drives action (Creswell 2013). Traditionally, scholar classifies paradigms of Information Systems (IS) research into positivism and interpretivism (Orlikowski and Baroudi 1991). Recently, other categories including pragmatism and realism are becoming acceptable to investigate social phenomena (Saunders et al. 2009). This section outlines the general research paradigms applied in the IS research and the focus is on the one selected for this study. The following subsections deliberate the differences between the three research paradigms.

4.3.1 Positivism Research

Positivist view the nature of reality as an objective and external entity of the social actors as an independent (Saunders et al. 2009). They claim that social phenomena such as social structure and human social behaviour are observable and fact data can be investigated through scientific methods of verification. The quantitative methods such as survey and official statistics are usually employed by the positivists. Furthermore, the positivist researchers are independent of the data and instruments to learn knowledge in a value-free way. They tend to test theories or relationships between two or more variables to enhance understanding of studied phenomena (Myers 2009).

4.3.2 Interpretivism Research

An interpretivist views the truth as subjective, socially constructed and potentially to be changed depending on the situation and object being studied (Creswell 2014). The interpretivist believes that knowledge has subjective meanings extracted from people experience and understanding of a situation in different ways through a qualitative method such as in-depth interviews and observations in a case study (Dyer and Wilkins 1991; Saunders et al. 2009). The researcher is part of what is being studied and views the world as the actors who undertaking the acting (Saunders et al. 2009).

4.3.3 Pragmatism Research

The pragmatic researchers argue that the truth or meaning of an ideology based on a practical way (Saunders et al. 2009). The philosophical underpinning of pragmatism believes in true if it practically works and creates values for society (Gray 2012). The research question is the most important determinant to drive this type of research (Saunders et al. 2009). Hence, it is acceptable to work within both positivist and interpretivist if their usefulness is to gain the research questions from the interaction with the world. Table 4.1 summarises the different IS research philosophies.

Table 4.1: Comparison of Information Systems research philosophies

	Ontology	**Epistemology**	**Axiology**	**Data collection techniques**
Positivism	External, objective and independent of social actors	Only observable phenomena can provide credible data and facts. Focuses on causality and law-like generalisations, reducing phenomena to the simplest elements	Research is undertaken in a value-free way, the researcher is independent of the data and maintains an objective stance	Highly structured, large samples, measurement, quantitative, but can use qualitative
Interpretivism	Socially constructed, subjective, may change, multiple	Subjective meanings and social phenomena. Focuses upon the details of the situation, a reality behind these details, subjective meanings motivating actions	Research is value bound, the researcher is part of what is being researched, cannot be separated and so will be subjective	Small samples, in-depth investigations, qualitative
Pragmatism	External, multiple, view chosen to best enable answering of	Either or both observable phenomena and subjective meanings can provide	Values play a large role in interpreting results, the researcher	Mixed or multiple method designs,

	the research question	acceptable knowledge dependent upon the research question. Focuses on practical applied research, integrating different perspectives to help interpret the data	adopting both objective and subjective points of view	quantitative and qualitative

Source: Adapted from (Saunders et al. 2009)

4.4 Research Approaches

The terms quantitative and qualitative are broadly used in Information Systems research to describe data collection techniques and analysis procedures. Research involving the used of numerical data during data collection and analyses are usually known as quantitative research while the one that applies non-numerical data is named quantitative research. However, research that uses a combination of numerical and non-numerical data in the data collection and analyses are called mixed-methods. The major differences between quantitative, qualitative and mixed methods are summarised in Table 4.2.

Table 4.2: Comparison of research approaches

Characteristics	**Quantitative Methods**	**Qualitative Methods**	**Mixed-Methods**
Method	Predetermined	Emerging Methods	Both emerging methods and pre-determined
Question	Instrument-based questions	Open-ended/Semi-structured questions	Both open-ended and close-ended questions
Data forms	Performance data, attitude data, observational data, and census data	Interview data, observation data, document data, and audio-visual data	Multiple forms of data drawing on all possibilities
Data analysis	Statistical analysis	Text and image analysis	Statistical and text analysis
Interpretation	Statistical interpretation	Themes, patterns interpretation	Across databases interpretation

Source: Adapted from (Creswell 2014)

4.5 Research Strategy: Case Study

Research strategy refers to the way research is truly conducted through data collection methods. Research questions and research objectives are the most important elements in guiding a research strategy (Saunders et al. 2009). A case study is an example of a research strategy to answer specific research questions using empirical data based on different kinds of evidence in order to manage the best possible findings (Gillham 2000). The case study strategy is frequently used in exploratory research to generate answers to the question ‘why’, ‘what’ and ‘how’ (Saunders et al. 2009).

4.6 Research Method: Interview

The interview is a qualitative research technique of data collection through a conversation. A research interview method is used when researchers need to explore in-depth information about individual opinions, views and experiences on specific issues. Scholars suggested interview as the best technique to collect data in many case studies (Yin 2009) in particular qualitative research involving sensitive topics (Gill et al. 2008). The details description of the interview implementation in this study is discussed in Chapter Five.

4.7 Selection of Research Paradigm, Approach, Strategy and Methods

This study applied a pragmatism research paradigm and utilised a mixed methods case study approach which uses interviews and data analytics techniques to address the research problem and answer the research questions. The arguments for selecting this research design are as following:

- The first part of this study seeks to identify how the BSD used in the LG that affect the decision-making in LG planning, operation and future policymaking. The study of literature related to this issue has been followed by in-depth interviews with internal stakeholders of LG for a better understanding of the problem.
- According to (Yin 2009), the qualitative approach is better to answer words such as ‘how’ and ‘what’ in the research questions.
- Scholars suggest that social interactions using social tools such as language could generate knowledge and understanding (Creswell 2013; Klein and Myers 1999). Hence, the researcher utilised the in-depth interview technique for better understanding the organisation context including operation, management and decision-making process in order to propose an appropriate solution to the problem.
- In the second part, the experiment through the operationalising of the proposed model using empirical data related to the case study is implemented to ensure that the model is practically worked and best

suited with the research questions. The qualitative data is transformed into quantitative data for further analysis using digital mixed methods (OHalloran et al. 2018).

4.8 Overview of Data Sources Used in the Study

The study used several data sources to understand the problem and proposed the model. In the first phase, electronic databases were used to study the literature followed by interviews with internal stakeholders of the chosen LG. Then, in the second phase, the texts from the various novel themes were employed to test the validity of the developed sentiment analysis tool. The tool has been trained and tested with predefined twitter data obtained from the National Research Council Canada (NRCC) (Mohammad and Turney 2013). Finally, in the third phase, the predefined twitter data from the NRCC were again used as the training data for the sentiment analysis model whilst the related twitter data related to the selected LG were used to test the data for the model in the sentiment analysis tool. Table 4.3 summaries the data sources used in this study.

Table 4.3: Data sources used in the study

Research Phase	**Data Source**
Phase I: Preliminary Study	Relevant publications in electronic databases. Interview with LG stakeholders (internal)
Phase II: Modelling	Text from Novel • The Adventures of Tom Sawyer (Author: Mark Twain) • Crime and Punishment (Author: Fyodor Dostoevsky) • (http://www.gutenberg.org/ebooks) Twitter data with predefined emotion • National Research Council Canada (NRCC) • (http://sentiment.nrc.ca/lexicons-for-research)

Phase III: Operationalising the Model	Twitter data with predefined emotion • National Research Council Canada (NRCC) • (http://sentiment.nrc.ca/lexicons-for-research) Twitter data related to the selected LG.

4.8.1 Data Protection

Research activity that uses personal data is subject to General Data Protection Regulation (GDPR). GDPR is a regulation in European Union (EU) law on data protection and privacy for citizens of the EU and the European Economic Area (GDPR 2018). When data was collected, this was prior to GDPR 2018. However, data collected was used in accordance with EU regulations and legislation prior to GDPR 2018.

Post GDPR, social media data performs are bond by GDPR and legislation governing data. Individual using Twitter have agreed to use of their data in the public domain. Local government have to abide by GDPR legislation and any data used will have to comply with EU regulations.

For this study, similar procedure was applied in which approval from the University Committee for Ethics in Research was obtained preceding the research activities and data collection processes.

Accordingly, the data collected during the interview session were anonymously used after gaining the consent from the participants. As for the Twitter data, it was mined from the Twitter public application programming interface (API) following the standard of data protection in storing, processing, and reporting. Since all data in this study was anonymised and privacy, this largely address data protection concerns.

4.9 Data Collection Techniques

The study implemented two types of data collection techniques: interview and empirical data (from Twitter).

4.9.1 Interview

The interviews with internal stakeholders of LG were conducted to understand the potential impact of BSD from a management perspective. The details description and analysis of the data collected from the interview are discussed in Chapter Five.

4.9.2 Twitter Data

The longitudinal study was applied in this research to identify the changes and developments of the BSD contents generated from the interaction between citizens and government in social media. Thirteen months of data collection attempt was conducted through Twitter.

Launched in 2006, Twitter, one of the popular social media platforms, facilitates online interaction among social media users through short messages up to 140 characters called tweet. Recently, selected users are allowed to send a single tweet up to 280 characters (Rosen and Ihara 2017). Tweets may consist of text, URL pages, images, hashtag and mentions to other users. The hashtag (a word preceded with the symbol “#”) is used to highlight certain issues or trending topics. The mentions (username preceded with the symbol “@”) are included to direct the tweet to the mentioned users. A tweet begins with mention, which can only be seen by the mention users, but a tweet containing mention in the middle or end of the text is broadcast to all followers (Cha et al. 2010).

Twitter users subscribe to (or “follow”) other users to receive status updates and develop social connections to interested people, groups or organisations. The Twitter users interact with each other by following other user’s posts, responding to other user’s tweets or forwarding the interesting tweets by retweeting them. These interaction patterns contain several types of networks such as follower networks, retweet networks and mention networks (Cha et al. 2010) which can be analysed using network analysis algorithms to measure the influence of the user and social roles on the Twitter social network. On the other hand, Twitter data are rich with information that can be analysed using content analysis to identify the discussions topics and sentiment of users towards certain issues.

4.10 Research Process

The research process of this study is divided into four phases as shown in Figure 4.2 . Each phase is elaborated, and the analysis techniques of each phase are discussed.

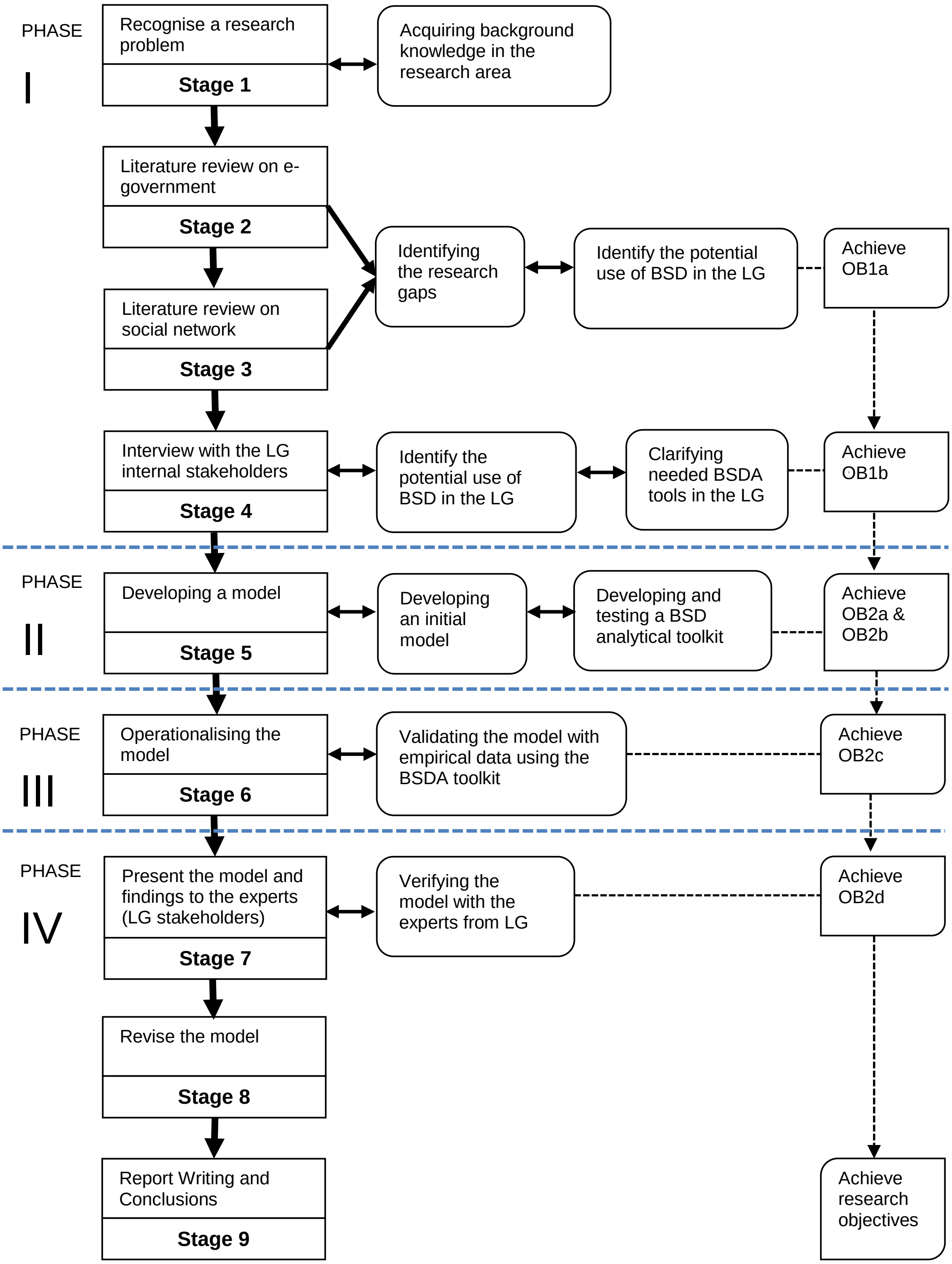

Figure 4.2: Research Process

4.10.1 Phase I: The initial study

This phase begins by exploring the literature related to e-government and social media network. The study extracted materials from research articles published in refereed journals. The theories, models and current research issues from the articles were collated, analysed and summarised.

Then, the interview sessions with the internal stakeholders of the selected LG were conducted to understand the operation, management and future planning of the organisation from the management perspectives. The qualitative thematic analysis was used to analyse the data by identifying the themes from the transcribed text.

4.10.2 Phase II: Developing a Model

In the second phase, the model was developed based on the findings from the previous phase. A set of analytical tools to operationalising the model was also developed and tested in this phase. The developed and tested tools were used in the next phase.

4.10.3 Phase III: Operationalising the Model

The proposed model from the second phase was operationalised in this phase using the empirical data. The longitudinal data gathered from the LG were mined, collected, and collated. The data were then analysed using a range of analytical tools and techniques. The findings were recorded, compared and reported. Overview of the data analysis techniques applied in this phase is described in the following subsections.

4.10.3.1 Content Analysis

The study applied content analysis to gain insight from the BSD accumulated from the selected LG. The content analysis was used to extract themes and topics from the collection of texts by employing the term frequency and topic extraction techniques. The term frequency technique counts each term that has been used in the data collection. The topic extraction technique identifies the potential topic of discussion using the Latent Dirichlet Allocation (LDA) algorithm. The algorithm classifies the respective words according to the related topics.

4.10.3.2 Sentiment Analysis

Sentiment Analysis is a computational technique to analyse public opinions, perspectives and emotions regarding certain topic or subject of discussion (Liu 2010). According to Stieglitz and Dang-Xuan (2013a), sentiment analysis refers to a methodical analysis of written text or speech using computer technology to extract individual feeling. This technique has become popular in determining subjective information such as opinion and attitudes that are expressed in texts (Mäntylä et al. 2018). The sentiment can be classified into positive, negative or neutral feeling (Bravo-Marquez et al. 2014; Tunggawan and Soelistio 2016; Pak and Paroubek 2010; Pang and Lee

2008). For instance, a positive sentiment could be extracted from the sentence "Great hotel to stay!" while "The customer service is horrible" conveys a negative sentiment. The neutral sentiment is showing no feeling such as "We are walking home".

In the nutshell, the term sentiment analysis refers to a classification of a piece of writing into positive, negative or neutral connotation using a systematic computational process. The written text or speech excerpts representing opinions or feedback to express the authors' or speakers' emotion towards a certain issue or target to create structure and actionable knowledge to assist in a decision-making process. The study of the relationship between information diffusion and sentiment of users in the political context found that the dissemination of emotional messages is more likely to be faster than neutral text (Stieglitz and Dang-Xuan 2013a). The sentiment analysis has been used widely in private sector to analyse customers' opinions in the online product reviews and recently, it has been used to analyse texts from the social media (Mäntylä et al. 2018).

Two popular approaches to implement the sentiment analysis are lexicon-based and machine learning (van Atteveldt et al. 2008). The lexicon-based approach uses corpus containing words in positive and negative polarities. The machine learning approach can be applied using different machine learning algorithms either supervised or unsupervised machine learning techniques. The supervised machine learning approach uses a set of data to train the model before examining the real dataset. The input from the training dataset will be used by the model to learn the possible value of polarity for each sentence or word. With the set of training dataset, the trained model is ready to process the actual dataset.

The sentiment analysis tool in this study has been developed using data mining software called RapidMiner Studio Educational version. The core of RapidMiner is open-source with limited functionality but the RapidMiner Studio Educational version has facilities to access the same functions as the commercial version. A supervised machine learning method has been applied to this sentiment analysis tool where the model is trained to determine six different emotions as predefined in the training dataset.

4.10.3.3 Social Network Analysis

Social network analysis (SNA) is a discipline of social science that seeks to make sense of the patterns or regularities in relationships across the social networks (Caulfield 2013). Other authors define SNA as a method that investigates the relationships between the social actors through analysis of the structure of the social network, with the use of relational data (Giannakis 2012). Moreover, SNA is defined as a technique that is increasingly used to identify the way information flows between different individuals, organisations, or entities (Benton and Fernández Fernández 2014). Nevertheless, the most important goal of SNA is detecting and interpreting patterns of social ties among actors (de Nooy et al. 2011)

The key objective of studying a social network is to understand the relationships among social actors which generate patterns of relations. The patterns can be examined to advance our knowledge in terms of the implications of these relationships and how the patterns of relations allocate resources in social network structure (Wellman 1988; de Nooy et al. 2011; Wasserman and Faust 1994). Furthermore, the patterns of relations also determined the characteristics and behaviours of the actors or known as a social role. Knowing the social roles in network structure can accelerate the opportunities, limitations, and threats related to it (Mislove et al. 2007).

The SNA has been applied to measure the social roles in many types of the social networks such as leadership (Fransen et al. 2015; Benton and Fernández Fernández 2014), authors (Hoffmann et al. 2015), public health (Valente and Pitts 2017), and sport management networks (Quatman and Chelladurai 2008)

In this study, SNA is defined as a technique to investigate the structure and pattern of the social network in the online community network focusing on the social media network. The SNA uses analytics network metric to evaluate the network structure and identify the position of actors within a network (Fuger et al. 2017).

4.10.4 Phase IV: Model Verification

The proposed BSDA model was reviewed by experts from the LG internal stakeholders. The feedback from the experts was used to improve the model. A report was prepared to record the research procedures, findings, conclusions and future research recommendations. Finally, the overall mixed-method strategy adopted for this research is summarised in Figure 4.2. As can be seen from the figure, the overall research strategy is derived from three directions involving selection and justification of research methods for data collection a) using qualitative interview technique to identify the issues; b) utilizing qualitative empirical data from Twitter to operationalising the model; and c) using qualitative expert's reviews approaches to verify the model.

4.11 Chapter Summary

This chapter provides an overview of the underlying philosophical assumptions of the research and methodological considerations of the study. The pragmatic research paradigm is used to understand the research phenomena and followed by the research approach, strategy and method of data collections. The mixed-methods approach is mainly employed with case study strategy. The data collections methods were conducted through semi-structured interviews and qualitative data mined from social media (Twitter). Moreover, this chapter presents the analysis techniques implemented in this study.

5

CHAPTER 5: CASE STUDY

5.1 Introduction

The previous chapter outlined the methodological consideration of this study. This chapter introduces the background of the UK local government before focusing on the selected council to be used as a case study in this research. The findings of the case study are also explained in this chapter. The quantitative data gathered from the interviews with the internal stakeholders of the selected local council were analysed using thematic analysis to identify the issues and use of BSD in the local level government.

5.2 Context Background

Local government is a public administrative body for a specific region of town, city or state that has the authority to control and manage a particular geographic area. In the UK, there are 418 local authorities with 2.06 million employees (Office for National Statistics 2018). The biggest number of LGs in the UK is England with 353 local authorities, followed by Scotland with 32 and 22 unitary authorities respectively, and North Ireland with 11 district councils. The English local authorities comprised of 27 counties and 201 district councils as well as 125 unitary authorities (Sandford and Mark Sandford 2018). One of the unitary authorities known as the metropolitan district is responsible for all the LG functions within its region. Table 5.1 lists the metropolitan districts in England.

Table 5.1: Metropolitan districts in England

Metropolitan county	Metropolitan districts
Greater Manchester	Manchester, Bolton, Bury, Oldham, Rochdale, Salford, Stockport, Tameside, Trafford, Wigan
Merseyside	Liverpool, Knowsley, St Helens, Sefton, Wirral
South Yorkshire	Sheffield, Barnsley, Doncaster, Rotherham
Tyne and Wear	Newcastle upon Tyne, Gateshead, South Tyneside, North Tyneside, Sunderland
West Midlands	Birmingham, Coventry, Dudley, Sandwell, Solihull, Walsall, Wolverhampton
West Yorkshire	Leeds, Bradford, Calderdale, Kirklees, Wakefield

This study examined one of the metropolitan districts that represent unitary authorities that carry out all the government functions and services offered to the citizen in their regional area. There are many issues and challenges faced by the local council in order to manage the district up to a standard level. It can be clearly seen that the population of the citizens of the metropolitan district are larger than the other councils. Moreover, citizens of the metropolitan districts are actively using social media compared to other local areas. For example, the selected local council in this study has more than 20,000 Twitter Followers who actively post more than 25,000 messages on Twitter.

The selected local council is one of the largest metropolitan districts in England with more than 500,000 populations and has grown at a rate of 0.6 per cent (Office for National Statistics 2018). The population is dominated by the young age groups with 70 per cent aged less than 50 years old. The district has nearly 200,000 households and most of them possess its own homes. There are 90 elected councillors representing 30 wards in the district led by the District Lord Mayor. The Chief Executive Officer leads the council office that has more than 3000 employees.

5.3 Qualitative Data Analysis

5.3.1 Data Collection Process

The qualitative data was collected through semi-structured interviews with the selected LG internal stakeholders to understand the decision-making process and the use of social media in the LG. The initial meeting with four representatives of the selected LG management team was conducted to introduce the research background. This was followed by nine interview sessions. The interviewees, who are the experts in LG, were suggested by the LG management personnel based on two criteria; (i) the person who involved in the decision-making process from different departments and (ii) the person who involved in the LG social media channel. Most of the experts are leading the departments and familiar with the decision-making processes in the LG.

Each semi-structured interview session lasted around one to two hours. The interviewees were required to answer questions related to the LG decision-making process, and LG engagement with citizens in enhancing the decision-making process as well as to offer better public services. The interview guidelines and the corresponding questions can be referred to in Appendix C. The interviews were audio recorded and transcribed following permission from the participants. The interviewees comprised of one Assistant Director of Policy, Programmes and Change, five Managers from various departments, two Senior Officers and one new Officer. Further details of the interviewees are shown in Table 5.2.

Table 5.2: List of interviewees

ID	Position
SO1	Senior Officer
M1	Manager
AD1	Assistant Director
SO2	Senior Officer
O1	Officer
M2	Manager
M3	Manager
M4	Manager
M5	Manager

The main objective of conducting the interviews is to understand the council operation and decision-making process. It is related to how the BSD can be used by the council to improve decision-making process for improving services to citizen and operational issues. The interviews aim to identify and answer several questions including:

(1) What are the main issues in LG?

(2) How does the decision-making process being implemented in the LG?

(3) How does LG acquire feedback from their citizens?

(4) How the LG used social media to engage their citizens in the decision-making process,

(5) How the LG utilised its BSD for a better understanding of citizens' needs and expectations.

5.3.2 Data Analysis Process

Using the thematic analysis technique, the data were analysed in six stages (Braun and Clarke 2006; Braun and Clarke 2013). In the first stage, the researcher transcribed all the interviews and familiarised with the data. The initial coding was performed in the second stage by using the NVivo software application, whilst searching for the relevant themes was conducted in the third stage. In stage four, after refining and grouping, some of the themes were deleted while others were collapsed into each other. Next, in stage five, the themes were defined and named defining and naming as presented in Table 5.3. Finally, in stage six, the report was generated.

Table 5.3: Themes and sub-themes

Theme	Sub-themes
A. Council Background	A.1 Budget and main issues A.2 Council Plan A.3 Social media team
B. Decision-Making Process	B.1 Decision-making process B.2 Understanding the problem B.3 Information for decision-making B.4 Data for decision-making
C. Citizen Consultation and Feedback	C.1 Citizen consultations C.2 Citizen feedback C.3 Social Media feedback C.4 Feedback respond processes
D. Social media in the Council	D.1 Promoting/campaign/broadcasting D.2 Potential use of social media D.3 Young generation
E. Channel of Communications	E.1 Digital channel of communication E.2 Social Media channel of communication E.3 Council other channel of communication
F. Data	F.1 Data collection in the Council F.2 Data analysis
G. Social Media Data Analysis	G.1 Council requests G.2 Content Analysis G.3 Topic of conversation G.4 Social Network Analysis

5.3.3 Council Background

This theme describes the background of the selected Council for the case study in this research. There are three sub-themes extracted from the data namely budget and main issues, council plan, and social media team. Table 5.4 summarises the sub-themes.

Table 5.4: Sub-themes of Council Background

Theme	Sub-themes
A. Council Background	A.1 Budget and main issues A.2 Council plan A.3 Social media team

5.3.3.1 A.1 Budget and main issues

The selected LG is a large organisation that offers various services to citizens with an annual budget up to 400 million pounds as stated by one of the interviewees:

> *"We're a huge organisation with a 390-million-pound budget, delivering thousands of different services to hundreds and thousands of different people on the daily bases." AD1*

The cost to manage the country is increasing over the years which has affected the general budget of the Central government. Thus, the Central government has reduced the yearly budget granted to the local councils in order to survive for the country. The budget shrinking creates new challenges for the local councils to maintain the quality of public services. These challenges were reported by most of the interviewees. The following are some of the examples:

> *"The council know we've got a 20% cut next year so therefore that means for your budget you've got to lose so much money." SO2*

> *"The fact that the council needs to change, and we can't do everything that we've always done. Urmm so it's not like we want a big, come and tell us what you need, garish because we've gotten blank chequebook and we can just do whatever so that's we, we can't go there because we're not in that world we've never have been but definitely not in that world, now." AD1*

The local council incomes come from different sources such as council taxes, fees and charges, borrowing and investments, and other government grants (Department for Communities and Local Government 2017). Historically, the Council had received external grants to manage the district. Unfortunately, the application for such grants is getting harder in recent years that make it more challenging for the council to manage all the services up to the standard level. This issue was highlighted by one of the managers as follows:

> *"What I would say also to that urm is in experience is that in from probably 2000, 2000 to urmm 2011, the Council was very good at bringing in external money (urm) from largely government ground, Trust Funds, even private sector and certainly from Europe urmm*

that though, the majority I would say are those kinds of funded things are now disappeared so it's making it more difficult, much more difficult." M2

Subsequently, the local council has reorganised their planning and operations strategies to be more creative in identifying alternatives to maintain good public services. One of the new strategies is to collaborate with external organisations that have the same objectives and visions, as illustrated in the following example:

"The biggest challenge for the local authorities we don't have resources that we have previously. So, what we have to rely on is working across the partners and coming out with the shared agenda and we got the shared priority, the shared the vision, and we need to then carrying [sic] on to share delivering, that's the challenges." M3

5.3.3.2 A.2 Council plan

A "Council New Deal Plan" drives a direction of the council and the general plan of the district including strategic, service and digital plans. This is clarified as the followings:

"Where do we plan is usually come from our council plan so there's council overall, Council's New Deal plan, if you check on the website, there's something called New Deal so that's what called the overall arching direction of the council comes to." M1

"It used to be called New Deal for the district and they've sort of did everything on that and that's a document that usually publishes September late September-October time." SO2

"What the district plan gives… give us the strategic plan and also help then the policy state and direction as well." M3

"We then got something known as a district plan, which universities and colleges we've been working towards." M1

"We have something known as a digital plan so the digital plan is done by my director, someone known as Mr X and he provides sort of digital, sort of strategy on what needs to go, what's a need to happen going forward." M1

5.3.3.3 A.3 Social media team

A special team was developed by the council to manage public responses in the social media channels. The team is responsible to improve government-citizen interaction using social media and other digital channels. This is highlighted by one of the interviewees:

"We do have like a regular work group that gets together. It's leads by myself but attended by people who use social media and another digital channel across the council. We will get together and when we talk about something up on coming channels, we'll talk about some of the changes to existing channels." SO1

5.3.4 Decision-Making Process

This theme discusses the decision-making procedures in the local council that relate to public services. The sub-themes involved are decision-making process, understanding the problem, information for decision-making and data for decision-making, as summarised in Table 5.5.

Table 5.5: Decision-making process sub-themes

Theme	Sub-themes
A. Decision-Making Process	B.1 Decision-making process B.2 Understanding the problem B.3 Information for decision-making B.4 Data for decision-making

5.3.4.1 B.1 Decision-making process

Decision-Making is an act or process of making an important decision collectively or individually. The local council decision-making process involves different teams based on the related issues and amount of budget. For example, the annual budget will involve all the elected members of the council and the policies are decided in the full councils meeting. Once the annual budget setting decision has been made, the council officers will be in charge of the implementation. These processes are explained in the given examples:

> *"The budget setting process so every year in February at full council, the councils which is the 90 elective members that make up the council urm set the budgets for the next financial year." AD1*

> *"First it goes to executive [sic], the councillors' executive, which is the cabinet, they make the decision, they has [sic] to ratify that full council.*

Officers don't make decision [sic]. So, officers informed policy, members make the decision, officers then implement the decision that been agreed." M3

"Full council make some decision on the big issues like urm the budget setting process urm and then the executive is responsible for urm policy decision and for urm delivery through the year…" AD1

"The policy direction set by members, they give us the envelope with the parameters. We have to then work on design how I could work. So, what we haven't got is, you need to give X them [sic] out…X happen sometimes… and you'll appreciate it. That's how decision sometimes can be made." M3

The council officers implemented the council plan based on the budget allocated to their departments. However, they can decide on the methods of delivering services to the citizens and related issues. This is indicated as follows:

"Once that budget set then officers are responsible for getting that money and spending it on the things that the budgets have been agreed by the full council." AD1

"The Strategic Directors have their own budget and they use their budget to deliver those outcomes … they're responsible for delivering that budget and providing the services that they think the citizens need." AD1

> *"The autonomy is that once an approach of policy said, and the financial envelope around the outcomes that we need to deliver our set... how in global delivery mean. How officers based on their professional judgment." M3*

5.3.4.2 B.2 Understanding the problem

A clear understanding of the problems to be solved is crucial in the decision-making process in order to regulate the right solutions for the right problems. The understanding process should take into consideration the needs and expectations of all citizens, entities affected by the related problem, and consequences of the decision to the citizens and the environment. All information related to these issues must be carefully identified, collected and analysed. This process is very time consuming and incurs a high cost. The processes will be more critical with limited resources and strict council policy. These issues were highlighted in the following interviews:

> *"You've got to understand urm what the problem is, who can deal with it, which is, which is kinda [sic] very difficult in a, in a, an age where austerity obviously being very hard to clean as in adult social care over the last kind of few years you know our budgets have been kind of urm slashed." M2*

> *"I think there's a consistency in wanting to understand urm the needs of people and the aspirations and designs. People here always see that and here's been a consistency of wanting to work in partnership*

both with people but with organisations across the district and beyond so that doesn't substantially shift." M4

"We need to understand more about what's getting in the way and what's blocking citizens from doing the things they wanna [sic] do, on what needs on be met urm because we're absolutely about making sure that the people in this district get what, what they need." AD1

"In term of decision making, what they have to do in term of, they had to go and reprioritise the type of services based on residents need, projected needs, demand and pressure and each service area has been task with coming out with an assessment of what those currently meant are and the risks of actually saying we can't afford to do this." M3

"What should normally happen is as part of a policy review or service review or service development process, you would look at the implications, the risks, so one of the issues like you would look at within that if we are going from weekly to fortnightly is what you mine mental risks as well." M3

5.3.4.3 B.3 Information for decision-making

Good decision-making comes from the availability of good information provided to the decision-making team as mentioned by one of the managers:

> *"We can only make decisions, good decisions on good basic information urmm so as I said as a report is out, making sure that through that processes, understanding what's need to be changed or what's need to happen in people's life to affect change or to support them in a particular area care or service that you want." M2*

The council officers are responsible to prepare sufficient information related to the issue to be discussed in the council decision-making team. For example, a full case study including the background and risk assessment of the issue is presented to ensure that the decision-making team has a clear understanding of the problem. In certain cases, the officers should suggest alternative solutions to the problem be decided by the decision-making team. These are examples to illustrate this statement:

> *"My role is to work with urm officers and with the executive to develop the ideas that go into that budget setting process urrm and to look at urm intelligent around our demographics and the pressures we've got in organisation and the big priorities that urm our face and our citizens and come up with a plan that makes sure we priorities the money and spend it on the things that matter most and make the biggest difference." AD1*

> *"Officers are always to provide an option that have [sic] been risk assessed against those issues that I mentioned. I'll present them to*

members. Its members will make that decision in terms of whether that option will go forward or not." M3

"We have to give them full details business case has their optional appraisal against the public-sector duty." M3

"The way should work; we should give them an option list. So, we should give them a long list. Because what they would say is, at the start of the year, would be, we know base our projection, financial projection, this year we need to make X some out of saving. And the executive will look at that and look at the proportion against each of their priority areas." M3

"So, its officers have to come back with options and say we think these are areas that you could consider stopping in terms of the service provision however, these are the risks, these are the one that you have to consider providing added to strategy requirements or because they are important for the well-being of the district. We have to give them those options and is a long list of options with this is the most we have to do that and risks of not doing that is we have to face legal sought." M3

"Members get change [sic] to review and until say… yeah, okay… that list top six we have to. Not sure about those. Go away and come back with some alternatives or we might think at 20% cut on all of them. So, depending on how members feel based on the information we have

> *given and what's still we give, officers will then go away and then come out with plan B or plan C." M3*

5.3.4.4 B.4 Data for decision-making

Good information is required to support the decision-making team in the decision-making process. For that purpose, the council officers applied a range of techniques to collect public opinions on related issues to be discussed by the team. Among the techniques are face to face interviews, neighbourhood forums and personal chatting. However, these traditional ways of data collection have become costly and time-consuming. Therefore, it is crucial to implement new methods through digital channels such as website and social media. This issue was pointed out by the following participants:

> *"I know that there is a great potential for the organisation using data more to inform a decision about how we run services and how we don't run services, how we re-priorities services and how we engage with people that precisely how we do that and what should we do that." SO1*

> *"There are neighbourhood officers who will have neighbourhood forums and will meet up with citizens. They are councillors themselves. So, a vital part of a local authority, they have their own council surgeries where they see face to face, meet where their residents are, and they have various channels of communications over here, what…what residents…what residents' needs." SO1*

“We have urmm different services do a consultation on different things so highway engineers putting in a new urm traffic calming system will consult the residents in that area before they go out and do it so that they make sure they’ve got all that.” AD1

“The biggest public consultation we do every year is the budget setting process…by the first week in December we will be publishing our budget proposal… and then from end November through to end of February that out for public consultation and my department is responsible for any consultation that happens, will pull that back in and collect that so there’ll be a kinda snap survey, electronic survey … and people can write in whatever and people can raise issues.” AD1

“There are some social media pages set up where they can feedback, people can send ideas, so it can be quite... it can be done formally in that respect...” SO2

“We’ve got feedback options on all the page on websites and also through social media not to the self-help team, to the customer services, get a lot of feedback coming through the contact centre. People tweeting and posting on Facebook and active so that help to give an understanding of what users’ needs.” SO1

“They’re going to the Parish Councils’ meeting and things. I did that on … we just went on our own back because it was just like there’s no budget to pay us overtime … but we wanted that information and it was like, it’s worth it. It’s worth me going for that hour that night just

you know because it gave me the information to make my job an awful lot easier well I'm prepared to do that but to do that properly, need resources..." SO2

5.3.5 Citizen Consultation and Feedback

This theme explores methods of consultation employed by the council in collecting citizens' feedback. Some of the methods are time-consuming and expensive to be implemented. The interviews explored these issues in several sub-themes as listed in Table 5.6.

Table 5.6: Sub-themes of Citizens consultation and feedback

Theme	Sub-themes
C. Citizen Consultation and Feedback	C.1 Citizen consultations C.2 Citizen feedback C.3 Social media feedback C.4 Feedback respond processes

5.3.5.1 C.1 Citizen Consultations

The council has conducted initial consultations with the citizens before deciding on an important issue. The biggest public consultation is issues related to the yearly budget setting. This was mentioned in the interviews as the followings:

"The biggest public consultation we do every year is the budget setting process…" AD1

"There'll be conversations around budget consultation starts at the beginning of December, for decision in February and implementation in April. Starts you know start work on it in summer." M4

> *"I think consultation around the budget is something that we're working on every year" AD1*

> *"That really is what seems to be driving things probably in the last maybe four years urmm so we have urm a budgetary consultation process which starts roughly about now." SO2*

The local council employed various methods of consultation to collect citizens' feedback such as forums, workshops, interviews, personal chatting, and surveys. For instance, a face-to-face discussion approaches including forums and interviews are applied with other techniques over digital channels. Through the direct forums, the councillors could experience from the real problem of the citizens and answer immediately to their questions. This is an example of such an assertion:

> *"There are neighbourhood officers who will have neighbourhood forums and will meet up with citizens. They are councillors themselves. So, a vital part of a local authority, they have their own council surgeries where they see face to face, meet where their residents are and they have various channels of communications over here, what…what residents…what residents' needs." SO1*

The council used workshops to update the public with current issues and challenges of district management including services, financial pressures and other related topics to increase citizen awareness. Since feedback from the citizens is valuable to improve the public services, the workshops also act as a medium to collect the general feedback. This is illustrated by the following example:

> *"We had workshops where we went into local communities, and those workshops were open treasuries where we talked about the challenges facing the council, we talked about some other services and demographic demand issues that we know that coming up, or the horizon, and we also talked about the financial pressures, not just for the council but the wider public sector, voluntary sector, and based on that we asked the members of public what would you prioritise if you're given the sort of blank canvas." M3*

A personal interview is one of the effective ways to talk to individuals or groups in getting their views on certain issues even though it is an expensive method. The followings are some of the issues and challenges regarding the use of personal interview:

> *"It would be urm interview going out, talking to either individuals or groups. We have urm we ask for both information on compliment and complains so you'd be getting you know a rounded view of, of, of other service." M2*

> *"Door knocking invaluable but it's so expensive." SO2*

> *"They're going to the Parish Councils' meeting and things. I did that on … we just went on our own back because it was just like there's no budget to pay us overtime … but we wanted that information and it*

> *was like, it's worth it. It's worth me going for that hour that night just you know because it gave me the information to make my job an awful lot easier well I'm prepared to do that but to do that properly, need resources." SO2*

5.3.5.2 C.2 Citizen Feedback

The councils were concerned about their citizens and had always welcomed all suggestions and feedback from the public for the betterment of their services. They received a lot of positives and negatives feedback from the citizens as indicated in these examples:

> *"There is a lot of criticisms but it's not 100% criticisms." SO1*

> *"There is a lot of appreciation for stuff that the council does. As well as negative and it's not all negatives." SO1*

However, the council was more focused on accomplishing the citizens' needs and expectations as they believed that by giving high priority to the customers, it will reflect their business objectives. This is depicted in the following responses:

> *"And also from the council's point of view, one of the big things that I am going keen on is encouraging the council to always think of users first, so think of making things that not necessary things that will help meet council business objectives but thing that would meet user*

needs, cause by meeting user needs, you are, in a lot of cases automatically can be meeting a business needs by doing that." SO1

"We need to understand more about what's getting in the way and what's blocking citizens from doing the things they wanna [sic] do, on what needs on be met urm because we're absolutely about making sure that the people in this district get what, what they need." AD1

"…we have demographic, we have, we have a sense of data, we have the ONS data releases that we get on our regular basis urmm so we're trying to understand our customers, we're trying to the citizens in the district." AD1

5.3.5.3 C.3 Social Media Feedback

Currently, the council receives feedback from the public through social media channels. Some feedback is directly addressed to the council by tagging or sending to the council social media channel's official account. However, some are not recognised by the council. This is mentioned during the interview:

"There are some social media pages set up where they can give feedback, people can send ideas, so it can be quite... it can be done formally in that respect." SO2

"We've got feedback options on all the page on websites and also through social media not to the self-help team, to the customer

services, get a lot of feedback coming through the contact centre. People tweeting and posting on Facebook and active so that help to give an understanding of what users' needs." SO1

"There are sometimes people report issues with the video so for instance, I can think of one particular instance where somebody reported a pothole and sometimes people would include a photograph and putting it on Facebook or Twitter so on particular person that included a video, and that was actually pretty useful, because we can actually get a better understanding of exactly where it was." SO1

"If they just put the video out there and not actually sending it to us, or tagging us in it, we never gonna [sic] know about it. That obviously applies to more than just videos, applies to anyone on the social media that's talking about an issue that is effected by the council but not actually directly at us." SO1

5.3.5.4 C.4 Feedback Respond Processes

In regular cases, the contact centre is responsible to handle feedback from the citizens. However, if the council received a high volume of complaints related to the same issue, it will be forwarded to the senior management of the particular service. This is highlighted in these responses:

"We have a contact centre that always monitors the tweets so they've got back to that person." O1

"It depends whether it's a one of or whether it's part of the series. So, taking an example of places recycle centre, with that, that was sent to the service manager and senior management within that service in case they need to know when their staffs are doing the good things. So, stuff like that, well, if it's noticed." SO1

"Sometimes things won't get flat up because the contact centres are mainly there just to deal with issues that meet resolutions, so often they might like or favourite, sometimes it's come in positive, but they might have the capacity to pass it on to the web service. So, when I see them, I will pass them to the relevant service." SO1

"In terms of negative stuff, it will leave to me to just respond and let it deal by the contact centre or if there are, if there is a high volume of criticism about something, then those will be not totally comprehensively quantified, but the contact centre might, for instance, keep in touch with the greeting team." SO1

"In a contact centre, they have a CRM, Customer Relations… Customer Relation Management system, I think it is… urmm, and that keeps a lot of enquiries that come in from each individual. So, they are able to provide reports and what has been enquired about there, also the web team are able to provide mechanism back to the digital teams." SO1

5.3.6 Social Media in the Council

The social media in the Council theme is categorized into four subthemes as shown in Table 5.7.

Table 5.7: Sub-themes of Social media used in the Council

Theme	Sub-themes
D. Social media in the Council	D.1 Social media used in the council D.2 Potential use of social media D.3 Young generation

5.3.6.1 D.1 Social media used in the Council

There are different purposes for using social media in the council. For example, the manager uses social media for directing the public to the main council website as mentioned below:

> *"What we try to achieve with it so with some post we are actually trying to direct people to a particular page on the website to fill in a form or take up a service, so the actual objective is clicked through from the post to the page." SO1*

> *"We're trying to get these messages out, here a link to our website and I use that on Twitter and also I filmed some interviews that have happened, and I've uploaded them on Facebook and Twitter with a link to our website for further information..." O1*

Other departments in the LG use social media to promote a specific support group. An example of the usage is as follows:

> *"We're using social media for peer support, so I got dementia or my partner got dementia, my mom got dementia. I am going through a really tough time supporting that person, or a tough time for myself. Urmm so I am still being able to kinda [sic] get my messages across on social media to, to kinda [sic] share that with people and have a sense of community around that social media model. Urmm so we can feel like it is almost like a virtual peer support group." M2*

The marketing team uses social media to promote awareness on certain issues or events as highlighted in these examples:

> *"With others, it's just like, it might be a video, who want to raise awareness about something, or for people to celebrate something or for them to enjoy something and it might actually tell you how many people have watched that video." SO1*

> *"It tends to be promoting the service… We use it more in a proactive way than a [sic] you know, and obviously, we do respond to certain people as well." SO2*

> *"We as marketing people we'll tend to have a look, when we know we've got a campaign going on urm we'll be heavily involved in that." SO2*

> *"I filmed in interviews with managers talking about Universal Credit and I've put that on Twitter and Facebook." O1*

5.3.6.2 D.2 Potential use of social media

The respondents agreed that the use of social media in the council can give impact to enhance understanding of their citizens' needs and expectations as mentioned in this example:

> *"If we can use social media it's some sort of analytical tool that would be brilliant." SO2*

A strategic way of analysing the council BSD is to identify the key people in the council social media communities. This strategy can assist the council in disseminating information to the citizens effectively. This is highlighted in this statement:

> *"If we knew who these sort of social media people are… and if there was a flood or something we can send it to them, they can send it to their network and say actually you know what avoid A650 for example because we know that they sort of key council, key XXX champion I would call them so yeah that would be really good." M1*

A social media data contains an online social network which can be used to push the council for a rapid response on the citizens' complaints and feedback. This is illustrated in the following example:

> *"And what would be really useful is, is when you doing the social media is knowing how many followers they have or how many urm say, followers. That that would be really good. That would tell you in*

terms of you know is it a hard priority or is it a low priority person so then if they have like I said, if it's someone famous called and say I want my bin picked up and put it on social media and say you know I put complaint to the XXX Council to pick my bin up, let's see how long it takes them. Actually, it took them three weeks to do it and we can say it gone up to three million people thinking owh God, three million people. Look how crap [sic] the council." M1

5.3.6.3 D.3 Young generation

Communication through social media is more popular among young generations. The council realised that in the next few years, this generation will be their main customers. This is mentioned during the interview:

"We're getting to new generations, I think even if, even if mom or dad or grandma don't have a smartphone then the kids did." AD1

"If you look at the Council profile in terms of age and stuff. We've got a lot of young people. Urmm… probably says between 7, 8,9,10 years old sort of thing are [sic] now becoming teenagers next 5, 6 years." M1

"I think the younger demographic are [sic] likely to be there and engaged, the younger demographic like to be on Snapchats looking and see what's happening." SO1

Thus, the council has to be creative in understanding this young generation in order to engage them in the council discussion. This issue is highlighted by one of the interviewees:

> *"I think a definite work needs to be done to engage younger people, which isn't easy when it's the council. Again, because it is all about what I mentioned earlier, the reasons people will connect with services are entertainments on social channels. A young person is far more likely to engage with the celebrity than they are with the local authority, particularly they're not even responsible to put things out because their dad put the bin out." SO1*

5.3.7 Channel of Communications

This theme describes the channel of communications employed by the council to interact with the citizens. Table 5.8 presents a list of sub-themes.

Table 5.8: Sub-themes of Channel of Communications

Theme	Sub-themes
E. Channel of Communications	E.1 Digital channel of communication E.2 Social media channel of communication E.3 Council other channel of communication

5.3.7.1 E.1 Digital channel of communication

The council provides a digital channel of communications such as website and blog with comprehensive information to encourage citizens to explore required information by themselves. This is pointed out by two of the interviewees:

> *"Through digital channels, encourage a citizen to self-serve, to be able to get information on main transactions with the council digitally themselves rather than having to go through more slower [sic], more labour intensive ways of ringing us up into the contact of centre." SO1*

> *"We've gone about that is we've made sure that our website is informative, we've done a lot of work on that urm to make it easy to read, to make us have clear messages, there's a, a mapping urm page on our website where you can see where you live and where you can go online for free access. All the access point there urm on the map on the website you can see in your area where you can get advice urmm we also signpost people we've got ..." O1*

5.3.7.2 E.2 Social media channel of communication

Other than website and blog, the council also used the social media channel to interact with the public. This channel disseminates council information and collects feedback from the citizens as stated in the following responses:

> *"We will be putting budget consultation on Twitter and also on Facebook, but we won't put budget consultation on Instagram." SO1*

> *"A few years back we had a massive Facebook campaign in particular issue." M3*

"We have a twitter account and we have a LinkedIn account, both which are used primarily broadcast within rather than to interact." M5

A special purpose of social media channel is also used for special groups of people as declared in this statement:

"One of those things we've done is we are trying I think called Rally Round… I don't know if you've ever heard of Rally Round? Rally Round is a social media based product which is like a kinda [sic] Facebook type of thing where urm we've got licenses to set, to give it, we've bought the license urm and we provide it to a voluntaries bodies or to individual that basically what it was, Rally Round is, is Rally Round a vulnerable person so what would you do is, pretend it's my you know my other way, urm "I feel that she's you know she's having the difficulties with particular part of her life." So, what you do is build a social media typed community around supporting that person." M2

5.3.7.3 E.3 Council other channel of communication

Besides the digital channel of communication, the council also uses the traditional methods of communication including newsletter, face to face forums, leaflets, posters, and telephone.

"I am the only one that is specialized in digital channels. Other officers do actually, it's not that they don't use digital channels, but they use for instance a colleague affidavit doesn't actual a newsletter for their audience that people are all in it to posters and leaflets." SO1

"There are actual events that take place like consultation events, neighbour forums, so council does actually have non-pro advice, or is it endlessly the telephones and the face to face contacts so there are ways that the council is a put-engage within the community and non-digital way." SO1

"We also go on local radio as well and just we've had a series of interviews over upcoming weeks with the different partners where we get the information out urm like a little slot on the radio informing people of the changes." SS

"How to target areas so I can post a campaign or urm I can possibly urmm you know have urm telephone and phonebook, you know the telephone, what they called telephone boxes. You can put posters in particular areas that will target those areas but that only something recently." O1

5.3.8 Data

This theme describes the data collection and data analysis by the council. Table 5.9 presents a list of sub-themes.

Table 5.9: Sub-themes of Data

Theme	Sub-themes
F. Data	F.1 Data collection in the Council F.2 Data analysis

5.3.8.1 F.1 Data Collection by the Council

The council has rich data collection from various sources including internal and external systems related to the council. This is highlighted by one of the managers:

> *"We collect all sort of data so like citizen data, we collect data from aaaaa stuff like a quality system, we collect footfall data, we collect Rev Bens which is Revenue Benefit data, we collect urmmm electro register data, urmmm environmental health data, planning data, anything you could think of in term of local authority, we collect that data." M1*

However, the council did not collect the data from the social media channel as suggested in this response:

> *"we don't do anything with social media information at the moment... Urmmm the only time we used urr we do monitor is… for security purposes reason not for data purposes." M1*

5.3.8.2 F.2 Data Analysis

Analysing the BSD of the local council is crucial to understand the publics' needs and expectations. However, the council do not have enough resources to analyse its BSD. Moreover, there is no available guidance to analyse the BSD. The issue is implied from these answers:

"Through my role, I will occasionally 'dip my toe' into social media and see what's happening but I haven't really got my finger on, for the fact that we don't really, we don't have a way of capturing, we don't have the capacity to analyse the data." SO1

"I do get questions about, you know, urm, how I might be able to help with analysing, or helping out with, urm, communicating but often just because of the workload and my help I just have to, as I've said, we don't have the capacity to do that so within my role, I don't have the capacity to be, urm, doing that sort of work with lots of services." SO1

"I'm asking my officers to look at trends in, in services. I'm looking at as you say, complains urm compliments. Just making sure that we've got a whole lot of information that builds up a holistic kind of view of a, of a particular service." M2

5.3.9 Social Media Data Analysis

This theme analyses the council needs and expectations on their social media data in four sub-themes as shown in Table 5.10.

Table 5.10: Sub-themes of Social Media Data Analysis

Theme	Sub-themes
G. Social Media Data Analysis	G.1 Council request G.2 Content analysis G.3 Topic of conversation G.4 Social network analysis

5.3.9.1 G.1 Council requests

The social media offers enormous opportunities to have a better understanding of citizens' needs and expectations. Thus, the council are interested to explore their social media data in order to understand the conversation in their social media network. These examples depict this concern:

> *"I'm more interested in your ability to mine social media than our own data." M4*

> *"So, for me, that's two things, the sort of formal data that we captured, we can be sometimes very rich but the issues that we have is the informal information, it's the conversations that taking [sic] place event waste management for example. People out there if you ask them what their view are, they'd say we pay our council tax, I want my bin collected every week. Now, there are other people that not even bothered." M3*

> *"What people worried about in their area, in their neighbourhood?" AD1*

> *"What's getting on people's skins, what are they prepared to just talk about on Facebook or tweet about or whatever it is. Urmmm so that we can, if we can address some of that or at least point it in the right direction. What area people urm shouting about, celebrating about." AD1*

The council realised that people are discussing issues related to the council and public services in the social media channel and they are interested to understand in detail. An example related to this is:

> *"I did see many individuals tweeting about it but there were hundreds of people there so where people taking pictures and saying owh this is where I am today or whatever so I think there's a little bit of urm what people celebrate, what people worried about urmm where are people talking about the council urm so that we can look at if the theme coming up." AD1*

However, the council has no clear guides on how to analyse its BSD. The issues are recorded during the interview sessions as follows:

> *"We don't spend a lot of time analysing actually we tend to use the hashtags to see which hashtags are relevant. We don't have a consistent way of analysing the use of hashtags, largely because the fact that Twitter itself doesn't provide analysis for it, the varies the third person doesn't provide us an analysis on hashtags. So, we just tend to do it." SO1*

5.3.9.2 G.2 Content Analysis

A proper way to analyse the council BSD can assist in the decision-making process. The council is interested to know the social media users' profiles, popular hashtags, discussion topics and people involved in the discussion. These examples illustrated the suggestion from the interviewees:

> *"I'd love to have the capacity to do would be to actually properly profile the audiences on these channels so to ensure that everything we do is relevant and timely and could use about time as well." SO1*

> *"…actually, we tend to use the hashtags to see which hashtags are relevant. We don't have a consistent way of analysing the use of hashtags, largely because the fact that Twitter itself doesn't provide analysis for it, the varies the third person doesn't provide us an analysis on hashtags. So, we just tend to do it." SO1*

> *"What people [sic] saying about the council? What are people saying about what's important to them? Are there particular issues that urm and you know, this the hard thing about working for the council in this arena so we, we have a duty of wellbeing. Count, it comes in everything." M4*

> *"One of the colleagues is working on a blog where we trigger issue so we publish something say plan to do X and this is what it will do, what's your views and then see what that triggers. Then we'll, we'll retweet that, put it on Facebook and see what, what, what it generates and also what we need to do as part of that was ask people what are the issues that they all concerned about, that we should be talking about*

to get people's views to generate that sort of urm informal feedback." M3

"I want to know what other demographics. What to certain social media effects… what, which demographics? So, is Facebook for an older audience or is Instagram for younger audience or…? That's what I'd like to know." O1

5.3.9.3 G.3 Topic of Conversation

The council can provide a better response if they know the topics being discussed among social media users. Precise solutions can be proposed for relevant issues. This is highlighted as examples below:

"If people are talking about diabetes a lot, we care about that. If they're talking about the state of the economy, we care about that… We can't change everything but we in an understanding what people health priorities are, that should shape our conversations about what we, about what we do." M4

"If you could identify an extract, your best resource on tomorrow but if you, if you could identify well, actually it's in a small pocket in XXX that there are massive chatter and tension and lots of stuff that is verging on hate crime but isn't hate crime. Then we would look to work with colleagues in other agencies." M4

> *"Brexit as an example so using social media to gage in community tension would be a good one." M4*

5.3.9.4 G.4 Social Network Analysis

Social media data contains rich information. Knowing the correct techniques to analyse the BSD can give new insight to the council and assist them in the decision-making process. The council is interested to know the behaviours and characteristics of the social media channels' users including those who engage in a particular issue, who are following who, and who are the influential people in the social network. Moreover, the council is also interested in the sentiment related to certain issues. These are illustrated in the following examples:

> *"It would be very useful to be able to analyse urmm the reach and engagement on specific hashtags." SO1*

> *"People express these types of concerns and these are the type people because in some cases, I don't know how you'll be able to define who's who but there should be a way of being able to take, filter that out, to tease that out." M3*

> *"…would want to know with the hashtag, I would want to know… how many people have used it, where those people are, how many people have seen and engaged with the tweet or tweets, plural collectively? This is not so much of quantity thing but also the sentiment that has*

been used with that hashtag and also any media been shared with the hashtag like photos and videos.” - SO1

“…who are the people that can have influence in different conversations around, around diabetes or whatever…” M4

“And what would be really useful is, is when you doing the social media is knowing how many followers they have or how many urm say, followers. That that [sic] would be really good. That would tell you in terms of you know is it a hard priority or is it a low priority person.” M1

5.4 Conclusion

A budget reduction from the central government is one of the main challenges faced by the local council. However, it is not a strong justification to reduce the quality of public services. Thus, the council must be creative in planning and managing strategies to understand citizens’ needs and expectations in order to utilise the available resources for optimum citizen satisfaction. One of the strategies is utilising internet technology in the government-citizen interaction in order to understand the public at a minimum cost. This interaction creates a new set of data known as BSD. The appropriate methods of analysing the BSD can give new insights to the local council.

5.5 Chapter Summary

In summary, this research applied a case study of one of the local councils in the United Kingdom. The local council was selected based on two criteria; (i) the Council is active in using social media as a medium of interaction with the citizens and (ii) the size of the organisation is reasonable which offers various services to the public.

The qualitative data from the nine interviews with internal stakeholders of the local council were analysed using thematic analysis. A number of interesting themes and sub-themes were extracted which include council background, decision-making process, citizen consultation and feedback, social media in the council, the channel of communications, data, and social media data analysis. The Chapter was closed with a conclusion of the main findings.

6

CHAPTER 6: DEVELOPING A MODEL

6.1 Introduction

This chapter proposes a BSDA model that was developed based on the findings from the literature reviews (Chapter Two and Chapter Three) and interviews with the LG internal stakeholders (Chapter Five). The chapter begins by summarising the literature reviews and findings from the case study followed by proposing and describing the components of the BSDA model.

6.2 Summary of the Literature Review

The literature reviews in Chapters Two and Three argue that the used of social media for e-government services is no longer an option, as it has been recognised as a necessity to be implemented in the government agencies. The new generation citizens specifically the young generations prefer to communicate through social media which are available 24/7 without barriers and with less protocol (Boyd and Ellison 2007). Currently, a survey in the United States shows that 95% of young adults have accessed to the internet and active in social media (Anderson and Jiang 2018). The same study reported that 30% of the respondents believe in the positive benefits of social media used in their daily life. These statistics show that the use of social media by future generation citizens is highly demanding. Thus, it is crucial for government at all levels including LG to adapt to this new way of interactions.

The government-citizen interactions through social media generate an enormous amount of data known as BSD that contains valuable insight to be extracted including online social relationships and structure. However, government authorities, in particular, the LGs have not yet utilised the availability of BSD due to the lack of proper ways on these types of data processing.

Scholars agreed that formal guidance on the BSD analysis techniques and methods could bring new impacts to organisations (Chang 2018; Tursunbayeva et al. 2017) Thus, researchers from various disciplines are exploring different techniques of analysing BSD and proposing methods to understand the content of discussion among social media users (Peng et al. 2018; Lee 2017; Agarwal and Vasant 2014). In business and marketing, for example, BSD has been used to understand consumers' behaviour and preferences of products and services (Rapp et al. 2013). Analysing these data could help businesses to advance and highly focus on the real needs and expectations of customers such as providing better customer services, improving marketing strategies and venturing in new business opportunities (Holsapple et al. 2014).

However, in the public sector, government agencies have not yet utilised these facilities due to the lack of proper guidance and policy. It is evidenced by previous research that analysing the content of BSD could benefit the local authorities especially in having a better understanding of citizens and improving public services. In addition, many studies proved that social media analytics could be used to analyse citizens' feedback and engagement with government services (Wan and Paris 2014; Hou and Lampe 2015; Haro-de-Rosario et al. 2018).

Advanced analytical techniques to analyse BSD including content, sentiment, and social network analyses (SNA) have been applied by business organisations to gain new insights. Content analysis is widely used to understand customers' feedback, whilst sentiment analysis is getting popular with social media technology and has been the current trend in understanding customers feeling towards certain products and services. SNA also has been applied in analysing network and relationships between customers to identify the social roles and understand the characteristics of the social network structure.

Although SNA has been applied in various contexts to identify social roles in the online social media network, the used of SNA in the public sector is yet to be discovered. Thus, a study on how to utilise SNA in the public sector especially in the LG is critical in order to understand the citizen needs and expectations.

6.3 Summary of the Case Study

The interviews with the LG internal stakeholders indicate that the decision-maker teams in government agencies need comprehensive information in the decision-making process to ensure that the team members can clearly understand the issues and respond to the right assumption. This information is prepared by the council officers who collect and analyse the citizens' feedback. Hence, various data collection techniques have been applied including interviews, survey, observation and community forum. All these methods involve a high cost to be implemented. Currently, the government experiences new challenges with the austerity of the yearly budget which imposed them to revise their current practice. Accordingly, an alternative of data collection methods which could minimise the cost has to be identified including the use of social media channels.

The implementation of social media in the LG could enhance government-citizens' interaction, increase public engagement and receive positive feedback from the citizens (Ellison and Hardey 2014; Skoric et al. 2016; Bonsón et al. 2015). This interaction generates an enormous amount of data called BSD. The BSD is available to be mined and analysed in order to understand the citizen needs and expectations towards public services. However, findings from the interviews show that the LG is struggling in analysing their BSD due to lack of resources and guides to process the data.

6.4 Conceptual Model

The conceptual model was developed based on the literature reviews presented in Chapters Two and Three together with the findings from the interview with LG stakeholders to provide a roadmap for this study.

The governments are consistently reviewing factors that contribute to the enhancement of the service quality continuous improvement and their perceptions including citizen satisfaction, information dissemination and future policy-making. The analysis of the citizens' feedback is the key source in understanding the citizens' satisfaction, enhancing government information dissemination and improving future planning for public policy implementation since they are the main customers of various public services.

The proposed BSDA model as illustrated in Figure 6.1 consists of three types of services namely service provision, service usage and future service improvement. The service provision aims to achieve customer satisfaction while service usage and future service improvement are targeted to increase the effectiveness of government information dissemination and future service improvement respectively.

In a seminal paper, Cardozo (1965) argues that customer satisfaction has a significant relationship with need and expectation. The customers' expectation influences their behaviour in determining products or services. Dissatisfaction in customer expectations may affect sales and risk of negative word-of-mouth campaign (Cardozo 1965). Building on this seminal work, satisfaction has been developed further and has been defined by scholars as personal feelings or individual emotion that are subjective towards certain situations as the prior expectation (Cleverley et al. 2017; Wixom and Todd 2005).

More recent research suggests that prior expectation and performance are the main factors that contribute to citizen satisfaction which was tested in the local and federal governments (Morgeson 2013). Reddick and Roy (2013) argue that the experience of dealing with e-government leads the citizens to continue using the services, increase engagement and take participation in future services. Moreover, a study of e-government services in Jordan highlights that knowing the actual needs, desires and expectations of citizens is the main driver to citizen satisfaction (Alawneh et al. 2013). Furthermore, the way governments manage and solve citizens' complaints would also contribute to citizen satisfaction (Istanbulluoglu 2017; Reddick and Roy 2013). Thus, citizens' feedback and reactions on the government services are a valuable input to enhance government understanding of citizen's need and expectations. Applying accurate analysis techniques could transform the available data in the LG into interesting insights and meaningful inputs to drive the decision-making teams for a better solution for the citizens' requests and issues.

Accordingly, the utilisation of the BSD analysis could exceed better impact on government services particularly in operation, communication and future policy-making. This can support the government aims to increase customer satisfaction, enhance the effective way of disseminating information and improve future policy-making. A range of tools and techniques for analysing BSD in the context of LG can be categorised into three groups: (1) Content analysis, (2) Network analysis and (3) Prediction.

The content analysis employs three different techniques; sentiment analysis, term frequency, and topics identification as to enable in-depth exploration of related matters. The sentiment analysis extracts emotion based on a combination of words used in the text (Pang and Lee 2008). The basic sentiments could be positive, negative or neutral to represent the feeling of the authors. Other than that, details emotions such as joy, sadness, anger, and disgust could also be identified using the sentiment analysis. The findings of sentiment analysis could be used by the government to understand the citizens' feeling towards their services or newly implemented policy.

The term frequency technique organises hashtags, user accounts and specific keywords requested by users in order to extract the most repeated words and identify the active users during the data collection stage. The most repeated words could represent the issues being discussed among the social media users that eventually could be used by the government to acknowledge active users for better future strategic planning.

The topic identification technique is utilised to understand the discussion topics among social media users. This technique classifies the content into similar themes to detect potential discussion topics. The selected words that are related to similar themes are then grouped together to represent the contents.

The findings from the content analysis processes represent the discussion topics themes and sentiments of citizens regarding a particular issue. These findings will become valuable inputs for LG to understand citizens' needs and expectations of LG services. Furthermore, LGs can improve their service quality when they know and understand the citizens' needs and expectations accurately. Thus, citizen satisfaction of government services could be increased, and the impact could be realised while managing the operation and service provisions of LG.

The second group of the analysis techniques is network analysis which can be applied to identify an existing or new group of participants in a social media network. The relationships between group members can be interpreted based on their conversations and participation such as skills, knowledge and influence on others. The characteristics of the group can also be determined by studying the behaviours of actors in the network. The network characteristics could give an overview of how the process of information dissemination occurs among participants in social media. Moreover, SNA tools such as UCINET or Pajek are available for analysing the social media network.

The implication on the management planning communications strategies can also be investigated to improve service usage in LG.

Finally, the third group of analysis known as predictive analysis can be implemented based on the collection of BSD and findings from the content and network analysis. Content analysis techniques can be used to predict the future events, locations and services might happen in the district. The real-world events and locations can be predicted based on the conversations and information sharing in the social media network. Moreover, the forecasting services needed by the public can be predicted using a set of statistical tests and tools. As a result, the prediction analysis could give an impact on the future policy-making and budget allocation strategy.

In a nutshell, the proposed conceptual model is used as a blueprint for empirical data collection and analysis as well as in assisting the establishment of a comprehensive overview of the BSDA model implementation in the context of the LG in the United Kingdom. The model was revised in Chapter 7 based on the findings from validation and verification processes.

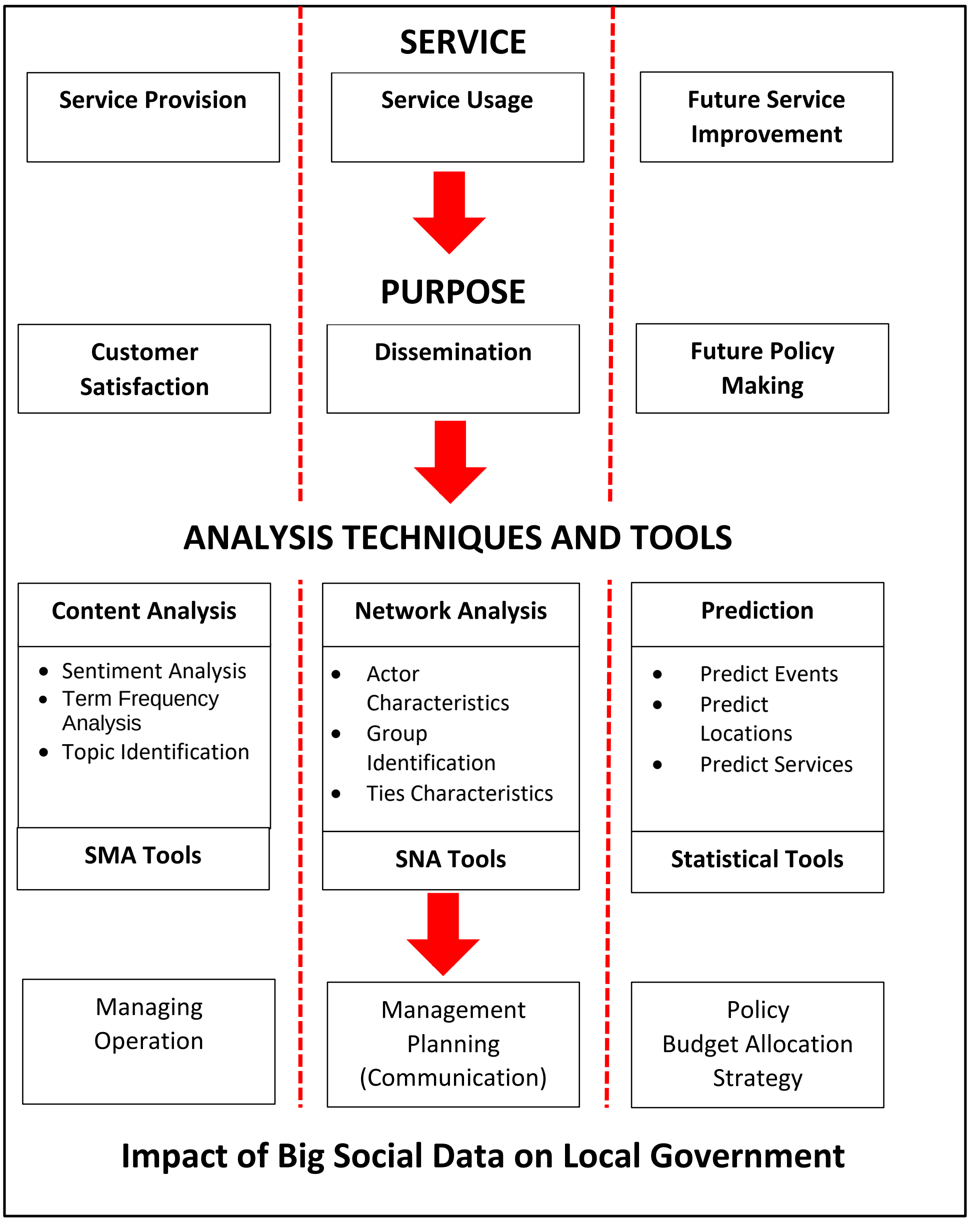

Figure 6.1: Conceptual Model

6.5 Chapter Summary

In summary, a BSDA model is proposed based on the findings from the study of literature in Chapters Two and Three, and interviews with the LG internal stakeholders. The literature reviews reveal a large potential of e-government using social media to enhance public services particularly in improving the government-citizen engagement and interaction. Moreover, citizen engagement through social media will generate BSD which contains valuable insight to be mined and analysed. However, the use of analytical techniques such as social media analytics and social network analysis is still lacking within the LG context.

Another interesting finding in this study comes from the interviews with the internal stakeholders which indicates that the decision-making processes in the LG need input from the citizens on the issues being discussed. The LG applies various methods to collect feedback from citizen including public forums, face-to-face interviews, survey, and community consultations. All these methods involved a high implementation cost and currently, the LG is facing austerity on their yearly budget. This situation creates new challenges to the LG management teams. At the same time, the LG is actively using the social media channel as a platform to interact with their citizens. The LG management teams believe that social media has the potential to complement the current method of collecting feedback from the citizen with minimum cost. However, they have not yet utilised the available BSD to understand their citizen needs and gain new insight due to the lack of proper way on how to process data. Thus, the proposed BSDA model in this study could assist LG in their decision-making process. The BSDA model contains a set of techniques and tools to accommodate three different services including service provision, service usage and future service improvement with the purpose to increase customer satisfaction, improve information dissemination and enhance future policy-making. These involve the managing operation, planning on communication management and devising policy budget allocation strategy.

7

CHAPTER 7: OPERATIONALISING THE MODEL

7.1 Introduction

The BSDA model developed in Chapter Six is based on empirical and secondary data collected from a LG in the UK. This chapter operationalises the proposed BSDA model with empirical data specifically Twitter data which is the type of the BSD. The chapter begins by describing the data collection procedures and software tools related to this process. The data mining and analysis processes using a set of developed analytical tools related to content, sentiment and social network analyses are evaluated. The original findings were presented to the local council for verification. Based on their feedback and comments, the proposed BSDA model in Chapter Six was revised and validated. The final operationalised model presented in Figure 7.14.

7.2 Analysing Big Social Data

The proposed BSDA model in Chapter Six classifies the analysis technique and tools into three groups including content analysis, network analysis and prediction. This study focuses on applying the content and network analyses techniques and tools. The content analysis was mainly used to test term frequency, topic identification and sentiment analysis while the network analysis was to examine actor identification and ties characteristics. This study also emphasises on a particular type of BSD which was generated through interaction between citizens and LG through Twitter. A set of analytical tools was developed to operationalise the proposed BSDA model using empirical data from a selected LG office in the UK.

Four different open source software was used to develop the analytical tools and empirically test the BSDA model. Firstly, the data collection and content analysis processes were utilised by using a data mining software called Konstanz Information Miner (KNIME). The KNIME is an open source platform for data analytics, reporting, visualisation and integration (Silipo and Mazanetz 2016). A workflow concept in KNIME integrates a few components through a series of nodes for data mining and machine learning using a friendly graphical interface. The basic workflow covers data preprocessing, modelling, data analysis and visualisation.

Secondly, another data mining software, RapidMiner Studio, was used to develop the sentiment analysis tool in this study. The core of RapidMiner is an open source with limited functionality but the RapidMiner Studio Educational version licence opens their access to full functions of the software within a limited period of time.

Finally, the social network analysis process was accomplished by using a combination of two open source software known as Pajek and Gephi. Based on the Windows program, Pajek is widely used for analysing and visualising network structures from small into the larger scale of networks with thousands of nodes (Mrvar and Batagelj 2016). On the other hand, Gephi has better features in visualising the social network and graphs.

7.2.1 Data

The data were collected on a daily basis using KNIME and stored in a database. The main twitter account of a selected LG (@bradfordmdc) had been used as a searching keyword in the data collection process. It means that only the tweets or retweets that include or mention “@bradfordmdc” were considered in this study. Since the Twitter user account name is not case-sensitive, other terms such as @BradfordMDc, @bradfordMDC or @BRADFORDMDC were also considered in the data collection. The KNIME workflow in Figure 7.1 shows a sample of the data collection process.

In total, 29,891 Twitter posts including tweets and retweets were mined from 01 March 2016 to 31 March 2017. The number of data was only a small sample from the actual amount of tweets as the Twitter public application programming interface (API) policy only allow the actual data collection to be mined up to one per cent and only published tweets of the past seven days were allowed to be retrieved using Twitter search API (Twitter 2017). Thus, these constraints limited the number of data used in this study but sufficient to test the proposed model (Wang et al. 2015). However, commercial feed such as Twitter Firehose allows full access to public tweets which is not applied in this study.

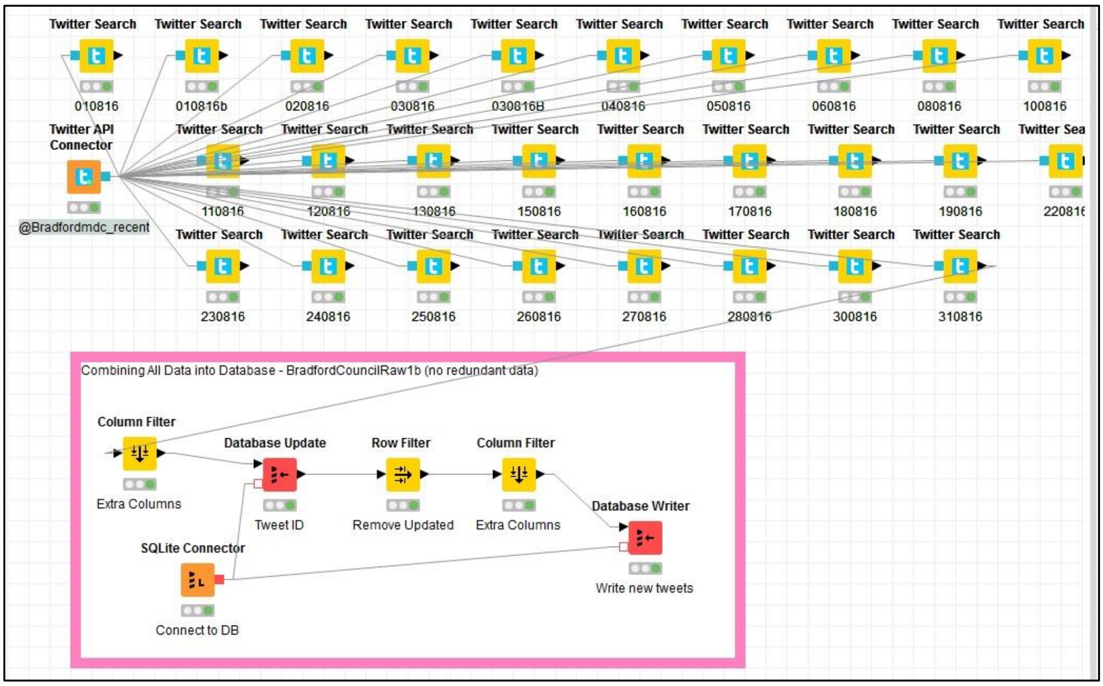

Figure 7.1: A workflow for the data collection process

The histogram in Figure 7.2 illustrates the number of monthly data collection including tweets and retweets over a period between March 2016 and March 2017. It can clearly be seen from the chart that in the first month of the data collection, nearly 2000 Twitter posts were mined but it decreased to 1500 in the following month before sharply rising to 2300 in the third month. The data collection started to decline in June until August 2016 and fluctuated between September and December 2016. Since January 2017, the data collection gradually increased and was at a peak at 3700 in March 2017. The overall trend of the number of monthly tweets and retweets between the citizens and LG had significantly increased from around 2000 tweets in March 2016 to almost double in March 2017. This figure indicated an increasing interest of the citizens to communicate with the LG through social media channel particularly through Twitter. The detailed number of monthly collected data can be referred to in Table 7.1. The data distribution between tweets and retweets are summarised in Figure 7.3. From the total of 29,891 data which had been collected, 34 per cent (10,032) were tweets and the remaining (19,859) were retweets.

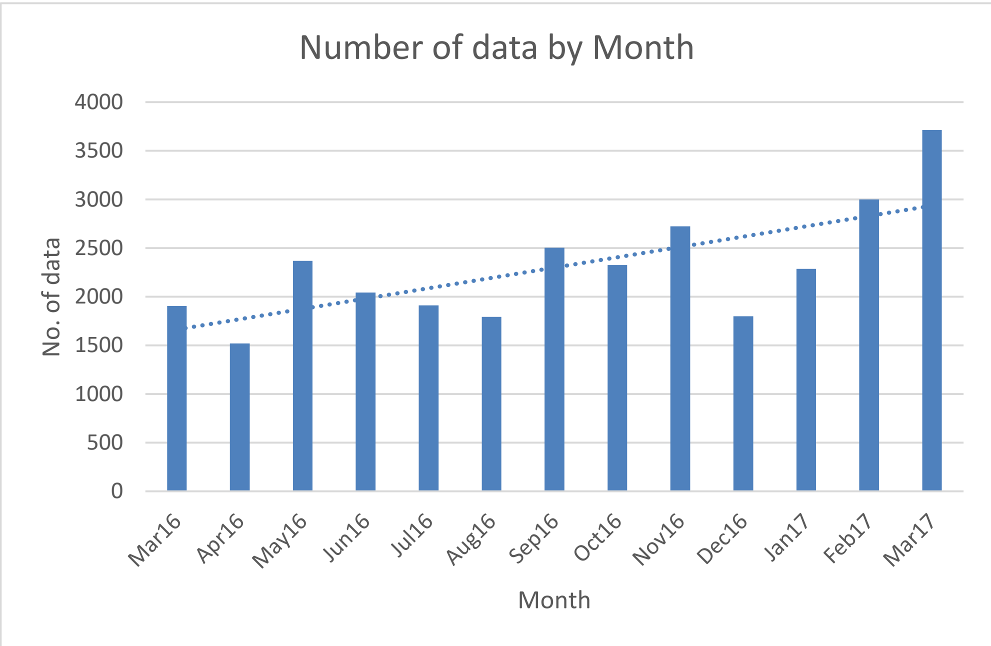

Figure 7.2: Number of Data

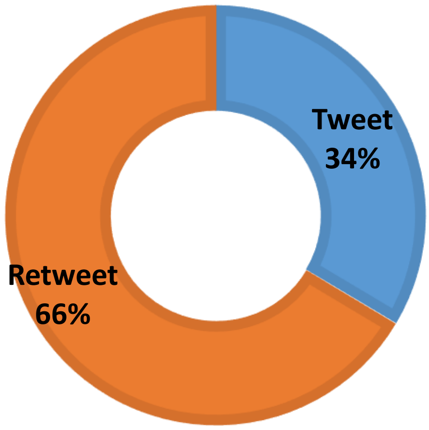

Figure 7.3: Tweets and Retweets Distribution in Data Collection

Table 7.1: Data distribution by month

Month	Tweet	Retweet	Total
Mar-16	824	1081	1905
Apr-16	587	934	1521
May-16	893	1476	2369
Jun-16	611	1430	2041
Jul-16	616	1296	1912
Aug-16	552	1239	1791
Sep-16	715	1789	2504
Oct-16	825	1502	2327
Nov-16	994	1729	2723
Dec-16	646	1153	1799
Jan-17	830	1456	2286
Feb-17	918	2081	2999
Mar-17	1021	2693	3714
Total	10032	19859	29891

7.2.2 Content Analysis

A content analysis tool was developed using KNIME to collect and analyse the BSD of the selected LG in the case study. In order to enhance our understanding and gain new insights from the data, the tool applied two levels of analysis.

The first level of analysis includes messages posted by the users including both tweets and retweets. This level of analysis is important to analyse the collection of text in order to identify the term frequency and discussion topics. The term frequency applied a numerical statistic to reflect the importance of the specific word in the collection of text. For example, words that are preceded by a hash sign (#) and at sign (@) or specific keywords assigned by the user could be analysed to understand the level of importance in the collection of a document. Another vital analysis is the topic extraction approach, which was used to analyse the text using Latent Dirichlet Allocation (LDA) methods to generate potential topics of discussion from the collection of tweets or retweets. The tools listed a certain number of related words in a group to form a certain topic. The number of words for each group and the number of topics to be generated were determined by the user.

The second level of analysis examines the users or authors of the text to understand and identify their characteristics and behaviours. The content analysis tool can determine the active users based on the frequency of tweets and retweets posted. Another function at this level is identifying the popular users who were actively being retweeted by other users. Figure 7.4 shows the main workflow of the content analysis tool and Table 7.2 summarises the main functions of the content analysis tool.

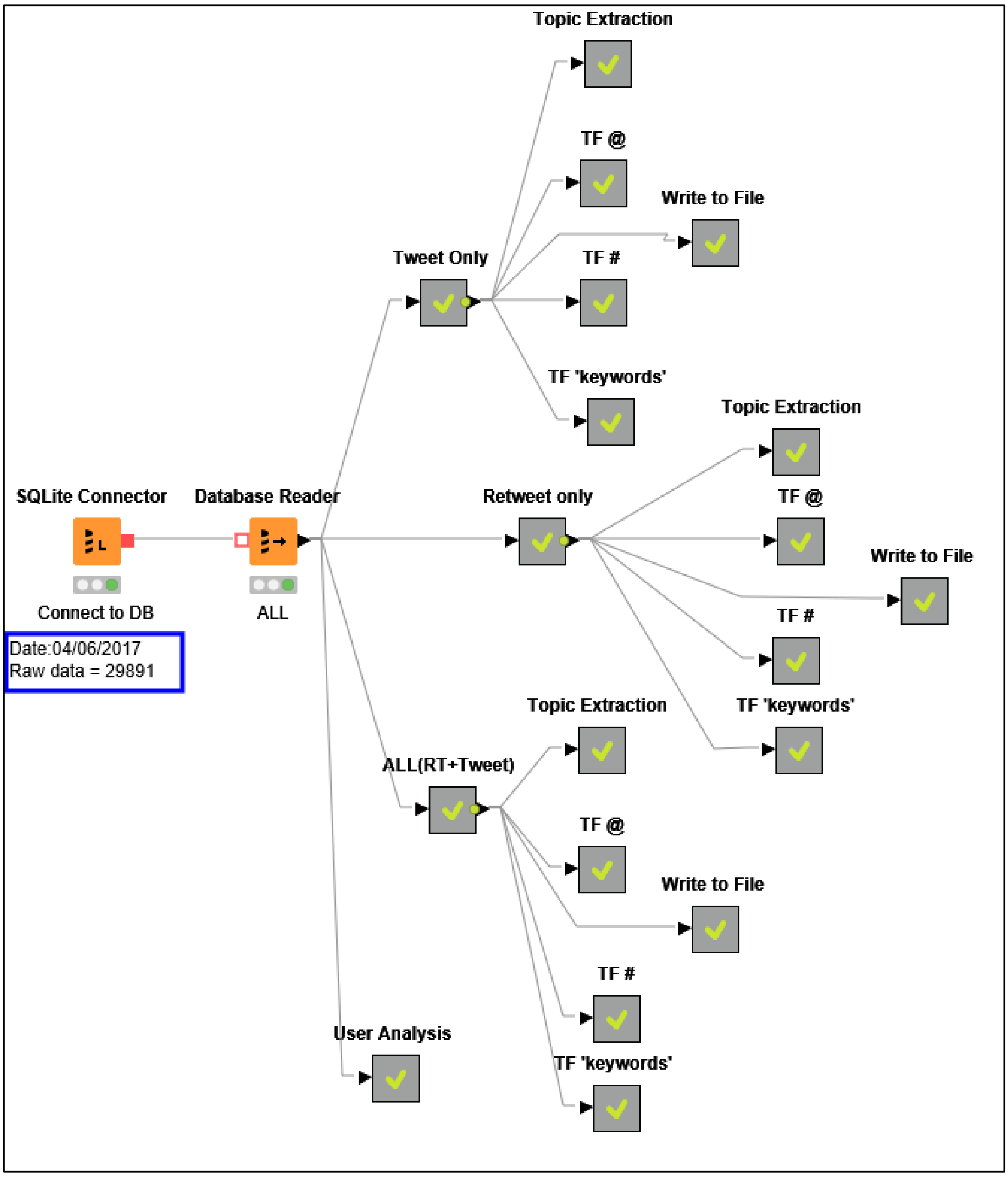

Figure 7.4: The Main Workflow of Content Analysis

Table 7.2: Main Functions of Content Analysis Tool

Functions	Description
Total Number of Tweets	Only the original tweets will be counted and listed.
Total Number of Retweets	Only the Retweets will be counted and listed.
Total Number of Tweets and Retweets	Count the total number of tweets and retweets
Topic Extraction	Identify the potential topic of discussions.
Popular Hashtag in Tweets	List the most popular hashtag in Tweets.
Popular Hashtag in Retweets	List the most popular hashtag in Retweets.
Popular Hashtag in all (Tweets and Retweets)	List the most popular hashtag in Tweets and Retweets
Popular user account mention in Tweets	List the most popular user account mention in Tweets.
Popular user account mention in Retweets	List the most popular user account mention in Retweets.
Popular user account mention in all (Tweets and Retweets)	List the most popular user account mention in Tweets and Retweets.
Words Analysis using keywords	Using keywords to identify popular words used in tweets, retweets or both.
User Analysis	Four types of users ranking: • Active users in Tweets and Retweets. • Active users in Tweets. • Active users in Retweets. • Popular Retweeted user.

7.2.2.1 Term Frequency Analysis

The term frequency analysis was categorised into three including words preceded by a hashtag ("#"), at ("@") symbols and specific keywords. The words preceded by hashtag represent the important term to be highlighted by the author and the words preceded by the "@" means that the author mentioned another user in the text. Table 7.3 presents a sample of the ten most popular hashtags in each month generated from the entire data collection. There are slightly different words appeared on the monthly list. Interestingly, the findings show that the hashtags used in LG community twitter highlights the name of city, location, events and activities that happen or will happen around the LG area.

Table 7.3: List of Popular Hashtags in Tweets and Retweets

Mar 2016	**Apr 2016**	**May 2016**	**Jun 2016**	**Jul 2016**
#Bradford	#Ilkley	#BLF2016	#Bradford	#BradfordFestival
#Ilkley	#Bradford	#bradfordvotes	#OrlandoShooting	#Bradford
#Keighley	#RegisterToVote	#Ilkley	#Ilkley	#LoveBradford
#SR16	#LGChallenge	#LE2016	#BradfordGXn	#BradfordGXn
#Shipley	#registertovote	#Bradford	#foxred	#GreatNort
#InternationalWomensDay	#CentenarySquare	#BradfordGXn	#labrador	#Ilkley
#bradford	#bigupbradford	#bigupbradford	#EURefResults	#BradfordClassic
#registertovote	#Saltaire	#peoplecanbd	#loveislove	#Somme100
#CartwrightHall	#BLF2016	#flooding	#lovebradford	#PokemonGoUK
#ListerPark	#bradford	#PCC2016	#WW1BD	#TheHairyBuilder
Aug 2016	**Sep 2016**	**Oct 2016**	**Nov 2016**	
#LoveBradford	#LoveBradford	#ForestofLight	#OurDay	
#Ilkley	#GreatNorthExpo2018	#Bradford	#takeoverchallenge	
#Bradford	#BradfordGXn	#TdY	#Bradford	
#Haven	#Ilkley	#ForestOfLight	#orange	
#MoreInCommon	#Bradford	#WOWBradford	#Ilkley	
#comms2point0jobs	#BradfordGXN	#LoveBradford	#TakeoverChallenge	
#Missingdog	#WTUCongress	#teambradford	#BDXmas	
#comms	#lovebradford	#bradford	#CllrAwards2016	
#dogsoftwitter	#bigupbradford	#orgreavejustice	#ourday	
#woofwoofwednesday	#mybradford	#YENExpo16	#Befikre	
Dec 2016	**Jan 2017**	**Feb 2017**	**Mar 2017**	
#communitystars	#Bradford	#CreativeStreetsBd	#InclusiveGrowth	
#Bradford	#HMD2017	#Bradford	#Bradford	
#bdxmas	#BradfordJobsHour	#LGBTBD	#CreativeStreetsBd	
#BDXmas	#SmearForSmear	#gritting	#bfdschoolawards	
#ToWalkInvisible	#gritting	#BeBoldForChange	#BradfordJobsHour	
#gritting	#CCPW	#BradfordPrideAwards	#IWD2017	
#TdY	#lgbtbd	#LGBTHM17	#bradford	
#SAVETHEDATE	#bettermentalwellbeing	#bradford	#colourful	
#Safeguarding	#bradford	#lgbtbd	#fountain	
#Saltaire	#Craven	#IWD2017	#lovebradford	

The term frequency analysis also can be applied separately to tweet and retweet data collection. For example, the separate analysis of hashtags between tweets and retweets for data collection in March 2016 is depicted in

Table 7.4. From the table, the findings slightly listed different terms in tweet and retweet, but some words appear in both lists. This indicates that some words with high frequency in tweets data collection are not necessarily important in the retweet data collection.

Although the main purpose of using the hashtag either for marketing, event promotion, or any other intentions is not obscure, the findings suggest that the monthly conversation among the LG social media community centres on the certain topic of discussion.

This study proves that automated content analysis can comprise of both the quantitative and statistical analysis (e.g. term frequency) even though for a large size document such as BSD. Further analysis of the data collection related to the topic of discussion can enhance our understanding of the LG BSD. Furthermore, the term frequency analysis can be used together with sentiment analysis in order to measure the relationship between the frequently used term and emotion of the social media users of LG digital community.

Table 7.4: Popular Hashtag in Tweet and Retweet (Mar 2016)

No.	Hashtag in Tweet	Frequency		Hashtag in Retweet	Frequency
1	**#Bradford**	33		**#Bradford**	86
2	#bradford	16		#Ilkley	47
3	**#Keighley**	8		**#Keighley**	33
4	#SpreadASmileDay	7		#SR16	27
5	#CSEDay16	6		#registertovote	25
6	**#Shipley**	6		#InternationalWomensDay	23
7	#Saltaire	5		#CartwrightHall	20
8	#floodaware	5		**#Shipley**	20
9	#spreadasmileday	5		#ListerPark	17
10	#Esholt	4		#NAW2016	16

The term frequency can also be applied to the specific keywords in order to understand the popularity and importance of certain keywords. The study examined three keywords in the first three months of the data collection. The findings are illustrated in Figure 7.5. From the bar chart, it can be seen that the word 'bin' shows a decreasing trend over the first three months of this study period, but the word 'recycle' shows an increase in the same period of study.

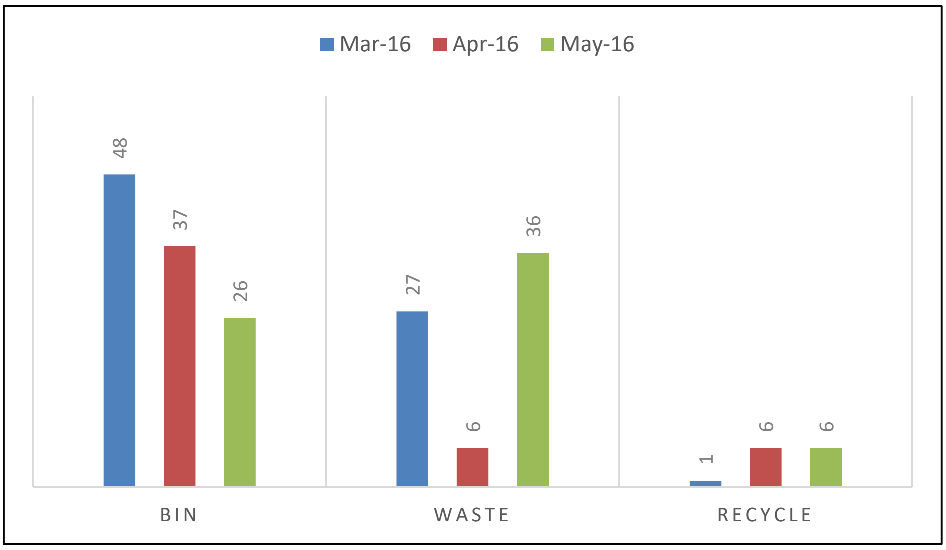

Figure 7.5: Keyword Frequency

Another term frequency analysis investigated in this study is the most popular user account mentioned in the data collection. It is not surprising that @user1, an official Twitter account of the selected LG used in this study, is placed at the top as shown in Table 7.5. The list of most popular user account mentioned in the data collection as listed in Table 7.5 can be used together with another analysis tool to enhance our understanding of the data and scenario related to it. For example, the most popular users account mentioned in tweets and retweets can be analysed together with social network analysis in order to understand the important users in the LG social media network.

Table 7.5: List of the most popular user account mentioned in Tweets

No.	User	Frequency		No.	User	Frequency
1	@user1	9360		26	@user26	54
2	@user2	315		27	@user27	54
3	@user3	304		28	@user28	54
4	@user4	286		29	@user29	53
5	@user5	283		30	@user30	52
6	@user6	231		31	@user31	51
7	@user7	118		32	@user32	50
8	@user8	98		33	@user33	50
9	@user9	96		34	@user34	48
10	@user10	96		35	@user35	48
11	@user11	92		36	@user36	48
12	@user12	88		37	@user37	48
13	@user13	83		38	@user38	47
14	@user14	82		39	@user39	46
15	@user15	77		40	@user40	46
16	@user16	77		41	@user41	46
17	@user17	74		42	@user42	45
18	@user18	71		43	@user43	42
19	@user19	70		44	@user44	42
20	@user20	62		45	@user45	41
21	@user21	62		46	@user46	41
22	@user22	62		47	@user47	41
23	@user23	61		48	@user48	40
24	@user24	57		49	@user49	39
25	@user25	56		50	@user50	39

7.2.2.2 Analysis of Discussion Topic

The discussion topic is extracted from the collection of tweets and retweets. At the word level, the content analysis tools classified all the related words to a certain topic in a group to assist the user in determining a potential topic of discussion. For example, in Table 7.6, the words are classified into five different groups. In each group, ten related words with frequency value are listed to guide the user in developing the appropriate topic of discussion. In March 2016, five groups of words were generated. According to the words listed in the first group, we could infer that the discussion is about bin collection issue.

Hence, it could conceivably be hypothesised that an automated content analysis tool can be applied to extract discussion topic from the BSD such as Twitter messages with a maximum of 140 characters using a topic model technique such as Latent Dirichlet Allocation (LDA). Furthermore, citizens' conversation in social media channel (e.g. Twitter) are using very basic words and less formal language.

Table 7.6: Topic Extraction

Group	Mar2016	frequency	Group	Apr2016	frequency	Group	May2016	frequency
1	bradfordmdc	881	1	bradfordmdc	870	1	bradfordmdc	867
1	http	430	1	http	640	1	http	670
1	bin	202	1	lgchalleng	301	1	bradford	263
1	bradford	129	1	regist	293	1	servic	168
1	council	108	1	vote	170	1	job	166
1	dai	91	1	tcobxpztgolzo	138	1	citi	155
1	thank	84	1	pamgos	134	1	vacanc	116
1	empti	76	1	bin	128	1	memori	113
1	team	72	1	thank	119	1	disast	112
1	collect	71	1	registertovot	110	1	31st	112
2	bradfordmdc	753	2	bradfordmdc	564	2	bradfordmdc	1153
2	http	498	2	http	411	2	http	451
2	bradford	209	2	ilklei	138	2	bradford	130
2	launch	76	2	shoot	132	2	kerstenengland	122
2	hall	74	2	grous	131	2	thank	116
2	charg	70	2	moor	128	2	council	106

2	fund	60	2	time	121	2	bradfordlitfest	102
2	garden	56	2	stoptheshoot	113	2	bradfordbreweri	92
2	wast	56	2	bradford	111	2	bin	90
2	call	54	2	visitor	98	2	garden	78
3	bradfordmdc	791	3	bradfordmdc	544	3	bradfordmdc	792
3	http	408	3	http	383	3	http	769
3	rspcaoffici	298	3	fantast	93	3	flood	194
3	bellaaadora	232	3	lgchalleng	82	3	bradford	160
3	rspcabradford	204	3	dai	72	3	local	156
3	animalwelfareuk	164	3	april	70	3	manag	146
3	help	140	3	happi	66	3	public	122
3	rspca	110	3	thank	61	3	event	121
3	disgust	98	3	birthdai	58	3	risk	114
3	bradford	96	3	bradford	58	3	consult	108
4	bradfordmdc	661	4	bradfordmdc	603	4	http	1007
4	http	524	4	http	469	4	bradfordmdc	958
4	bradford	165	4	bradford	395	4	bradford	561
4	flood	100	4	tanda	123	4	festiv	289
4	look	84	4	citi	99	4	literatur	286
4	ilklei	80	4	outsid	72	4	blf2016	250
4	road	78	4	hall	58	4	dai	192
4	citi	76	4	light	56	4	ilklei	131
4	keighlei	76	4	fridai	52	4	tcodve5nyfkfd	130
4	week	73	4	set	51	4	citi	121
5	bradfordmdc	662	5	bradfordmdc	423	5	bradfordmdc	920
5	http	598	5	http	275	5	http	817
5	bradford	207	5	ilklei	210	5	bradford	222
5	tcobxpztgolzo	82	5	moor	206	5	bradfordvot	193
5	vote	78	5	stoptheshoot	205	5	vote	176
5	regist	72	5	shoot	200	5	le2016	138
5	tanda	71	5	grous	199	5	ward	114
5	registertovot	70	5	take	154	5	regist	102
5	site	64	5	leav	135	5	elect	96
5	hall	61	5	bird	134	5	hold	88

Group	Jun2016	frequency	Group	July2016	frequency	Group	Aug2016	frequency
1	bradfordmdc	870	1	bradfordmdc	815	1	bradfordmdc	782
1	http	758	1	http	727	1	http	724
1	bradford	527	1	bradford	289	1	bradford	221
1	exhibit	282	1	bradfordfestiv	215	1	cityparkbd	145
1	bid	246	1	citi	116	1	comm	110

1	north	230	1	school	85	1	lovebradford	96
1	bradfordgxn	176	1	park	82	1	hall	88
1	citi	134	1	help	81	1	visitbradford	84
1	district	125	1	dai	79	1	road	78
1	host	106	1	festiv	78	1	citi	77
2	bradfordmdc	737	2	bradfordmdc	661	2	bradfordmdc	792
2	http	529	2	http	379	2	http	288
2	bradford	347	2	bradford	116	2	bradford	230
2	centenari	150	2	cityparkbd	92	2	haven	202
2	squar	150	2	children	88	2	bdcft	172
2	silenc	121	2	pleas	67	2	thecellartrust	172
2	findmegan2	116	2	silenc	64	2	partnership	146
2	foxr	116	2	fill	60	2	servic	109
2	labrador	116	2	minut	58	2	altern	82
2	nwdogrescu	116	2	thank	58	2	dai	75
3	bradfordmdc	903	3	http	790	3	bradfordmdc	600
3	http	499	3	bradfordmdc	747	3	http	552
3	park	140	3	bradford	292	3	bradford	190
3	bradford	121	3	exhibit	148	3	lovebradford	170
3	bin	98	3	north	140	3	health	162
3	citi	94	3	shortlist	120	3	mental	160
3	dai	88	3	lovebradford	119	3	peopl	148
3	support	87	3	host	104	3	support	138
3	celebr	80	3	bradfordgxn	101	3	servic	124
3	tanda	74	3	new	98	3	world	124
4	bradfordmdc	702	4	bradfordmdc	849	4	bradfordmdc	776
4	http	654	4	http	657	4	http	666
4	victim	296	4	bradfordfestiv	246	4	park	282
4	flag	283	4	thank	157	4	citi	244
4	shoot	274	4	school	128	4	cityparkbd	236
4	vigil	218	4	stori	106	4	team	166
4	citi	216	4	road	104	4	watch	140
4	ilklei	208	4	storifi	92	4	bradford	133
4	moor	196	4	bradford	81	4	event	127
4	orlandoshoot	190	4	includ	76	4	fanzon	115
5	bradfordmdc	820	5	bradfordmdc	712	5	bradfordmdc	584
5	http	552	5	http	493	5	http	624
5	vote	289	5	bradford	230	5	ilklei	270
5	bradford	288	5	citi	155	5	moor	260
5	referendum	128	5	read	124	5	shoot	240
5	district	107	5	park	112	5	grous	230
5	kerstenengland	107	5	car	78	5	stoptheshoot	166
5	poll	104	5	vintag	72	5	thank	102
5	eurefresult	100	5	develop	68	5	theatr	100
5	state	88	5	tanda	66	5	call	72

Group	Sep2016	frequency	Group	Oct2016	frequency	Group	Nov2016	frequency
1	bradfordmdc	1161	1	bradfordmdc	976	1	bradfordmdc	1074
1	http	1069	1	http	575	1	http	653
1	record	644	1	bdcft	175	1	bradford	251
1	lovebradford	606	1	bradford	165	1	takeoverchalleng	231
1	world	466	1	positivepracti1	140	1	peopl	165
1	cityparkbd	294	1	nhsengland	112	1	look	159
1	set	265	1	nhsbradford	110	1	cityparkbd	146
1	thursdai	230	1	congratul	98	1	ilklei	110
1	attempt	228	1	thank	78	1	event	109
1	bradford	225	1	award	74	1	shoot	102
2	bradfordmdc	875	2	bradfordmdc	852	2	bradfordmdc	1034
2	http	591	2	http	365	2	dai	458
2	bradford	252	2	orgreavejustic	134	2	http	451
2	lovebradford	234	2	thank	119	2	park	401
2	citi	227	2	bradford	114	2	orang	394
2	greatnorthexpo2018	220	2	rdunbar83	102	2	citi	383
2	park	219	2	uniofbradford	96	2	women	274
2	record	182	2	celebr	80	2	fountain	272
2	bradfordgxn	181	2	council	73	2	internat	260
2	world	174	2	inquiri	72	2	violenc	260
3	bradfordmdc	831	3	bradfordmdc	793	3	bradfordmdc	1091
3	http	594	3	http	688	3	http	447
3	ilklei	313	3	forestoflight	262	3	road	278
3	shoot	282	3	light	208	3	grit	188
3	grous	280	3	cityparkbd	178	3	gritter	150
3	stoptheshoot	280	3	bradford	165	3	bradford	134
3	moor	278	3	look	160	3	temperatur	112
3	call	181	3	start	137	3	tonight	103
3	bill	174	3	miss	135	3	drive	94
3	tcorwgkydr5ta	164	3	forest	126	3	rout	90
4	bradfordmdc	1091	4	bradfordmdc	867	4	bradfordmdc	1114
4	http	1069	4	http	495	4	http	604
4	greatnorthexpo2018	658	4	bradford	413	4	bradford	283
4	bradford	588	4	visitbradford	278	4	light	144
4	bid	364	4	cityparkbd	244	4	cityparkbd	125
4	bradfordgxn	309	4	tanda	190	4	bin	100
4	fridai	308	4	forestoflight	172	4	thank	95
4	support	294	4	event	132	4	school	88
4	north	238	4	weixinliang	108	4	bdxma	86
4	exhibit	235	4	look	60	4	week	80
5	bradfordmdc	970	5	bradfordmdc	1002	5	bradfordmdc	973
5	http	527	5	http	671	5	http	461
5	bradford	278	5	citi	380	5	bradford	310
5	district	83	5	park	330	5	council	130
5	park	83	5	forestoflight	320	5	bradfordcolleg	106

5	citi	79	5	dusk	238	5	thank	106
5	bin	72	5	bradford	235	5	tax	100
5	dynamomagician	72	5	week	214	5	help	93
5	vacanc	72	5	10pm	200	5	email	90
5	event	71	5	sundai	185	5	awar	84

Group	Dec2016	frequency	Group	Jan2017	frequency
1	bradfordmdc	794	1	bradfordmdc	786
1	http	381	1	http	443
1	bradford	192	1	bradford	201
1	christma	167	1	yorkshir	86
1	recycl	125	1	busi	74
1	bin	104	1	thank	68
1	communitystar	93	1	post	64
1	bdxma	78	1	fund	62
1	local	78	1	close	60
1	servic	74	1	excit	58
2	bradfordmdc	586	2	bradfordmdc	827
2	http	233	2	http	750
2	bfdcityoffilm	114	2	bradford	370
2	set	85	2	council	135
2	support	80	2	app	124
2	saltairewebsit	78	2	citi	123
2	pleas	75	2	cancer	114
2	roseandbrown	73	2	free	108
2	haworth	70	2	budget	104
2	invisibl	62	2	ag	103
3	bradfordmdc	770	3	bradfordmdc	836
3	http	357	3	http	539
3	council	200	3	bradford	164
3	budget	108	3	council	90
3	bradford	95	3	hmd2017	81
3	propos	94	3	holocaust	70
3	look	72	3	thank	69
3	monei	72	3	read	62
3	tax	72	3	hall	60
3	peopl	63	3	servic	59
4	bradfordmdc	688	4	bradfordmdc	1131
4	http	490	4	http	502
4	bradford	272	4	grit	348
4	2017	195	4	road	208
4	wypbradford	176	4	gritter	192
4	wypshiplei	146	4	bradford	137
4	amtrump4pres	144	4	district	97
4	tco	144	4	tonight	96

4	letouryorkshir	135	4	hall	95
4	nazshahbfd	128	4	week	90
5	bradfordmdc	682	5	bradfordmdc	844
5	http	349	5	http	810
5	grit	232	5	bradford	308
5	road	147	5	lgbtbd	160
5	tonight	119	5	job	142
5	bell	80	5	vacanc	134
5	gritter	76	5	access	122
5	temp	74	5	guid	108
5	forecast	68	5	award	103
5	citi	67	5	nomin	92

Group	Feb2017	frequency	Group	Mar2017	frequency
1	bradfordmdc	1354	1	bradfordmdc	1426
1	http	747	1	http	1137
1	bradford	511	1	bradford	445
1	inciner	202	1	dog	226
1	lgbtbd	159	1	march	207
1	vacanc	140	1	free	189
1	job	128	1	servic	158
1	tanda	126	1	thank	150
1	aireinciner	108	1	event	122
1	vallei	107	1	creativestreetsbd	116
2	bradfordmdc	1121	2	bradfordmdc	1438
2	http	1086	2	http	822
2	bradford	374	2	bradford	295
2	march	344	2	support	171
2	council	209	2	kerstenengland	164
2	hall	191	2	council	153
2	citi	180	2	march	138
2	yorkshir	180	2	women	127
2	dog	144	2	hall	126
2	roadshow	142	2	exhibit	124
3	bradfordmdc	1243	3	bradfordmdc	1377
3	http	845	3	http	753
3	bradford	434	3	bradford	472
3	citi	358	3	event	347
3	launch	218	3	march	265
3	hall	148	3	citi	264
3	talk	146	3	april	242
3	lgbtbd	127	3	hall	212
3	district	125	3	free	206
3	tour	117	3	inclusivegrowth	206
4	bradfordmdc	1067	4	bradfordmdc	1507

4	http	717	4	http	968
4	bradford	198	4	bradford	325
4	lgbtbd	156	4	visitbradford	164
4	school	146	4	cityparkbd	157
4	look	110	4	thank	146
4	thank	105	4	school	137
4	help	91	4	primari	128
4	dai	90	4	team	121
4	free	90	4	award	119
5	bradfordmdc	1057	5	bradfordmdc	1456
5	http	721	5	http	770
5	bradford	345	5	bradford	325
5	march	175	5	citi	234
5	grit	170	5	local	190
5	free	161	5	look	148
5	april	158	5	commun	123
5	event	152	5	leed	120
5	creativestreetsbd	145	5	commut	115
5	town	142	5	daili	104

7.2.2.3 Analysis of Users

The main purpose of users' analysis is to understand the LG social media user's characteristics and behaviours. The analysis can identify the most active users in the LG social media network. The active user is a user who actively posts messages (tweets) and reposts other user's messages (retweets).

The top 50 Twitter users who actively tweet and retweet in the LG social media network are represented in Table 7.7. In general, the users prefer to retweet rather than to post their own tweet. It is apparent from this table that the number of a retweet is greater than the number of tweet for most of the users except a few numbers of them such as "User8", "User30", and "User31" where they are actively tweeting rather than a retweet. The most surprising aspect of the data is that a few numbers of users are actively retweet but not posted any single tweet such as “User1”, “User25”, “User32”, and “User34”.

It is interesting to note that there are only 12 tweets from the selected LG official Twitter account (“User14”) recorded in this study as listed in Table 7.7. This indicates that the data collection in this study had not considered those tweets that come from the official Twitter account of the selected LG. The reason is that the authors only mentioned another user account in their tweet rather than their own. Since the selected LG official Twitter account was used as a keyword in the searching process, it is not surprising that tweets from their account were not mined except those listed in **Error! Reference source not found.**.

Further investigation of the structural behaviours of these active users was conducted using the social network analysis approach and the results are explained in subsection 7.2.4.

Table 7.7: List of top 50 Active Twitter Users

No.	User	Tweet	Retweet	Total
1	User1	0	661	661
2	User2	105	373	478
3	User3	8	388	396
4	User4	56	334	390
5	User5	14	210	224
6	User6	44	177	221
7	User7	45	146	191
8	User8	171	16	187
9	User9	51	135	186
10	User10	66	115	181
11	User11	48	132	180

12	User12	20	142	162
13	User13	9	149	158
14	User14	12	145	157
15	User15	7	142	149
16	User16	12	122	134
17	User17	20	98	118
18	User18	30	84	114
19	User19	29	81	110
20	User20	51	55	106
21	User21	3	103	106
22	User22	2	102	104
23	User23	41	58	99
24	User24	24	72	96
25	User25	0	96	96
26	User26	49	47	96
27	User27	37	58	95
28	User28	46	44	90
29	User29	4	85	89
30	User30	69	19	88
31	User31	74	13	87
32	User32	0	86	86
33	User33	27	56	83
34	User34	0	82	82
35	User35	40	41	81
36	User36	28	53	81
37	User37	28	50	78
38	User38	39	39	78
39	User39	2	75	77
40	User40	21	56	77
41	User41	32	43	75
42	User42	14	61	75
43	User43	19	55	74
44	User44	6	66	72
45	User45	9	63	72
46	User46	3	66	69
47	User47	10	57	67
48	User48	3	64	67
49	User49	27	39	66
50	User50	9	56	65

Table 7.8 lists the top 10 user accounts on which their tweets were retweeted by other users in the social media network. From the total number of retweets (19,859) in the data collection, 58 per cent were retweeted from "*User14*", an official Twitter account for the selected LG, as shown in Figure 7.6. The figure indicates that more than half of the retweets in the LG social media network originated from the tweets of the official Twitter account of the selected LG.

Table 7.8: Popular user account being retweeted

No.	User Account	No. of time being retweeted
1	User14	11588
2	User51	652
3	User4	209
4	User28	181
5	User8	144
6	User52	122
7	User38	109
8	User53	102
9	User2	90
10	User9	87

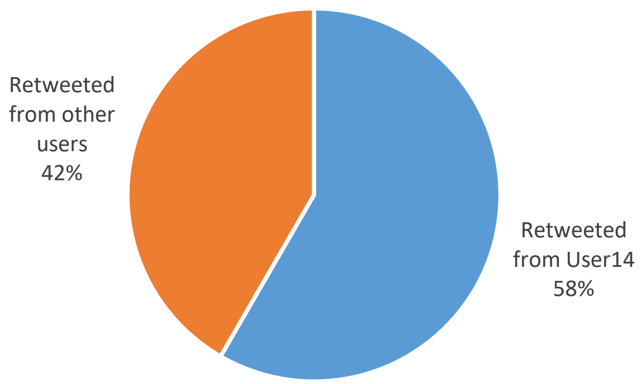

Figure 7.6: Distribution of retweeted users

In summary, the BSD (e.g., Twitter data) contains rich information of very basic words and less formal language. Thus, applying an appropriate technique to analyse these types of data can bring new insights to the organisation. The public-sector organisations such as a LG could have a better understanding of the citizens' conversation and public opinions through extracting and analysing the textual data of BSD. In addition, the developed content analysis tool is able to process the textual data to identify the topic of discussion and important terms highlighted in the conversation among the social media communities. The topic extraction process for 'big' collection of data also requires an automated content analysis tool which can reduce the processing time and operational cost. Finally, the automated content analysis can process a large amount of data that involve quantitative and statistical analysis (e.g., terms frequency) in a reasonable time.

7.2.3 Sentiment Analysis

Sentiment analysis is a part of content analysis groups in the BSDA model. As discussed in Chapter Four, this study applied emotion analysis as part of the sentiment analysis to the data collection. The emotion analysis tool in this study was developed using a machine learning method. The developed emotion analysis tool focused on identifying the six basic emotions including anger, disgust, fear, joy, sadness and surprise as described in Chapter Four. A supervised machine learning algorithm, Naïve Bayes (Naïve), was applied to train the model using a predefined dataset from the National Research

Council Canada (NRCC) Emotion Lexicon (Mohammad and Turney 2013; Mohammad and Turney 2010). The training dataset was created by crowdsourcing where each tweet was assigned with an appropriate emotion (Mohammad 2015). The tool development process was divided into two stages as described in the following steps.

In the first stage, the model was trained using a training dataset which contained a list of tweets with predefined emotion label. The process began by retrieving the training dataset from the SQLite database. Then, the pre-processing and cleaning data were introduced to transform all letters into lower cases and separated the tweets into a sequence of tokens or words. Next, each token was filtered using English stop words to eliminate non-English words from the list. Consequently, a series of consecutive tokens with two lengths was created known as n-Grams. This step was implemented to ensure that words such as ‘good’, ‘not’ and ‘not good’ could be recognised correctly. Then, the data were feed into the training model and processed through the Naïve algorithm. The performance was recorded and the applied model was trained and ready to process the real dataset.

In the second stage, the real dataset known as test dataset was used as an input to the applied model. The test dataset completed the same sequence of pre-processing and data cleaning processes before it was run into the applied model. The algorithm in the applied model analysed each line of a tweet based on the knowledge given in the training stage. Finally, the model assigned an appropriate emotion for each tweet.

7.2.3.1 Naïve Bayes Algorithms

Prior to the decision to the applied Naïve algorithm in the developed sentiment analysis tool, two other supervised machine learnings were tested including Voting Features Intervals (VFI) and Decision Strump (DS). The algorithm selection process was carried out into two stages and tested with two types of dataset.

The first stage, the developed sentiment analysis tool was tested with all the three-selected supervised machine learning algorithms in separate sessions. In each session, the NRCC dataset was used as a training dataset and 30 selected samples from the same dataset which equally represented each category of emotions were used as a test dataset. The NRCC dataset was a collection of tweets with the predefined sentiment. The main purpose of using a sample from the training dataset was to ensure that the tested algorithm could assign the same emotion as training dataset in the findings. This process could confirm the accuracy of the selected algorithm without in-depth investigation of that algorithm. The findings of this stage can be referred to in Table 7.9. The first algorithm, VFI, distributed the tweets into three categories of emotions with 87 per cent of tweets were assigned as sadness. The second algorithm, Decision Strump, allocated 97 per cent of the tweets into joy emotion. Eventually, Naïve was found to be the only algorithm that distributed the tweets equally in all categories as defined in the training dataset.

Table 7.9: Findings of the NRCC Sample

Algorithm	VFI		DS		Naïve	
Emotion	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
anger	2	6.7	0	0	5	16.7
disgust	0	0	0	0	5	16.7
fear	2	6.7	1	3.3	5	16.7
joy	0	0	29	96.7	5	16.7
sadness	26	86.7	0	0	5	16.7
surprise	0	0	0	0	5	16.7
Total	30	100	30	100	30	100

In the second stage, the same processes were repeated to test the developed sentiment analysis tool with the three selected algorithms. The same dataset from the NRCC was used as training dataset but two different texts from well-known literature with different themes were used as a test dataset. The first text, literature with horror theme by Fyodor Dostoyevsky, Crime and Punishment (CAP), was tested with all the three algorithms in separate sessions. The preparation process was applied to the original text to prepare the text as an input for the sentiment analysis tool. In the preparation process, the original text was cleaned and all the paragraphs were transformed into sentences. Then, the processed text was used as input for test dataset for the sentiment analysis tool. The same preprocessing was applied to the test dataset before it was feed into the applied model. The same process was repeated with the second literature text, the Adventures of Tom

Sawyer (TATS) by Mark Twain. The second text theme was expected to be more of joy and less horror.

Table 7.10 summarises the findings for both types of literature. It is apparent from this table that for the first text, Crime and Punishment, the VFI algorithm assigned 95 per cent of the text as sadness emotion. On the other hand, the DS algorithm categorised the whole text into joy emotion. Interestingly, the only algorithm that distributed the text into all categories of emotion is Naïve. The Naïve algorithm assigned 18 per cent of the text as joy, 30 per cent as disgust and 45 per cent as a combination of anger, fear and sadness.

As shown in Table 7.10, the first two algorithms, VFI and DS, assigned nearly similar emotion to the second text to the finding in the first text. However, it is slightly different from the third algorithm. The Naïve algorithm allocated relatively high percentage for joy emotion up to 25 per cent although disgust received 30 per cent and 39 per cent for the combination of anger, fear and sadness.

The sentiment analysis findings for both types of literature were presented to the expert readers who had experienced reading both types of literature to obtain their feeling and feedback regarding the emotion involved in the texts. Generally, the readers preferred to choose findings of Naïve compared to other algorithms. Based on the two stages experiment with a developed sentiment analysis tool, the Naïve algorithm had been selected to be applied to the actual case study data of this research.

Table 7.10: Findings of Different Algorithms Applied on CAP and TATS

Emotion	**VFI**		**DS**		**Naïve**	
	CAP (%)	**TATS (%)**	**CAP (%)**	**TATS (%)**	**CAP (%)**	**TATS (%)**
anger	1.00	1.00	0.00	0.00	16.70	11.40
disgust	1.30	1.50	0.00	0.00	30.10	30.10
fear	0.80	0.70	0.00	0.40	16.00	13.80
joy	1.30	2.10	100.00	99.60	18.40	25.00
sadness	94.90	93.80	0.00	0.00	11.90	14.00
surprise	0.70	0.90	0.00	0.00	6.90	5.70

7.2.3.2 Findings of Emotion Analysis

The sentiment analysis was applied to the full data collection of the selected LG in this study. The findings are summarised in Figure 7.7 and Figure 7.8, as well as Table 7.11 and Table 7.12. The line graphs in Figure 7.7 demonstrate the changes in the percentage of the citizens' emotion towards the LG through Twitter messages between March 2016 and March 2017. The graph begins in March 2016 with joy and sadness almost at the same level of 30 per cent. However, in April 2016 both emotions are divided where the joy increased from five to 35 per cent while the sadness level decreased to nearly 25 per cent. The joy emotion began to decline during the third month of the study while the sadness emotion rose gradually up to more than 30 per cent in June 2016. Interestingly, both emotions arrived almost at the same point in July 2016 and the sadness emotion arrived at the peak in the following month before slowly decreased two months later. The trend of both joy and sadness emotions fluctuated until the joy emotion arrived at the peak by the end of the study while the sadness emotion dropped to the lowest percentage in March 2017.

The fear emotion similarly followed the joy trend over the period of the study with a moderate percentage each month. The anger and disgust emotions were maintained with the lowest percentage compared to other emotions in each month. The surprise emotion was maintained between fear and anger emotions but in one of the months, it had sharply increased close to fear emotion. On the other month, the surprise emotion decreased sharply close to anger emotion. The only time that the percentage of surprise emotion was higher than the fear emotion was in October 2016. Generally, joy and sadness had comparatively dominated the percentage of citizens' emotions over the years while the lowest percentage emotion detected over the period of the study were anger and disgust.

In general, while the trend of joy and surprise emotions had been increasing, the trend of sadness emotion was decreasing and the others were stable over the period of the study as illustrated in Figure 7.8. The sentiment analysis findings could be compared with other content analysis findings such as a topic of discussion for further understanding.

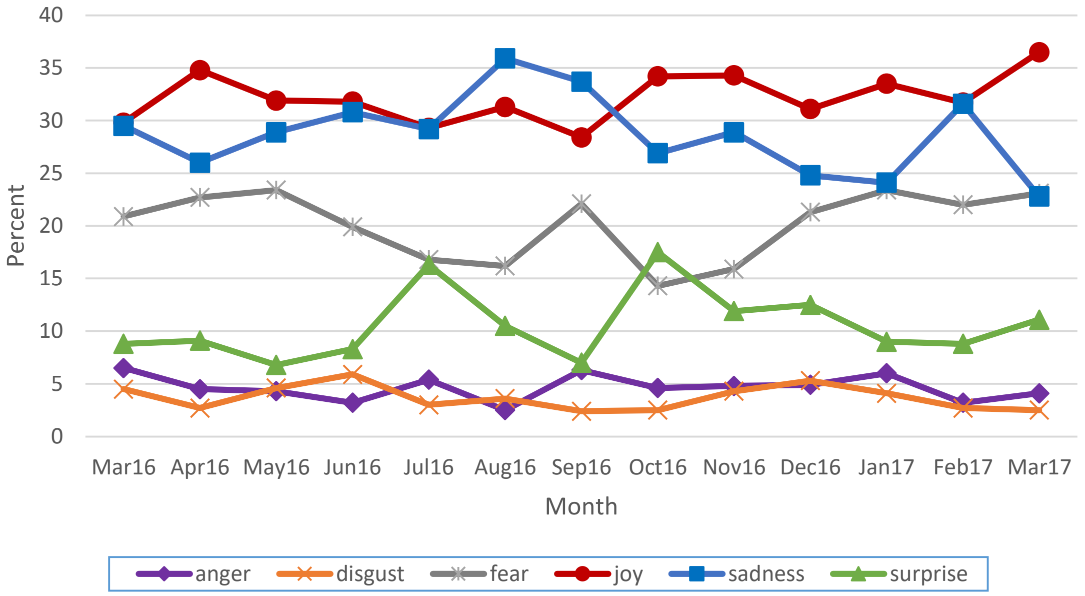

Figure 7.7: Percentage of emotion for tweets and retweets by month

Table 7.11: Number of emotions by month

Emotion	**Mar16**	**Apr16**	**May16**	**Jun16**	**Jul16**	**Aug16**	**Sep16**	**Oct16**	**Nov16**	**Dec16**	**Jan17**	**Feb17**	**Mar17**
anger	123	69	103	65	103	45	163	107	130	89	137	97	151
disgust	86	41	110	121	57	64	62	59	116	96	93	80	91
fear	399	346	554	407	322	291	572	333	432	384	535	660	857
joy	**567**	**530**	**756**	**650**	**560**	560	734	**795**	**934**	**560**	**766**	**950**	**1357**
sadness	562	396	684	629	559	**643**	**872**	625	786	446	550	948	845
surprise	168	139	162	169	311	188	181	408	325	224	205	264	413
Total	1905	1521	2369	2041	1912	1791	2584	2327	2723	1799	2286	2999	3714

Table 7.12: Percentage of emotions by month

Emotion	Mar16	Apr16	May16	Jun16	Jul16	Aug16	Sep16	Oct16	Nov16	Dec16	Jan17	Feb17	Mar17
anger	6.5	4.5	4.3	3.2	5.4	2.5	6.3	4.6	4.8	4.9	6.0	3.2	4.1
disgust	4.5	2.7	4.6	5.9	3.0	3.6	2.4	2.5	4.3	5.3	4.1	2.7	2.5
fear	20.9	22.7	23.4	19.9	16.8	16.2	22.1	14.3	15.9	21.3	23.4	22.0	23.1
joy	**29.8**	**34.8**	**31.9**	**31.8**	**29.3**	31.3	28.4	**34.2**	**34.3**	**31.1**	**33.5**	**31.7**	**36.5**
sadness	29.5	26.0	28.9	30.8	29.2	**35.9**	**33.7**	26.9	28.9	24.8	24.1	31.6	22.8
surprise	8.8	9.1	6.8	8.3	16.3	10.5	7.0	17.5	11.9	12.5	9.0	8.8	11.1
Total	100	100	100	100	100	100	100	100	100	100	100	100	100

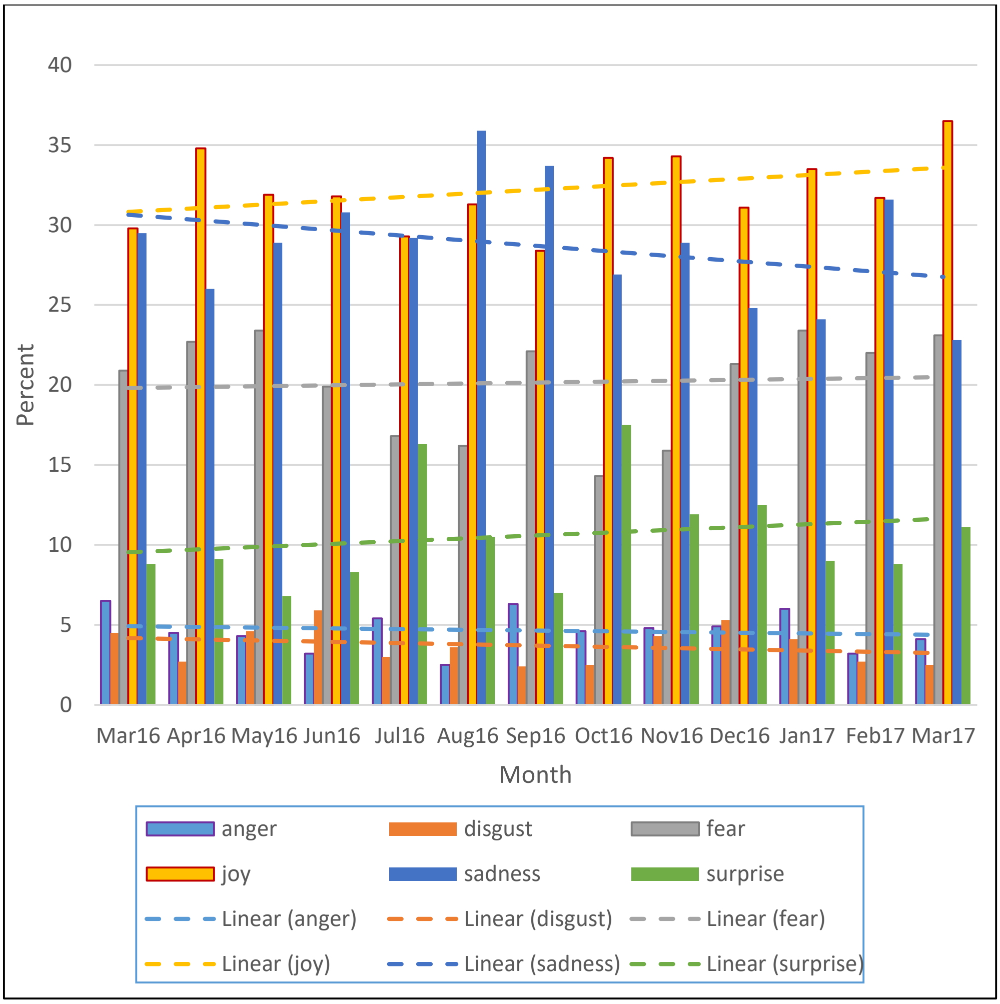

Figure 7.8: Emotion trends for tweets and retweet

The emotion analysis finding shows that the BSD of LG generated from the interaction between citizens and the LG contains rich information including different sentiments. The citizens' sentiment towards LG can be extracted by analysing the textual data using sentiment analysis techniques. The findings also proved that by applying the emotion analysis methods to the BSD can give a better understanding in more details of the public sentiment towards government (e.g., anger, disgust, fear, joy, sadness, and surprise) and not only positive or negative sentiment.

7.2.3.3 Combination of Content Analysis Techniques

The findings from three analysis techniques in the content analysis group can be combined to advance government understanding of citizens. Hence, related issues that impact on citizens' sentiment can be identified. In this study, sentiment analysis was applied to the data collection to identify six types of citizens' emotions over the years. Topic modelling and term frequency were also employed in classifying potential discussion topic and frequent words used in the Twitter posts. Table 7.13 summarises example of findings based on data from four selected months. It can be seen from the table that in July 2016, joy and sadness emotions are almost at the same point whilst in August 2016, sadness emotion is slightly higher than joy. An investigation on discussion topic listed that in July 2016, topics such as '*Bradfordfestival*' and '*Lovebradford*' are among the top listed in topic modelling analysis which represent joy emotion. Further investigation from the term frequency analysis found that words with a hashtag such as '#Somme100' was used to highlight the history of the largest battle in the First World War which occurred in July 1916. From these analyses, the government can understand that citizens' sentiment in July 2016 is at a given level due to a balance between joy and sadness emotions. The analysis can be applied to a complete data set in order to understand the citizens' sentiment and the cause over the years.

The findings show that content analysis technique including sentiment, topic identification and term frequency analyses can be applied on BSD to gain new insights for the government in understanding the public.

Table 7.13: Example of Content Analysis Group Findings

Month	Sentiment (%)	Discussion topic	Term Frequency
July 2016	Joy (29.3) Sadness (29.2) Fear (16.8) Surprise (16.3) Anger (5.4) Disgust (3)	Bradfordfestival Citypark Lovebradford Bradfordfestival Citypark	#BradfordFestival #Bradford #LoveBradford #BradfordGXn #GreatNort #Ilkley #BradfordClassic #Somme100 #PokemonGoUK #TheHairyBuilder
August 2016	Sadness (35.9) Joy (31.3) Fear (16.2) Surprise (10.5) Disgust (3.6) Anger (2.5)	Common Haven Lovebradford Citypark Shoot	#LoveBradford #Ilkley #Bradford #Haven #MoreInCommon #comms2point0jobs #Missingdog #comms #dogsoftwitter #woofwoofwednesday
September 2016	Sadness (33.7) Joy (28.4) Fear (22.1) Surprise (7) Anger (6.3) Disgust (2.4)	Lovebradford Lovebradford Shoot Greatnorthexpo2018 Park	#LoveBradford #GreatNorthExpo2018 #BradfordGXN #Ilkley #Bradford #WTUCongress #lovebradford #bigupbradford #mybradford
October 2016	Joy (34.2) Sadness (26.9) Surprise (17.5) Fear (14.3) Anger (4.6) Disgust (2.5)	Positivepractice Orgreavejustice Forestoflight Visitbradford Forestoflight	#ForestofLight #Bradford #TdY #ForestOfLight #WOWBradford #LoveBradford #teambradford #bradford #orgreavejustice #YENExpo16

7.2.4 Social Network Analysis

There are three types of BSD as discussed in Chapter Three including digital self-representation data, technology-mediated communication data, and digital relationships data. Twitter data contains digital relationship data that reveal the digital social relationships pattern. In this study, this type of data was used to examine the selected LG social media network. Both types of digital relationships data were discovered using two network structures called “Follower Network” and “Retweet Network” to represent explicit and implicit data respectively. The Follower network represents the network structure of “who follows who” based on the follower's relationships of the Twitter users. The Retweet network represents a network structure of Twitter users based on “who retweet from who”. The following subsections explain in detail about these networks.

7.2.4.1 Follower Network

In the Follower network, the actors are Twitter user accounts which represent users on Twitter and the arrows between users indicates the relationship between the users as a follower of another user. A high number of arrows coming into a node indicate that the user has many followers and a high number of the arrow coming out from a node means that the user has followed many other users.

The selected LG's Twitter account in this study has more than 16,000 followers and each of the followers was followed by another hundred users. Thus, drawing a network that contains all the followers is not practical and less effective in the analysis. Thelwall (2014) suggested that a network structure with 50 nodes is a reasonable number to be effectively analysed. Accordingly, the study selected the top 50 active users based on the findings from user analysis in the subsection 7.2.2. The study developed the Follower network with relationships between actors as illustrated in Figure 7.9. From the figure, it can be seen that if A is a follower of B, the graph representation will be A → B, and read as A follows B. In directional relations (directed graph) of the graph used in the Follower network, input to actors represents prestige. Actors who are prestigious tend to receive many nominations or choices (Wasserman and Faust 1994).

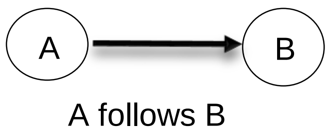

Figure 7.9: Actors and relationship in the Follower Network

7.2.4.2 Findings of the Follower Network

The main purpose of analysing the network structure in this study is to identify the social roles in the LG social media network. The findings of this analysis can give a clear picture to the decision-makers in the LG to utilise these social roles in order to enhance citizen engagement and effectively disseminate the government information to the citizens. Thus, based on the explicit data from Twitter, the Follower network is developed to investigate the LG social media structure and identify the social roles. The study utilised two open source software, Pajek and Gephi, to analyse and visualise the Follower network.

A list of potential social roles including opinion leader, brokerage and disseminator was investigated in the Follower network. The metrics applied in the investigation were based on the theory discussed in Chapter Three. The indegree centrality was used to identify the opinion leaders and the betweenness centrality to determine the brokerages. Since the follower network was not strongly connected, the closeness centrality could not be computed. Thus, the disseminators were measured using harmonic centrality (Rochat 2009).

The visualisation of Follower network based on the betweenness centrality is shown in Figure 7.10 and complete findings of these investigations are summarised in Table 7.14. From Figure 7.10, the large orange circles indicate the most important social role as brokerage and the linkages between them indicate the follower relationships.

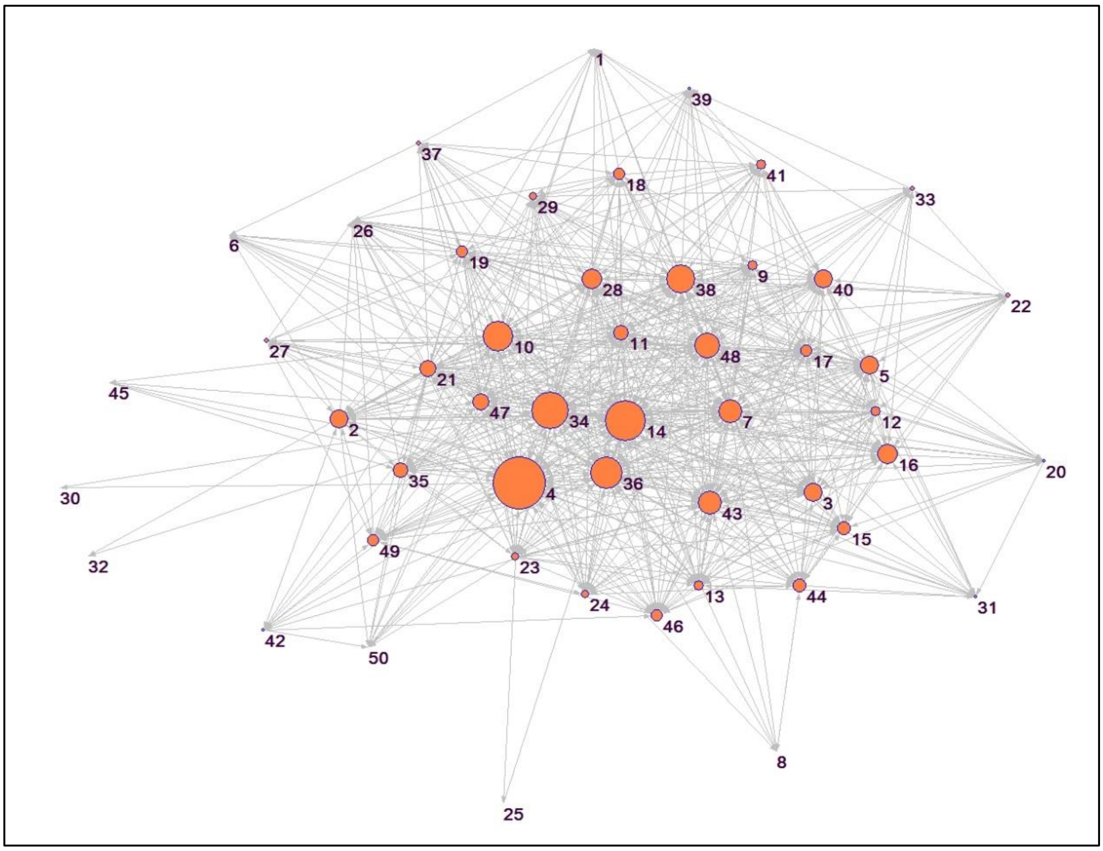

Figure 7.10: The Brokerage in the Follower Network

What is interesting in the findings is that a single user can have more than one social roles (e.g: brokerage, opinion leader, etc). For example, “User4”, a Twitter account for LG Chief Executive, received the highest score in betweenness and harmonic centralities to become the top brokerage and disseminator. Surprisingly, the “User4” was also placed among the top in indegree score to act as an opinion leader.

The unexpected finding was that “User34” who established a high score in the harmonic and betweenness centralities, received a lower score for indegree centrality. This indicates that “User34” was located in the strategic position for the disseminator and brokerage but less strategic for the opinion leader role.

In general, the users located in the peripheral in indegree centrality did not perform in the other two centralities. This suggests that these group of users are less important in influencing other users in the LG social media network.

Table 7.14: The Follower Network Findings

No.	Label	Indegree	Ranking	Betweenness	Ranking	Harmonic	Ranking
1	User14	42	1	0.0580	2	0.827	8
2	User7	40	2	0.0195	8	0.704	23
3	User4	38	3	0.0936	1	0.929	1
4	User36	34	4	0.0362	4	0.827	10
5	User48	33	5	0.0233	7	0.816	11
6	User17	32	6	0.0048	22	0.639	33
7	User38	31	7	0.0293	6	0.888	5
8	User43	30	8	0.0190	9	0.786	14
9	User16	27	9	0.0144	10	0.765	17
10	User40	27	10	0.0129	14	0.711	22
11	User10	26	11	0.0315	5	0.898	3
12	User28	25	12	0.0140	11	0.827	9
13	User34	25	13	0.0471	3	0.918	2
14	User44	25	14	0.0061	21	0.650	32
15	User5	24	15	0.0132	13	0.827	7
16	User13	24	16	0.0038	29	0.650	30
17	User46	23	17	0.0047	23	0.684	26
18	User47	23	18	0.0105	16	0.803	12
19	User9	22	19	0.0039	28	0.701	25
20	User29	22	20	0.0025	32	0.578	38
21	User35	22	21	0.0085	18	0.724	20
22	User2	21	22	0.0111	15	0.765	16
23	User3	21	23	0.0132	12	0.714	21
24	User15	21	24	0.0066	20	0.724	19
25	User24	21	25	0.0023	33	0.633	35
26	User26	21	26	0.0000	46	0.000	47

27	User11	19	27	0.0073	19	0.867	6
28	User19	17	28	0.0047	25	0.765	18
29	User23	16	29	0.0026	31	0.786	13
30	User41	16	30	0.0041	27	0.673	27
31	User18	14	31	0.0042	26	0.704	24
32	User20	14	32	0.0006	38	0.588	36
33	User1	13	33	0.0000	43	0.000	45
34	User31	13	34	0.0003	40	0.531	41
35	User33	13	35	0.0008	36	0.585	37
36	User49	13	36	0.0047	24	0.673	28
37	User21	12	37	0.0104	17	0.898	4
38	User50	12	38	0.0000	50	0.000	50
39	User6	11	39	0.0000	44	0.000	46
40	User39	11	40	0.0004	39	0.527	42
41	User37	10	41	0.0010	34	0.639	34
42	User27	9	42	0.0010	35	0.653	29
43	User12	7	43	0.0036	30	0.776	15
44	User42	7	44	0.0003	41	0.578	39
45	User8	5	45	0.0000	42	0.561	40
46	User22	5	46	0.0007	37	0.650	31
47	User30	2	47	0.0000	47	0.000	48
48	User32	2	48	0.0000	48	0.000	49
49	User45	2	49	0.0000	49	0.517	43
50	User25	1	50	0.0000	45	0.503	44

7.2.4.3 Retweet Network

The Retweet network is a collection of Twitter user account (actors) based on the “retweet from” relationships (ties). Figure 7.11 illustrates the relationship in the Retweet network and read as “an actor A retweets from an actor B”. The arrow coming in (indegree) means that the user’s tweets being retweeted by another user. The high number of indegree means that a user is an important person in the network structure because his or her tweets are highly retweeted by other users. The arrow coming out (outdegree) represents the activity of user retweets from another user. The high number of outdegree indicates the high volume of retweeted activities by the user in the network.

In total, 19,859 retweets from the data collection were used to develop the Retweet network which involved 6123 Twitter user accounts and 9301 relationships.

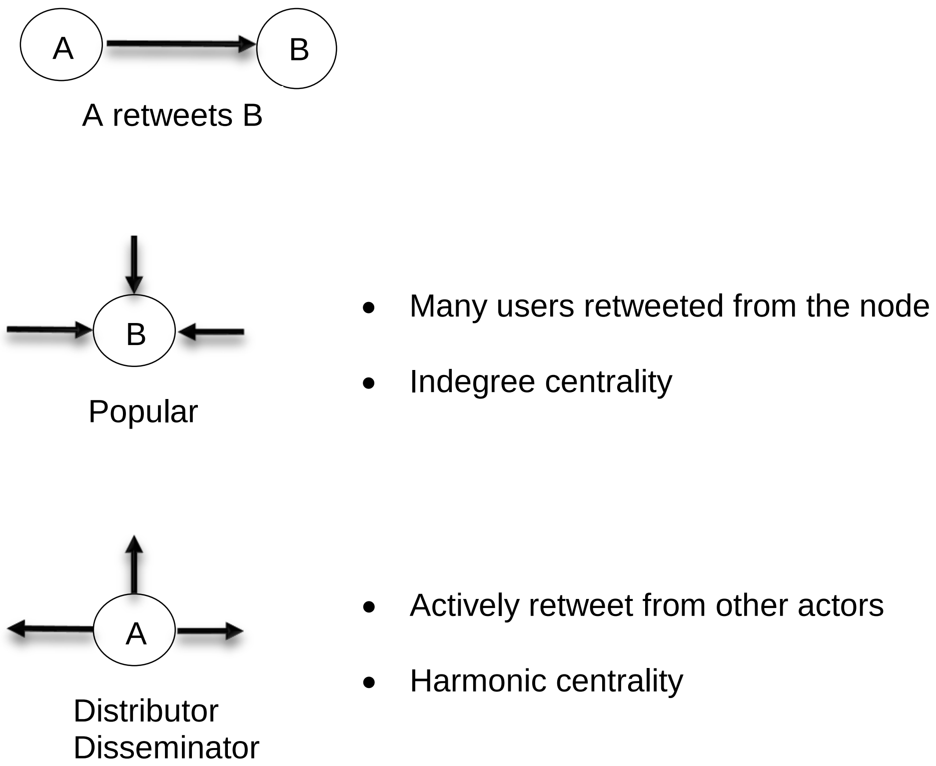

Figure 7.11: Retweet Network

7.2.4.4 Findings of the Retweet Network

In order to measure the Retweet network structure, three centrality metrics were applied including indegree, betweenness and harmonic centralities. The first two metrics (indegree and betweenness) were used to identify the opinion leaders and the brokerage in the network structure respectively. Since Retweet network is an unconnected network, the harmonic centrality is applied as an alternative to closeness centrality to identify the disseminator (Rochat 2009).

The findings of analysis assigned all the 6123 users in the Retweet network with the score from the three centralities metrics. The visualisation of social network structure for Retweet network is shown in Figure 7.12 and Table 7.15. lists the top 20 users from the indegree and betweenness centralities findings. The harmonic centrality score for these users is also recorded in the table. It is apparent from this table that *"User101", an* official Twitter account of the selected LG, received the highest score for indegree and betweenness centralities. However, the same user received considerably lower (0.51) score for harmonic centrality. The second user in the indegree ranking, *"User102"*, is not listed at the top 20 in betweenness centrality but received a maximal score (1.0) for harmonic centrality. Another user that received a maximal score for harmonic centrality is *"User105"* who was placed fifth in the indegree centrality. Interestingly, both are the only users who received a maximal score for harmonic centrality as listed in the table. The third position in the indegree ranking, *"User103"*, is graded in the second place for betweenness centrality although the harmonic score is considerably lower (0.47).

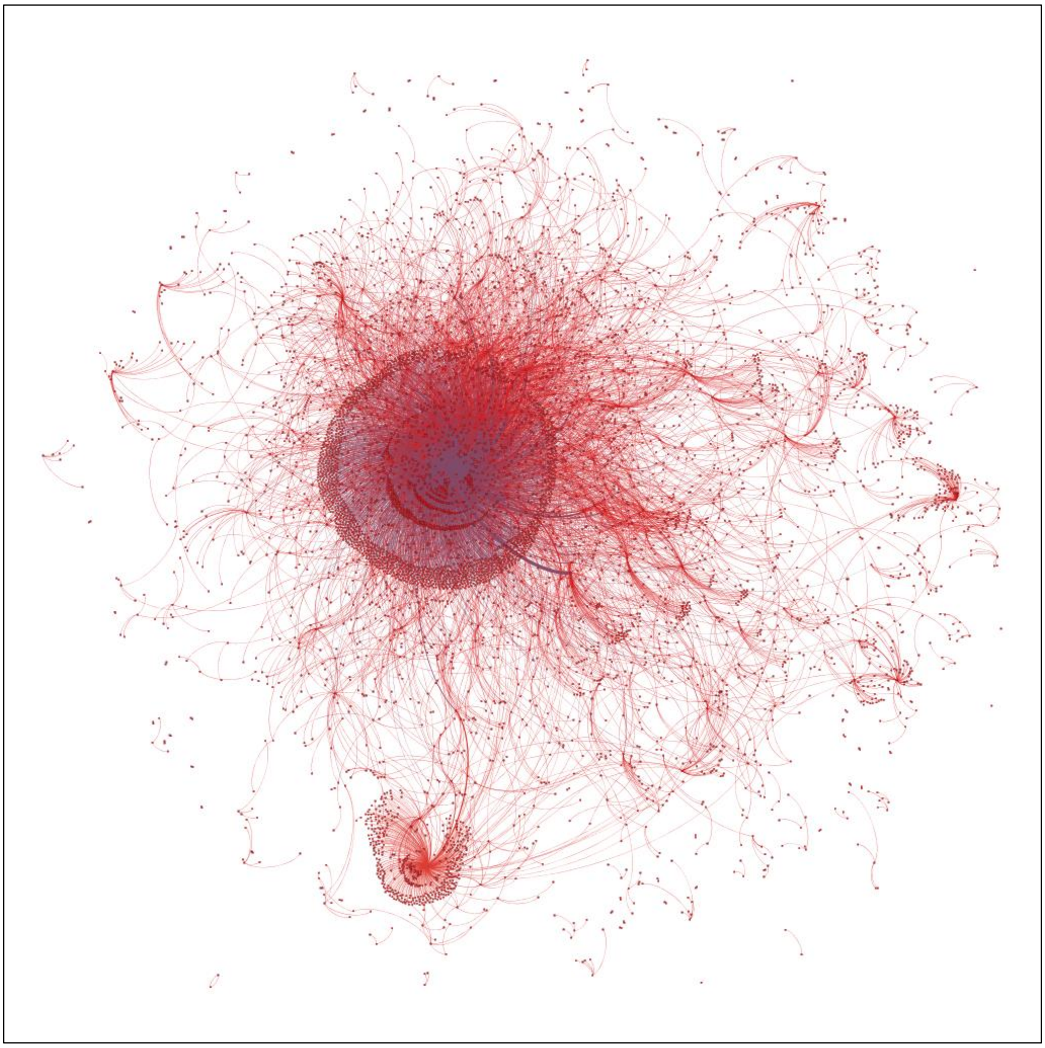

Figure 7.12: Social Network Structure of Retweet Network

As seen in Table 7.15, the indegree score for *"User101"* is extremely high compared to all other users' scores. This means that the official Twitter account of the selected LG was mainly retweeted by the LG social media community users.

The harmonic centrality findings recorded that 856 users received a maximal score (1.0). It means that these users are in the centre of the network and have the shortest accessed to all other users connected to them. These users are important to be the disseminators in the network. However, only 2 users (*"User102"* and *"User105"*) are listed in Table 7.15.

Table 7.15: Retweet Network (Indegree, Betweenness, Harmonic Centrality)

No.	User Name	Indegree		Betweenness		Harmonic
		Value	Ranking	Value	Ranking	Value
1	User101	2751	1	0.0509	1	0.5134
2	User102	436	2			1.0000
3	User103	129	3	0.0062	2	0.4674
4	User104	120	4	0.0023	10	0.3840
5	User105	90	5			1.0000
6	User106	80	6	0.0012	20	0.3545
7	User107	67	7			0.3280
8	User108	65	8	0.0045	6	0.4832
9	User109	62	9			0.3369
10	User110	61	10			0.3255
11	User111	59	11	0.0040	7	0.4372
12	User112	57	12	0.0047	5	0.4455
13	User113	56	13	0.0014	15	0.3604
14	User114	50	14	0.0019	11	0.3515
15	User115	46	15			0.0000
16	User116	46	16			0.3633
17	User117	45	17			0.3515
18	User118	45	18			0.0000
19	User119	44	19	0.0024	9	0.4009
20	User120	44	20			0.3837
21	User121			0.0056	3	0.4766
22	User122			0.0052	4	0.3451
23	User123			0.0040	8	0.4249
24	User124			0.0017	12	0.3585
25	User125			0.0017	13	0.4227
26	User126			0.0017	14	0.4287
27	User127			0.0014	16	0.3833
28	User128			0.0013	17	0.3742
29	User129			0.0012	18	0.3444
30	User130			0.0012	19	0.3872

7.2.4.5 Opinion Leader

Further analysis of the 20 users with high indegree score shows that 50 per cent (10 users) of the Twitter account are individual user accounts and another 50 per cent are group accounts. From the individual user accounts, 60 per cent (6 users) are LG internal stakeholders including two councillors. As part of the group user accounts, three users are official LG Twitter accounts. Overall, nine out of the twenty or 45 per cent of the user accounts come from the internal stakeholder of the selected LG. This means that 45 per cent of the top opinion leaders in the Retweet network come from the internal stakeholders of the LG. Table 7.16 and Figure 7.13 summarise the category of users with high indegree score.

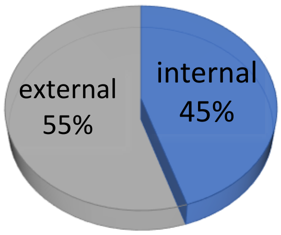

Figure 7.13: Percentage of users with high indegree score by category

Table 7.16: Category of users with high indegree score

No.	Label	indegree	Category	Category
1	User117	45	group	External/non-official
2	User109	62	group	External/non-official
3	User110	61	group	External/non-official
4	User120	44	group	External/non-official
5	User114	50	group	External/non-official
6	User102	436	group	External/non-official
7	User105	90	group	External/non-official

8	User106	80	group	Internal/official
9	User101	2751	group	Internal/official
10	User119	44	group	Internal/official
11	User107	67	individual	external
12	User115	46	individual	external
13	User116	46	individual	external
14	User118	45	individual	external
15	User104	120	individual	Internal/Councillor
16	User113	56	individual	Internal/Councillor
17	User103	129	individual	internal
18	User108	65	individual	internal
19	User111	59	individual	internal
20	User112	57	individual	internal

7.2.4.6 Brokerage

The advanced analysis on top 20 users of the betweenness centrality findings suggest that from the Twitter accounts category, nine users are individual, another nine are a group and the other two are a public institution as shown in Table 7.17, whilst 55 per cent (11 users) are LG internal stakeholders. This result can be considered as somewhat counterintuitive to the indegree centrality findings in Figure 7.13. Thus, the study can conclude that the internal stakeholders of LG are acting as a brokerage more than the opinion leader in the social media network.

Table 7.17: Category of users with high betweenness score

No	Label	Betweenness centrality	Category	Category
1	User121	0.0056	group	External/non-official
2	User114	0.0019	group	External/non-official
3	User124	0.0017	group	External/non-official
4	User122	0.0052	group	External/non-official
5	User125	0.0017	group	External/non-official
6	User106	0.0012	group	Internal/official

7	User101	0.0509	group	Internal/official
8	User123	0.0040	group	Internal/official
9	User119	0.0024	group	Internal/official
10	User126	0.0017	individual	external
11	User129	0.0012	individual	external
12	User104	0.0023	individual	Internal/Councillor
13	User113	0.0014	individual	Internal/Councillor
14	User103	0.0062	individual	internal
15	User112	0.0047	individual	internal
16	User108	0.0045	individual	internal
17	User111	0.0040	individual	internal
18	User128	0.0013	individual	internal
19	User127	0.0014	organisation	Public
20	User130	0.0012	organisation	Public

In summary, the BSD contains explicit and implicit information to be explored in order to enhance our understanding of the interaction among LG social media network. By applying the network analysis techniques such as social network analysis to the LG BSD can advance our knowledge and explore new insights to aid the LG decision-maker team in the decision-making process. The study proved that the SNA measurement, in particular, the metrics applied in this case study are sufficient to determine the social roles from the digital community of LG.

7.3 Revise the BSDA Model

The findings from the operationalisation were collected and presented to the experts from the LG internal stakeholders in order to get feedback and suggestions. Their feedbacks were analysed and illustrated as the following:

The experts are positively agreed and suggested that the BSDA model offers value added to guide the council in analysing and understanding the citizens' needs and expectations. This is illustrated by the following example:

> *"In terms of the rest of what you're doing, I do think it's potentially [sic], it's something quite a valuable and I've sort of suggested the answer to some of the questions that are things that I would love to have the capacity to do. Urmm which project like this could actually help to achieve."SO1*

In general, the experts are positively agreed with all the components included in the BSDA model. Examples of feedback related to this statement are stated as follows:

> *"There's a lot of conversation but it doesn't hit our radar and to mine that, and to be able to understand what that is telling us and what the content trying to filter through it or having a tool that enables that. For me, that's a real positive." IR*

> *"So that contextual analysis is I think quite interesting." M2*

> *"In terms of the service provisions, service usage urm and then what we're looking for in the future and I can see that." M2*

However, one of the experts prefers to use the term 'citizen satisfaction' instead of 'customer satisfaction' to represent the main target of the LG services.

> *"Well suppose from a, from a community leadership point of view, the only, the only bit I'd want is, is so it's not necessarily about service provision and customer satisfaction, it's about citizen's satisfaction … it's more about how people feel about a place urmmm so I suppose that's right, … it's that citizens' satisfaction rather than customers' satisfaction" SP*

Moreover, the experts are interested in the analysis techniques proposed in the BSDA model particularly SNA, which can assist the LG in identifying the social roles through the social media network. This was mentioned in the following feedbacks:

> *"I think would be useful. I think the, the network that in who are the influences I think it's really interesting." M4*

> *"As I was saying, part of my role is about engagement and we support a community of interest engagement, so I don't do geographical stuff, but I think from frank I think how we do some of that is probably stuck in about 5 years ago." M4*

Furthermore, the analysis techniques to identify discussion topics also attracted the internal stakeholders of the LG. The application of this technique can support the LG's decision-making team to understand public interest as pointed out by the experts through this statement:

> *"The topics identification for me would be the some of this the what sort of service that people are looking for, what sort of appetite people have to urm deal with things by themselves where we're working. … I think it's got a real application so anything that will help but I think it's got a real contribution too, to what we're doing at the moment." M4*

The experts also agree that the model could be used to guide the council in their future policy plan. This example depicts this concern:

> *"I think one of the most interesting things is that is understanding trend and understanding where that trend goes in the future and then using these tools or model service to be more future proof." M2*

Based on the abovementioned analysis from the expert feedback that represents the internal stakeholders of LG, the proposed BSDA model was revised and updated. Figure 7.14 illustrates the final BSDA model used in this thesis. All the components proposed in the initial BSDA model are retained except the term "customer satisfaction", which has been changed to "citizen satisfaction".

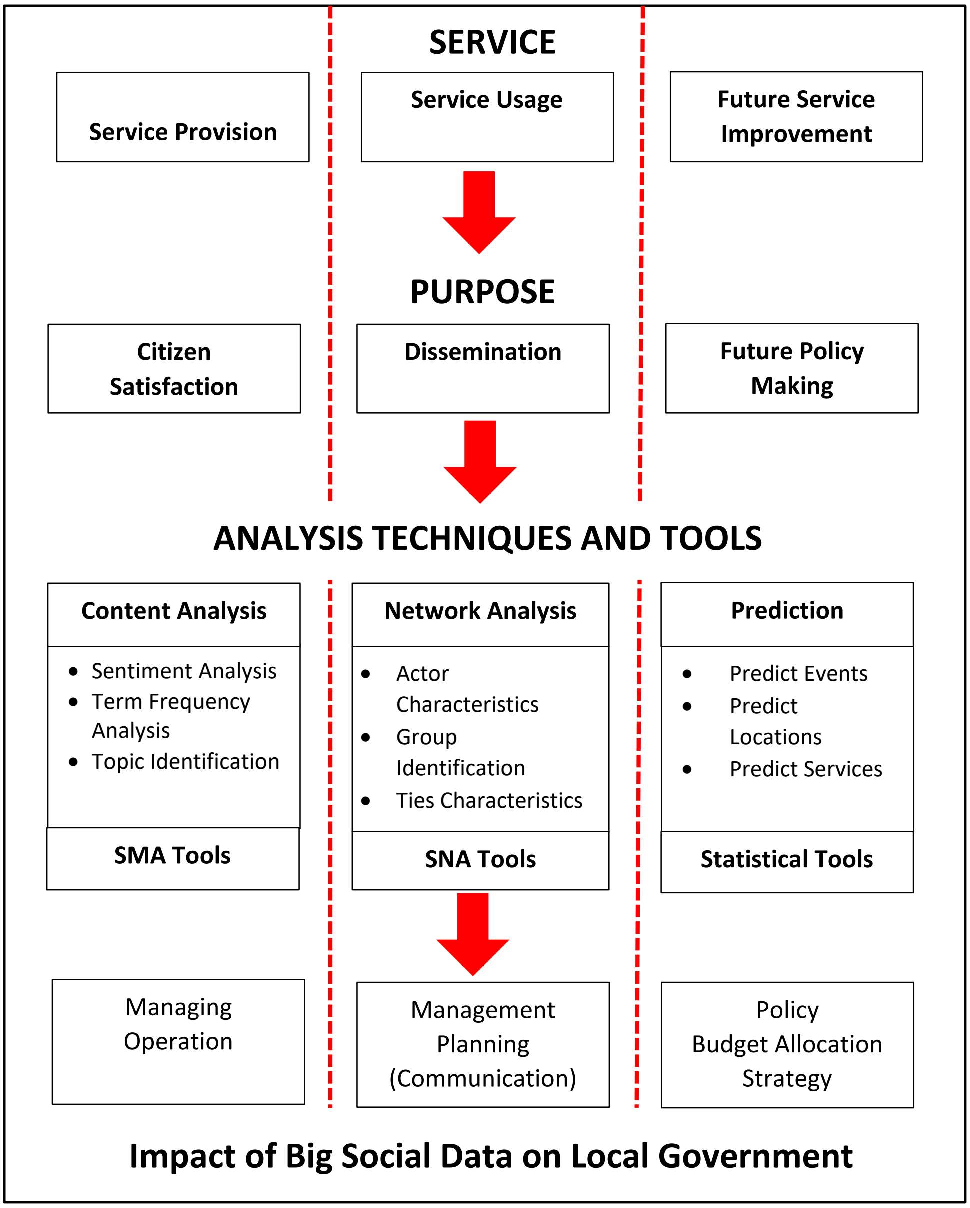

Figure 7.14: Big Social Data Analytics Model (Revised)

7.4 Chapter Summary

This chapter describes the operationalisation of the BSDA model using empirical data. As a case study, a LG in the UK was selected to be examined. The process began with data collection from a selected social media channel called Twitter. Then, the data cleaning process was implemented to prepare for the analysis stage. The cleaned data were analysed using a set of analytics tool and techniques including content, sentiment and social network analyses. The findings in each analysis stage were recorded. Using developed content analysis tools, term frequency was applied to understand the most popular terms in the data collection. The analysis found that in each month, a different list of terms was listed to represent different issues discussed in the social media. This is supported by the findings from the analysis of the topic of discussion whereby the data collection of each month listed different topics of discussion. On the other hand, by using the sentiment analysis, social media users feeling towards LG were measured and categorised into six basic emotions including anger, disgust, fear, joy, sadness and surprise. BSD contains implicit and explicit networks to be explored. The study examined both types of networks through follower and retweet. The findings from these networks found that in general, users located in the peripheral are less influential compared to those in the centre. The study revealed that the internal stakeholders of LG play important social roles as brokerages in the social media network.

The findings from the operationalisation together with the proposed BSDA model were presented to the local council officers for their feedbacks. The feedbacks were analysed in this chapter and used to revise and update the BSDA model. Finally, the final version of the BSDA model is proposed.

8

CHAPTER 8: DISCUSSIONS AND CONCLUSIONS

8.1 Introduction

This chapter provides the discussions and comparisons based on the related literature, case study, and findings from the previous chapters with regards to the proposed research questions in Chapter One. It also discusses the key contributions of this research to the academic literature particularly in e-government and social media disciplines followed by the theoretical and practical implications, limitation of the study, and potential future research.

8.2 Discussions

This thesis aims to evaluate the BSD body of knowledge in the context of the LG in the United Kingdom. A BSDA model is proposed to guide the LG in analysing the BSD in order to understand citizens' needs and expectations as well as to gain new insights from the government-citizens interaction through social media. From the conducted interviews, the LG internal stakeholders indicate that the local council is using the social media to interact with the citizen. The interaction through this media helps in generating BSD. However, the local council has not yet utilised the BSD due to the lack of resources and proper way to process this data. Thus, this thesis proposes a BSDA model that can guide the LG in analysing the BSD. The proposed BSDA model was examined using the empirical data gathered from a selected local council. As a result, the proposed techniques were proven to be workable in analysing the BSD.

The following three research questions are formulated to address the problem of this study:

RQ1 How can the local government decision-makers use BSD for planning, managing and delivering services to citizens?

RQ2 What are the BSD tools and techniques that can be used in the context of local government?

RQ2a How can the identified tools and techniques be applied towards better understanding of the social network users engaging with local government?

RQ2b How can the identified tools and techniques identified be used by decision-makers in the local government?

RQ2c How can the roles of social network users engaging with local government be identified?

RQ3 How does the social network theory (SNT) been applied in the BSDA model in the context of the public sector?

The discussion in the subsequent sections is deliberated in accordance to the three research questions proposed in this study.

8.2.1 Discussions on the use of BSD by the local government decision-makers for planning, managing and delivering services to citizens

Comprehensive information is extremely important to support decision-making team in selecting the best solution on a given issue. However, the data collection process, which is the main step in generating information, is usually expensive especially when using the traditional methods. Hence, internet technology particularly the social media can be employed to complement the traditional data collection process. This is vital to improve the knowledge creation in facilitating the planning, management, and delivery of public services by the decision-making team.

Previous researchers have asserted that analysing the BSD generated from the government-citizen interactions through social media has significantly created a new way of understanding citizens. The richness information offered by the BSD, specifically those that relate to various discussion topics and social network such as prominent people, can enhance the government understanding of citizens' needs and expectations. By applying advanced analytical techniques in extracting such information can support government decision-making teams in managing the operation, disseminating public information and being more responsive to the citizens' feedback (Eom et al. 2018; Haro-de-Rosario et al. 2018; Moss et al. 2015; Williamson and Parolin 2013).

The literature review in Chapter Two describes the advantages of BSD utilisation in terms of planning, managing and delivering of public services. At the early stage of the e-government implementation, the focus is to improve the efficiency of information delivery to citizens and enhance organisational management using ICTs. Currently, the adoption of social media has successfully shift the e-government implementation in public sector one step ahead towards promoting citizen engagement and participation in various public policy decision-making processes (Haro-de-Rosario et al. 2018; Skoric et al. 2016; Bonsón et al. 2015; Shahsavarani 2014; Ong 2014). Ultimately, the government will become more transparent by disclosing more public information, and get better access in reaching out to the lower income citizens (Guillamón et al. 2016).

In addition, the social media can complement the existing methods of government-citizen interaction particularly in setting up advance data collection strategies (Moss et al. 2015). For instance, the social media platform offers opportunities for citizens to share direct feedback with government authorities without any barrier. As a result, the real voice of the public can be collected, collated and analysed to measure and enhance public services.

It is also evidenced from previous researches that LG can improve the efficiency of government information dissemination by identifying the key people of the specific social media network (Eom et al. 2018; Dubois and Gaffney 2014). To broadcast government information through key people in strategic social networks will not only increase access to related information but also distribute awareness on numerous public issues. Even though Panagiotopoulos et al. (2017) suggest that BSD could be part of policy evidence, further research is required to explore on its implementation.

This study indicates that numerous decisions related to district matters are decided at the LG level. These decisions are supported by comprehensive information during the decision-making processes. At the moment, the citizens' feedbacks are obtained by the council officers through traditional data collection methods such as door-to-door interviews, face-to-face discussions, observations, and survey. As discussed in Chapter Five, the interviewees have highlighted the high cost of the traditional methods especially when working in a strict government budget. Hence, the LG has to manage the available resources wisely in order to maintain good quality of public services. To counter such distressing consequences, LGs need to connect with the publics through social media that offers an alternative solution at minimum cost (Moss et al. 2015; Janet 2013). From the interviews, it is also found that social media directly facilitate users who visited the council's website by keeping them updated with current news, events and related issues. Most importantly, the LG uses social media to encourage support groups for the targeted community around the region.

When discussing the potential use of BSD pertaining to the planning, managing and delivering of services to citizens, the respondents agreed that

BSD utilisation provides advantages to the local council in understanding the citizens' needs and expectations by identifying the discussion topics in the LG social media network. This was also pointed out by Bonsón (2015) that citizens prefer to discuss issues related to public services which are relevant to their daily life compared to marketing contents. Thus, in enabling the collection of citizens' feedback on a given issue, the LG should be able to identify the most relevant topics to be discussed.

The LG also is concerned about the citizens' sentiments and interested in identifying citizens' feelings on public services. The LG emphasises on the importance of citizens' feelings in representing the quality of public services and as an indicator of citizens' awareness with government policies. Similarly, Zavattaro (2015) reveals that positive sentiment of citizens on governments significantly promotes participation and engagement in e-government applications.

Moreover, the LG can utilise BSD to identify the key people in the social media communities to enable efficient government information dissemination as discussed in Chapter Two. Obviously, knowing the key people in the social media network can assist the government in communication planning as mentioned by Kavanaugh (2012). Furthermore, BSD can also be applied in public policy-making processes. For instance, during the interview, the LG indicates that its interest in using BSD for future policy planning such as strategic planning for future services, events and locations detection, as well as budget allocation. This is consistent with previous studies that highlighted BSD an extremely important source for prediction systems such as event (Kursuncu et al. 2018) and location detections (Chi et al. 2016; Inkpen et al. 2017). The findings from the prediction systems can be used to assist the LG decision-makers team in taking appropriate action.

8.2.2 Discussions on BSD tools and techniques that can be used in the context of local government

Local governments are increasingly adopting social media to interact with citizens. The extensive used of this platform produces an enormous amount of user-generated data called BSD. As discussed in Chapter Two, the government has not yet utilised BSD due to the lack of appropriate guidance and resources. Thus, identifying relevant techniques and tools to analyse BSD can bring impact in managing, planning, and delivering current and future public services.

Previous studies indicate that LGs can utilise BSD by applying a range of analytical tools and techniques such as content, sentiment and social network analyses to gain new insights for the decision-making teams (Lee 2017; Stieglitz et al. 2014; Stieglitz and Dang-Xuan 2013b). BSD can be analysed in order to understand citizens' conversation in the government's social media channels. Content analysis can be implemented to identify discussion topics, term of frequency, and active users. The discussion topics provide a general overview of discussed issues by the citizens in the social media whilst term frequency represents popular words posted in the social media discussions. In addition, sentiment analysis can be employed to understand citizens' feeling on public services. Finally, social network analysis can be implemented to study social roles in a LG social network structure.

In this study, tools and techniques to analyse BSD in understanding citizens' needs and expectations were identified, developed, and tested. The study classified the tools and techniques into three groups, namely content analysis, network analysis and prediction. A set of tools to apply all techniques in the first two groups were developed and tested with empirical data from a selected LG in the UK. However, the third group, prediction, was not tested in this study because the implementation of new policy in public services takes time and requires comprehensive data. The prediction tool and technique is needed since previous researchers have verified that social media data are significantly relevant to be used in a prediction system (Alsaedi et al. 2017; Kursuncu et al. 2018; Petrovic et al. 2010; Becker and Gravano 2011; Wang 2013; Vavliakis et al. 2013; Vieweg et al. 2014; Hasan et al. 2018; Yılmaz and Hero 2018).

This study found that a set of accurate techniques and methods is required to analyse BSD due to its richness of information in order to bring immediate insights to the organisation. An automated content analysis tool was developed in this study to examine the BSD that are generated from government-citizen interaction through social media. The tool was applied to analyse BSD textual data in identifying term frequency and discussion topics. The study proved that an automated content analysis tool is capable in extracting discussion topics from a collection of simple texts (not more than 140 characters in each message) using statistical techniques such as Latent Dirichlet Allocation (LDA). The study also demonstrated that certain analysis of BSD techniques which are unable to be implemented using manual content analysis are now able to be solved by automated content analysis tools.

Furthermore, this study showed that citizens use basic words and less formal language in their conversation through social media channel (e.g. Twitter). A hashtag sign (#) in social media posting such as Twitter can be used in identifying the relevant topic of discussions in social media conversations. The identified topics can then be analysed using the content analysis tool to provide general ideas for further investigation by the government authorities.

Another analytical technique proposed in this study is sentiment analysis, which includes three basic classifications; positive, negative and neutral. However, in this study, emotion analysis, a subset of sentiment analysis, was applied because it has more specific classifications such as joy, sadness, anger, disgust, fear, and surprise. This study demonstrates that the application of the emotion analysis through a supervised machine learning algorithm (Naïve algorithm) into simple text (maximum 140 characters per text) is capable in detecting the six basic emotions. Hence, through the emotion analysis, the LG is able to have more in-depth understanding regarding public sentiments compared to the basic classifications. The study also indicated that the combination of the three techniques in the content analysis group can enhance the LG's understanding of citizens' needs and expectations. The underlying reasons behind the citizens' sentiment can be investigated through term frequency and topic identification techniques as discussed in Chapter Two and demonstrated in Chapter Seven.

Understanding the key influential people in a LG social media network is important to support decision-making teams in planning a better government information dissemination strategy. This study utilises SNA to identify social roles in the LG social media network. A set of SNA measurement was employed to identify opinion leaders, brokerage and disseminators in the LG social media network. The study proves that social roles can be extracted not only from an explicit but also implicit network such as Retweet network. The implicit network represents real conversations between social media users in the network. This is consistent with previous studies that pointed out the identification of social roles and influential actors can be performed through the social media network such as Twitter (Stieglitz, Mirbabaie, et al. 2018).

The study also indicated that the internal stakeholders of the LG performed important roles in the LG social media network. For instance, the Chief Executive Officer (CEO) of LG was identified to be an important role as brokerage and disseminator in Follower network whilst in the Retweet network, the CEO played the roles as brokerage and opinion leader. This is depicted by Eom et al. (2018) by specifying the mayor of a local council who plays an important role as a brokerage in the social media network.

8.2.3 Discussions on the applied of SNT in the BSDA model in the context of public sector

Social network theory (SNT) explains about a network structure, relationships between actors and the position of the actors. Therefore, the theory can be used to describe the social role of users in a network. The most advantageous actors are those with certain criteria of relationships that are located in strategic positions. This study adopted these concepts based on the integration of three prominent SNTs known as Strength of Weak, Structural Hole and Social Role. This study also revealed that by applying the SNT, the LG can advance their understanding of the online community engagement and participation in discussing issues related to public services in the social media network.

The SNT has been applied in this study to develop the BSDA model. The model proposed that BSD from the government-citizen interaction which contains rich information related to the social network have the potential to be analysed in order to understand the relationships between the participants and gain new insights for the LG decision-making team.

Based on the social role theory, the key actors in the social network structure can be identified by applying a set of social network measurements. For instance, this study was able to identify opinion leaders in the LG social media network using indegree centrality while the brokerage was identified using betweenness centrality. Generally, the Social Network Analysis (SNA) measurement was adopted in to identify the social roles. As a result, it is found that SNT can be applied in analysing LG BSD in order to understand the social roles of a participant in the social media network. One of the metrics used is to measure the relationships.

Although the social roles in the digital social media networks are not necessarily similar to the traditional roles in social networks, this study proved that traditional measurement of SNT can be applied to measure digital social media network. This is consistent with previous studies that applying SNT on social media data such as Twitter can give new ways of understanding public (Eom et al. 2018). Thus, this concludes that SNT is not only relevant to measure traditional social networks but also becoming important to measure digital social media networks as applied in the model of this study.

8.3 Theoretical Contributions

This study offers several theoretical contributions as follows:

1. Theoretically, this study is the first of its kind that aims to evaluate the BSD body of knowledge in the context of LG in the United Kingdom (UK).

Most related previous studies were conducted to identify the advantages of e-government using social media such as to increase transparency, promote citizen participation and engagement, and advance government-citizen communication without exploring the content of such interaction. This developed BSDA model in this study was tested empirically using a case study from a selected LG in the UK. This study also highlights the need of appropriate guidance for the LG team to analyse their BSD as described in Chapter Five. In this respect, this study proposes a model to analyse BSD that will assist practitioners in the public sector to better understand the citizens' needs and expectations.

2. Using the SNT as a lens, the researcher has successfully identified potential techniques and tools to be integrated in the BSDA model which are categorised into three groups; 1) content analysis, 2) network analysis, and 3) prediction. From this study, it is evidenced that the used of these techniques in analysing BSD can provide new insights for the LG decision-making teams to have better understanding of their citizens.
3. This study contributes to the existing knowledge in terms of enhancing and applying the SNT in the case of social media implementation in the LG. The study was able to integrate and apply three prominent SNTs, namely the Strength of Weak, Structural Hole and Social Role theories

in order to understand and analyse the BSD in the LG social media network.

4. Besides the e-government planning and technology innovation, this study also contributes to the social media and BSD literature specifically in the case of LG. The literature review in Chapter Two extracted potential uses and benefits of BSD in the LG which can also be applied in other public sector organisations. Furthermore, the critical positions and social roles in the digital communities of social media network structure have been reviewed and identified in Chapter Three.
5. In terms of the methodological contribution, this study has developed a computational analytical approach such as content, sentiment and social network analyses to determine the impact of BSD in public services. Based on the research process described in Chapter Four, similar study may be reproduced in different contexts.

8.4 Practical Contributions

Empirically, the developed BSDA model is applied in this study to guide the interpretation of the case study findings of the use of Twitter in one of the LGs in the UK. The Twitter postings related to LG with a longitudinal data covered in 13 months of data collection were analysed in this study. The data contains the history of series communications and interactions between the LG and citizens performed through the social media channel. A set of toolkits including content and sentiment analysis tools was developed using open-source software. The sentiment analysis tool applied a supervised machine learning technique to analyse text and extract six different emotions. The tools can also be applied in other contexts. Practically, this study makes several important contributions. Firstly, it provides practitioners, decision-makers in public sectors, with a strategic tool in analysing the available BSD in their organisations. The applied model known as BSDA model can be used in utilising the BSD in the public sector particularly the LG. This model is important in order to understand the citizens' needs and expectations of the government services. Hence, the government could improve citizen satisfaction, enhance information dissemination and deliver better decision-making in the future policy.

Secondly, this study offers a new set of measures to identify the social roles in the LG social media network particularly to decision-makers and government officers. As a result, LG decision-makers can be more strategic in disseminating the government information through the prominent actors in the LG social media network.

Finally, the decision-makers and government officers can employ the open-source social network analysis tools to analyse two types of relationships from the BSD. From the explicit data, relationships between the social media users can be analysed based on the followers of the users. On the other hand, implicit relationships such as reposting messages (e.g. retweet) between social media users are potential to be analysed in order to identify the key actors in the network structure.

8.5 Measures of Success Revisited

As mentioned previously, the success of the work completed in this research was measured using criteria outlined in Chapter One. The following section will discuss each of these criteria in turn, in order to judge the success of the research.

Firstly, the research questions and sub questions listed in section 1.5 must be answered.

- The research questions and sub questions were answered and described in the section 8.2.

Secondly, an investigation illustrating whether the proposed BSDA model can be implemented in the real world, and thus be used commercially.

- The proposed BSDA model was implemented and empirical tested using Twitter data collected in a real environment. The findings suggest that a set of techniques and tools proposed in the BSDA model has the capability to analyse real world data, and thus can be used commercially.

Finally, the findings from the validation process has to be verified by the experts from LG.

- The findings from the validation process were presented to the experts from a selected LG and the feedback was discussed in the section 7.3. Subsequently, the proposed BSDA model was revised to produce the final model.

8.6 Research Limitation

Several limitations of this are summarised as follows:

- The case used in this is based on one selected LG in the UK, so it may be difficult to know whether the impact of analysing the BSD will be consistent or varying in the other areas of the country.
- The toolkits in this study were developed purposely for testing the empirical data from Twitter without considering other social media platforms.
- The algorithms employed to develop the toolkits were limited to certain numbers without comprehensively tested other algorithms.
- The data used in this study is limited to the text while the actual data in the social media coversation include images, photos, videos and emoji.
- The training dataset for the sentiment analysis tool in this study were limited. By increasing the number of dataset for training can increase the accuracy of the system.
- The study acknowledge post Cambridge analytics. The issue around data manipulation is of concern. However, this study at the time focused on constructive and ethical use of BSD to improve provision of local services

to citizens. The unethical manipulation use of BSD is beyond the scope of this study and could be a very rich area for future research.

8.7 Suggestion for Future Research

Based on the limitations and findings from the current study, the followings are a range of suggestions for future research directions:

- A comprehensive study should involve data collection from other cities and rural areas of LGs. It would be useful to collect the data from different level of LGs and compare the conversation between social media users whether it is consistent or varies according tothe different regionals.
- The current toolkits can be upgraded using other algorithms and techniques to increase the results accuracy. Hence, the tools can be tested with the same or other data formats from various social media platforms.
- Future research can explore on the similar techniques used in this study with numerous types of data including image, photos, audio, video and emoji. These types of data offer more opportunities to be explored in order to provide in-depth understanding of the issues.

8.8 Chapter Summary

This chapter provides a summary of the findings with the discussions based on the research questions stated in Chapter One. This thesis presents a BSDA model as a guidance for the decision-makers to analyse public sectors social media data. The model was discussed in Chapters Six and operationalised in Chapter Seven. The techniques to analyse and visualise the data were tested in Chapter Seven, whilst the discussion on the literature review, the case study and findings were presented in this chapter. The chapter also discusses the key contributions of this research to the academic literature in e-government and social media disciplines, theoretical and practical implications, limitation, and future potential research.

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APPENDICES

Appendix-A E-Government Evolvement and Benefits

The evolvement of e-government main purpose can be seen from the series of United Nations (UN) e-government survey reports as listed in Table 1.0. From the table, it is depicted that each report used a different theme to achieve various objectives in their assessment of e-government development status for the 193 UN state members. The report began in 2002 with a clear objective of assessing e-government in the context of efficiency in delivering and accessing government information to citizens. Over the years, the evaluation evolves to public sector reform for greater operation and improved productivity. Currently, the e-government is expected to offer multiple channels of interaction to increase citizen engagement in government decision-making processes.

Table 1.1: United Nation E-Government Survey

Year	Theme	Explanation
(2002)	Benchmarking e-government	The report is concerned about the current level of e-government implementation in the UN member states. E-government is defined as a technology that advanced delivery and access to public services and government's information through ICTs (Ronaghan 2002).
(2003)	E-government creates a significant opportunity for all	*E-government is about the opportunity. Opportunity for the public sector is to reform towards achieving greater efficiency and efficacy. Opportunity to reduce costs and increase services to society. Opportunity to include all in public service delivery.* (UNPAN 2003, p.58).
(2004)	Towards accessing opportunity	The focus of this report is to evaluate gaps in access-divide among the societies where opportunities should be given to all citizens to access public services. The link between ICTs, knowledge civilisation and growth is highlighted (UNPAN 2004).
(2005)	From E-government to E-inclusion	The term 'e-inclusion' was introduced to explain the activities executed by the government that involved ICTs to reduce access gap between communities and leverage chances to everybody to use e-government facilities for better economic growth (UNPAN 2005).
(2008)	From e-Government to Connected Governance	*Assessment of the new role of the government in enhancing public service delivery, while improving the efficiency and productivity of government processes and systems* (UNPAN 2008, p.xii).
(2010)	Leveraging e-government at a time of financial and economic crisis	*E-government is a mean of enhancing the capacity of the public sector, together with citizens, to address development issues* (UNPAN 2010, p.2).
(2012)	E-Government for the People	*Areas deserving special emphasis include expanding usage of e-government services through multiple channels, and a whole-of-government approach in promoting equity and bridging the digital divide by extending service delivery to all,*

		particularly the vulnerable groups (UNPAN 2012, p.2).
(2014)	E-government for the future we want	*Addressing the multi-faceted and complex challenges that our societies face today* (UNPAN 2014, p.3)(UNPAN 2014)(UNPAN 2014)(UNPAN 2014)(UNPAN 2014)(UNPAN 2014)(UNPAN 2014)(UNPAN 2014)
(2016)	E-government in support of sustainable development	Improving e-government to increase citizen engagement in government decision-making processes towards transparency and accountability of public services (UNPAN 2016).

In the early 2000s, the scholars referred to e-government as a transformation method of accessing and delivering government services to citizens and other government's stakeholders through ICTs (Deloitte 2000; Gant and Gant 2002; Layne and Lee 2001). Despite the differences, an agreed definition on e-government was the one referred to as the utilisation of ICTs mainly the internet to reform the delivering method of government services to citizens. Nevertheless, this definition has evolved over the years from accessing and delivering to participation and interaction (Halchin 2004; Yanqing 2010) as listed in Table 1.2.

In this phase, government-citizen interactions are less formal and more regular through the use of modern technologies such as online forum, web site and blog. More recent attention of e-government focuses on the provision of government in utilising social media technology to enhance citizen empowerment in accessing information and engaging in government decision-making processes (Bertot et al. 2010; Tursunbayeva et al. 2017). These initiatives and strategies are used to increase transparency, reduce corruption, and raise revenue in open government environment (Bertot et al. 2010; World Bank 2015).

Table 1.2: The evolvement of e-government definitions

Elements focused on the definition	Authors	Examples
Accessing and delivery	(Deloitte 2000) (Layne and Lee 2001) (Holmes 2001) (Gant and Gant 2002) (Ronaghan 2002)	"*E-government, the delivery of government services online, provides an opportunity to increase access to government, reduce government citizen bureaucracy, increase citizen participation democracy, and enhance agency responsiveness to citizen needs*" (Gant and Gant 2002, p.2).
Participation and interaction	(Halchin 2004) (Carter and Belanger 2005) (Yanqing 2010)	"*A form of organisation that integrates the interactions and the interrelations between government and citizens, companies, customers, and public institutions through the application of modern information and communication technologies*" (Halchin 2004, p.407).
Engagement and empowerment	(Bertot et al. 2010) (UNPAN 2014) (World Bank 2015) (Tursunbayeva et al. 2017)	*"E-government can be referred as the use and application of information technologies in public administration to streamline and integrate workflows and processes, to effectively manage data and information, enhance public service delivery, as well as expand*

		communication channels for engagement and empowerment of people" (UNPAN 2014, p.2).

Benefits of e-government

The implementation of e-government has significantly transformed the public-sector administrations whereby currently there is a great opportunity for citizens to engage with the government towards enhancing public services. The implementation of e-government produces many important benefits to governments, firms and individuals (Weerakkody et al. 2015) that could be categorised into administrative and political benefits (Bretschneider et al. 2003)

The administrative benefits have a direct impact on the governments and citizens such as reducing processing time (Hackney et al. 2007; Carter et al. 2012), saving operational costs (Moon 2002; Hackney et al. 2007; Wang and Liao 2008; Zafiropoulos et al. 2014), and decreasing human mistakes (Carter et al. 2012). For instance, putting online broadcasting takes a shorter time to reach the target audiences with minimal cost compared to traditional methods such as newspaper or postal letters (Zafiropoulos et al. 2014). Hence, the higher efficiency in public administration could increase the quality of e-government services (Reddick 2004).

On the other hand, examples of political benefits include enhancing citizen satisfaction (Alawneh et al. 2013; Carter and Belanger 2005; Kamal et al. 2009; Teo et al. 2009), increasing transparency (Bertot et al. 2010; World Bank 2015), and advancing public participation and engagement (Chu et al. 2008; Warren et al. 2014). These are potential indicators to promote the better perception of citizens towards government services (Magro 2012). The prior study argued that positive perception of e-government drives to the positive satisfaction of e-government services (Reddick and Roy 2013). As such, the implementation of e-government can improve service quality and increase positive perception of citizens towards e-government services.

Appendix-B Preliminary Study on E-Government Research

Understanding the Corpus of E-Government Research: An Analysis of the Literature Using Co-Citation Analysis and Social Network Analysis

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Abstract

The growing body of published e-government literature highlights the importance of e-government in society and the need to make sense of e-government by academia. In order to understand the future of e-government, it is important to understand the research that has been conducted and highlight the issues and themes that have been identified as important by empirical study. This paper analyses the corpus of e-government research published from 2000 to 2013 using Bibliometric and Social Network Analysis (SNA) methods to develop an intellectual structure of e-government research. Factor analysis, multidimensional scaling and centrality measurement are also applied to the e-government dataset using UCINET to identify the core influential articles in the field. This study identifies three core clusters of e-government research that centre around (i) e-government development models (ii) adoption and acceptance of e-government, and (iii) e-government using social media and highlights areas for future research in the field.

Introduction

After nearly two decades of e-government implementation globally, the body of literature related to e-government research and evaluation has also grown considerably over the decades (Heeks and Bailur 2007), highlighting the importance of e-government in society and the need to make sense of it which has attracted researchers from different disciplines to identify new strategies, theories, techniques, methods and applications to advance the field of e-government research (Lean et al. 2009). Whether e-government is categorised as a research discipline in its own right or as a sub-domain of Information System and/or Public Administration has also been a topic of debate (Irani and Dwivedi 2008) making e-government a truly interdisciplinary area of research. However, after two decades of e-government implementation and near ubiquitous implementation across the world, has e-government now reached maturity and if so where is research in this field going in the future?

In order to address this question and understand the future of e-government research, it is important to investigate the research that has been conducted and highlight the issues and themes that have been identified as important by empirical study. Many studies that have reviewed the e-government literature have applied different methodologies to evaluate it, for example, content analysis (Heeks and Bailur 2007) and systematic literature review (Dwivedi 2009). These studies analysed e-government related conference and journal publications presenting different perspectives and identifying some of the important and relevant issues central to the study of e-government. Heeks and Bailur (2007) argued the current e-government research had not enough contribute neither in theory nor practical recommendations because of certain factors that influenced researchers in selecting research approach and Dwivedi (2009) discovered that researchers with information systems background contributed the largest number of articles in the analysed journal.

Other studies have focused on specific themes, for example design and methodologies used in e-government research (Irani et al. 2012), issues related to e-government implementation (Weerakkody et al. 2015), studies of e-government research in specific country (Paiva 2014; Snead and Wright 2014), e-government research related to policy (Kromidha and Cordoba-Pachon 2014), theories and application used in e-government research (Rana et al. 2011) and e-government adoption research (Rana et al. 2013a; Rana et al. 2013b). While some studies have described e-government research from a qualitative perspective, few studies have reviewed the current status of e-government research from a quantitative perspective. To date, and to the best knowledge of the authors, there has been no published study that has evaluated the intellectual structure of e-government literature. This paper therefore addresses this omission and presents the findings of an intellectual structure analysis of published e-government research from 2000 to 2013, using Bibliometric and Social Network Analysis (SNA) methods. In addition, this paper provides additional insights to the structure of the research by applying factor analysis, multidimensional scaling and centrality measurement to the e-government publications dataset using UCINET to identify the core influential articles in the field. The remainder of this paper is organised as follows. The methodology section explains in detail the methods used, the process of analysis applied and the constituents of the dataset of e-government publications. The results of the analysis are then presented, and the findings discussed. The conclusions highlight the implications of the study and the findings.

Methodology

The methodology used in this analytical process of reviewing the e-government literature is divided into four phases summarised in Figure 1. The first phase was to compile the dataset of e-government publications, followed by a process of citation analysis, co-citation analysis and then social network analysis. Each of these phases is described in more detail in the following sections.

First phase.

The Scopus database, one of the largest collections of academic publications, was used in this case as the bibliographic database for interrogation. The Scopus contains citations published in more than 20,000 peer-reviewed journals (Anon 2013) including Government Information Quarterly, Electronic Government, International Journal of Electronic Government Research, Information Polity, Transforming Government People, Process and Policy, International Journal of Public Administration, and Public Administration Review. In addition, only 54% of journal titles indexed in the Scopus are covered in Web of Science database (Gavel and Iselid 2008). Furthermore, coverage of the Scopus database in term of citations is 20 percent higher than the Web of Science (Falagas et al. 2008) with full citation analysis accessible from 1996 onwards (Bar-Ilan 2010).

A keyword method was adopted to identify a collection of representative research articles from Scopus. The string/keywords used for the search process were “e-government” OR “electronic government” OR “egovernment” which appeared in the publication title, abstract or keyword sections. Selected publications had to be categorised as article, written in English and a “journal” publication for our purposes. In addition, manual checking was implemented to ensure only the publications related to e-government were selected. The outcome of this phase was a list of articles related to e-government research.

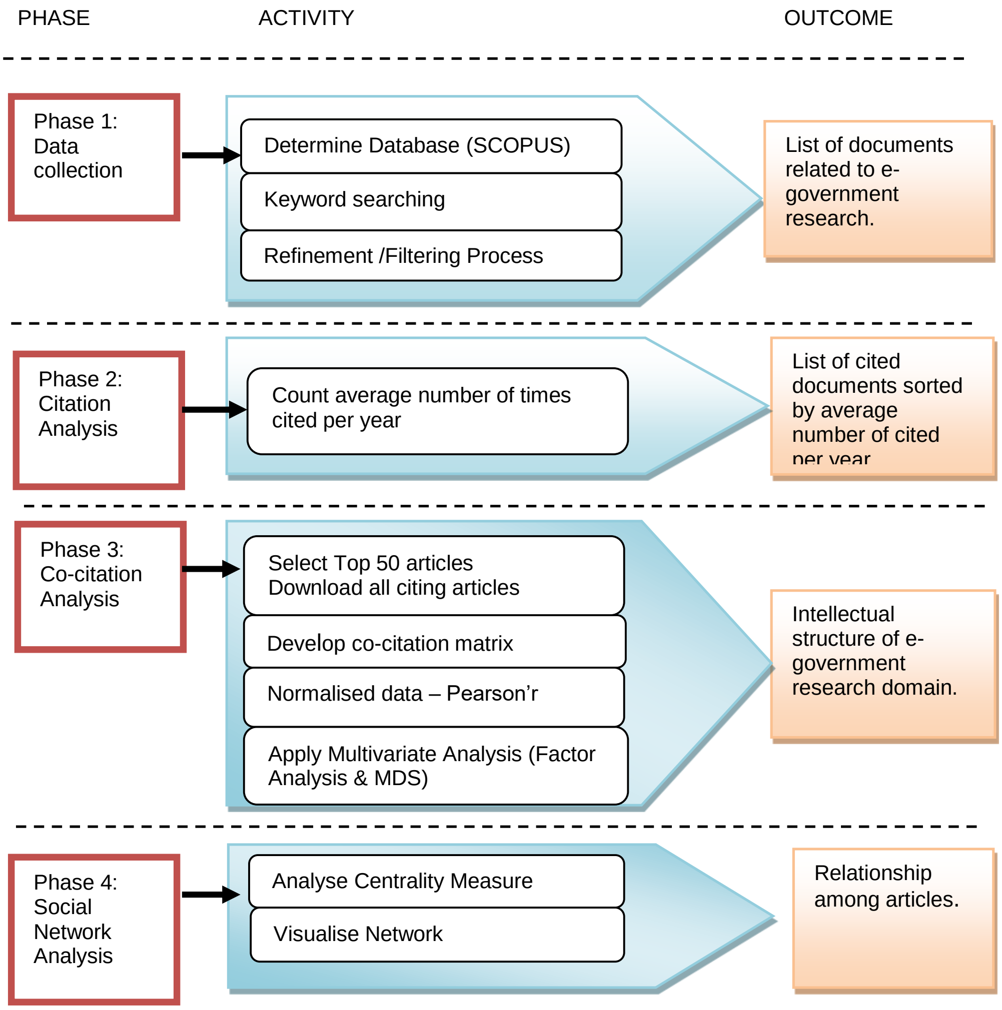

Figure 1: Analytical Process for Reviewing the E-Government Literature

Second phase.

Citation analysis is the ranking of publications based on the number of times an article has been cited in other articles. A high publication ranking score reflects more influence on the discipline (Culnan 1986). In this phase, information from all selected articles were imported into a spreadsheet and sorted by number of times it was cited up to 01 December 2014. The results list the highest cited article at the top and the lowest cited at the bottom. Obviously, the longer the articles had been published, the more likely they are to have been cited and this could influence the rankings considerably. To address this potential problem, we developed a measurement which considered the publication date independently of the length of time it was published. An average number of times each article was cited per year was counted using the following formula:

$$\text{Average number of times cited per year} = \frac{\text{(total number of times cited)}}{\text{(2014 – Publication year)}}$$

For example, an article by Bertot, Jaeger and Hansen (Bertot, Jaeger and Hansen 2012) was cited by 60 articles. After applying the above formula, the article received 30 citations per year. Another example, an article by Cater and Weerakkody (2008) only received 20 citations yearly although the total number of citations is 120.

Thus, applying the above formula will give an equal chance that all articles selected are ranked in the list according to citations independent of length of time. Thus, a new list of articles sorted by the above formula was formed for co-citation analysis in the next phase. This list was called cited documents.

Third phase.

The co-citation analysis method of White and Griffith (1981) was adopted in this phase to achieve the objective of identifying the intellectual structure of the body of e-government literature. Co-citation is a frequency count of earlier publications cited together in later publication (Small 1973). The use of the co-citation analysis method to interpret the intellectual structure of research has been applied by several scholars in a number of studies (White and Griffith 1981; Ponzi 2002; Pilkington and Meredith 2009; Hsiao and Yang 2011; Shiau and Dwivedi 2013). Co-citation analysis identifies similarities between units of analysis of which there are three types - document, author and journal. Small (1973) introduced document co-citation analysis to analyse the intellectual structure of scientific specialties. This method has been extended to author co-citation analysis to measure intellectual structure of information science (White and Griffith 1981) and journal co-citation analysis for mapping economics journals (Mccain 1991) through literature. More recently, scholars have used author co-citation or document co-citation analysis to interpret the intellectual structure of scientific studies. For instance, using document co-citation analysis to demonstrate that documents published in journals are more reliable after having gone through a review process (Ramos-Rodríguez and Ruíz-Navarro 2004) and are normally based on high quality research (Webster and Watson 2002).

However, co-citation is not without its limitations. For instance, author co-citation analysis is biased in that it only analyses the first author and disregards the co-authors. Furthermore, authors are likely to work in the same research discipline over a period of time and are therefore likely indulge in self-citation, legitimately building on the work they have done previously. Therefore, we consider document co-citation analysis to be a more accurate way of representing the intellectual structure of, in this case, e-government research and an appropriate measure of an article's influence within the body of e-government research.

For document co-citation analysis, two sets of documents were used to develop a co-citation matrix. The first set of documents were cited documents (source documents) which represented highly cited articles sorted by average number of citations per year. The second set of documents were citing documents, which cite source documents. This phase was initiated with imported information of cited documents from the previous phase and meta-data of citing documents downloaded from Scopus into a relational database. Then, a frequency of co-citation for each pair of cited articles was counted and transformed into a 50 by 50 square symmetrical co-citation matrix with the diagonal value treated as zero to represent no single article citing itself (McCain 1990; Ramos-Rodríguez and Ruíz-Navarro 2004). The threshold problem was solved using the trend of an average number of co-citations per article. The average number of co-citations was compared with the number of cited documents and plotted in a graph as shown in Figure 2, which shows how the average number of co-citations decreased when the number of cited documents increased. This trend stabilised at 30 cited documents which is acceptable as a threshold. However, in order to provide more accuracy to our study, we increased the threshold to 50 cited documents which were included in our dataset to improve the validity and reliability of the factor analysis results (Hair et al. 2010; Comrey and Lee 1992).

The co-citation matrix was normalized using Pearson's correlation coefficient for multivariate analysis. Pearson's correlation coefficient was chosen as a degree of similarity measurement that specifies the likeness relationship between all articles and to solve the problem of unlimited divergence between two related articles for the reason of differences in a scale (White and Mccain 1998). The first multivariate analysis techniques implemented using normalized co-citation matrix is factor analysis (FA) which is used to identify the core structure of research (Tabachnick and Fidell 2008). FA reduces and groups items according to their similarity and differences as factors and allows an item (article) to be placed in multiple factors. Factor loadings greater than +-0.7 were used to identify the most appropriate items (McCain 1990; Hair et al. 2010).

The second multivariate analysis technique adopted in this study was multidimensional scaling (MDS), a routine to visualize patterns of proximities among a group of items. In this study, articles were plotted according to the similarity value where the higher the value the closer each pair of articles on the map (Leydesdorff and Vaughan 2006). Unlike FA, MDS maps each article only at a single point. MDS uses stress value to measure goodness of fit where the smaller value is the better representation. Stress values less than 0.2 are considered a representative fit (Hair et al. 2010; McCain 1990). NetDraw (Borgatti 2002) was used to visually map the MDS result. The outcome of this third phase was to present the intellectual structure of e-government research.

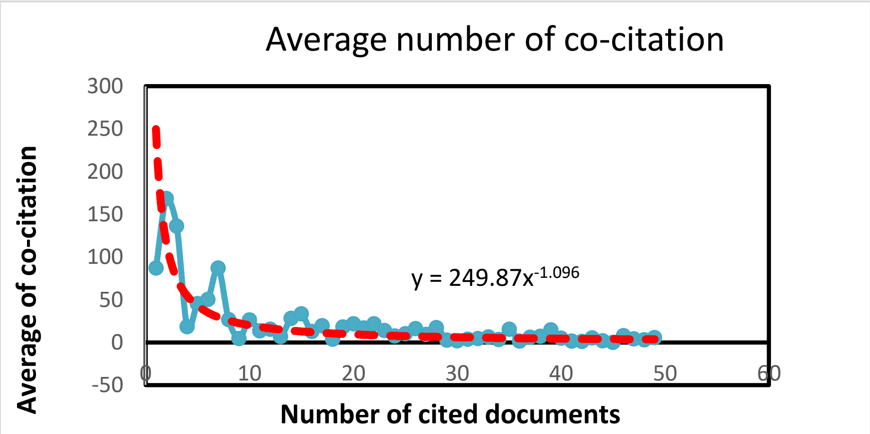

Figure 2: Trend of average number of co-citations

Fourth phase.

Analysis of document co-citation is critical to understanding the influence and impact of articles on the sub-domain of research and Social Network Analysis (SNA) was used in this instance to achieve this objective. SNA uses centrality measure to identify the most important and influential nodes or articles in the network map. Based on a raw document of co-citation matrix, using UCINET (Borgatti et al. 2002) creates a co-citation network map to measure the actual proportional relationships between articles (Wang and Chen 2014). The three centrality measures of SNA were then applied. Firstly, degree centrality also known as local centrality indicates the popularity ranking of an article and was applied to measure the number of direct links between articles. Second, betweenness centrality was used to measure the number of times an article has been used as the shortest path between two other articles. The higher the value of betweenness centrality indicates the greater influence the article has in the network and is perceived as a leader and likely to manage network processes (Freeman 1979). Finally, eigenvector centrality was used to measure the central article which is connected to other prominent articles (Bonacich 1972). The higher the eigenvector centrality score, the greater the influence of the article on other key articles in the network domain.

Analysis and Findings

The number of e-government articles published in refereed journals has increased gradually over the years as illustrated in Figure 3. In total, 1,932 articles were published from 2000 to 2013, beginning with seven articles in 2000 increasing steadily over the next thirteen years with a couple of minor dips in 2004 and 20011. This broadly mirrors the increasing interest in and implementation and adoption of e-government across the globe.

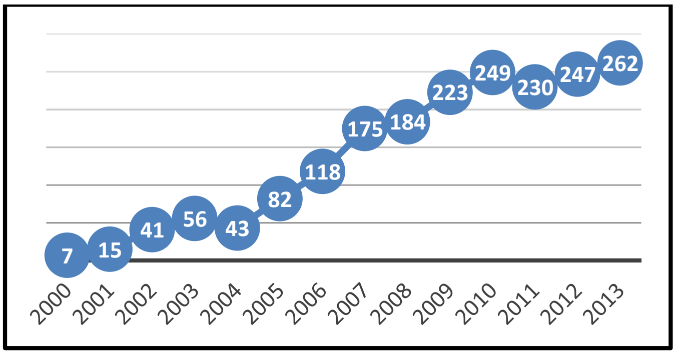

Figure 3: Number of E-government Articles Published Annually (2000-2013)

Having established the dataset of e-government articles, the three-phase analytical process described earlier and summarised in figure 1 was applied. The rest of this section will present the findings as follows: (i) the citation analysis will explain the citation results of the dataset. (ii) the co-citation analysis will present the multivariate analysis test results and finally, (iii) the Social Network Analysis will describe the findings of the network analysis tests.

Citation Analysis

The search process yielded 1,942 cited documents and 26,057 citing documents related to e-government research from 2000 to 2013. A further manual checking process identified seven anonymous articles and three further articles that were not relevant to e-government and these were excluded from this study. The remaining 1,932 cited documents were further analysed. The cited documents were ranked according to the average number of citations per year. The top 50 cited documents are listed in Table 1. The highest cited document per year taken as an average was (Layne and Lee 2001), followed by (Carter and Belanger 2005), (Moon 2002) and (West 2004). Using the yearly average counting method allows more recent articles to be included in the top 50 for example articles by (Norris and Reddick 2013), (Bertot, Jaeger and Hansen 2012) and (Bonsón et al. 2012). In total 11 articles published from 2010 to 2013 were listed. This counting method also provides better rankings for (Carter and Belanger 2005) compared to (Moon 2002) even though the total number of citations for (Moon 2002) is higher. Surprisingly, the article by (Bertot et al. 2010) was listed in the top five ranking which highlights an emerging research theme related to social media that has attracted researchers in the field of e-government research.

Table 1: List of 50 Most Cited E-Government Articles

ID	Authors	Publication Year	No. of Citations	Average Yearly Citations
1	Layne & Lee (2001)	2001	839	64.5
2	Carter & Belanger (2005)	2005	515	57.2
3	Moon (2002)	2002	661	55.1
4	West (2004)	2004	476	47.6
5	Bertot, Jaeger & Grimes (2010)	2010	190	47.5

6	Heeks & Bailur (2007)	2007	267	38.1
7	Yildiz (2007)	2007	257	36.7
8	Ho (2002)	2002	436	36.3
9	Belanger & Carter (2008)	2008	197	32.8
10	Bertot, Jaeger & Hansen (2012)	2012	60	30.0
11	Coursey & Norris (2008)	2008	143	23.8
12	Teo, Srivastava & Jiang (2009)	2009	116	23.2
13	Wang & Liao (2008)	2008	137	22.8
14	Saebo, Rose, Skiftenes (2008)	2008	133	22.2
15	Andersen & Henriksen (2006)	2006	177	22.1
16	Thomas & Streib (2003)	2003	243	22.1
17	Verdegem & Verleye (2009)	2009	109	21.8
18	Ebrahim & Irani (2005).	2005	195	21.7
19	Bonson, Torres, Royo & Flores (2012)	2012	43	21.5
20	Carter & Weerakkody (2008)	2008	120	20.0
21	Reddick (2005)	2005	179	19.9
22	Hung, Chang & Yu (2006)	2006	155	19.4
23	Moon & Norris (2005)	2005	168	18.7
24	Horst, Kuttschreuter & Gutteling (2007)	2007	127	18.1
25	Shareef, Kumar, Kumar & Dwivedi (2011)	2011	53	17.7
26	Helbig, Gil-Garcia & Ferro (2009)	2009	88	17.6
27	Jaeger & Thompson (2003)	2003	186	16.9
28	Lean, Zailani, Ramayah & Fernando (2009)	2009	84	16.8
29	Gupta & Jana (2003)	2003	179	16.3
30	Sandoval-Almazan & Gil-Garcia (2012)	2012	32	16.0
31	Norris & Reddick (2013)	2013	16	16.0
32	Jaeger & Bertot (2010)	2010	63	15.8
33	Guijarro (2007)	2007	110	15.7
34	Kim, Kim &Lee (2009)	2009	78	15.6
35	Scholl & Klischewski (2007)	2007	109	15.6
36	Reddick (2004)	2004	146	14.6
37	Linders (2012)	2012	29	14.5
38	Klievink & Janssen (2009)	2009	71	14.2
39	Ebbers, Pieterson & Noordman (2008)	2008	85	14.2
40	Jaeger (2003)	2003	155	14.1
41	Gil-Garcia, Chengalur-Smith &Duchessi (2007)	2007	98	14.0
42	Bertot, Jaeger & Grimes (2012)	2012	28	14.0
44	Kim & Lee (2006)	2006	109	13.6
43	Fu, Farn & Chao (2006)	2006	109	13.6
45	Picazo-Vela, Gutierrez-Martinez & Luna-Reyes (2012)	2012	27	13.5
46	Evans & Yen (2006)	2006	106	13.3
47	Schuppan (2009)	2009	65	13.0
48	McDermott (2010)	2010	52	13.0
49	Irani, Elliman & Jackson (2007)	2007	88	12.6
50	Gil-Garcia & Martinez-Moyano (2007)	2007	86	12.3

Co-citation Analysis

A Co-citation matrix was drawn from the dataset of 50 most cited documents (table 1) and 8,195 citing documents. Pearson's correlation coefficient was applied to normalise this co-citation matrix before statistical analysis using UCINET. FA and MDS were applied to identify intellectual structure and visualise the distribution of the articles.

FA was performed using principal component analysis with Varimax (orthogonal) rotation. In UCINET, we are allowed to set eigenvalue and number of factors as a cut-off point. Initially an eigenvalue greater than 1 was set and number of factors selected was 10. At this point, the analysis generated six factors with total variance explained was 80.1 percent. This resulted in factors four, five and six having only one item each which were articles by (Norris and Reddick 2013), (Kim and Lee 2006) and (Bertot et al. 2010) respectively. For the next iteration of analysis, the eigenvalue remained at greater than 1 but number of factors was reduced to three. Consequently, three factors resulted in 71.4 percent total variance explained. In social science research, total variance greater than 50 percent is acceptable and more than 70 percent is considered high (Hair et al. 2010). The articles by (Norris and Reddick 2013) and (Bertot et al. 2010) were placed in factor two with factor loadings greater than 0.45 and the article by (Kim and Lee 2006) was placed in factor three with factor loading -0.384 as shown in Table 2.

Table 2: Factor Analysis, Total variance explained: 71.4%

ID	Author	Factor 1	Factor 2	Factor 3
P36	Reddick (2004)	0.935	0.028	-0.173
P11	Coursey & Norris (2008)	0.91	0.05	-0.151
P29	Gupta & Jana (2003)	0.882	-0.053	-0.313
P38	Klievink & Janssen (2009)	0.877	0	-0.012
P23	Moon & Norris (2005)	0.861	0.06	-0.305
P8	Ho (2002)	0.857	0.073	-0.106
P15	Andersen & Henriksen (2006)	0.849	0.017	-0.12
P18	Ebrahim & Irani (2005).	0.838	-0.014	-0.341
P49	Irani , Elliman & Jackson (2007)	0.836	-0.018	-0.374
P50	Gil-Garcia & Martinez-Moyano (2007)	0.832	-0.054	-0.186
P4	West (2004)	0.824	0.029	-0.179
P47	Schuppan (2009)	0.82	0.092	-0.287
P40	Jaeger (2003)	0.811	-0.059	-0.423
P27	Jaeger & Thompson (2003)	0.808	0.01	-0.342
P16	Thomas & Streib (2003)	0.783	0.066	-0.291
P46	Evans & Yen (2006)	0.766	-0.038	-0.465
P34	Kim, Kim &Lee (2009)	0.759	0.322	-0.275
P6	Heeks & Bailur (2007)	0.758	-0.073	-0.266
P3	Moon (2002)	0.758	0.016	-0.15
P7	Yildiz (2007)	0.755	-0.083	-0.257
P21	Reddick (2005)	0.751	0.024	-0.459
P41	Gil-Garcia, Chengalur-Smith &Duchessi (2007)	0.74	-0.117	-0.181
P1	Layne & Lee (2001)	0.715	-0.015	-0.127
P33	Guijarro (2007)	0.705	-0.214	-0.164
P14	Saebo, Rose, Skiftenes (2008)	0.692	0.233	-0.163
P26	Helbig, Gil-Garcia & Ferro (2009)	0.661	0.041	-0.496
P35	Scholl & Klischewski (2007)	0.642	-0.136	0.155
P39	Ebbers, Pieterson & Noordman (2008)	0.641	0.069	-0.397
P2	Carter & Belanger (2005)	0.606	-0.182	-0.345
P42	Bertot, Jaeger & Grimes (2012)	-0.166	0.912	0.062
P30	Sandoval-Almazan & Gil-Garcia (2012)	0.033	0.88	-0.04
P45	Picazo-Vela, Gutierrez-Martinez & Luna-Reyes (2012)	-0.222	0.877	0.108
P19	Bonson, Torres, Royo & Flores (2012)	-0.097	0.858	0.17
P37	Linders (2012)	-0.116	0.844	0.146
P32	Jaeger & Bertot (2010)	0.084	0.807	-0.018
P48	McDermott (2010)	0.142	0.796	0.097
P10	Bertot, Jaeger & Hansen (2012)	-0.131	0.787	0.17
P31	Norris & Reddick (2013)	0.336	0.521	0.151
P5	Bertot, Jaeger & Grimes (2010)	0.221	0.496	0.083
P28	Lean, Zailani, Ramayah & Fernando (2009)	0.078	-0.169	-0.913
P24	Horst, Kuttschreuter & Gutteling (2007)	0.177	-0.141	-0.899
P44	Fu, Farn & Chao (2006)	0.124	-0.081	-0.887

P12	Teo, Srivastava & Jiang (2009)	0.316	-0.068	-0.863
P9	Belanger & Carter (2008)	0.244	-0.088	-0.846
P22	Hung, Chang & Yu (2006)	0.245	-0.133	-0.838
P13	Wang & Liao (2008)	0.323	-0.204	-0.808
P20	Carter & Weerakkody (2008)	0.42	-0.031	-0.806
P25	Shareef, Kumar, Kumar & Dwivedi (2011)	0.454	-0.057	-0.758
P17	Verdegem & Verleye (2009)	0.456	-0.155	-0.695
P43	Kim & Lee (2006)	0.372	-0.222	-0.384
Variance Explained		23.934	7.373	4.402
Percent of Variance Explained		47.9	14.7	8.8

Factor 1 explained 47.9 percent of the variance and most of the articles received higher factor loading. For that reason, it is difficult to select an appropriate label to represent all articles in this factor. However, it contains most of the early e-government research including e-government development models (Reddick 2004; Coursey and Norris 2008; Klievink and Janssen 2009; Andersen and Henriksen 2006; Layne and Lee 2001), e-government frameworks (Gupta and Jana 2003; Guijarro 2007), evolution of e-government (Moon 2002; Gil-Garcia and Martinez-Moyano 2007), citizen interactions (Thomas and Streib 2003; Reddick 2005) and critical review of e-government research and implementation (Jaeger 2003; Jaeger and Thompson 2003; Yildiz 2007; Heeks and Bailur 2007). Two articles had factor loadings more than 0.9. The first article is (Reddick 2004) which examined the current development of e-government implementation in American cities using the first two stages of Layne & Lee's (2001) model. The second article empirically analysed five different e-government development models (Coursey and Norris 2008). Based on these works, factor 1 was labelled as e-government development model.

Factor 2 was dominated by articles related to suitability of e-government using Web 2.0 technology and social media in order to improve transparency (Bertot, Jaeger, Grimes, et al. 2012; Bonsón et al. 2012; Jaeger and Bertot 2010; McDermott 2010; Bertot et al. 2010), citizen interaction and collaboration (Sandoval-Almazan and Gil-Garcia 2012; Picazo-Vela et al. 2012; Norris and Reddick 2013; Linders 2012) and government policy and regulation related to anti-corruption and trust issues (Bertot, Jaeger and Hansen 2012)(McDermott 2010). The variance explained by this factor was 14.7 percent.

Factor 3 focused on adoption and diffusion of e-government. Multiple theories of adoption and acceptance were tested to measure intention of citizen towards e-government implementation in different levels. More specifically, intention to use e-government (Lean et al. 2009), adoption (Horst et al. 2007; Carter and Weerakkody 2008; Shareef et al. 2011), acceptance (Fu et al. 2006; Hung et al. 2006), user satisfaction (Verdegem and Verleye 2009; Wang and Liao 2008) and trust (Teo et al. 2009; Bélanger and Carter 2008).This factor explained 8.8 percent of the variance.

The FA method means that an article can appear in more than one factor. In contrast, MDS limits an article to being graphically located only in one point. Thus, MDS can complement FA findings to position an article in a major sub-research domain. Thus, all 50 articles in this dataset were located on a network map as shown in Figure 4 which only displayed links with values (correlation coefficient) exceeding 0.7. The stress value is 0.105 (lower than an acceptable value 0.2). Clearly, three main groups can be seen where group 1 (in the middle) is the biggest group with most articles from factor 1, group 2 (bottom left) with articles from factor 2 and group 3 (top right) with articles from factor 3. The MDS findings were consistent with those of the FA confirming the grouping of articles and enabling us to confidently extract the major themes and issues from these groups.

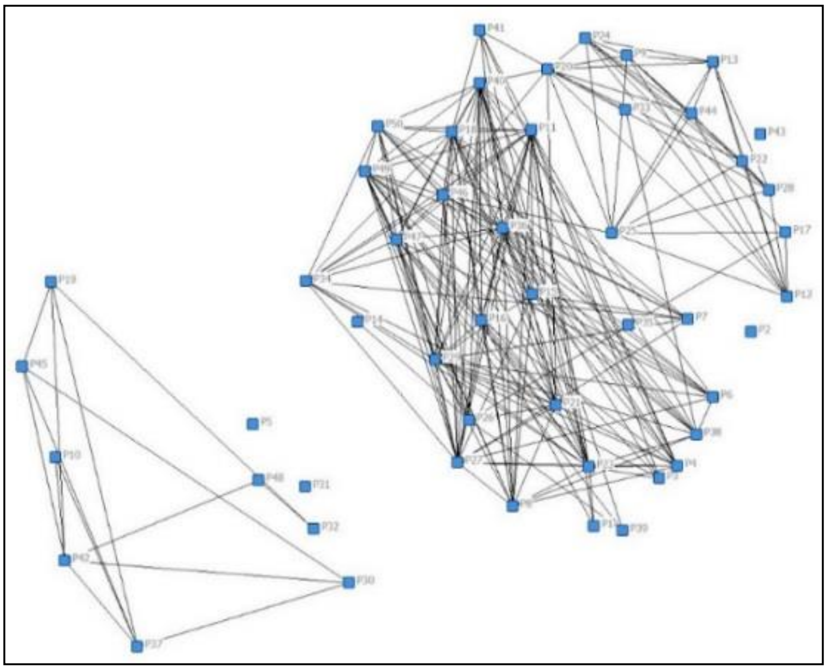

Figure 4: Network Map (Multidimensional Scaling)
*(correlation coefficient >=0.7)

Social Network Analysis (SNA)

Studying the relationships between research articles through SNA exposes the characteristics and level of ties among articles in a network map. Further investigation revealed the impact of certain articles on the sub domain of e-government research. SNA was applied using three centrality measures as discussed in the methodology section.

Table 3 provides an overview of the key e-government articles based on their three different centrality measures. The article by (West 2004) clearly dominated the centrality measure results. Degree centrality results showed an article by (West 2004) received the largest connection in the network map. Five other articles (Layne and Lee 2001), (Moon 2002), (Bertot et al. 2010), (Ho 2002), and (Coursey and Norris 2008) shared the second place. An article by (Norris and Reddick 2013) received the lowest degree centrality score.

A high value of betweenness centrality has the potential to link between establish researchers and new comers (Abbasi et al. 2012) because new researchers mostly link to betweenness centrality. Results of betweenness centrality showed the same article by (West 2004) received the highest score followed by three other articles in the second place including (Moon 2002), (Ho 2002) and (Coursey and Norris 2008). An article by (Bertot et al. 2010) was in the fifth place followed by (Layne and Lee 2001). An article by (Kim and Lee 2006) received zero score of betweenness centrality.

An eigenvector centrality results changed the network map relationship. An article by (Moon 2002) received the highest score followed by (Layne and Lee 2001). An article by (West 2004) dropped to the third place followed by (Ho 2002). Interestingly, an article by (Bertot et al. 2010) received low score in eigenvector centrality measure compared with the first two centrality measures.

Table 3: Result of Centrality Measures

Author	Degree	Author	Betweenness	Author	Eigenvector
West (2004)	49	West (2004)	9.351	Moon (2002)	60.204
Layne & Lee (2001)	48	Moon (2002)	7.966	Layne & Lee (2001)	57.932
Moon (2002)	48	Ho (2002)	7.966	West (2004)	46.77
Bertot, Jaeger & Grimes (2010)	48	Coursey & Norris (2008)	7.966	Ho (2002)	45.217
Ho (2002)	48	Bertot, Jaeger & Grimes (2010)	7.881	Carter & Belanger (2005)	37.467
Coursey & Norris (2008)	48	Layne & Lee (2001)	7.649	Thomas & Streib (2003)	28.125
Carter & Belanger (2005)	47	Thomas & Streib (2003)	7.182	Heeks & Bailur (2007)	25.26
Heeks & Bailur (2007)	47	Carter & Belanger (2005)	6.759	Yildiz (2007)	23.807
Yildiz (2007)	47	Yildiz (2007)	6.493	Andersen & Henriksen (2006)	22.557
Thomas & Streib (2003)	47	Heeks & Bailur (2007)	6.264	Moon & Norris (2005)	21.722
Belanger & Carter (2008)	46	Belanger & Carter (2008)	6.126	Reddick (2004)	21.716
Andersen & Henriksen (2006)	46	Saebo, Rose, Skiftenes (2008)	6.036	Reddick (2005)	19.266
Reddick (2005)	46	Reddick (2005)	5.993	Gupta & Jana (2003)	18.705
Moon & Norris (2005)	46	Kim, Kim &Lee (2009)	5.973	Jaeger (2003)	18.459
Jaeger & Thompson (2003)	46	McDermott (2010)	5.558	Ebrahim & Irani (2005).	18.362
Kim, Kim &Lee (2009)	46	Helbig, Gil-Garcia & Ferro (2009)	5.25	Coursey & Norris (2008)	17.827
Saebo, Rose, Skiftenes (2008)	45	Moon & Norris (2005)	5.154	Jaeger & Thompson (2003)	17.365
Ebrahim & Irani (2005).	45	Jaeger & Thompson (2003)	5.042	Belanger & Carter (2008)	15.808
Helbig, Gil-Garcia & Ferro (2009)	45	Andersen & Henriksen (2006)	5.008	Carter & Weerakkody (2008)	14.657
Klievink & Janssen (2009)	45	Ebrahim & Irani (2005).	4.969	Hung, Chang & Yu (2006)	13.346
Verdegem & Verleye (2009)	44	Schuppan (2009)	4.575	Evans & Yen (2006)	10.762
Jaeger (2003)	44	Teo, Srivastava & Jiang (2009)	4.443	Horst, Kuttschreuter & Gutteling (2007)	10.488
Teo, Srivastava & Jiang (2009)	43	Sandoval-Almazan & Gil-Garcia (2012)	4.409	Gil-Garcia & Martinez-Moyano (2007)	10.262
Hung, Chang & Yu (2006)	43	Klievink & Janssen (2009)	4.264	Wang & Liao (2008)	10.193
Reddick (2004)	43	Jaeger (2003)	4.224	Verdegem & Verleye (2009)	9.6
Ebbers, Pieterson & Noordman (2008)	43	Jaeger & Bertot (2010)	3.951	Irani , Elliman & Jackson (2007)	8.726
Evans & Yen (2006)	43	Verdegem & Verleye (2009)	3.726	Helbig, Gil-Garcia & Ferro (2009)	8.632
Shareef, Kumar, Kumar & Dwivedi (2011)	42	Bertot, Jaeger & Hansen (2012)	3.66	Teo, Srivastava & Jiang (2009)	8.448
Gupta & Jana (2003)	42	Ebbers, Pieterson & Noordman (2008)	3.337	Ebbers, Pieterson & Noordman (2008)	7.834
Gil-Garcia, Chengalur-Smith &Duchessi (2007)	42	Hung, Chang & Yu (2006)	2.75	Bertot, Jaeger & Grimes (2010)	7.719
Schuppan (2009)	42	Lean, Zailani, Ramayah & Fernando (2009)	2.649	Klievink & Janssen (2009)	7.628
Wang & Liao (2008)	41	Evans & Yen (2006)	2.437	Kim, Kim &Lee (2009)	7.07
Carter & Weerakkody (2008)	41	Reddick (2004)	2.237	Lean, Zailani, Ramayah & Fernando (2009)	6.67
Guijarro (2007)	41	Gil-Garcia, Chengalur-Smith &Duchessi (2007)	2.11	Gil-Garcia, Chengalur-Smith &Duchessi (2007)	6.456

Gil-Garcia & Martinez-Moyano (2007)	41	Bonson, Torres, Royo & Flores (2012)	2.1	Shareef, Kumar, Kumar & Dwivedi (2011)	6.139
Horst, Kuttschreuter & Gutteling (2007)	40	Gil-Garcia & Martinez-Moyano (2007)	2.038	Fu, Farn & Chao (2006)	5.814
Lean, Zailani, Ramayah & Fernando (2009)	40	Gupta & Jana (2003)	1.872	Schuppan (2009)	5.743
McDermott (2010)	40	Picazo-Vela, Gutierrez-Martinez & Luna-Reyes (2012)	1.686	Guijarro (2007)	5.583
Irani , Elliman & Jackson (2007)	39	Wang & Liao (2008)	1.527	Saebo, Rose, Skiftenes (2008)	5.075
Sandoval-Almazan & Gil-Garcia (2012)	38	Guijarro (2007)	1.448	Scholl & Klischewski (2007)	4.231
Jaeger & Bertot (2010)	38	Shareef, Kumar, Kumar & Dwivedi (2011)	1.395	Jaeger & Bertot (2010)	2.754
Bertot, Jaeger & Hansen (2012)	37	Linders (2012)	1.319	McDermott (2010)	2.746
Fu, Farn & Chao (2006)	37	Horst, Kuttschreuter & Gutteling (2007)	1.139	Sandoval-Almazan & Gil-Garcia (2012)	1.905
Scholl & Klischewski (2007)	32	Carter & Weerakkody (2008)	1.012	Bertot, Jaeger & Hansen (2012)	1.873
Bonson, Torres, Royo & Flores (2012)	29	Norris & Reddick (2013)	0.817	Bonson, Torres, Royo & Flores (2012)	1.533
Linders (2012)	24	Bertot, Jaeger & Grimes (2012)	0.695	Norris & Reddick (2013)	1.451
Kim & Lee (2006)	24	Fu, Farn & Chao (2006)	0.651	Kim & Lee (2006)	1.371
Picazo-Vela, Gutierrez-Martinez & Luna-Reyes (2012)	24	Irani , Elliman & Jackson (2007)	0.617	Linders (2012)	0.88
Bertot, Jaeger & Grimes (2012)	23	Scholl & Klischewski (2007)	0.325	Bertot, Jaeger & Grimes (2012)	0.838
Norris & Reddick (2013)	21	Kim & Lee (2006)	0	Picazo-Vela, Gutierrez-Martinez & Luna-Reyes (2012)	0.653

Discussion

The initial objective of this study was to better understand the intellectual structure of the body of e-government research and identify the works that have had the greatest impact on the field. Using the statistical methods of FA and MDS the findings showed that the articles clustered around three major themes namely (1) e-government development models (2) adoption and diffusion; and (3) social media.

The first cluster contained more than 50 percent of articles in this study highlighting the early focus on e-government development models and frameworks, the way citizen interacts with e-government and critical reviews of e-government research. The early years were influenced by the predominance of staged e-government models and similar e-government based frameworks largely driven by practitioner-based stage models of e-government development showing the different phases through which e-government would progress, summarised in Table 4. In particular Layne and Lee (2001) introduced a four stages of e-government development model as a guideline for public administrators to implement e-government in their organisations. West (2004) built on this and examined government service delivery and public attitudes towards e-government using the four stages of e-government transformation. The study found that technology used in government could improve democratic processes through better response to citizens' requests and increase government effectiveness. However, the same study revealed that implemented e-government had not yet reached its potential to transform service delivery and public trust in government.

Author	Development Model
(Layne and Lee 2001)	Four Stages: Catalogue; Transaction; Vertical integration; Horizontal integration
(Moon 2002)	Five Stages (adapted from (Hiller and Belanger 2001): Simple information dissemination (one-way communication) Two-way communication (request and response) Service and financial transactions Integration (horizontal and vertical integration) Political participation
(West 2004)	Four stages: Billboard Partial service delivery Portal with fully executable and integrated Interactive with public out-reach
(Klievink and Janssen 2009)	Five dynamic stages: Stovepipes Integrated organisations Nationwide portal Inter-organisational integration Demand-driven, joined-up government

Table 4: Literature Cluster 1: E-government development models

Moon (2002) adopted a five-stage framework introduced by (Hiller and Belanger 2001) in order to measure activities in local government. The study revealed immature e-government implementation (at stage I or stage II) and highlighted how government were struggling with limited budgets and technical aspects. Reddick (2004) built on this study with empirical data from three perspectives government to citizen (G2C), government to government (G2G) and government to business (G2B). Using Layne & Lee's (2001) model of e-government development they found G2C was lagging behind G2G and G2B having only reached Stage I while the others had reached Stage II. Andersen and Henriksen (2006) further highlight the limitations of the four stages model proposed by (Layne and Lee 2001) and propose an e-government maturity model known as Public Sector Process Rebuilding (PPR) maturity model.

Table 4 provides an overview of how e-government development models and frameworks were extended by researchers to better reflect issues involved in the implementation of e-government and thus evaluate its implementation. However, scholars have argued that these development models are neither representative of the stages through which e-government implementation progresses neither can they forecast the development of e-government (Coursey and Norris, 2008). While there have been recommendations for additional factors to be incorporated such as dynamic capabilities (Coursey & Norris, 2008) and incorporating national perspectives in addition to the organisation level (Klievink and Janssen 2009). Overall, the e-government development model has continued to be a topic of interest in e-government research until 2006 but interest has subsequently moved to new topics such as adoption and acceptance.

This second cluster of e-government research covers the period from 2006 to 2009 and focuses on topics related to adoption and diffusion of e-government which examined the issues related to post implementation and usage by citizens, summarised in Table 5. Here, theories of adoption and acceptance, such as Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behaviour (TPB), Theory of Reasoned Action (TRA), and Diffusion of Innovations (DOI) were applied to measure multiple perspectives and factors related to e-government, including trust, intention to use, user acceptance, and user satisfaction. Trust was found to be a particularly important factor of investigation in e-government adoption studies, as more than 50 percent of research in this cluster examined trust.

Author	Theory
(Horst et al. 2007)	Trust
(Teo et al. 2009)	Trust, DeLone and McLean model
(Lean et al. 2009)	Trust, TAM, DOI
(Carter and Weerakkody 2008)	Trust, TAM, UTAUT
(Bélanger and Carter 2008)	Trust, TRA
(Fu et al. 2006)	TAM,TPB
(Hung et al. 2006)	TPB
(Wang and Liao 2008)	DeLone and McLean model
(Shareef et al. 2011)	Trust

Table 5: Literature Cluster 2: Adoption Theory and Trust

The third cluster of e-government research focuses on current technology trends and use of social media to improve interaction and collaboration with citizens, reduce corruption and increase transparency. E-government research in this area is still in the early stages. A number of studies review transparency issues related to e-government. For instance, considerations and challenges of social media usage to open up access to government (Jaeger and Bertot, 2010); exploring the potential of e-government and social media to create a culture of transparency (Bertot et al. 2010); exploring ICT and social media to enhance collaboration between government and the public in order to promote transparency (Bertot et al. 2012); and the impact of social media on e-participation and transparency in EU countries (Bonsón et al. 2012). These and other studies show how social media has great potential to increase participation and improve communication between government and citizens (Picazo-Vela et al. 2012) and improve services particularly at a local level (Sandoval-Almazan and Gil-Garcia 2012; Norris and Reddick 2013). However, there is still a need to ensure that government policies, laws and regulations are able to deal with the changes and implications of using these technologies (Bertot, Jaeger and Hansen 2012; McDermott 2010).

A Social network analysis approach was applied to identify the most influential articles contributing to e-government research and the interrelationships between them. West (2004) was the only article found to have the maximum number of ties highlighting this as the most important and influential article in e-government research between 2000 to 2013. Using a four-stage model of e-government transformation, West (2004) links government service delivery and public attitudes which attracted many subsequent researchers to explore advanced strategies and solutions for better government services. This article was found to have been cited as a central reference around the world. Interestingly, there no single article was categorised as isolated which means that all articles were in some way connected in the network. The same article (West 2004) was also found to be important as a central article that providing a link bridging the most articles in the network together. At the other extreme, the article by Kim & Lee (2006) was found to have no influence and was the least important in this network map. Furthermore, the articles by Moon (2002) followed by Layne & Lee (2001) were found to be in the central position and connected to the other important articles in the network map. The article focusing on social media and e-government (Bertot et al. 2010) was found to have the lowest score and consequently was the least connected indicating the relative newness of the paper and the topic in the body of e-government research.

Conclusion and limitations

Evaluating the intellectual structure of e-government research provides some very interesting insights to the literature published from 2000 to 2013. We can see the subject area is dynamic as evidenced in the development and evolution of themes and issues from the literature over the past 14 years. The research has moved from the rather static evaluation of e-government through frameworks and models in the first cluster, highlighting issues of users, citizen inclusion and implementation of e-government in the second cluster and finally, emerging in line with the changing technological trends and digital environments to issues of new technologies and social media in the third cluster. This provides fertile ground to further develop a greater understanding of e-government in the context of the ever-changing landscape of new technologies and related phenomena of social media.

While the data analysis process has been rigorous as with any research, this study has several limitations which could be addressed in future research. First, the database used for data extraction was limited to Scopus. Some other journals might not be covered in this database. Future study is recommended to apply the same techniques using other database as a complimentary to this study. Second, the keywords used in this study were specific to terms related to “e-government”. Since this research domain is new and evolving, new terms are expected to be introduced and used. Other keywords such as digital government, seamless government and online government can be added into search process. The keywords used in the search process could be extended to enhance comprehensive coverage of e-government articles. Third, document co-citation was used in this study as a unit of analysis. Alternatively, other type of analysis (author co-citation or journal co-citation) can be applied. While we have adopted three centrality measures in SNA, there are other techniques in SNA can be used to measure different level of relationships.

This study has used some novel analytical techniques to shed some light on and deeper understanding of the body of e-government research to date. It provides some insights not only on the dominant themes that have pre-occupied the community of scholars but has also provided some deep insights to the inter-connectedness of research that enriches our understanding of the e-government field and presents opportunities for identifying future areas of research.

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Appendix-C Interview Guidelines

1) What is your role in the council? What are your responsibilities?
2) How are decisions made regarding the development of council services for citizens?
   a) What data do you use?
   b) Who is involved?
   c) How much autonomy do you have?
   d) Who are the core decision makers within the organisation and outside the organisation (probe for the role of citizens here)
3) What kind of data do you currently collect? How do you manage this data?
   a) Probe for the kind of analysis they currently use within the council and for what purpose?
4) How does the council currently manage the design and delivery of public services –
   a) How do you decide if a “new” public service is needed? Can you talk me through the process?
5) How do you plan for future public services?
   a) Who is involved?
   b) What is the process?
   c) What information do you need to plan?
   d) What are the timescales?
   e) What do you consider the future to be? (What are the planning cycles?)
   f) Is this effective? Can it be done better if so how?
6) Can you tell me what your experiences of social media are?
   a) What value do you think social media has from an individual personal perspective? And from an organisational perspective
7) Does the council currently use social media?
   a) If yes, what kind and for what purpose? Probe for use with citizens and anything related to public services
   b) If not, why not?
8) Does the council have a policy related to social media use – can you tell me what it is? If not, why not?
9) Do you think data from social media would be valuable in your organisation? If yes, how? If no, why not?
10) If money was no object, what is the single thing as a council you would want to do to improve services to citizens.