Mining Dubai Government Twitter Accounts

تحليل حسابات تويتر للجهات التابعة لحكومة دبي

by

ZAINAB ISMAIL ALKASHARI

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Abstract

Social media plays a critical role in the public sector as it allows the government to interact with the citizens. With the United Arab Emirates being active on social media platforms, this study then aims to identify the level of citizen engagement in Dubai government's Twitter through the use of the data mining techniques. Decision makers in the government entities aim to engage the citizens in the various activities to better understand their perceptions, needs and expectations and accordingly take better informed decisions. This supports the transparency and trust of the government decisions. In this dissertation, the purpose is to contribute to the current research on social media by filling the gap on how local governments, especially in the United Arab Emirates, can increase citizens' engagement on Twitter as preferred social media channel. Post engagement the total number of citizens' interactions with a tweet and can be measured using different tweet attributes including retweets, mentions, hashtags and likes among others. Moreover, this study investigates the impact of the twitter post characteristics on the citizens' engagements level. Thus, we collected, prepared and processed 74,037 tweets that represents all tweets for Dubai government twitter accounts during 2018. These tasks were followed by statistical analyses of the impact of post characteristics on the citizens' engagement level. Next, we implemented various machine learning models to evaluate the performance of using the post characteristics and post content to predict the engagement level of citizens. Results indicate that citizen engagement level in Dubai government's Twitter is significantly impacted by all post characteristics. It is also revealed in the study that citizen engagement is higher during weekdays compared to weekends. Furthermore, the machine learning models achieved promising results to predict the citizens' engagement with highest accuracy for Random Forest and Linear Support Vector Machine of 78.3% and 78.2% respectively.

Keywords: Data Mining; Government Twitter, Dubai Government; Machine Learning; Twitter Data Analysis; Citizens' Engagement.

ملخص

تلعب وســـائل التواصـــل الاجتماعي دورًا مهمًا في القطاع العام لأنها تتيح للحكومة فرصـــة للتفاعل مع المواطنين مباشــرة. مع كون دولة الإمارات العربية المتحدة نشـطة على منصـــات وســـائل التواصـــل الاجتماعي، تهدف هذه الدراسة إلى تحديد مستوى مشاركة المواطنين في الحسابات الخاصة بالقطاعات الحكومية لامارة دبي في تويتر من خلال اســـتخدام تقنيات اســـتخراج البيانات. يهدف صـــانعو القرار في الجهات الحكومية إلى إشــراك المواطنين في مختلف الأنشطة لفهم تصوراتهم واحتياجاتهم وتوقعاتهم بشكل أفضل، وبالتالي اتخاذ قرارات مستنيرة بشكل أفضل مما يدعم شـفافية وثقة القرارات الحكومية. الغرض من هذه الرســالة هو المســاهمة في البحث الحالي حول وســائل التواصـــل الاجتماعي عن طريق ســـد الفجوة في كيفية قيام الحكومات المحلية، وخاصـــة في دولة الإمارات العربية المتحدة، بزيادة مشـــاركة المواطنين في تويتر كاحدى قنوات التواصـــل الاجتماعي المفضـــلة لديهم. التفاعل مع التغريدات المعلنة من خلال حســب إجمالي عدد تفاعلات المواطنين مع تغريدة ويمكن قياســـها باســـتخدام ســـمات التغريدات المختلفة بما في ذلك ردود التغريدات، والإشـارات، وعلامات التصـنيف وما شـابه ذلك. علاوة على ذلك، تبحث هذه الدراســة في تأثير خصــائص التغريدات على مســتوى تفاعل المواطنين. وبالتالي، قمنا بحصــر، واعداد، وتجهيز 74,037 تغريدة تمثل جميع التغريدات لحســـابات تويتر الحكومية في دبي خلال عام 2018. وتلت هذه المهام تحليلات إحصائية لتأثير خصائص التغريدات على مستوى تفاعل ومشاركة المواطنين. بعد ذلك، قمنا بتطبيق العديد من نماذج التعلم الآلي لتقييم أداء اســتخدام خصـــائص التغريدات ومحتواها للتنبؤ بمســتوى تفاعل ومشـــاركة المواطنين. تشير النتائج إلى أن مستوى تفاعل المواطنين في حسابات تويتر التابعة لجهات حكومة دبي تأثرت بشكل كبير من قبل جميع خصائص التغريدات. كما تبين في الدراسة ان نسبة مشاركة المواطنين اعلى خلال ايام الاسبوع مقارنة بعطلة نهاية الاســبوع. علاوة على ذلك، حققت نماذج التعلم الآلي نتائج واعدة للتنبؤ بنســبة تفاعل المواطنين بدقة عالية على وصــــلت إلى 76.3% لنموذج (Linear Support Vector Machine) و 76.2% لنموذج (Random Forest).

Dedication

I dedicate my dissertation work to my grandfather, my parents, my husband and my whole family whose fondness, love, reinforcement, and prays of day and night make me able to get such honor and victory. I will always appreciate them for the whole of my life.

Acknowledgement

I would like to persist my gratitude and thankfulness for Allah who gives me the health, power, persistence as well as surrounded me with the all good people in my life and that is considered as an honor.

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1. Chapter One: Introduction

Along with the rise of technology and the Internet, the use of social media has consequently become widespread. As a matter of fact, social media has shaped societies and the way people go about their lives. According to Siddiqui and Singh (2016), social media has transformed communication and has improved human connections. Furthermore, social media is used in several fields including education, business and in public service. This explains the reason why governments area also adopting social media to increase their efficiency in the service delivery to the public. As indicated by Mishaal and Abu-Shanab (2015), the critical role of social media in the government lies on how it enables collaboration and interaction between the citizens and the public sector. During the Arab Spring, the social media played an important part in disseminating information to the public and at the same time, it served as an avenue for expression among citizens. As a result, it changed the relationship between the government and the citizens.

As the study explores the concept of data mining of twitter data in Dubai government, this particular chapter focuses on providing an overview of what data mining is and how it is used in social media. The general context of social media is also presented in this chapter in order to broaden the understanding on the role of social media in the government specifically in Dubai. The purpose and objectives as well as the problem statement will also be highlighted in the chapter. Other important aspects that are included are the research questions and research rationale, which serve as the solid foundation of this study. It is emphasized that the introduction focuses on providing a background relevant to the topic of the study.

1.1. Background

The significant developments of social media are aligned with the drastic improvement in technology. As pointed out by Chukwuere and Chukwuere (2017), social media, as a widely used tool for communication, has become an integral part of today's society. It allows people to interact freely among each other – sharing information, provide feedback and participate in social discussions online. Because of the steadily growing popularity of social media in the society, it has now become one of the essential mediums used for education, business and even in the government. There are several social media platforms used nowadays such as Facebook, Twitter and YouTube. Akram and Kumar (2017) entailed that these popular social media platforms have shaped the way people communicate. For one, Twitter, as a microblogging site, is commonly used by businesses for advertisements and for interacting with potential clients. Even with restriction on the number of characters per tweet, there are still a lot of active Twitter users who make use of the platform to share information and engage in relevant social discussions.

The use of social media in the government is not at all a new concept. With the rise of social media comes the recognition that it can be an effective tool to be used in the public sector. According to Karakiza (2015), government agencies consider social media as part of their strategy in serving their mission better. As a result, governments were able to take advantage of several opportunities that come along with using social such as increased government transparency and trust, increased engagement and participation of the citizens in public issues and improved collaboration within the public sector and between the government and the stakeholders. In that context, it is subsequently deemed that social media positively influences the relationship between the government and the public.

The use of social media in the public sector is evidenced by the implementation of e-government which has successfully helped government agencies improve their service delivery and at the same time, strengthen their engagement and participation with the citizens. One example is the Jordanian e-government initiative which focuses on increasing Jordan's online. From building the official website, the Jordanian e-government is also active on social media platforms such as Facebook. It was through social media that the government is able to reach out to its citizens – learning their perspectives about significant public issues and gathering their feedback and opinions that could help improve the quality of service the government provides (Khasawneh & Abu-Shanab 2013). In line with the implementation of e-government, it is indicated by Nica et al. (2014) that use of social media fosters e-participation, thereby allowing the government to engage with the citizens in relevant discussions. More so, e-participation paves the way for stronger ties between the government and the public.

With social media used as a tool for communication and interaction between the public sector and the citizens, the importance of data mining is thereby underpinned. According to Alzahrani (2016), data mining is generally used to find different patterns within a dataset. These patterns reflect the connections inside the information based on the dataset. In order to measure the engagement of the citizens with the government, data mining is used in social media analysis. Aside from data mining, text mining is also a commonly used approach in analyzing social media presence as it helps provide a better understanding of the information from the users. It is used to analyze user comments which can be of huge help in identifying citizen feedbacks and opinions – both negative and positive. All these can be essential in the government's pursuit of improving their services and their overall efficiency, thereby resulting in increased government trust and transparency (Zatari 2015).

1.2. Purpose and Objectives

The primary purpose of this paper is to determine the level of citizen engagement in Dubai government's Twitter. Since the agency has been using Twitter as social media has long been promoted in UAE, the study aims to explore the effectiveness of the initiatives implemented by Dubai government to increase its presence on said social media platform. Data mining technique is used in order to further delve into the study, denoting that it is the most suitable method to use to measure citizen engagement with Dubai government on Twitter. In relation, there are also key objectives that this study seeks to accomplish:

- Discuss the growing importance of social media in the society at present;
- Examine the extent of social media usage in the government, specifically in UAE;
- Identify the implication of using social media in the government;
- Explore the concept of eParticipation;
- Identify the components and/or types of Twitter Data;
- Determine how post characteristics (i.e. type, day, time, language, etc.) impact user engagement;

- Understand data mining; and
- Investigate the process of Twitter data analysis through data mining.

1.3. Problem Statement

As already mentioned in the previous pages of this study, social media plays an important role in the lives of people nowadays. It is evidenced by the fact that it is widely used in several fields including education, business and even in the government. The increased presence of the government on social media has made significant implications, especially in enhancing citizen engagement and in improving the relationship between the government and the citizens. As this study intends to determine the level of engagement between citizens and the Dubai government on Twitter, the research further centers on the effectiveness of the initiatives implemented by Dubai government in increasing its presence on said social media platform. This entails the success of the government agencies in Dubai to interact and collaborate with the public, especially since UAE is collectively working towards complete adoption of social media alongside the implementation of its e-government initiative (Touq 2014).

Furthermore, the study focuses on how the Dubai government's presence on Twitter contributes to increased citizen engagement, provided that Dubai is currently pushing forward the use of social media in communicating and in collaborating with the public. With that said, it is also the research's intent to discover how citizen engagement with Dubai government correlates with the premises of the social media engagement theory which is the study's primary theoretical framework. It is consequently denoted that even with significant evidence on the integral role of social media in the government and in promoting engagement and participation among the citizens, there are still several significant challenges identified. One of which relates with the need for policies to regulate the use of social media in the country and at the same time, establish an infrastructure to be used in addressing the risks and in embracing the opportunities that come along with using social media in the government. As what Mainka, Hartmann, Stock and Peters (2014) indicated, the use of social media in the government is fueled by its theoretical benefits which include transparency, enhanced trust, enhanced participation and cost reduction. Nevertheless, all these still require a deeper research and through this study, it will be determined how social media usage in Dubai Government, specifically on Twitter, has created an impact on participation and engagement among the citizens.

1.4. Research Questions

Based on the main purpose and the underlying objectives stated in the previous pages of this study, the following are the research questions that it aims to answer:

- **RQ1**: Do post characteristics impact the users' engagement in Dubai Government Twitter accounts?
- **RQ2**: Can we predict the user's engagement based on post characteristics?
- **RQ3**: Can we identify the main keywords resulting in higher engagement?

1.5. Rationale for the Research

One of the primary factors that have fueled the researcher to explore more on the level of citizen engagement on Dubai Government's Twitter is the need to understand how social media has influenced or shaped the way governments interact with the public. It is common knowledge that social media has become a very important tool for communication among all people and with that being considered, it is thereby worthy to know how the governments, specifically Dubai government, are making full use of social media to improve its services and its relationship with the citizens. In that regard, the importance of this research lies on how it expands one's understanding on the role of the social media in the government's delivery of service. It is also significant in determining how social media platforms such as Twitter can affect engagement, given that it is now widely used by governments.

In that regard, this topic can be used for future researches that concentrate on how governments can effectively use social media to increase citizen engagement and participation. More so, the study can be used to better understand how governments specifically those that are implementing the e-government initiative can integrate the use of social media in order to improve their e-government services and at the same time, the relationship between the government and the citizens.

1.6. Thesis Structure

The study is outlined in the following details:

Chapter 1: Introduction – It provides an overview of the research which include the background of social media, the use of social media in the government, and the use of data mining in social media. Primarily, this section highlights the purpose of the study, research questions, the problem statement and the research rationale.

Chapter 2: Literature Review – This chapter presents detailed information about the relevant concepts involved in the study, particularly about the data mining, eParticipation and Twitter data. It also expounds the application of social media in the government.

Chapter 3: Methodology – The third chapter presents the method used in the study to accomplish the objectives of the research. For this study, machine learning techniques and SPSS are used to analyze the collected Twitter data of Dubai government. Aside from the presentation of the research design and instrument used, this section also includes the limitations of the research.

Chapter 4: Results – This chapter shows the outcomes and results of the study which will subsequently supported with relevant literature. The supporting literature used are obtained from existing sources.

Chapter 5: Discussion – It shows a deeper and more profound interpretation of the results. The discussion will then focus on answering the research questions of this study and the rational to the literature.

Chapter 6: Conclusion and Future Prospects – This chapter provides details that can be concluded from the study, particularly on how the level of citizen engagement has been influenced by Dubai Government's use of Twitter. Recommendations for Dubai Government are still provided in this section. These suggested actions relate to how the Dubai Government can increase their Twitter presence in order to consequently increase citizen engagement and eParticipation.

2. Chapter Two: Literature Review

Social media has become one of the primary factors that continue to shape today's society and along with this, local governments have considered social media as a tool to connect and provide services to the community. This study explores the use of social media in the government, particularly Twitter, for the purposes of enabling citizen engagement that propel efficient governance. The literature reviewed examines mining tweets and the use of social media in general can impact citizen engagement with Dubai Government. It also explores how the government can assess and improve user engagement through the use of Twitter.

A literature review was conducted in order to discuss the various significant aspects that underline the conceptual framework for this study. This relates to the growing role of social media in the society, denoting that with globalization and rapid advancements in technology, it has hugely influenced the social systems, the government, the economy, and the people, among others. The emerging importance of social media presence is also discussed in terms of how the government makes use of the tool to increase engagement and interaction with the citizens. Despite this study being focused on Dubai government, the literature review includes a general perspective of the government's adoption of social media in reaching out to the community, especially the use of Twitter – one of the most popular and most commonly used social media platforms at present.

Apart from discussing the role of social media in the government, this chapter consequently presents relevant information about the concept of e-Participation as well as the process of data mining of social media. This is in association with how twitter data of the government can possibly be used to determine citizen engagement. More so, the relationship between increased use of Twitter in the government and user engagement is explored. Finally, the literature review includes a conclusion regarding the relevance of social media in the government, placing an emphasis on how increased presence on

Twitter can translate to high engagement between the public and the government. The primary consideration of this chapter is to present extensive literature on social media engagement in the government.

2.1. Conceptual Analysis

Based on the research questions stated in the first chapter of this study, the following concepts are explored:

- Post Characteristics – as this study presents relevant information regarding Twitter data, it is thereby important to determine how the characteristics of the posts including the type of posts, the time, the data and the text on the tweet can be used as prediction attributes of user engagement on Dubai Government's Twitter account.
- eParticipation and User Engagement – this is primarily the dependent variable of the study, denoting that it will be the one measured based on the post characteristics obtained from the data collected. As what is relentlessly emphasized in the previous pages, this study aims to determine how social media, particularly Twitter, fosters citizen engagement and eParticipation, specifically for the Dubai Government.

2.2. Theoretical Framework

As this study underpins the increased use of Twitter in Dubai Government with the notion that such can be linked with increased citizen engagement, one theory is examined for this research. Social media engagement theory, according to Di Gangi and Wasko (2016), entails how social media serves as the platform that allows social interactions among users widely distributed in all parts of the world. It explains how social media, being one of the most prominently used technologies nowadays, influences the way people connect with one another. With that said, the social media engagement theory therefore highlights the premise which denotes that social media is a driver of social connections and user engagement. The relevance of this theory in the study is reflected on how it builds the understanding that use of social media can increase engagement and interaction among people. In the context of social media in the government, the continued use of the platform to connect to the community will then lead to positive outcomes which include higher citizen engagement and participation.

Social media engagement theory additionally points out that with increased user engagement, the use of social media as a platform for social connection is subsequently increased as well (Di Gangi & Wasko 2016). In line with the study's purpose, it can be determined that under the said theory, increased engagement between the citizens and Dubai Government would mean increased use of social media in the public sector. For one, the use of Twitter by the government is deemed a factor that could not only increase people's engagement with the government per se; but it will also increase people's usage of the platform. This usage, however, will also extend to building social connections with others in the community.

2.3. What is Social Media?

With globalization and rise of technological advancements, social media has become a tool that individuals and organizations alike make use of. It has opened a wide array of challenges and opportunities and has revolutionized the way people and organizations communicate and interact. As indicated by Siddiqui and Singh (2016), there are several significant impacts of social media – from increasing people's social networking to shaping the different economic sectors of a particular country including education, business and society in general. There are different definitions of social media as cited by Ngai et al. (2015, p. 771). Among these include:

> Social media is a hybrid in that it springs from mixed technology and media origins that enable instantaneous, real-time communications, and utilizes multi-media formats and numerous delivery platforms with global reach capabilities (Mangold & Faulds 2009, p. 359).
>
> [. . .] social media is collaborative online applications and technologies that enable participation, connectivity user-generated content, sharing of information, and collaboration amongst a community of users (Henderson & Bowley 2010, p. 239).
>
> [. . .] a group of internet-based applications that build on the ideological and technological foundation of Web 2.0, and that allow the creation and exchange of User Generated Content (Kaplan & Haenlein 2010, p. 61).
>
> [. . .] social media are the tools that facilitate the socialization of content [. . .] social media services encourage collaboration, interaction, and communication through discussion, feedback, voting, comments, and sharing of information from all interested parties (Malita 2010, p. 748).

These definitions all point out to the same notion regarding social media, which indicates that social media, being one of the main technologies used in the society, is one that fosters collaboration, interaction and communication between and among all users worldwide. It is an online platform that allows users to make conversations and share information, thereby creating social connections (Ngai et al, 2015). One of the most popular social media sites is Twitter. According to Akram and Kumar (2017), Twitter's popularity as a social media platform is reflected on its more than 320 million active monthly users. Even with the posts restrictive to 140 characters, this social networking site is used by many including businesses to interact with other users. It can also be used to target specific audiences and for businesses to engage with their potential customers (Akram & Kumar 2017).

Considering the extensive use of social media in today's society, it can be deduced that there are challenges and opportunities in using this technology. In a study by Lad (2017), the effects of social media on the society are widespread – both negative and positive. For one, social media might have led to increased connectivity between users and has paved the way for increased and convenient access to information; however, it has also bred significant issues including addiction, hacking, and cyber bullying. Amidst these adversities brought by the use of social media, its importance is still immutable. As what Samuel and Shamili (2017) noted, it is a helpful tool for business organizations, specifically in marketing and in communications.

With this study focusing on the use of Twitter, it is pointed out by Curran, O'Hara and O'Brien (2011) that as microblogging service, this social media platform is popular among many users. Although Twitter lags behind other social media sites such as Facebook, it is still continually used because of its different model that enable users, organizations, and media outlets to engage in discussion on various relevant and important topics. Sharing information through tweets has become a mainstream in the world of social media. In fact, it was revealed in the study conducted in 2010 that people in the United States have become more aware of Twitter's existence as a social media platform. Despite lacking a clear value proposition unlike Facebook and LinkedIn, Twitter is deemed to be largely useful, especially in the field of marketing (Curran, O'Hara & O'Brien 2011).

2.4. Social Media in UAE

The popularity of social media is consequently eminent in UAE. As a matter of fact, the Arab country, with its unprecedented economic growth, is propelling its relentless technological advancements. In that aspect, the growth of social media in the Emirati society is therefore not a new concept. According to Al Jenaibi (2013), several countries in the Arab region are actively using social media platforms such as Facebook and Twitter. From raising political awareness to sharing news updates, social media is deemed as a valuable medium in UAE and this is due to the reason that said technology is a recognized as the driver to mobilization. In the report by The Media Lab (2019), social media audience in UAE is on a high. As shown on the figure below, about 99% of the total population of the country are active social media users and about 92% use their mobile phones to access social media sites. Based on these figures, it can be purported that social media use in the Gulf country has become even more widespread.

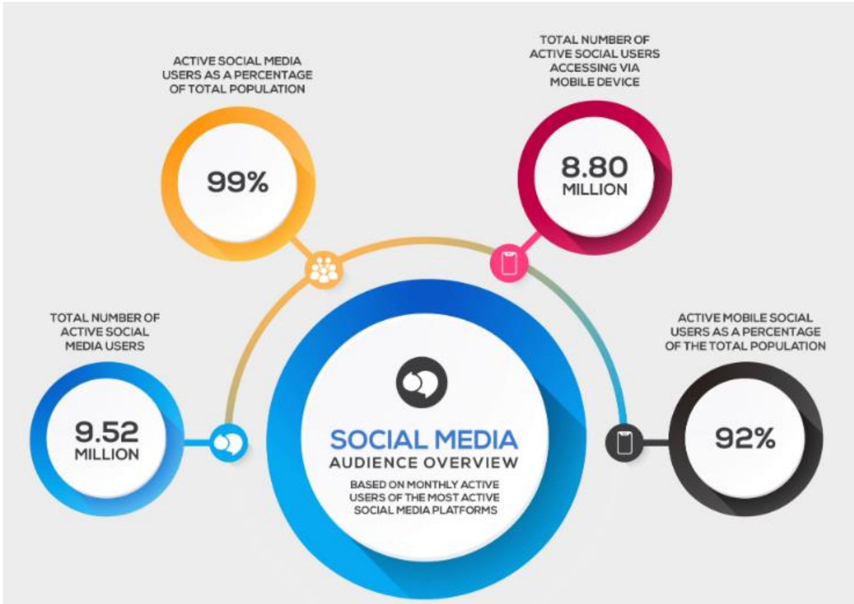


Figure 1: UAE Social Media Overview 2019; Source: The Media Lab, 2019

As mentioned in the previous pages of this study, there are several social media platforms available. These include Facebook, YouTube, LinkedIn, and Twitter, among others. As indicated by El-Sayed, Firoz and Dzamtoska (2015), the most used social media is Facebook, followed by Twitter. Twitter, for one, has made a significant contribution in UAE during the Arab Spring. This was because it had an important role in bringing people together at the time of crisis. In 2009, Twitter had seen tremendous growth, with its membership expected to grow at 300 percent. The popularity of Twitter in UAE is reflected on the growing number of people in the UAE who have shifted to using Twitter in order to create virtual relationships. Even businesses have also used Twitter to effectively market their brand and products and services to potential customers (Kannan, Menezes & McKechnie 2010).

The figure found on the next page reveals the percentage of Twitter audience in UAE. It is indicated that advertisements posted on Twitter can reach about 2.30 million people in the country. From that, 27 percent are adults, ageing 13 and above. The immense audience reach of said social media platform is particularly evidenced by the estimated quarter on quarter growth of 5.5 percent. Since businesses are commonly using Twitter as a marketing tool, it is thereby not new for the said platform to be used widely for reaching a specific target audience in advertising, In addition, it was revealed in the report of Hamdan (2018) that female users in UAE and Saudi Arabia use Twitter for news updates, for following public figures and for connecting with different brands. Gulf News (2014) further noted that in 2013, UAE had an estimated total number of 360,000 active Twitter users, with about 2.5 million tweets daily.

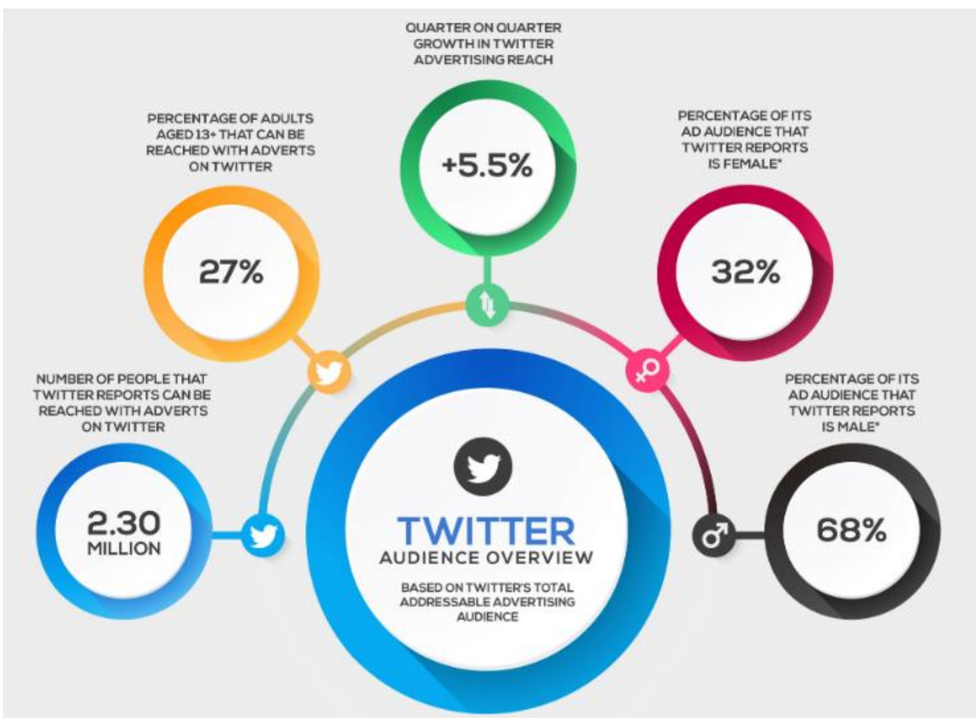


Figure 2: UAE Twitter Audience Overview 2019; Source: The Media Lab, 2019

2.5. Use of Social Media in the Government

With the increased popularity of social media in the society, it is not only a tool used by private individuals and organizations; but it is also widely used in the public sector. As a matter of fact, it is indicated by Graham and Johnson Avery (2013) that embracing social media in the government could foster civic engagement and community building. More so, it also encourages a more open and a more transparent government. The relevance of social media in the public sector is significantly evident on its critical role in strengthening government-citizen relations. It is also pointed out by Mishaal and Abu-Shanab (2015) that the importance of social media in governments is acknowledged specifically during the Arab Spring, with it being the tool used to change the relationship between the citizens and the governments and bring them together. With citizens given the freedom to express their opinions through various social media platforms, governments can consequently get feedback from their citizens. This then opens the dialogues between the government and the citizens Information dissemination propelled in different social media channels and increased citizen engagement can be utilized for effective decision-making. Apart from easy access of information provided by the governments, there are other significant benefits from using social media in governments. These include transparency, participation and collaboration (Mishaal & Abu-Shanab 2015).

According to Landsbergen (2010), the use of social media in the public sector creates several advantages. For one, adopting social media in the government increase social capital, otherwise called trust, which then leads to the improvement of governance and/or public administration. Trust enables citizens to evaluate the government, the information it provides and its overall administration. At the same time, it is noted that trust in the field of public administration involves the need for administrators to respond to the people, specifically ensuring that the efforts of the government are maximized in pursuit of accomplishing public goals. In that aspect, it can be denoted that social media increases the level of trust between the people and the government given how it helps creates tighter social networks. It is through these social media platforms that governments effectively communicate with the public (Landsbergen 2010).

Another advantage of using social media in the government is it helps in effectively using the dwindling resources. Social media allows the government to find creative and innovative ways to mobilize the use of its resources. This is made possible through networks of individuals, organizations and institutions that foster collaboration with the government (Landsbergen 2010). This is further noted by Khasawneh and Abu-Shanab (2013) that social media provides a new means of communication that has led the government to utilize the technology to enhance its services and its relationship with the stakeholders including businesses, institutions and the citizens. As mentioned in the previous pages, social media gives the government an opportunity to achieve transparency through better information access and services. The active communication channel maintained between the government and the citizens will empower the public and make them more involved. An interactive relationship is what most governments seek in order to achieve efficiency in governance and public administration.

With the emphasis on the significance of using social media in governments, Al-Badi (2013) mentioned the several essential benefits of putting social media into good use in the public sector. Among these advantages include (p. 8):

- Increased access to audiences that allows the government to improve its communications;
- Service to wider audiences with less financial constraints;
- Increased efficiency and productivity in the relationship between the government and its stakeholders;
- Bigger scope for adjustment in communications when necessary;
- Improved long-term cost effectiveness of communication;
- Increased public feedback and input;
- Wider reach for specific audiences regarding specific issues; and
- Reduced dependence of the government on traditional media platforms, with an effective counteraction to inaccurate press coverage.

In the UAE, the use of social media in the government is also extensive. In fact, it has implemented the initiative of introducing different types of brainstorming campaigns in social media in order to address the issues in public services relevant to health and education. At the same time, it encourages the public to think of innovative ideas to help redesign and co-deliver the services of the government. This explains why among the member countries of the Gulf Cooperation Council (GCC), UAE is the foremost in using social media as a means of communication with the public (Hidayat, Rafiki & Al Khalifa 2018). In addition, it is also identified by Darwish (2017) that integrating social media in the UAE government is a response to the increased usage of said platform in the country's population. It is also a way of realizing the government plans of becoming citizen centered. As a result, government agencies and officials in UAE are increasingly building their presence on several social media sites, denoting that this could increase the level of collaboration within the government and between the government and the citizens.

However, there are also challenges in adopting social media in the government. These obstacles are commonly faced by many government agencies specifically in the Middle East, thus the possibility that UAE government is confronted with the same set of issues in its pursuit of fully integrating social media in its services and in its relationship with the stakeholders. Al-Badi et al. (2016, p. 5) enumerated the following obstacles:

- Security concerns
- Privacy concerns
- Lack of IT infrastructure
- Lack of a national social media strategy or plan as part of the national IT plan
- Lack of skills among government staff
- Concerns regarding the legal terms and conditions of using social media
- Government censorship
- Concerns over the integration of social networking systems with other IT solutions
- Lack of resources to support (monitor/control and maintain, correct and update)
- Time consuming and tedious to use
- Concerns about employee use/misuse
- Not convinced about the value of social networking (ROI)

- Lack of accessibility
- Challenges concerning fair and equal involvement for all citizens (digital divide)

2.6. The Concept of eParticipation

The concept of eParticipation, as defined by Sanford and Rose (2007), is relevant to "the extension and transformation of participation in societal democratic and consultative processes, mediated by information and communication technologies (ICTs)" (p.406). It is significantly urged by governments as this will help enhance the overall legitimacy, acceptance and efficiency of political process. More so, it is a response to the public's demand for their involvement in democratic initiatives. The emergence of eParticipation is associated with the increased acceptance and utilization of the Internet, thereby prompting the government to extend its efforts in using social media to increase citizen engagement. In relation to this, Kassen (2018) underpinned that eParticipation, from the government perspective, consists of interactions between the government and other key players including businesses, citizens and the public sector itself. In particular, the government-to-citizens interactions denote an approach that is citizen centered, with emphasis on civic engagement and collaboration. With that said, it can be purported that the primary aim of eParticipation, based on the government context, is to encourage and promote a special regulatory and technology avenue for cooperation between the government and its stakeholders.

In line with this, it is entailed by Siyam et al. (2019) that eParticipation has three stages, as adopted by the UAE government. These are: (1) information stage; (2) consultation age; and (3) decision-making (active participation) stage. The first stage involves information dissemination to the public while encouraging the citizens to send in their requests for information. For the consultation stage, the government and the citizens engage in open dialogues regarding the different public services and policies and ways to improve them. Lastly, the decision-making stage which is the highest stage of eParticipation is focused on involving the citizens in the decision-making process related to public services and policies. More so, the most important consideration underscored in eParticipation is the need for the government to communicate with the citizens in order to effectively involve them in making critical decisions for the benefit of the entire public. The figure below shows the categorization of ePartcipation, which denotes that alongside the three stages of said process are three identical levels. For one, the information stage is the enabling stage; the consultation stage is the engaging stage; and the active participation stage is the empowering stage (Ali et al. 2015).

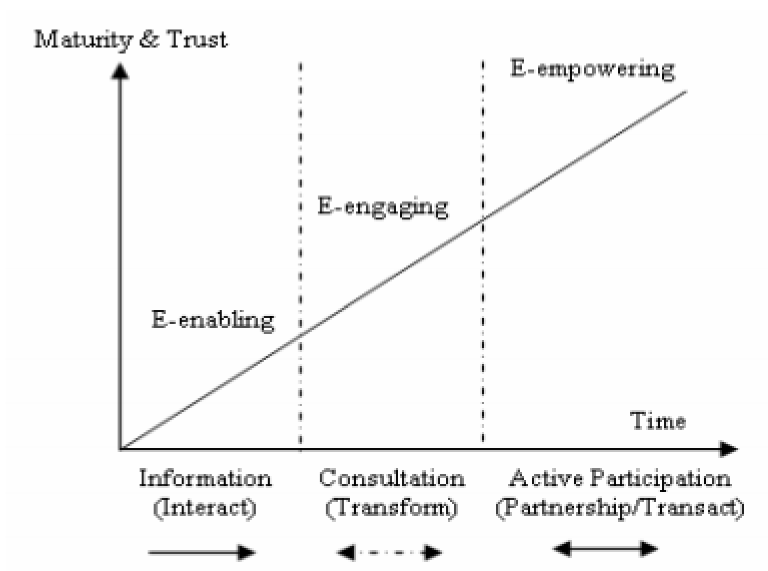


Figure 3: Integrated dimension of eParticipation (Ali et al. 2015)

The use of social media in the government has subsequently increased the importance of eParticipation. There are various tools that governments use in order to promote such including social network sites like Facebook and Twitter. As indicated by Siyam et al. (2019), these social media tools provide governments with opportunity in improving and innovating their services, thereby sustaining a citizen-focused approach. Moreover, Ali et al. (2015) have presented a framework which identifies the most suitable ICT tools that can be used for ever eParticipation objective. As seen on the table found on the next page, it is seen that for instance, electronic profiling, teleconferencing and online chat can be the most appropriate ICT tools to utilize for education and support building.

Although eParticipation can be difficult to measure, there are obtainable ways to indicate the level of public engagement with the social media activities of the government. For example, the number of comments and likes and shares can determine the audience reach of these activities. On the other hand, eParticipation in Twitter can be measured using the various elements of tweets that directly affect the interaction, impression and reach of the tweet. These include the content format, the content type, language style, the presence of hashtags (#), the mention of users or entities, and time of publishing (Siyam et al. 2019). In that aspect, all these varied metrics can be used to measure the level of eParticipation in Twitter which in turn, can be utilized by the government to improve its presence on the said platform and encourage more user public engagement.

2.7. Twitter Data

Microblogging, according to Goyal (2016), is a widely known and used tool for communication and knowledge sharing. Being one of the most popular microblogs, Twitter is used by many users around the world. The messages called "tweets" posted by the users are restricted to a few characters with optional additions of images, GIF and a 140-second video. In engaging with a post, users can like, retweet and comment on a tweet. It is revealed in the study of Okazaki et al. (2015) that in the Twitter environment, user engagement can be determined through data mining techniques. Similar to how firms increase customer engagement using electronic word-of-mouth (eWOM), the government can utilize social media sites such as Twitter to interact with the public and encourage them to be more actively involved with the updates posted by the government relevant to its services and policies. Although Twitter is commonly used by businesses for advertising purposes, the government can make use of the platform to engage in dialogues with the citizens.

Since Twitter also allows users to comment on tweets, these texts can be also included in measuring user engagement, as can be a good indicator of the perspectives of users. Regardless of the type of comments, each one of them are identified as part of user engagement (Siyam et al. 2019). In that manner, conducting Sentiment Analysis is essential in interpreting the textual data gathered from the Twitter comments. According to Rani and Arora (2016), Sentiment Analysis is otherwise referred as opinion mining as it helps determine whether a certain text is positive, negative or neutral. In interpreting Twitter comments, this procedure is used to classify whether users have positive, negative or neutral sentiments regarding the government, its services, its policies and its overall public administration. Sentiment Analysis is additionally used in monitoring the interactions between the government and the citizens, especially concerning significant topics or issues. With that said, conversations are made between and among users and the government.

Because there are several things that can be done on Twitter, posts or tweets can be classified into several categories such as status update, link, photo, and video. As indicated by Siyam et al. (2019), status updates are composed text only which could possibly include hashtags (#) and/or mentions (@). Those tweets identified as photo or video may also contain text along with the media content. Post vividness, which these types of posts are known as, is deemed to have a positive impact on user engagement. On the other hand, link tweets are posts consist of a link which when clicked, will direct users to another page. Unlike the photos and/or video posts, link tweets are found to have a contrasting impact on user engagement.

In relation to Sentiment Analysis, text mining approach is also popular, especially in interpreting Twitter data like mentioned above. Since posts on the said platform are mostly in textual form, it is emphasized by Salloum et al. (2017) that text mining largely helps in obtaining a meaningful and structured from irregular data patterns, especially since majority of the text available on social media platforms such as Twitter is unstructured. Although data mining and text mining are different from each other, text mining is useful in extracting proper words or sentences from the comments posted by users on Twitter. As a result, the words on the comments can be used to keep track of the sentiments expressed by the citizens that the government can transform into helpful suggestions for improvement of the policies and services that they provide the public.

2.8. Data Mining in Social Media

In analyzing and identifying the level of user engagement on social media platforms such as Twitter, data mining is performed. Also called Knowledge Mining, Information Harvesting, and Data Dredging, among others, data mining is "a process of analyzing data from many different dimensions or angles and summarizing it into useful information that can be applied in different fields to take proper decision" (Pushpam & Jayanthi 2017, p. 147). In other words, data mining is basically a computing process of varied patters obtained from databases that includes the use of several techniques such as AdaBoost, Artificial Neural Network (ANN), Apriori, Bayesian Networks (BN), Support Vector Machine (SVM), Decision Trees (DT), and Markov. Of all these data mining techniques, it is indicated by Injadat, Salo and Nassif (2016) that the most applied in social media are SVM, BN and DT. The figure found on the next page shows the data mining techniques used in social media as identified by different researchers. It also shows that government and organizations have plenty of options to choose from in terms of the most suitable technique to use in data mining.

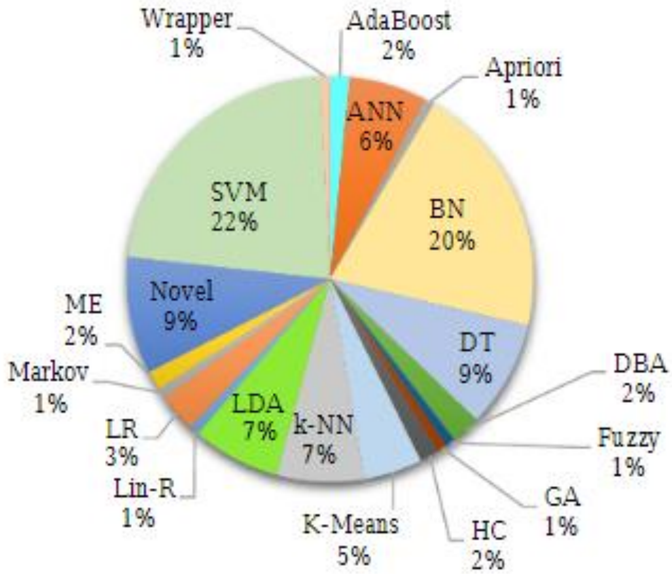


Figure 4: Data mining techniques among selected papers (Injadat, Salo, Nassif 2016)

In general, data mining system architecture consists of several primary components as shown on the figure found on the next page. In the study of Pushpam and Jayanthi (2017, p. 148), these components are:

- Database / Data Warehouse / Information Repository – acts as storage for large volumes of data
- Database / Data Warehouse Server – gets relevant data through data selection and data transformation
- Knowledge Base – includes concept hierarchies, user beliefs, thresholds and metadata in order to search the relevance of patterns
- Data Mining Engine – important in discovering patterns through a set of functional task modules including classification, characterization and association analysis
- Pattern Evaluation Module – incorporated into the mining module which uses interestingness thresholds to focus on interesting patterns

- Graphical User Interface – allows users to communicate and interact with the data mining system

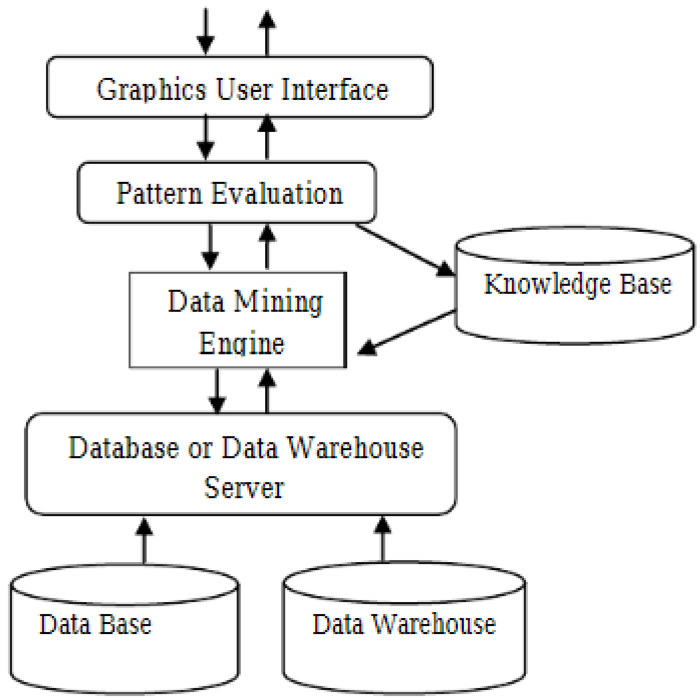


Figure 5: Architecture of data mining system (Pushpam & Jayanthi 2017)

Data mining in social media, according to Zatari (2015), involves analysis and extraction of patterns or trends from raw social media data, thereby giving significant and valid information to governments and organizations in designing and implementing strategies and services. For instance, the government can use data mining techniques to analyze and determine the influence of social media posts like those on Twitter in increasing user engagement. As pertained in the study of Siyam et al. (2019) posts can be classified into different content types and level of interaction of citizens can then be measured based on the number of retweets, comments and likes divided by the number of the followers. It is through this simple method that the government can maximize data mining process in determining the extent of its social media presence. However, the impact of the government on social media is yet to be determined, denoting that there is still a lack of enough metrics to use. The most important consideration in data mining in social media is the need to identify the indicators to be used. On Twitter, indicators mentioned in the previous pages including the number of likes, retweets and comments can be used. With the possible inclusion of hashtags (#) on the tweets, interaction between users and the government can be increased (Siyam et al. 2019).

With the application of data mining in this study, it is therefore explored how the indicators mentioned for analyzing Twitter data can be translated to measure the engagement of citizens with the Dubai government. Since comments on the tweets are most likely interpreted using text mining, it can be consequently determined whether the sentiments of the public are positive, negative or neutral, thereby using this information to design strategies for improvement of the policies and services provided by the government to the public. According to Kavitha (2017), use of data mining techniques in social media can be complex because of the large datasets included; however, the process is very much essential in fostering the effectiveness and productivity of the government and in enhancing government-citizen relationships as well.

2.9. Theoretical Findings and Conclusion

As reflected on the above review of related literature, this study focuses on eParticipation and the impact of Dubai Government's Twitter presence on citizen engagement. In that regard, the empirical results will show the level of citizen engagement on the Twitter account of Dubai Government, based on the characteristics of the posts which include time, day, the type of post, language, mentions and hashtags used.

In this chapter, the different significant themes relevant to the study of data mining of Twitter data from the Dubai government are discussed. It can be concluded that Twitter, just like other social media platforms, have significant implications on the interactions between the government and the citizens. Although the literature review did not particularly entail that user engagement increases with the use of Twitter in the government, information presented in the chapter can be used to further delve into the possible association between higher user engagement and increased Twitter activity of the Dubai government. More so, one of the most significant points emphasized in this chapter is the complexity and the importance of data mining in measuring the presence of the government on Twitter, especially as this will be used to make significant adjustments to the government's performance, services and policies for the benefit of the entire public.

3. Chapter Three: Methodology

The ground objective of this work is to clarify and identify the relationship between the tweet features and the expected citizens' engagement level. This study focuses on the tweets that are posted through the government sector in Dubai. Accordingly, the aim to clarify what kind of topics and in which format the citizens are normally interested in.

In this research, the impact of the twitter post characteristics on the citizens' engagements level is studied to answer the research questions. To achieve this objective, the following hypothesis have been formulated:

- **H1a** Post Type impacts Citizens' Engagement (Photo, Status, Video).
- **H1b** Post Time impacts Citizens' Engagement.
- **H1c** Post Day impacts Citizens' Engagement.
- **H1d** Post Weekday impacts citizen's Engagement.
- **H1e** Links in Tweets impacts Citizens' Engagement.
- **H1f** Mentions in Tweets impacts Citizens' Engagement.
- **H1g** Hashtags in Tweets impacts Citizens' Engagement.
- **H1h** Tweet Language impacts the Citizen's Engagement.
- **H2** Post engagement level can be predicted using machine learning techniques according to the various post attributes.
- **H3** The main keywords that results from higher engagement can be identified.

The conceptual framework of this study is shown in Figure 1. Figure 1 includes the research questions, hypothesis and the dependent and independent variables. This study adopts the proposed Knowledge Discovery in Databases (KDD) methodology by Azevedo and Santos (2008). The KDD methodology utilizes data mining techniques to discover hidden valuable knowledge from data. The KDD comprises of set of processes that are used to extract the desired knowledge such as selecting the target dataset, preparing the data, analyzing the data, interpreting the data and evaluating the results as shown in Figure 2.

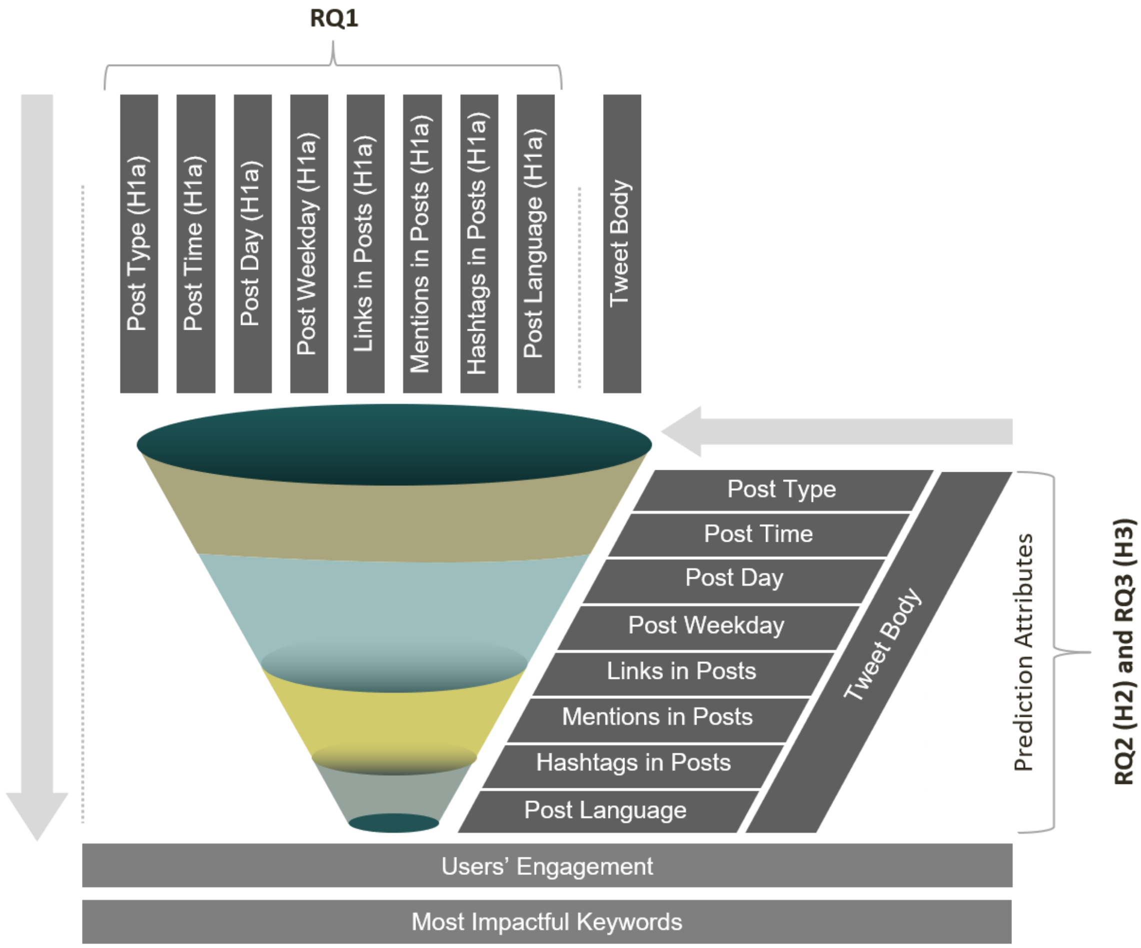


Figure 1: Research Conceptual Framework

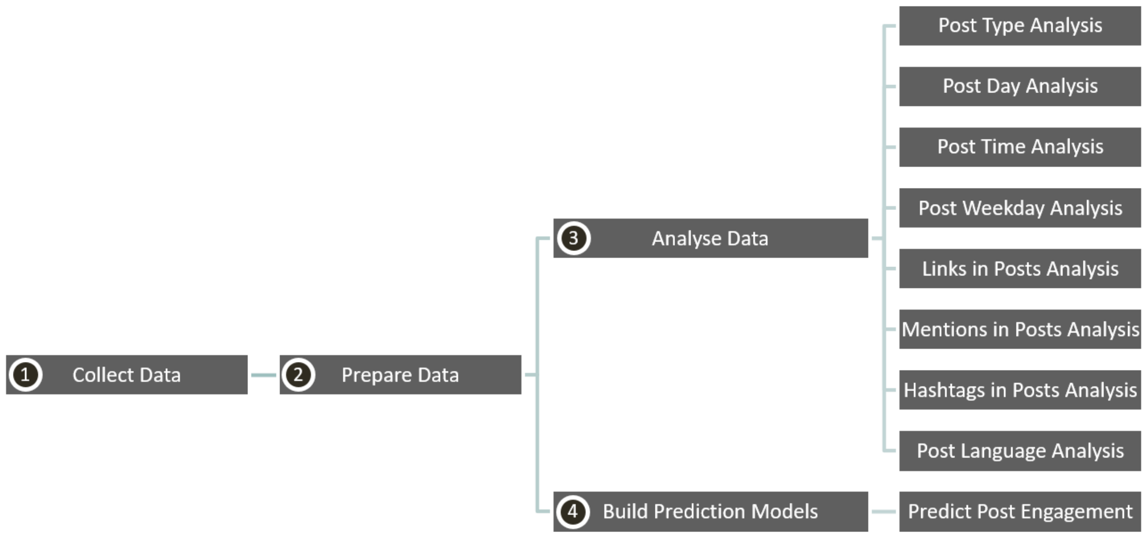


Figure 2: Research Methodology

This chapter starts by describing the source of tweets that are used in various experiments. Then, we move to analyze how the collected tweets can be used to answer the research questions followed by detailed description about the processes used in pre-processing the data. This section is concluded by illustrating the machine learning models that are used throughout the prediction process.

3.1. Collect Twitter Data

The data used in this study are collected using the publicly available open source utility tool termed as OrgneatUI[1]. OrgneatUI tool is used to extract historical tweets from twitter accounts. To extract the desired tweets for each of the government accounts, the twitter account name and date range parameters were provided to the tool. The collected data comprises of 74,037 tweets that represents the entire tweets history originated from

[1] OrgneatUI (https://github.com/rahulha/OrgneatUI)

government accounts during that year of 2018. The dataset was collected in Microsoft Excel file format. The dataset includes both tweets that were posted by the government entities as well as reply tweets by twitter users. This is identified in the dataset through three attributes; is part of conversation, is reply and reply user id. Each tweet consists of various attributes. Among these attributes are the tweet ID, date which also includes time as part of it, tweet body, and the government authority. These attributes can be recognized as the main features of the tweets. For instance, tweet ID represents the unique identifier for the tweet originator. The datetime stamp shows original post date and time. Tweet body represents the actual text of the tweet. The government authority represents the name of the government body who posted the tweet.

The government authorities in Dubai were identified using the dubai.ae website and their official twitter accounts were obtained from their official websites. According to dubai.ae, the government departments in Dubai consist of 47 departments (Government of Dubai 2019). Those government department with official twitter accounts were selected for data collection. The government departments that has official twitter accounts are 36 entities and are categorized into 7 categories as shown in Table 1.

Table 1: The Categories of Dubai Government Entities

#	**Category**	**Number of Government Departments**
1	Government Departments	12
2	Centers	1
3	Councils	2
4	Judical Entities	2
5	Law Enforcement Bodies	2
6	Law Enforcement Bodies	8
7	Public Corporations	9

These government departments play different roles and provide different kind of services according to their role and category. However, the government departments post similar kind of tweets in term of context. For instance, the tweets can represent promotions for new services, department achievements, polls, entities activities and achievements (Siyam et al. 2019). Table 2 shows some examples of tweets from different government entities along with the corresponding context.

Table 2: Samples for Government Entities Tweets Context

Government Entity	**Tweet**	**Context**
Smart Dubai	“Tired of having to physically sign and process documents? Allow #UAEPASS; The National Digital Identity and Signature Solution; to save you time; effort and paper! Digitally sign and validate documents at the comfort of your own home.#SmartDubaipic.twitter.com/K53AQSjmki”	Service Promotion
Smart Dubai	“#DubaiNow has made it easy and quick to top up ENOC VIP accounts.#SmartDubaipic.twitter.com/KNIPPku3sZ”	Service Promotion
Dubai Chamber	“Dubai free zones witnessed 22% trade growth in 2018; Free zones accounted for 41% of Dubai's total trade during the first nine months of 2018https://bit.ly/2LyS6en ”	*Achievements*
Dubai Courts	“ تطبيق نبراس بـ محاكم_دبي#https://youtu.be/WnNmP6fURQY ”	Service Promotion
Dubai Municipality	“Vote for our initiative "Smart Park" Al Mamzar that has been nominated for the Hamdan Bin Mohammed Smart Government Award. You can vote through the link below http://Vote.dtmc.gov.ae We care about your opinion!@DTMCentrepic.twitter.com/H9ABQsfjmU”	*Poll*
Smart Dubai	“We would like YOU to give your opinion about “What makes a city Smarter” by being part of a Smart Dubai video. DM us if you are interested! #SmartDubaipic.twitter.com/o6VLLodEMg”	*Poll*
Dubai Customs	“ إدارة الابتكار في الخدمات بجمارك دبي تنظم ورشة عمل لمدراء المراكز الجمركية وفرق السبع نجوم الداخلية حول متطلبات برنامج النجوم العالمي لتصنيف الخدمات#جمارك_دبي #الابتكار دبي#pic.twitter.com/D38A2zQbFv”	Activities
Dubai Cutoms	“#DubaiCustoms wins Organization-wide Innovation Award at Global Organisational Excellence Congress 2018. #Dubaipic.twitter.com/kk8mTnbVuV”	Achievements
Land Department	“Free real estate panels were held during Dubai Property Show in London; featuring experts and consultants in real estate and law that enabled visitors to understand the real estate investment options which will help make Dubai their	*News*

	first choice.pic.twitter.com/nKR1GDuRQ1”	

3.2. Prepare the Data

The collected data included 20 attributes. These attributes were used to produce the final dataset that is required to conduct our analysis and experiments. The data preparation stage is considered important due to its impact on the overall performance. The first stage in the data preparation included consolidating the collected data from the 36 government departments which resulted in 74,037 tweets. This study is focused to study the impact of post characteristics on the citizens’ engagement level for Dubai Government departments. Thus, the reply tweets were eliminated and only tweets that are posted by the government departments are considered. Moreover, duplicate and blank tweets were removed. The finally resulted dataset comprises 66,832 tweets.

Form the final dataset, some of the attributes were used without performing any processing such as the tweet body, language, number of replies, number of retweets, number of favorites and mentions. Whereas, other attributes were created from other native existing attributes such as “Is Weekday”, “Time of Day”, “Day”, “Has Link”, “Has Hashtag”, “Has Mention” and “Tweet Type”.

All tweets include text and the type varies based on the assigned content. Some tweets include photos or videos, and others do not have any assigned media content. Those tweets without photos and videos are considered as status tweets. The post type attributes has been computed based on the content of the tweet body. It has been noticed in the collected data set that all tweets with media content (photos and videos) has a link part of it that starts with “pic.twitter.com”. This link does not specify whether the content type is photo or video. Thus, a post type attribute has been created with "Status" default value. Then, a formula in Microsoft Excel that verifies if the tweet body includes "pic.twitter.com" has been created. If this formula returns a true hit, then the assigned post type will be set to "Photo". This "Photo" post type can be photo or video. Therefore, another formula has been created to check those tweets that include "Video", "Youtube", "'فيديو", "يوتيوب". If the second formula returns a true hit, then the post type attributes is updated from "Photo" to "Video" type. To verify the finally assigned tweet types, manual verification was conducted at random by accessing the tweet through the tweet link attribute. This is different from the study conducted by Siyam et al. (2019) in which the authors were dependent on the categorization of the post type produced by the Crowdbabble tool that they adopted to collect the dataset.

In addition, the post date was used to produce four other attributes using Microsoft Excel; post day, is weekday, post time and post time of day. Weekdays are those days from Sunday to Thursday according to the working days system in United Arab Emirates. The resulted value of the weekday attribute will be set to "Yes" if the post day value is one of the working days and the value will be set to "No" if the post day is not a working day (i.e. Friday and Saturday). The post time was classified into five time periods of the day similar to Siyam et al. (2019). The first time period is the "Early Morning" in which the time starts from 1 to 5:59. The second time period is the "Morning" in which the time starts from 6 to 11:59. The third time period is the "Afternoon" in which the time starts from 12 to 14:59. The fourth time period is the "Evening" in which the time starts from

17 to 21:59. The last time period is the "Late Night" in which the time starts from 22 to 11:59.

Furthermore, "Has Link", "Has Hashtag", "Has Mention" attributes were computed based on the content of the tweet body where the "Has Link" value will be set to "Yes" if the tweet has link as part of the tweet body, the "Has Hashtag" value will be set to "Yes" if the tweet has hashtag by checking the "#" sign as part of the tweet body, and the "Has Mention" value will be set to "Yes" if the tweet has at least one mention to any twitter account by checking the "@" sign as part of the tweet body. All other attributes such as ID and conversation ID among other were removed as they are important for this study.

Lastly, the engagement value was computed for each twitter post based on the number of interactions divided by the total number of followers of the corresponding twitter account. The number of interactions represents the summation of the total number of retweets, the total number of favorites and the total number of replies. Due to the total number of interactions variation from one government twitter account to another, wrong conclusions may take place because of the different number of followers for each account. Thus, the resulted engagement value is adjusted to reduce the impact of this variation. Formula 1 shows the computation of the engagement value (Trefzger, Baccarella & Voigt 2016). For instance, 1000 engagement value after adjustment means that a twitter post is able to produce total interactions of 1000 with one million followers. The resulted engagement value is then classified into two different groups. The first group is the "Low" engagement when the engagement value is less than or equal to (57.888796). And the second group is the "High" engagement when the engagement value is greater than to (57.888796). This value was computed to divide the tweets into low and high engagement equally.

Formula 1: $$adjusted\ engagement = \frac{total\ post\ interactions}{page\ followers} * 1\ million$$

Table X shows the dataset existing and the newly created attributes after applying the preparation tasks.

Table 3: Dataset Attributes after Preparing the Data

Attribute	Description
Weekday	The day on which the tweet was posted (Sunday, Monday, Tuesday, Wednesday, Thursday, Friday and Saturday)
Is Weekday	This attribute indicates if the tweet was posted in a week day (Yes) or during the weekend (No)
Time	The time on which the tweet was posted in 24 hours format "hh" (00 to 23)
Time of Day	The value of the time of day on which the tweet was posted. The possible values are: Early morning, Morning, Afternoon, Evening, and Late night.
Post Type	The media type of the post which includes status, photo and video.
Has Link	This attribute indicates if the tweet includes at least one link or not
Has Hashtag	This attribute indicates if the tweet includes at least one hashtag or not
Has Mention	This attribute indicates if the tweet includes at least one mention or not
Tweet Body	The textual content of the posted tweet
Number of Followers	The total number of followers for the government entity's twitter account of the posted tweet
Number of Replies	The total number of replies for a particular tweet
Number of Favourites	The total number of favourites (likes) for a particular tweet
Number of Retweets	The total number of retweets for a particular tweet
Engagement per 1 million	The adjusted value of Post engagement for the number of page followers
Engagement Level	The engagement level value. There are two values: Low and High engagement.

3.3. Conduct Data Mining Experiments

The data mining experiments comprises two parts namely, the statistical analysis part and the machine learning prediction models. In the statistical analysis part, the aim is to verify the eight hypotheses to test the extent to which the post characteristics (Post Type, Post Time, Post Day, Post Weekday, Links in Tweets, Mentions in Tweets, Hashtags in Tweets and Tweet Language) impact the engagement level for citizens on the Dubai government tweets. One-way ANOVA was used to analyse the impact of the Post Type (H1a), Post Day (H1c) and Post Language (H1h) on the citizens' engagement. To test the influence of the Post Time (H1b) on the citizens' engagement, the simple linear regression was used. Finally, a two-independent samples t test was used to test the impact of Post Weekday (H1d), Links in Tweets (H1e), Mentions in Tweets (H1f) and Hashtags in Tweets (H1g) on the citizens' engagement.

In the machine learning prediction models, the aim is to evaluate various machine learning models to test the second and third hypotheses (H2 and H3). In this vein, six machine learning models were implemented to test the combination of the tweet's standard features with the linguistic characteristics of the tweets' bodies. The six implemented machine learning models are: K-nearest Neighbour, Linear Support Vector Machine (SVM), Naïve Bayes, Multilayer Perceptron (MLP) Classifier, Decision Tree and Random Forest. These models were selected to cover a various machine learning models and approaches. Prior to the implementation of each machine learning model, data pre-processing tasks such as tokenization, removing stop words and text vectorization were performed. The final processed dataset will be used to train the machine learning models and then test the performance for each model.

4. Chapter Four: Experiments and Results

As study variables included both types, categorical and scale, descriptive summary is presented in two separate tables for each variable type. Categorical variables ("Day", "Is Weekday?", "Time of Day", "Language", "Has Link", "Has Hashtag?", "Has Mention", "Tweet Type", and "Engagement Level") are summarized using frequency and percentage statistics, see Table 1. Moreover, bar and pie charts are used to represent findings of Table 1 graphically, see Figures 1 to 7. Mean, Median, Standard Deviation, Minimum, Maximum, Skewness, and Kurtosis are descriptive statistics calculated and used to summarize scale variables: "Time", "Engagement", and "Engagement per 1M", reported in Table 2. Findings of Table 1 can be briefly summarized in the following points:

- The majority of tweets (85.3%) are posted during weekdays. The peek day is Tuesday, with 18.3% of tweets posted that day.
- 50% of the tweets are posted in the morning, 27.2% in the afternoon, while very few (0.1%) are posted at late night.
- The majority of the tweets (64%) are in Arabic language. The second language used is English 28.1%. And 7.6% of the tweets are written in both Arabic and English.
- The majority of the tweets (87.1%) have links, and 85.3% have hashtags, while only 20% mention other users.
- The most used tweet type is Photo (77.4%), followed by Status (21.1%), and finally Video 1.5%.
- Engagement Level is almost equally represented with 51.8% of tweets receiving low engagement and 48.2% of tweets receiving high engagement.

Table 4: Data Sample Profile of Categorical Variables (N = 66832)

	Frequency	**Percent**		**Frequency**	**Percent**
Day			**Has Link?**		
Saturday	4971	7.4	No	8617	12.9
Sunday	10523	15.7	Yes	58215	87.1

Monday	11673	17.5	**Has Hashtag?**		
Tuesday	12226	18.3	No	9853	14.7
Wednesday	11561	17.3	Yes	56979	85.3
Thursday	11053	16.5	**Has Mention?**		
Friday	4825	7.2	No	53493	80.0
Is Weekday?			Yes	13339	20.0
No	9796	14.7	**Tweet Type**		
Yes	57036	85.3	Photo	51735	77.4
Time of Day			Status	14127	21.1
Early Morning	8942	13.4	Video	970	1.5
Morning	33472	50.1	**Engagement Level**		
Afternoon	18192	27.2	Low	34602	51.8
Evening	6159	9.2	High	32230	48.2
Late Night	67	.1			
Language					
ar	42770	64.0			
en	18776	28.1			
mixed	5047	7.6			
Other	239	.4			

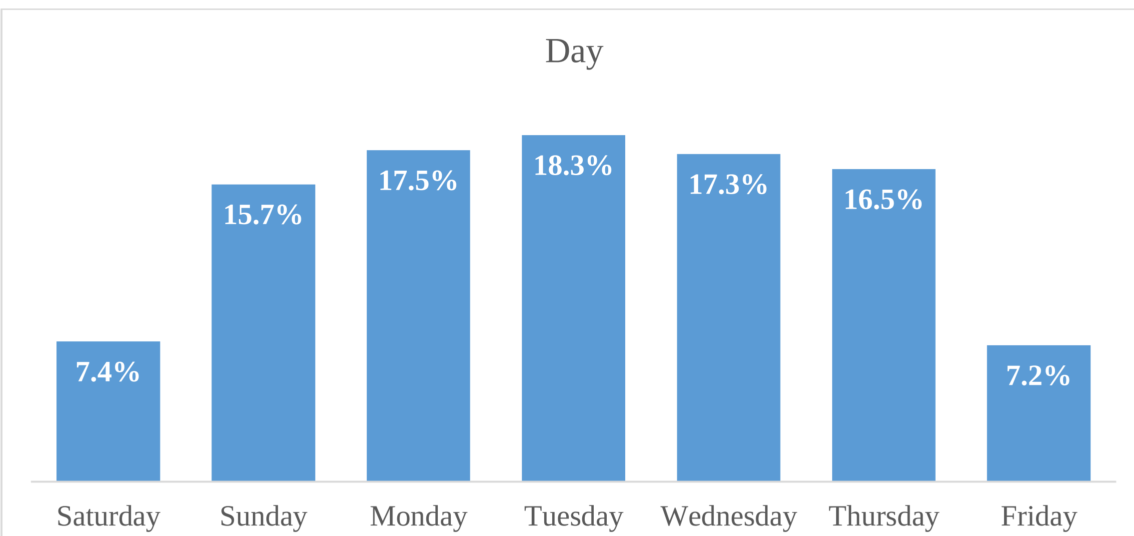


Figure 3: Bar Chart of "Day"

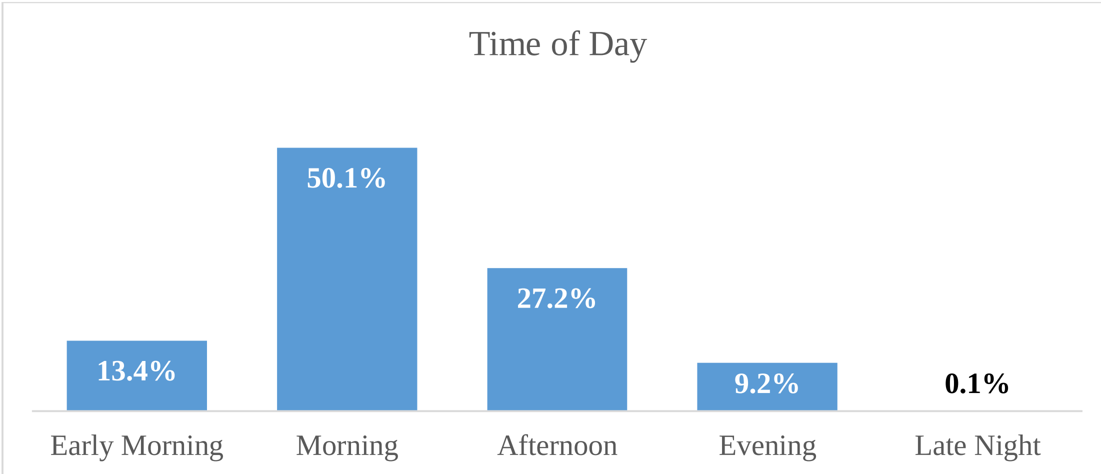
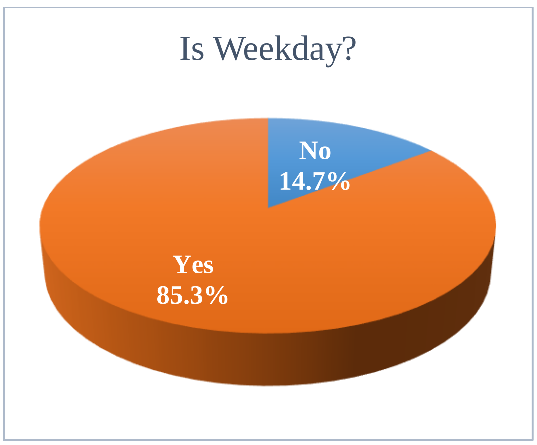


Figure 4: Bar Chart of "Time of Day"



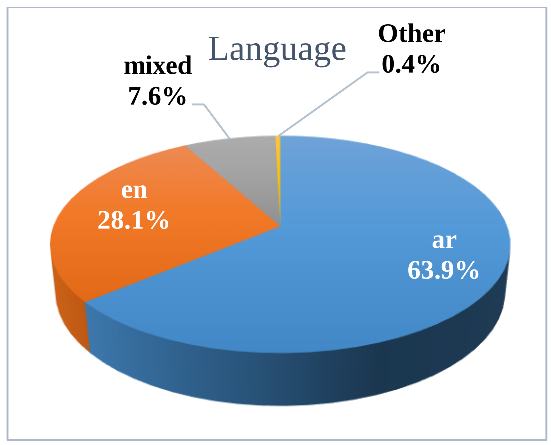


Figure 5: Pie Chart of "Is Weekday?"

Figure 6: Pie Chart of "Language"

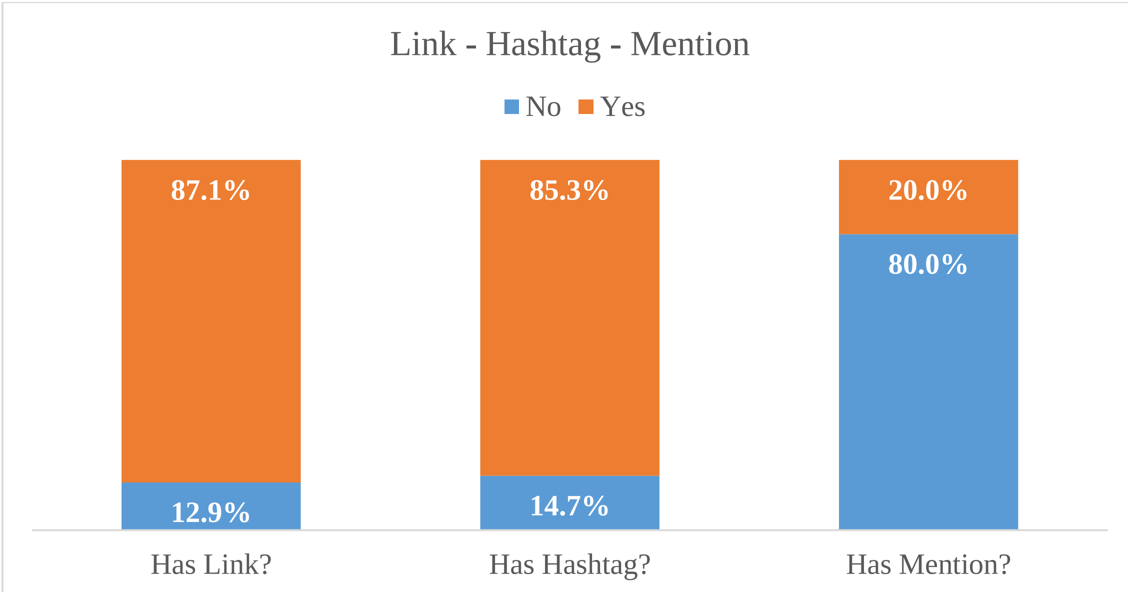
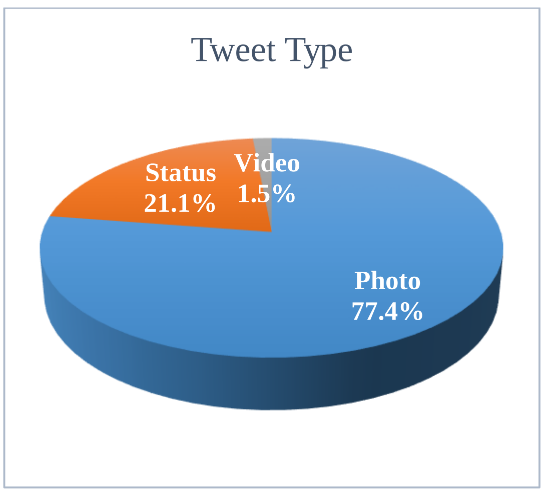


Figure 7: Bar Chart of "Link, Hashtag, Mention"



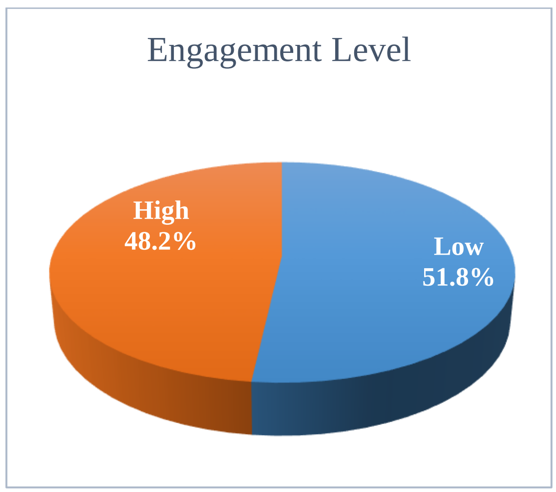


Figure 8: Pie Chart of "Tweet Type"

Figure 9: Pie Chart of "Engagement Level"

In Table 5, descriptive statistics for scale variables (Time, Engagement, and Engagement per 1M) are reported. In this study, we consider Time as a category (morning, afternoon, night, etc.) and as a scale from 0 to 23. In the previous analysis, it was found that most of the tweets were posted in the morning (6 to 11 am) and the number of posts decreases in the afternoon (12 to 16 pm) and then in the night (17 to 23 pm). Looking at Figure 8, we can see that the highest number of tweets are posted at around 10 am.

The mean “Engagement” is .000133652347284, which is higher than the median of .000057888795624, with a standard deviation of .001066293705485. The distribution of “Engagement” is very highly skewed to the right, Skewness = 72.382 and it has a Leptokurtic shape, Kurtosis = 6373.117, see the histogram in Figure 9. The variable “Engagement per 1M” has the same description as “Engagement”, with a mean of 133.652, median of 57.889, and a standard deviation of 1066.294. It has a very positive skewed distribution with a Leptokurtic shape, see Figure 10.

This indicates that the dependent variable “Engagement” or “Engagement per 1M” is not normal. That is, either variables have a highly skewed distribution to the right, which can be attributed to the existence of very high engagement records.

Table 5: Descriptive Statistics of Scale Variables (N = 66,832)

	Time	**Engagement**	**Engagement per 1M**
Mean	10.30	.000133652347284	133.652
Median	10.00	.000057888795624	57.889
Std. Deviation	4.211	.001066293705485	1066.294
Skewness	.312	72.382	72.382
Kurtosis	-.728	6373.117	6373.117
Minimum	0	.0000000000000000	.000
Maximum	23	.1108473059926360	110847.306

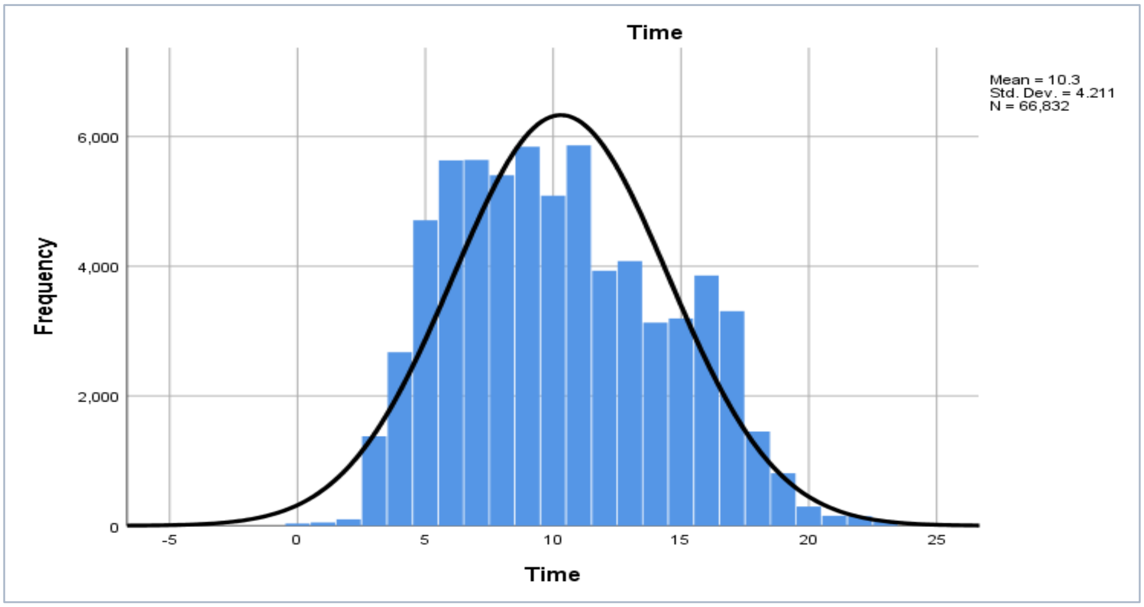


Figure 10: Histogram of “Time”

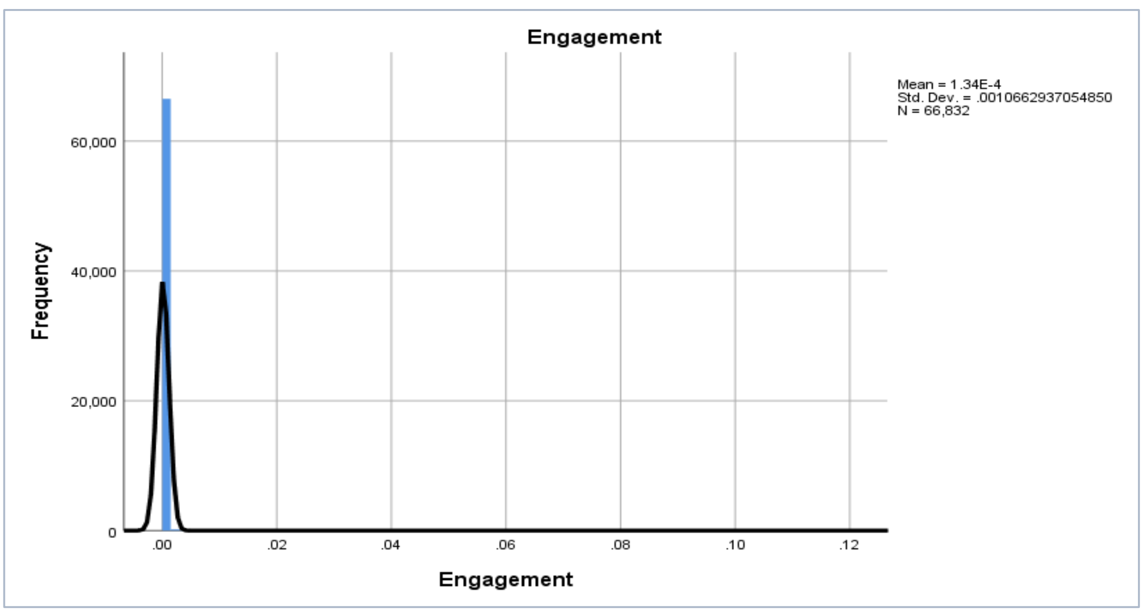


Figure 11: Histogram of "Engagement"

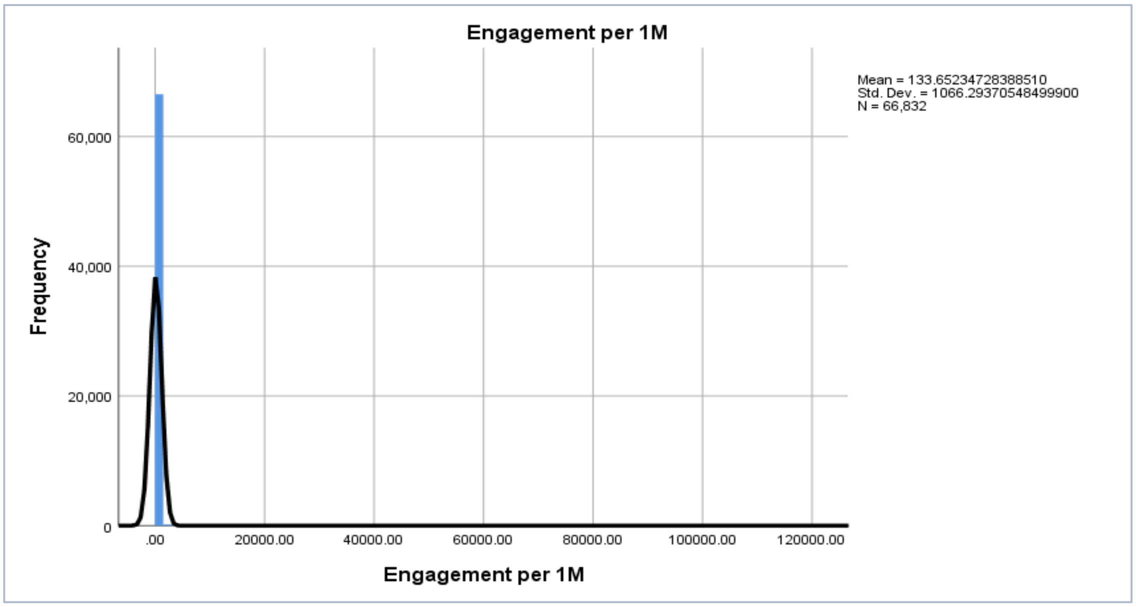


Figure 12: Histogram of "Engagement per 1M"

4.1. Normality Tests of "Engagement per 1M" across Citizens' Groups

Normality is one of the most common assumptions made in the development and use of statistical procedures (Thode 2002). Before performing hypothesis testing, normality of the dependent variable "Engagement per 1M" is tested numerically by examining the mean, median, skewness, and kurtosis values, in addition to Kolmogorov-Smirnov test of normality, and graphically by sightseeing Normal P-P plots. The results are reported in Tables (Table 6 to Table 13) and Figures (Figure **13** to Figure **39**), revealing the severe deviation of the "Engagement per 1 M" distribution from normality. Therefore, "Engagement per 1 M" is log transformed and used in hypothesis testing. Investigating the Normal P-P plots and Skewness measures of "Engagement per 1M" across all data groups, it is found that the distribution is positively skewed, and hence log transformation was used to normalize data. A variable that is positively skewed might benefit from a log transformation (log(x)) (Pett 1997).

4.1.1. Testing for Normality of "Engagement per 1M" across "Day"

Table 6: Normality Tests of "Engagement per 1M" across "Day"

	Saturday	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday
M	118.442	163.264	127.593	125.337	133.438	141.636	102.696
Mdn	48.249	57.889	57.889	57.889	57.889	57.889	45.073
SD	356.817	1665.032	627.489	479.060	714.740	1716.577	246.176
Min	.000	.000	.000	.000	.000	.000	.000
Max	16446.592	108517.301	57496.519	27099.109	38248.491	110847.306	11477.830
Skew	26.472	44.247	68.094	33.072	37.995	59.111	23.393
Kurt	1048.707	2313.032	6022.970	1589.425	1789.168	3602.894	969.428
Kolmogorov-Smirnov Normality Test							
Z	.370	.461	.419	.397	.426	.467	.338
df	4971	10523	11673	12226	11561	11053	4825
Sig.	.000	.000	.000	.000	.000	.000	.000

Normal Q-Q Plots of "Engagement per 1M" across "Day"

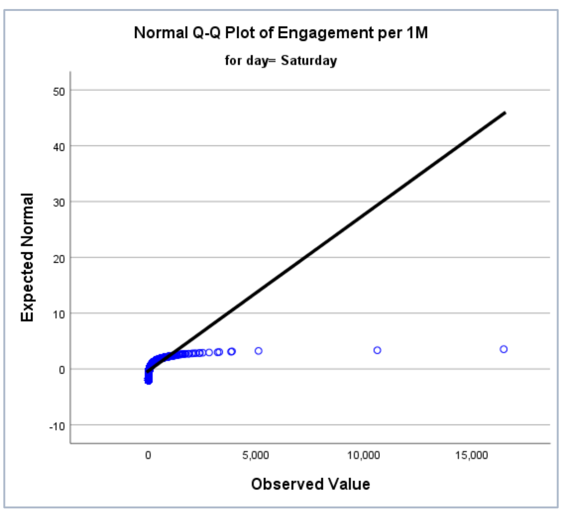


Figure 13: Normal Q-Q Plots of "Engagement per 1M" on Saturday

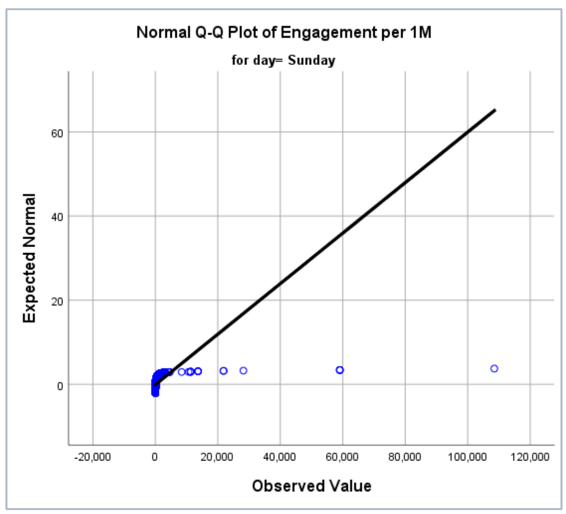


Figure 14: Normal Q-Q Plots of "Engagement per 1M" on Sunday

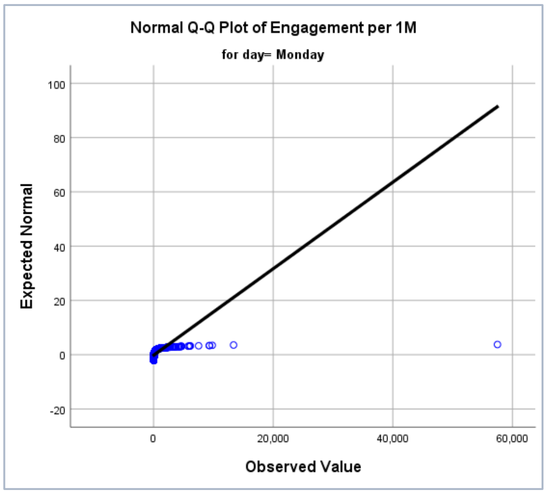


Figure 15**:** Normal Q-Q Plots of "Engagement per 1M" on Monday

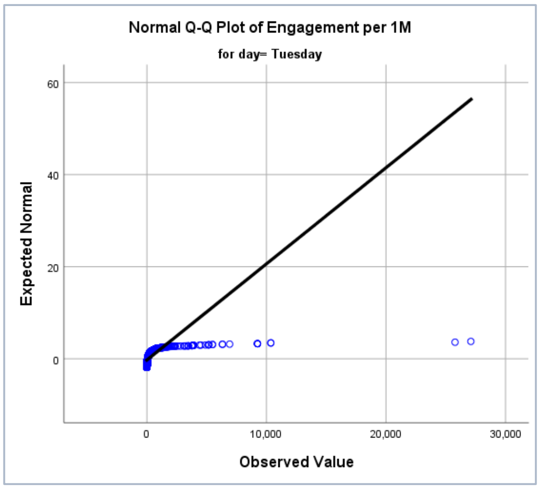


Figure 16: Normal Q-Q Plots of "Engagement per 1M" on Tuesday

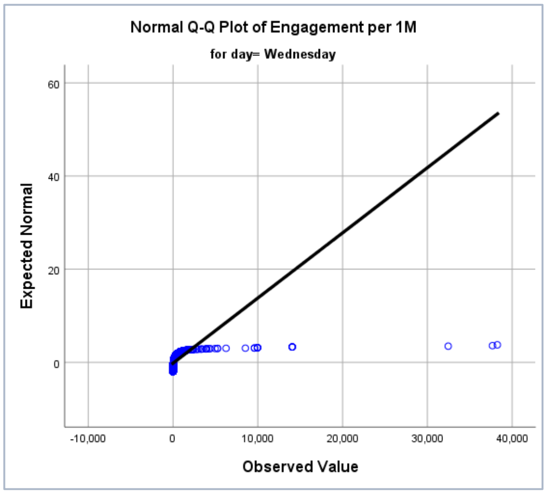


Figure 17**:** Normal Q-Q Plots of "Engagement per 1M" on Wednesday

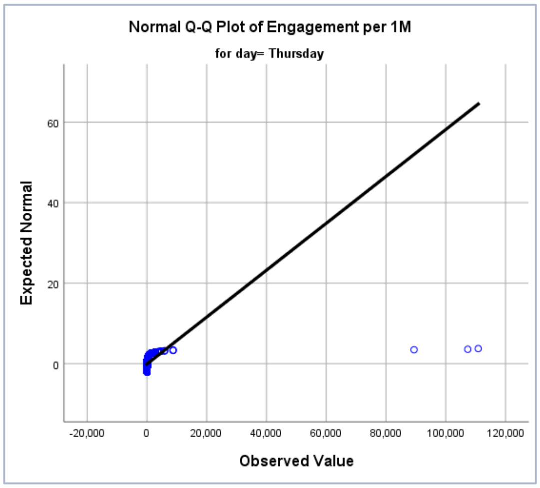


Figure 18**:** Normal Q-Q Plots of "Engagement per 1M" on Thursday

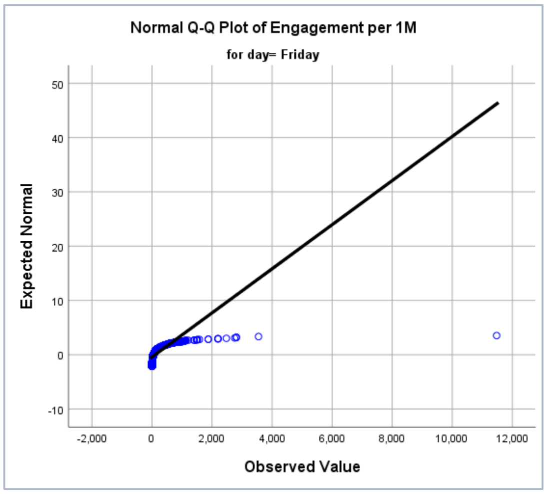


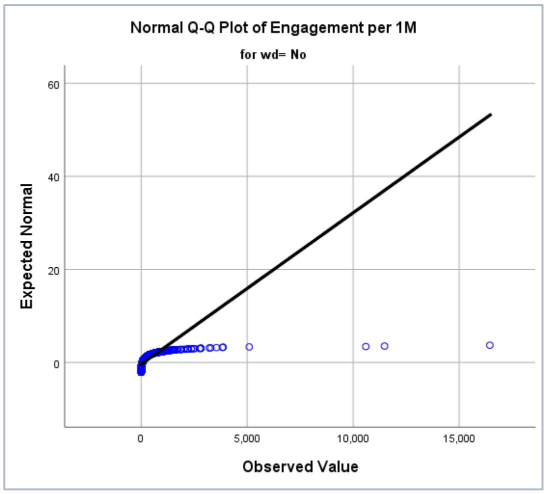
Figure 19**:** Normal Q-Q Plots of
"Engagement per 1M" on Friday

4.1.2. Testing for Normality of "Engagement per 1M" across "WeekDay"

Table 7: Normality Tests of "Engagement per 1M" across "WeekDay"

Is Weekday?	M	Mdn	SD	Min	Max	Skew	Kurt	Kolmogorov-Smirnov Normality Test		
								Statistic	**df**	**Sig.**
No	110.686	47.985	307.425	.000	16446.592	26.939	1163.168	.359	9796	.000
Yes	137.597	57.889	1147.139	.000	110847.306	68.018	5572.588	.452	57036	.000

Normal Q-Q Plots of "Engagement per 1M" across "WeekDay"



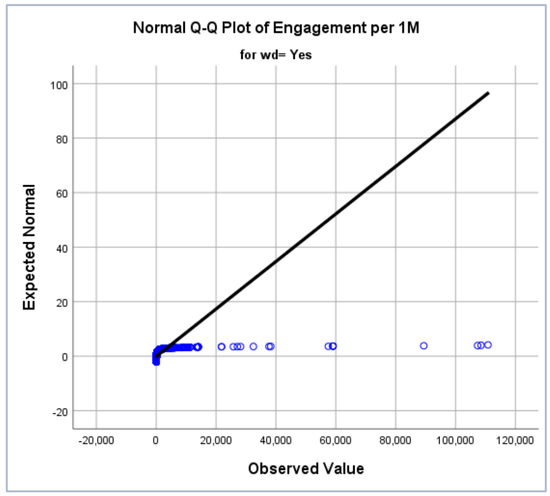


Figure 20: Normal Q-Q Plot of "Engagement per 1M" - Not a Week Day

Figure 21**:** Normal Q-Q Plot of "Engagement per 1M" on Week Day

4.1.3. Testing for Normality of "Engagement per 1M" across "Time of Day"

Table 8: Normality Tests of "Engagement per 1M" across "Time of Day"

	Time of Day				
	Early Morning	**Morning**	**Afternoon**	**Evening**	**Late Night**
M	147.033	134.669	123.856	135.597	321.446
Mdn	59.736	58.987	52.269	47.032	119.065
SD	1381.622	1102.030	905.148	726.499	1285.627
Min	.000	.000	.000	.000	.000
Max	59044.715	108517.301	110847.306	37680.117	10596.752
Skew	38.277	77.619	103.627	36.378	7.969
Kurt	1560.797	7000.374	12403.050	1609.815	64.572
Kolmogorov-Smirnov Normality Test					
Z	.458	.451	.446	.426	.407
df	8942	33472	18192	6159	67
Sig.	.000	.000	.000	.000	.000

Normal Q-Q Plots of "Engagement per 1M" across "Time of Day"

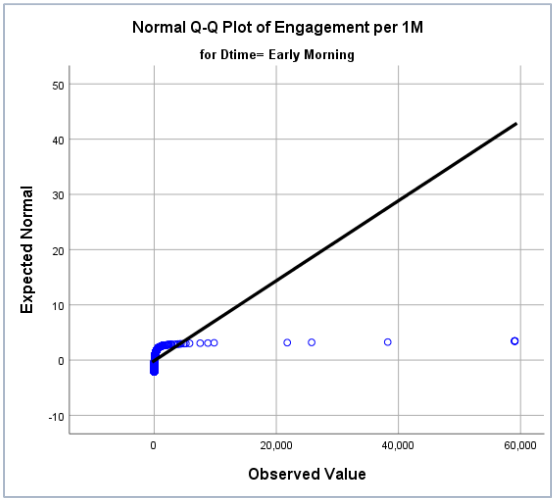


Figure 22**:** Normal Q-Q Plot of "Engagement per 1M" – Early Morning

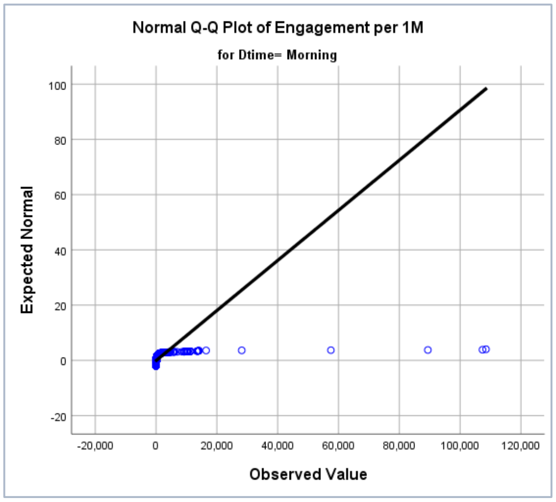


Figure 23**:** Normal Q-Q Plot of "Engagement per 1M" - Morning

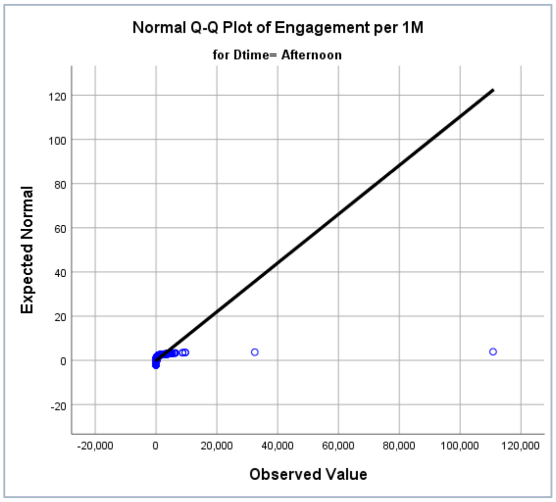


Figure 24**:** Normal Q-Q Plot of "Engagement per 1M" - Afternoon

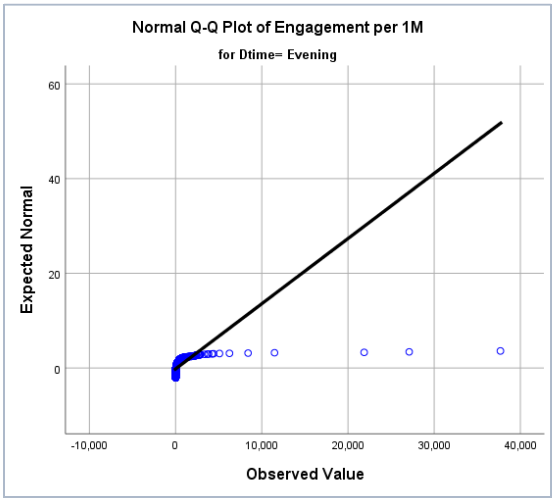


Figure 25**:** Normal Q-Q Plot of "Engagement per 1M" - Evening

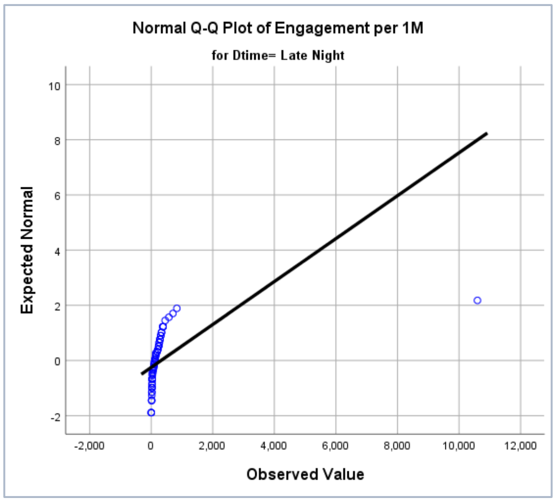


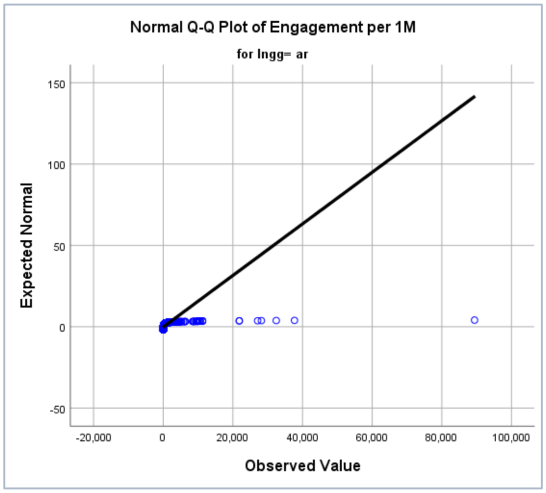
Figure 26**:** Normal Q-Q Plot of "Engagement per 1M" - Late Night

4.1.4. Testing for Normality of "Engagement per 1M" across "Language"

Table 9**:** Normality Tests of "Engagement per 1M" across "Language"

	Language			
	ar	**en**	**mixed**	**other**
M	111.595	182.652	135.591	190.519
Mdn	50.707	67.751	86.833	59.854
SD	630.904	1763.307	255.864	890.354
Min	.000	.000	.000	.000
Max	89390.610	110847.306	6004.957	11477.830
Skew	82.588	48.261	11.968	10.417
Kurt	10099.675	2650.343	208.610	119.059
Kolmogorov-Smirnov Normality Test				
Z	.430	.459	.298	.415
df	42770	18776	5047	239
Sig.	.000	.000	.000	.000

Normal Q-Q Plots of “Engagement per 1M” across “Language”



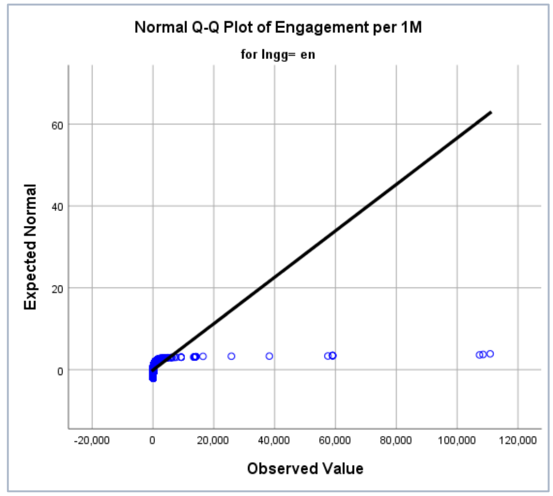
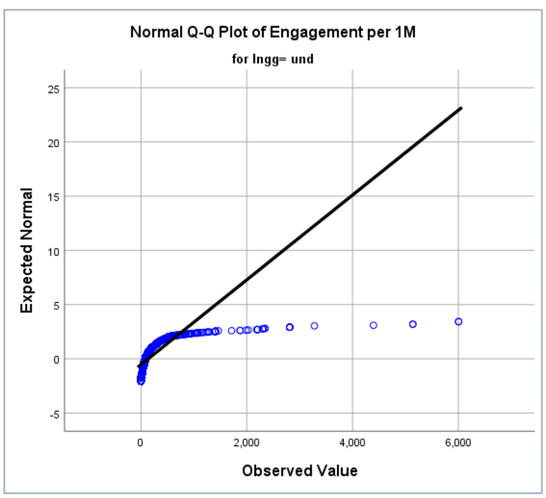


Figure 27**:** Normal Q-Q Plot of "Engagement per 1M" - ar

Figure 28**:** Normal Q-Q Plot of "Engagement per 1M" - en



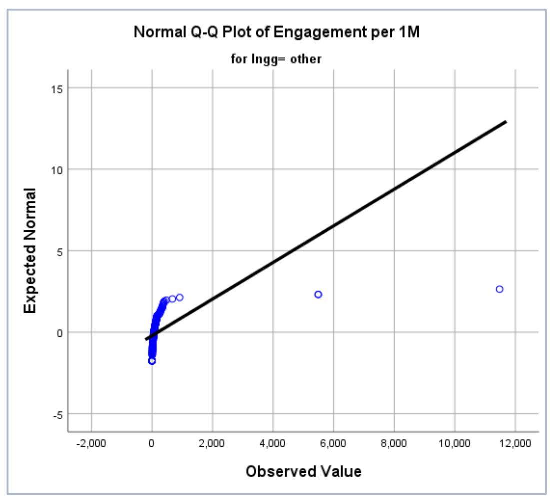


Figure 29: Normal Q-Q Plot of "Engagement per 1M" - mixed

Figure 30**:** Normal Q-Q Plot of "Engagement per 1M" - other

4.1.5. Testing for Normality of “Engagement per 1M” across “Link”

Table 10: Normality Tests of “Engagement per 1M” across “Link”

Has Link?	M	Mdn	SD	Min	Max	Skew	Kurt	Kolmogorov-Smirnov Normality Test		
								Z	df	Sig.
No	86.644	30.260	719.138	.000	57496.519	65.402	4919.144	.452	8617	.000
Yes	140.611	59.736	1108.316	.000	110847.306	71.344	6138.026	.450	58215	.000

Normal Q-Q Plots of “Engagement per 1M” across “Link”

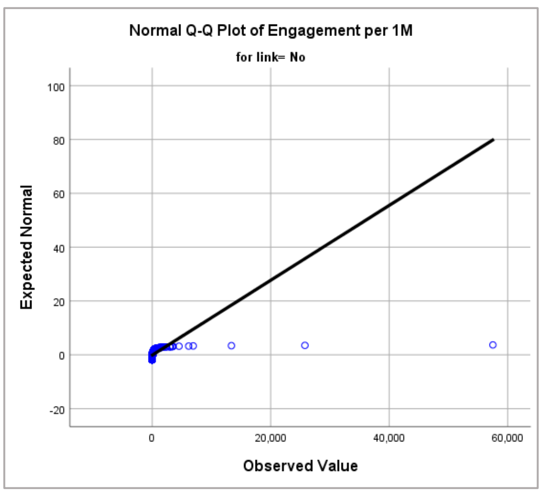


Figure 31: Normal Q-Q Plot of "Engagement per 1M" - No Link

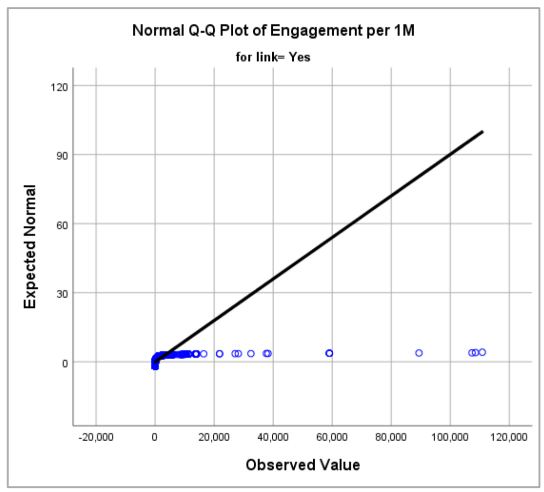


Figure 32: Normal Q-Q Plot of "Engagement per 1M" - Link

4.1.6. Testing for Normality of “Engagement per 1M” across “Hashtag”

Table 11: Normality Tests of “Engagement per 1M” across "Hashtag"

Has Hashtag?	M	Mdn	SD	Min	Max	Skew	Kurt	Kolmogorov-Smirnov Normality Test		
								Z	df	Sig.
No	180.592	64.654	1721.254	.000	89390.610	36.215	1450.442	.458	9853	.000

Yes	125.535	57.889	906.019	.000	110847.306	95.396	11067.442	.445	56979	.000

Normal Q-Q Plots of “Engagement per 1M” across “Hashtag”

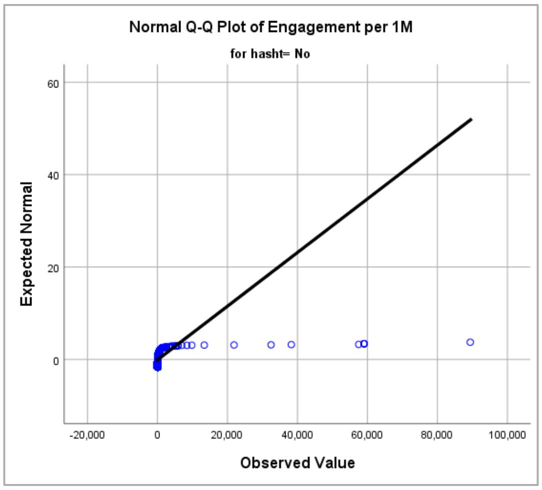


Figure 33: Normal Q-Q Plot of "Engagement per 1M" - No Hashtag

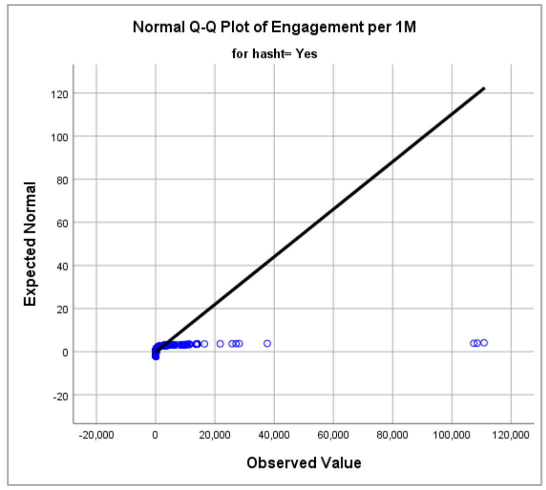


Figure 34: Normal Q-Q Plot of "Engagement per 1M" - Hashtag

4.1.7. Testing for Normality of “Engagement per 1M” across “Mention”

Table 12**:** Normality Tests of “Engagement per 1M” across “Mention”

Has Mention?	**M**	**Mdn**	**SD**	**Min**	**Max**	**Skew**	**Kurt**	**Kolmogorov-Smirnov Normality Test**		
								Z	**df**	**Sig.**
No	121.881	57.889	738.233	.000	59044.715	57.909	4152.432	.434	53493	.000
Yes	180.860	62.787	1873.093	.000	110847.306	52.631	2946.168	.462	13339	.000

Normal Q-Q Plots of “Engagement per 1M” across “Mention”

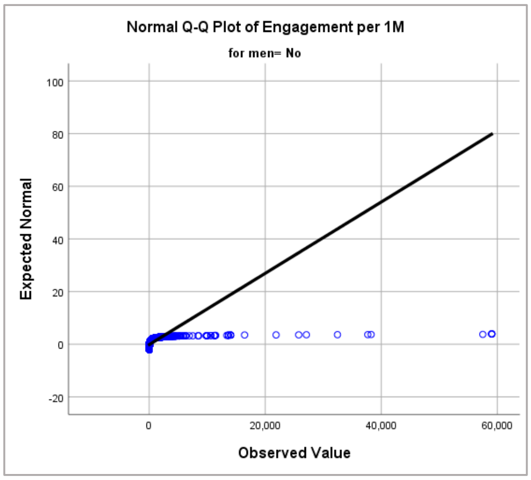


Figure 35: Normal Q-Q Plot of "Engagement per 1M" – No Mention

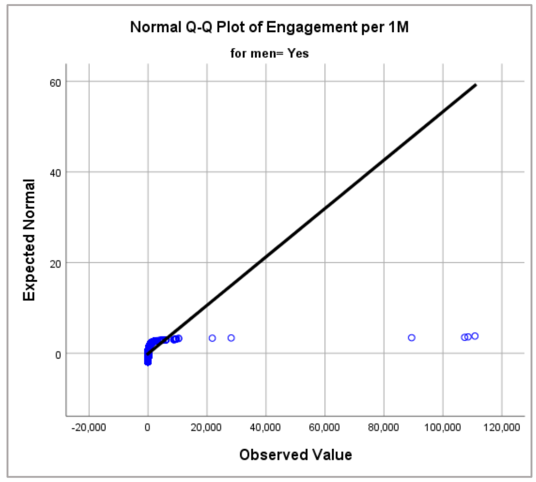


Figure 36: Normal Q-Q Plot of "Engagement per 1M" - Mention

4.1.8. Testing for Normality of "Engagement per 1M" across "Tweet Type"

Table 13: Normality Tests of "Engagement per 1M" across "Tweet Type"

Tweet Type	M	Mdn	SD	Min	Max	Skew	Kurt	Kolmogorov-Smirnov Normality Test		
								Z	df	Sig.
Photo	144.208	60.311	1169.034	.000	110847.306	68.361	5578.662	.451	51735	.000
Status	89.840	39.446	583.038	.000	57496.519	75.312	6947.101	.439	14127	.000
Video	208.723	57.889	676.633	.000	6316.398	6.325	43.092	.379	970	.000

Normal Q-Q Plots of "Engagement per 1M" across "Tweet Type"

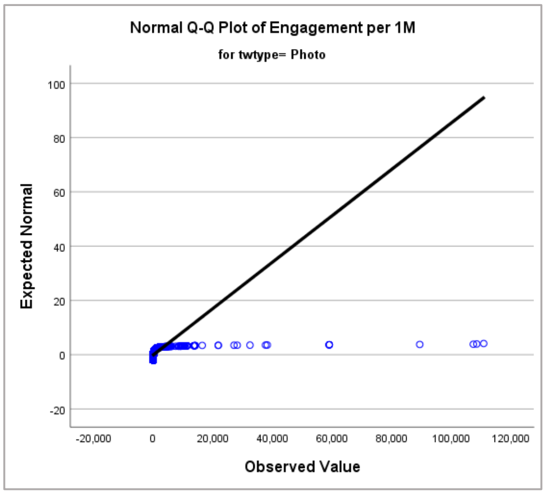


Figure 37**:** Normal Q-Q Plot of "Engagement per 1M" – Photo

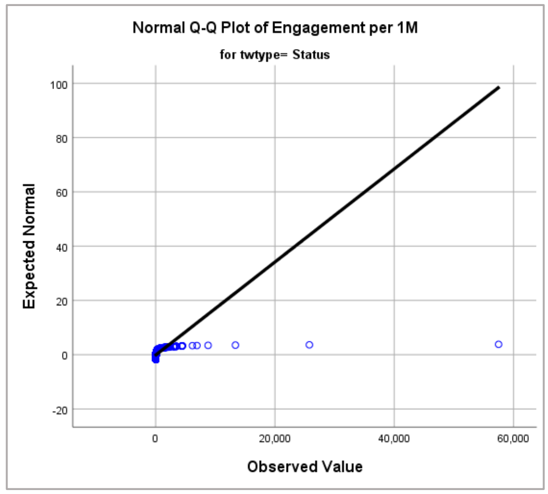


Figure 38: Normal Q-Q Plot of "Engagement per 1M" – Status

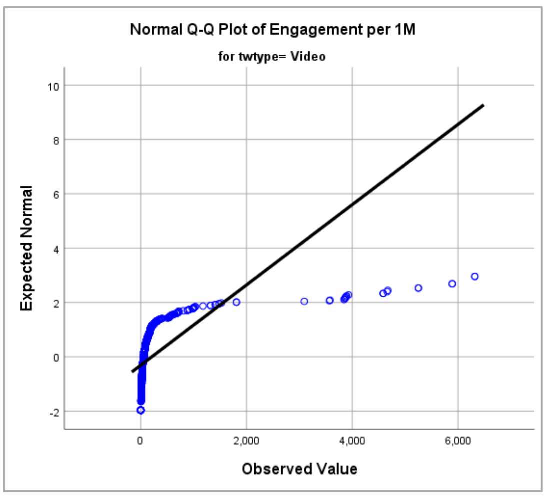


Figure 39**:** Normal Q-Q Plot of "Engagement per 1M" – Video

4.2. Log Transformed "Engagement per 1M" Univariate Analysis

The descriptive statistics of the log transformed Engagement per 1M show that the distribution has become more like a normal distribution. It is more symmetric as the mean value is close to the median, M = 4.11 and Mdn = 4.09. Skewness and Kurtosis values has become in normal range, .220 and .503, respectively. Although the Kolmogorov-Smirnov test of normality suggests that the distribution is not normal, p-value < 0.001; however, the histogram shows that the distribution looks much like a normal distribution, see Figure 38. Investigating the normal Q-Q plots in Figures 39 and 40, there can be noticed a small deviation from normality on the upper tail of the distribution, which is not severe and does not affect normality.

Table 14: Descriptive Statistics of Log Transformed "Engagement per 1M"

M	95% CI for M		Mdn	SD	Min	Max	Skew	Kurt
	LB	**UB**						
4.107	4.098	4.116	4.090	1.138	-.440	11.616	.220	.503

Table 15: Tests of Normality for Log Transformed "Engagement per 1M"

	Kolmogorov-Smirnov[a]		
	Statistic	**df**	**Sig.**
log(ENG1M)	.025	63649	.000
a. Lilliefors Significance Correction			

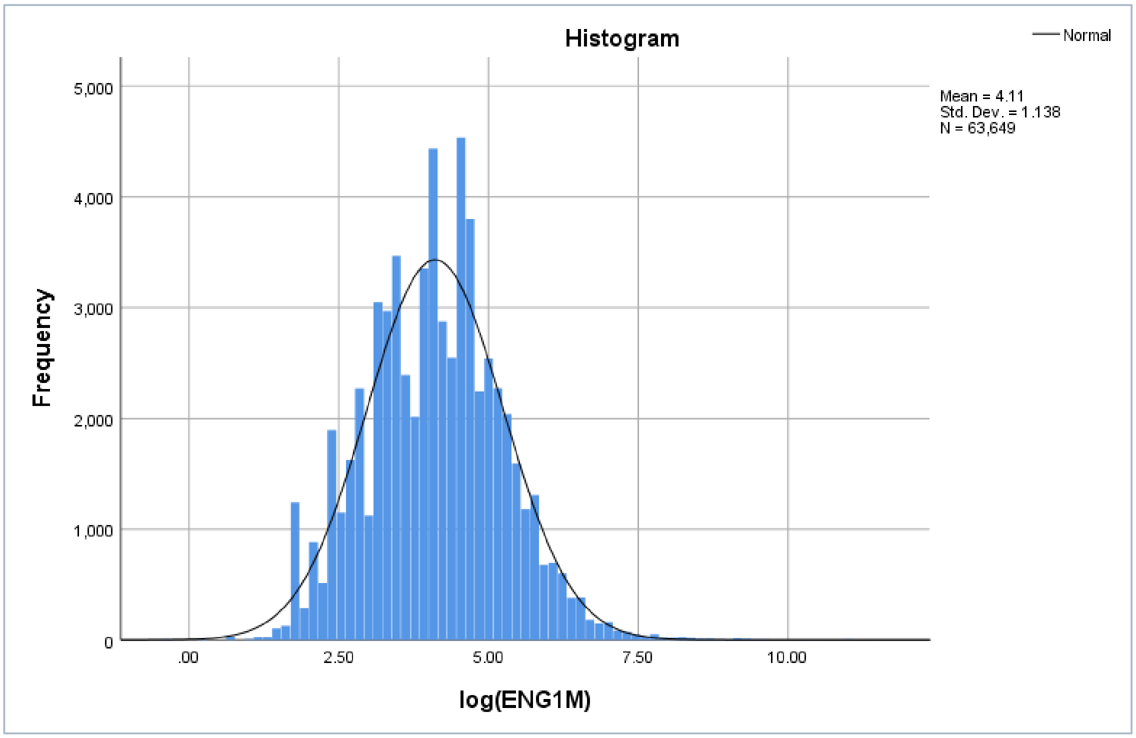


Figure 40. Histogram of Log Transformed "Engagement per 1M"

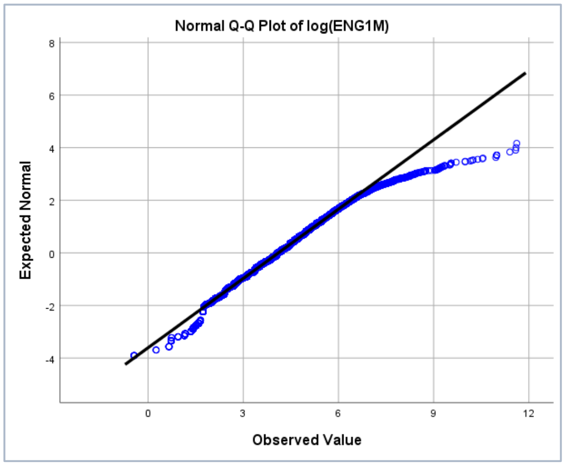


Figure 41. Normal Q-Q Plot of Log Transformed "Engagement per 1M"

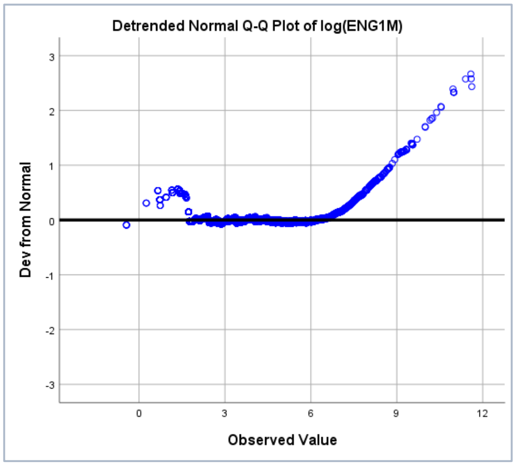


Figure 42. Detrended Normal Q-Q Plot of Log Transformed "Engagement per 1M"

4.3. Analyzing Data

The eight hypotheses of the current study are being tested with the dependent variable “Engagement per 1M” and the independent variables: “Post Type”, “Post Time”, “Post Day”, “Post Weekday”, “Links”, “Mentions”, “Hashtags”, and “Tweet Language”. Three statistical techniques are used to test these hypotheses based on type of data aiming for measuring significant impact of the independent variables on the dependent variable.

A one-way ANOVA was used to test H1, H3, and H8 since the independent variables “Post Type”, “Post Day”, and “Tweet Language” measure more than two categories. The purpose of a one-way ANOVA is to compare the means of more than two groups (the independent variable) on one dependent variable to find if the group means are significantly different from each other (Urdan 2005).

Simple linear regression was used to test H2. Simple linear regression is a technique that predicts a scale variable from a linear relation with another scale variable ("Simple Linear Regression - Quick Introduction" 2019). The predicted (dependent) variable is the “Engagement per 1M” (log transformed) and the independent variable is “Post Time”.

Two-independent samples t test was used to test H4, H5, H6, and H7. The two-independent samples t test is used to compare the means of two independent samples on a given variable (Urdan 2005). For these hypotheses, the independent variables “Post Weekday”, “Links”, “Mentions”, and “Hashtags” are divided into only two samples: “Yes” and “No”.

One of the assumptions of the one-way ANOVA and t test is homogeneity of variance. The Levene's test (Levene 1960) checks this assumption. If the Levene's test statistic is significant (p-value < 0.05), then the groups are not homogeneous (Norusis 1994). In the ANOVA case, there are two tests that can be applied when the assumption of homogeneity of variances has been violated: (1) Welch or (2) Brown-Forsythe test. Alternatively, Kruskal-Wallis H Test can be used, but for most situations it has been shown that the Welch test is best (Laerd Statistics 2019). The t test provides statistics for both cases: when the assumption is met and when it is violated. In the current study, the distribution of "Engagement per 1M" has been shown to have significantly different group variances across all dataset groups, p-value < 0.05. Therefore, Welch and Brown-Forsythe tests were used instead of the F test. The Welch and Brown-Forsythe tests are Robust tests of equality of means.

4.3.1. H1a: Post Type impacts Citizens' Engagement (Photo, Status, Video).

A one- way ANOVA was conducted and revealed that there was a significant difference among three groups of Post Type, in terms of mean Log(Engagement per 1M), Welch = 537.859 and p-value < 0.001. Post-hoc tests of multiple comparisons were performed using Games-Howell correction for unequal variances (based on results of test of homogeneity of variances in Table 13), to find significant differences among the pairs of groups. The multiple comparisons revealed that Video and Photo posts have significantly higher mean Log(Engagement per 1M) than Status posts, p-value < 0.001, see Figure 41.

Table 16**:** Test of Homogeneity of Variances across Post Types

		Levene Statistic	df1	df2	Sig.
log(ENG1M)	**Based on Mean**	5.633	2	63646	.004
	Based on Median	3.469	2	63646	.031
	Based on Median and with adjusted df	3.469	2	63352.375	.031
	Based on trimmed mean	4.659	2	63646	.009

Table 17**:** Robust Tests of Equality of Means across Post Types

	Statistic[a]	df1	df2	Sig.
Welch	537.859	2	2403.679	.000
Brown-Forsythe	473.462	2	2920.234	.000

a. Asymptotically F distributed.

Table 18**:** Games-Howell Multiple Comparisons for Log(Engagement per 1M) across Post Types

(I) Tweet Type	(J) Tweet Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	**Upper Bound**
Photo	Status	.36169*	.01105	.000	.3358	.3876
	Video	-.01318	.04193	.947	-.1116	.0852
Status	Photo	-.36169*	.01105	.000	-.3876	-.3358
	Video	-.37486*	.04277	.000	-.4752	-.2745
Video	Photo	.01318	.04193	.947	-.0852	.1116
	Status	.37486*	.04277	.000	.2745	.4752

**. The mean difference is significant at the 0.05 level.*

Table 19**:** Descriptive Statistics of Log(Engagement per 1M) across Post Types

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	**Upper Bound**		
Photo	49833	4.1801	1.12947	.00506	4.1702	4.1900	-.44	11.62
Status	12893	3.8184	1.11536	.00982	3.7991	3.8376	-.44	10.96
Video	923	4.1932	1.26455	.04162	4.1116	4.2749	1.51	8.75
Total	63649	4.1070	1.13802	.00451	4.0982	4.1158	-.44	11.62

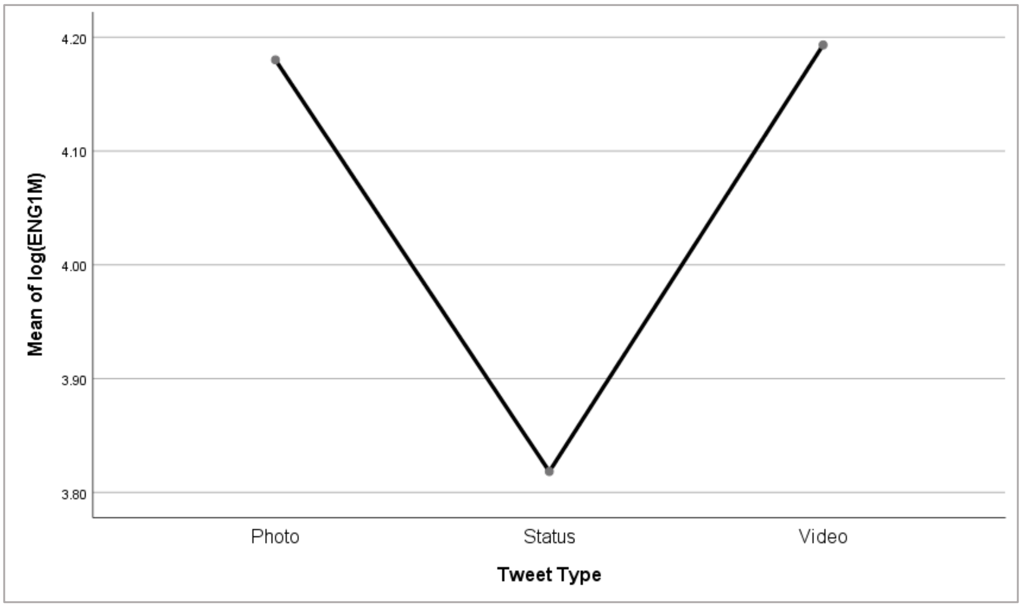


Figure 43: Means Plot of Engagement per 1M (Log) across Post Types

4.3.2. H1b: Post Time impacts Citizens' Engagement.

Simple linear regression was performed to predict Engagement by Time. Regression analysis is a statistical technique for investigating and modeling the relationship between variables (Montgomery, Peck & Vining 2012).

Simple linear regression was performed using the log transformed "Engagement per 1M". assumptions of regression were met. That is, residuals were nearly normally distributed, see Figure 42. Normal P-P plot (Figure 43) shows that all points were scattered on and around the diagonal line, indicating a normal distribution of residuals. The Predicted Value vs. Residuals Scatterplot (Figure 44) shows a random scatter around zero, indicating no specific patterns which meets regression assumption. The analysis results revealed a significant regression model that explained 0.3% (Table 17) of the variance in log(Engagement per 1M), $F(1,63647) = 161.893$ and p-value $< .001$. The regression coefficient is significant with a value equal to $B = -0.014$, $t = -12.724$ and p-value $< .001$.

This indicates that a one unit increase in Time decreases Engagement (log transformed) by .014 unit. That is, a one unit increase in Time decreases Engagement by 1.014 unit. The B value was transformed by taking its exponential to interpret the actual impact of Time on Engagement per 1M.

Table 20**:** Regression Model Summary of Post Time on Log(Engagement per 1M)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	**F Change**	**df1**	**df2**	**Sig. F Change**
1	.050[a]	.003	.003	1.13659	.003	161.893	1	63647	.000
a. Predictors: (Constant), Time - Dependent Variable: log(ENG1M)									

Table 21**:** ANOVA[a] of Post Time on Log(Engagement per 1M)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	209.139	1	209.139	161.893	.000[b]
	Residual	82221.417	63647	1.292		
	Total	82430.556	63648			
a. Dependent Variable: log(ENG1M)						
b. Predictors: (Constant), Time						

Table 22**:** Regression Coefficients[a] of Post Time on Log(Engagement per 1M)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	**Std. Error**	**Beta**		
1	(Constant)	4.247	.012		357.623	.000
	Time	-.014	.001	-.050	-12.724	.000
a. Dependent Variable: log(ENG1M)						

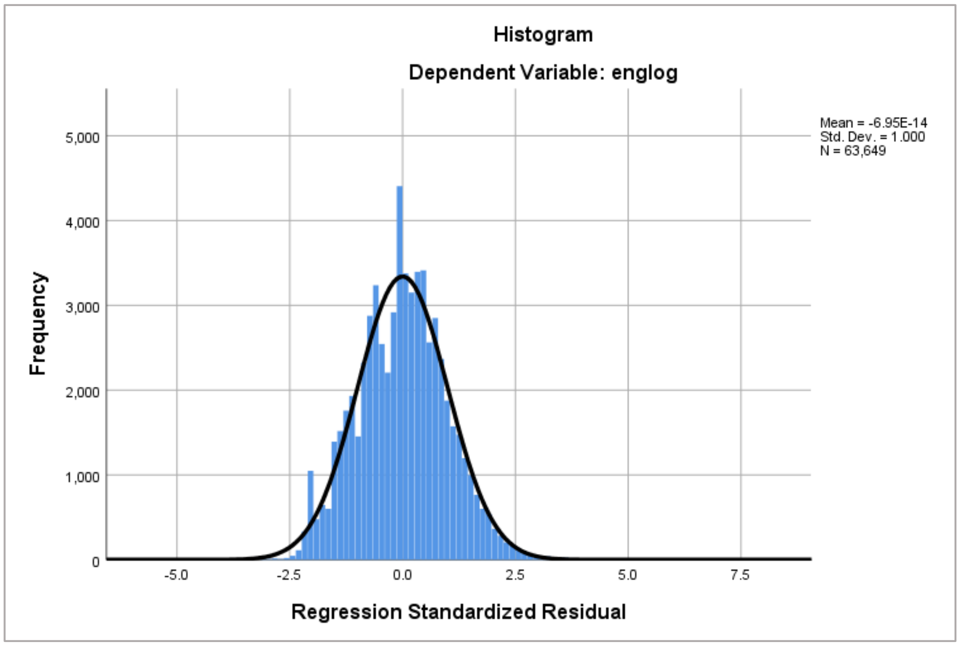


Figure 44**:** Regression Residuals Histogram – DV: Engagement per 1M (log)

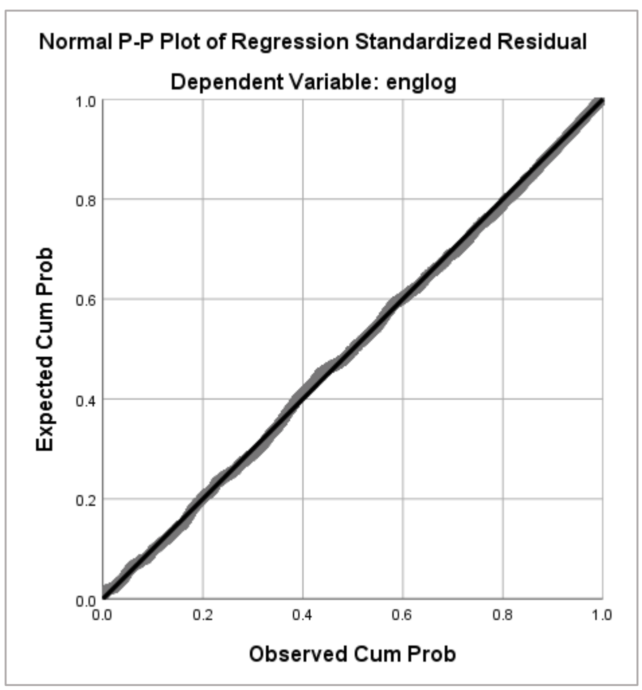


Figure 45: Normal P-P Plot of Regression Residuals – DV: Engagement per 1M (log)

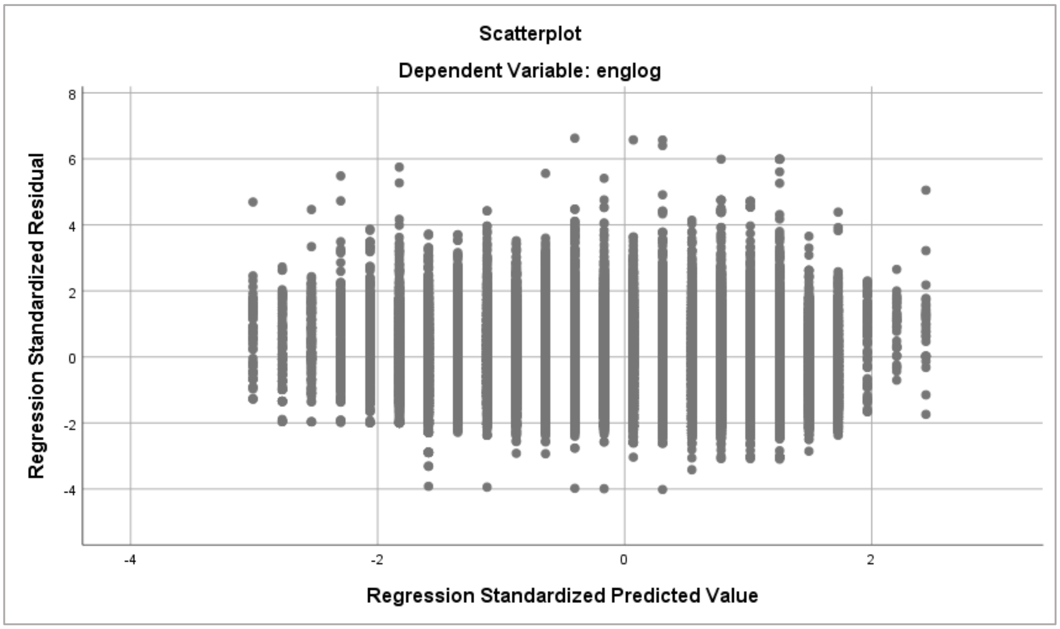


Figure 46: Predicted Value vs. Residuals Scatterplot – DV: log(Engagement per 1M)

4.3.3. H1c: Post Day impacts Citizens' Engagement.

As illustrated in testing H1, H3 is tested by performing a one-way ANOVA to find significant differences among week days in terms of Engagement per 1M. The test revealed significant differences among week days in terms of log(Engagement per 1M), Welch = 42.94 and p-value < 0.001. That is, days of the post day significantly impacts citizens' engagement.

The post-hoc multiple comparisons tests revealed that Friday and Saturday had significantly lower mean log(Engagement per 1M) than Sunday, Monday, Tuesday, Wednesday, and Thursday, p-value < 0.001. Moreover, Sunday had significantly higher mean log(Engagement per 1M) than Thursday, p-value = 0.022. Results can be visually investigated in Figure 45.

Table 23**:** Test of Homogeneity of Variances across Post Day

		Levene Statistic	df1	df2	Sig.
log(ENG1M)	Based on Mean	43.715	6	63642	.000
	Based on Median	43.329	6	63642	.000
	Based on Median and with adjusted df	43.329	6	63597.195	.000
	Based on trimmed mean	43.493	6	63642	.000

Table 24**:** Robust Tests of Equality of Means across Post Day

		Statistic[a]	df1	df2	Sig.
Welch		42.940	6	23273.841	.000
Brown-Forsythe		46.557	6	48119.071	.000
	a. Asymptotically F distributed.				

Table 25**:** Games-Howell Multiple Comparisons for Log(Engagement per 1M) across Post Day

(I) Day	(J) Day	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Saturday	Sunday	-.19366*	.02125	.000	-.2563	-.1310
	Monday	-.18698*	.02093	.000	-.2487	-.1253
	Tuesday	-.17068*	.02090	.000	-.2323	-.1090
	Wednesday	-.17783*	.02105	.000	-.2399	-.1158
	Thursday	-.14362*	.02106	.000	-.2057	-.0815
	Friday	.06649	.02526	.117	-.0080	.1410
Sunday	Saturday	.19366*	.02125	.000	.1310	.2563
	Monday	.00667	.01535	.999	-.0386	.0519
	Tuesday	.02298	.01532	.745	-.0222	.0681
	Wednesday	.01582	.01551	.950	-.0299	.0616
	Thursday	.05003*	.01553	.022	.0042	.0958
	Friday	.26015*	.02088	.000	.1986	.3217
Monday	Saturday	.18698*	.02093	.000	.1253	.2487
	Sunday	-.00667	.01535	.999	-.0519	.0386
	Tuesday	.01631	.01487	.929	-.0275	.0602
	Wednesday	.00915	.01507	.997	-.0353	.0536
	Thursday	.04336	.01509	.062	-.0011	.0878
	Friday	.25348*	.02055	.000	.1929	.3141
Tuesday	Saturday	.17068*	.02090	.000	.1090	.2323
	Sunday	-.02298	.01532	.745	-.0681	.0222
	Monday	-.01631	.01487	.929	-.0602	.0275
	Wednesday	-.00716	.01503	.999	-.0515	.0372
	Thursday	.02705	.01505	.550	-.0173	.0714
	Friday	.23717*	.02053	.000	.1766	.2977
Wednesday	Saturday	.17783*	.02105	.000	.1158	.2399
	Sunday	-.01582	.01551	.950	-.0616	.0299
	Monday	-.00915	.01507	.997	-.0536	.0353
	Tuesday	.00716	.01503	.999	-.0372	.0515
	Thursday	.03421	.01525	.272	-.0108	.0792
	Friday	.24433*	.02067	.000	.1834	.3053
Thursday	Saturday	.14362*	.02106	.000	.0815	.2057
	Sunday	-.05003*	.01553	.022	-.0958	-.0042
	Monday	-.04336	.01509	.062	-.0878	.0011

(I) Day	(J) Day	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
	Tuesday	-.02705	.01505	.550	-.0714	.0173
	Wednesday	-.03421	.01525	.272	-.0792	.0108
	Friday	.21012*	.02069	.000	.1491	.2711
Friday	Saturday	-.06649	.02526	.117	-.1410	.0080
	Sunday	-.26015*	.02088	.000	-.3217	-.1986
	Monday	-.25348*	.02055	.000	-.3141	-.1929
	Tuesday	-.23717*	.02053	.000	-.2977	-.1766
	Wednesday	-.24433*	.02067	.000	-.3053	-.1834
	Thursday	-.21012*	.02069	.000	-.2711	-.1491

**. The mean difference is significant at the 0.05 level.*

Table 26**:** Descriptive Statistics of Log(Engagement per 1M) across Post Day

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	**Upper Bound**		
Saturday	4765	3.9633	1.24811	.01808	3.9278	3.9987	.66	9.71
Sunday	10060	4.1569	1.11961	.01116	4.1350	4.1788	.25	11.59
Monday	11128	4.1502	1.11187	.01054	4.1296	4.1709	.66	10.96
Tuesday	11492	4.1339	1.12434	.01049	4.1134	4.1545	-.44	10.21
Wednesday	10956	4.1411	1.12735	.01077	4.1200	4.1622	.25	10.55
Thursday	10586	4.1069	1.11067	.01079	4.0857	4.1280	-.44	11.62
Friday	4662	3.8968	1.20484	.01765	3.8622	3.9314	-.44	9.35
Total	63649	4.1070	1.13802	.00451	4.0982	4.1158	-.44	11.62

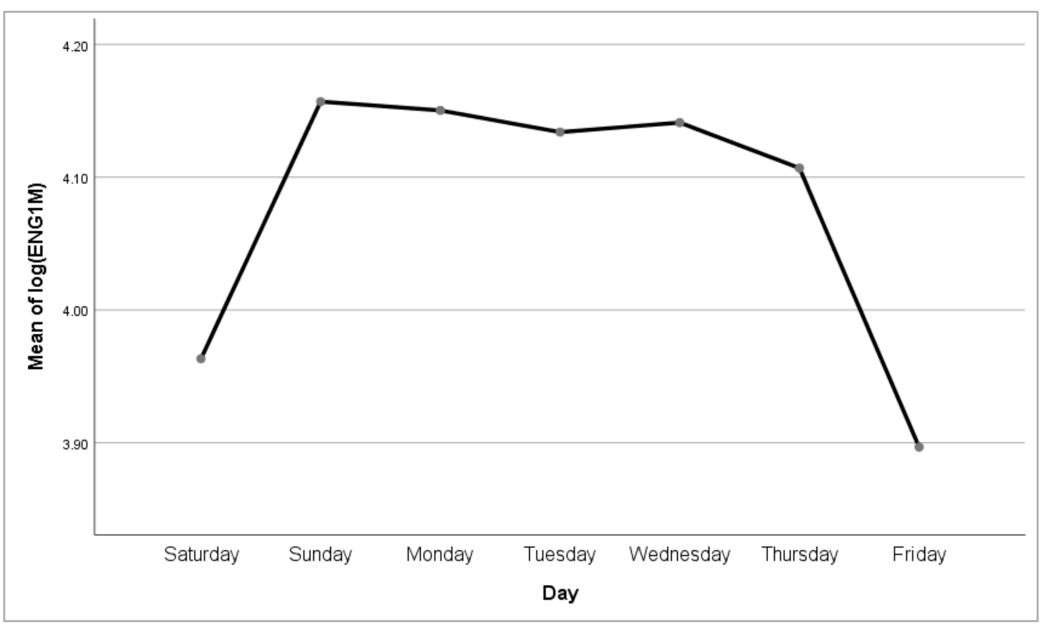


Figure 47**:** Means Plot of log(Engagement per 1M) across Week Days

4.3.4. H1d: Post Weekday impacts citizen's Engagement

A two-independent samples t test was performed to test whether there is a significant impact of weekday on citizens' engagement or not. That is, the test tests whether there is a significant difference between two groups: Weekday and Not Weekday. The t test revealed that there is a statistically significant difference between the two groups: Weekend and Not Weekend in terms of mean Engagement per 1M (log transformed), M = 4.138 and M = 3.93, respectively; t = -15.332 and p-value < 0.001. The Levene's test for equality of variances revealed that the two groups had significantly unequal variances, p-value < 0.001, and hence t test statistics for the case "equal variances not assumed" was used. From these results, we can conclude that post weekday significantly impacts citizens' engagement, as mean engagement per 1M was higher when the day is a weekday, while the mean engagement per 1M was lower when the day is not a weekday.

Table 27**:** Group Statistics of Log(Engagement per 1M) vs. Weekday

	Is Weekday?	N	Mean	Std. Deviation	Std. Error Mean
log(ENG1M)	No	9427	3.930	1.227	.013
	Yes	54222	4.138	1.119	.005

Table 28**:** Independent-Samples t Test of Log(Engagement per 1M) vs. Weekday

	Levene's Test		t-test for Equality of Means						
								95% CI of the Difference	
Equal Variances	**F**	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Mean Difference**	**SE Difference**	**Lower**	**Upper**
Assumed	251.068	.000	-16.361	63647	.000	-.207	.013	-.232	-.183
Not assumed			-15.332	12302.683	.000	-.207	.014	-.234	-.181

4.3.5. H1e: Links in Tweets impacts Citizens' Engagement.

A two-independent samples t test was performed to test the hypothesis that Links significantly impacts citizens' Engagement. The test revealed that there is a statistically significant difference between the two cases: has link and doesn't have link, t = -37.136 and p-value < 0.001. Posts with link had significantly higher mean log(Engagement per 1M) than posts without link.

Table 29: Group Statistics of Log(Engagement per 1M) vs. Links

	Has Link?	N	Mean	Std. Deviation	Std. Error Mean
log(ENG1M)	No	8056	3.670	1.131	.013
	Yes	55593	4.170	1.125	.005

Table 30: Independent-Samples t Test of Log(Engagement per 1M) vs. Links

	Levene's Test		t-test for Equality of Means						
								95% CI of the Difference	
Equal variances	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	SE Difference	Lower	Upper
Assumed	30.553	.000	-37.282	63647	.000	-.500	.013	-.527	-.474
Not assumed			-37.136	10499.338	.000	-.500	.013	-.527	-.474

4.3.6. H1f: Mentions in Tweets impacts Citizens' Engagement.

A two-independent samples t test was performed to test whether or not mentions significantly impacts citizens' engagement. The test was statistically significant, t = -15.68 and p-value < 0.001, indicating that there is a significant difference between posts with mentions and posts without. That is, posts with mentions had significantly higher mean log(Engagement per 1M) than posts without mentions, M = 4.255 and M = 4.071, respectively.

Table 31: Group Statistics of Log(Engagement per 1M) vs. Mention

	Has Mention?	N	Mean	Std. Deviation	Std. Error Mean
log(ENG1M)	No	51068	4.071	1.121	.005
	Yes	12581	4.255	1.195	.011

Table 32: Independent-Samples t Test of Log(Engagement per 1M) vs. Mention

	Levene's Test		t-test for Equality of Means					
	F	Sig.	t	df		Mean Difference	SE Difference	95% CI of the Difference

					Sig. (2-tailed)			Lower	Upper
Assumed	65.073	.000	-16.302	63647	.000	-.184	.011	-.206	-.162
Not assumed			-15.680	18406.700	.000	-.184	.012	-.207	-.161

4.3.7. H1g: Hashtags in Tweets impacts Citizens' Engagement.

A two-independent samples t test was conducted to test whether or not hashtags significantly impacts citizens' engagement. The test revealed that there was a statistically significant difference between posts with hashtags and posts without, t = 23.283 and p-value < 0.001. That is, the mean log(Engagement per 1M) for posts with hashtags (M = 4.067) was significantly lower than the mean log(Engagement per 1M) for posts without hashtags (M = 4.353).

Table 33: Group Statistics of Log(Engagement per 1M) vs. Hashtags

	Has Hashtag?	N	Mean	Std. Deviation	Std. Error Mean
log(ENG1M)	No	8967	4.353	1.066	.011
	Yes	54682	4.067	1.144	.005

Table 34**:** Independent-Samples t Test of Log(Engagement per 1M) vs. Hashtags

	Levene's Test		t-test for Equality of Means						
								95% CI of the Difference	
Equal variances	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	SE Difference	Lower	Upper
Assumed	114.010	.000	22.123	63647	.000	.286	.013	.260	.311
Not assumed			23.283	12603.555	.000	.286	.012	.262	.310

4.3.8. H1h: Tweet Language impacts the Citizen's Engagement.

A one-way ANOVA was conducted to test whether or not Tweet Language significantly impacts citizens' engagement. The test revealed that there was significant differences among the different groups of languages in terms of log(Engagement per 1M), Welch = 475.773 and p-value < 0.001. Post hoc multiple comparisons tests revealed that posts in "und" had significantly higher mean log(Engagement per 1M) than posts in en, ar, and other languages, p-value < 0.05. Moreover, posts in ar had significantly lower mean log(Engagement per 1M) than posts in en and other languages, p-value < 0.05; see the means plot in Figure 46.

Table 35**:** Test of Homogeneity of Variances across Tweet Language

		Levene Statistic	df1	df2	Sig.
log(ENG1M)	Based on Mean	123.739	3	63645	.000
	Based on Median	121.769	3	63645	.000
	Based on Median and with adjusted df	121.769	3	63139.468	.000
	Based on trimmed mean	123.144	3	63645	.000

Table 36**:** Robust Tests of Equality of Means across Tweet Language

	Statistic[a]	df1	df2	Sig.
Welch	475.773	3	1060.598	.000
Brown-Forsythe	438.853	3	1547.093	.000
a. Asymptotically F distributed.				

Table 37**:** Games-Howell Multiple Comparisons for Log(Engagement per 1M) across Tweet Language

(I) Language	(J) Language	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
ar	en	-.26921*	.01036	.000	-.2958	-.2426
	mixed	-.47180*	.01466	.000	-.5095	-.4341
	other	-.24079*	.07838	.013	-.4437	-.0379
en	ar	.26921*	.01036	.000	.2426	.2958
	mixed	-.20259*	.01611	.000	-.2440	-.1612
	other	.02842	.07867	.984	-.1752	.2320
mixed	ar	.47180*	.01466	.000	.4341	.5095
	en	.20259*	.01611	.000	.1612	.2440
	other	.23101*	.07935	.020	.0257	.4363
other	ar	.24079*	.07838	.013	.0379	.4437
	en	-.02842	.07867	.984	-.2320	.1752
	mixed	-.23101*	.07935	.020	-.4363	-.0257
**. The mean difference is significant at the 0.05 level.*						

Table 38: Descriptive Statistics of Log(Engagement per 1M) across Tweet Language

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	**Upper Bound**		
ar	40543	3.994	1.127	.006	3.983	4.005	-.44	11.40
en	18038	4.263	1.172	.009	4.246	4.280	-.44	11.62
mixed	4847	4.466	.943	.014	4.439	4.492	.66	8.70
other	221	4.235	1.162	.078	4.081	4.389	1.51	9.35
Total	63649	4.107	1.138	.005	4.098	4.116	-.44	11.62

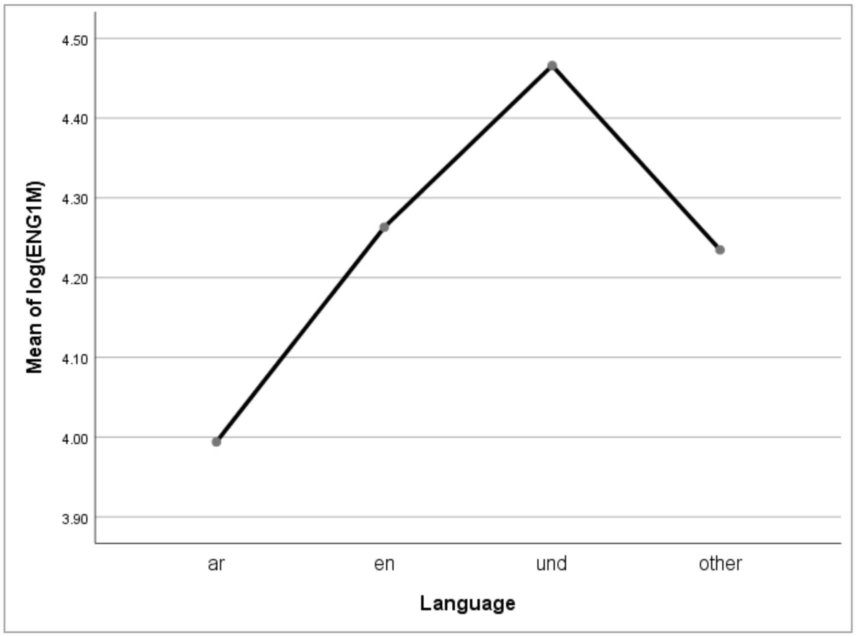


Figure 48: Means Plot of log(Engagement per 1M) across Tweet Language

4.4. Hypothesis Testing Summary

In Table 36, a summary of key findings and results of statistical tests used in hypothesis testing of the current study is reported. It worthy to say that all study hypotheses were significantly supported with p-value below 0.001, which is a very strong evidence of the significant effect reported of each independent variable.

Table 39: Key Findings of Hypothesis Testing

Hypothesis	Statistical Test	Sig.	Result	Impact
H1a: Post Type impacts Citizens' Engagement (Photo, Status, Video).	One- way ANOVA	$P < .001$	Post Type (Photo, Status, Video) significantly impacts Citizens' Engagement.	Photo and video posts have significantly higher engagement than status posts.
H1b: Post Time impacts Citizens' Engagement.	Simple Linear Regression	$P < .001$ $R^2 = 3\%$	Post Time significantly impacts Citizens' Engagement.	A one unit increase in Time decreases Engagement by 1.014 units.
H1c: Post Day impacts Citizens' Engagement.	One- way ANOVA	$P < .001$	Post Day significantly impacts Citizens' Engagement.	Friday and Saturday had significantly lower Engagement than Sunday, Monday, Tuesday, Wednesday, and Thursday. Sunday had significantly higher Engagement than Thursday.
H1d: Post Weekday impacts citizen's Engagement.	Two-independent Samples t Test	$P < .001$	Post Weekday significantly impacts citizen's Engagement.	Higher engagement was reported for week days, while lower engagement was reported for other days.
H1e: Links in Tweets impacts Citizens' Engagement.	Two-independent Samples t Test	$P < .001$	Links in Tweets significantly impacts Citizens' Engagement.	Posts with links have higher engagements than posts without links.
H1f: Mentions in Tweets impacts Citizens' Engagement.	Two-independent Samples t Test	$P < .001$	Mentions in Tweets significantly impacts Citizens' Engagement.	Posts with mentions have higher engagements than posts without mentions.
H1g: Hashtags in Tweets impacts Citizens' Engagement.	Two-independent Samples t Test	$P < .001$	Hashtags in Tweets significantly impacts Citizens' Engagement.	Posts with hashtags have lower engagements than posts without hashtags.
H1h: Tweet Language impacts the Citizen's Engagement.	One- way ANOVA	$P < .001$	Tweet Language significantly impacts the Citizen's Engagement.	Posts in "mixed" had significantly higher Engagement than posts in "en", "ar", and "other" languages. Posts in "ar" had significantly lower Engagement than posts in "en" and "other" languages,

4.5. Predicting Post Engagement

In this part, the dataset will be used to predict the citizens' engagement using the various tweet features before the tweet is posted. This can help the government entities in taking the decision when to post a tweet to gain the maximum engagement level. Various machine learning models were explored. These machine learning models are: K-nearest Neighbour, Linear Support Vector Machine (SVM), Naïve Bayes, Multilayer Perceptron (MLP) Classifier, Decision Tree and Random Forest. In this study, the models are designed to predict the engagement value for both Arabic and English languages as it represents 92% of the overall tweets. The dataset includes 61,546 tweets with Arabic and English languages. Figure **49** shows the approach that is followed to implement the machine learning models. As stated in section 3.2, the dataset was split into two equally groups based on the engagement value. The threshold value that splits the data equally is 57.888796. The following subsections illustrate the carried-out tasks and experiments to predict and evaluate the citizens' engagement.

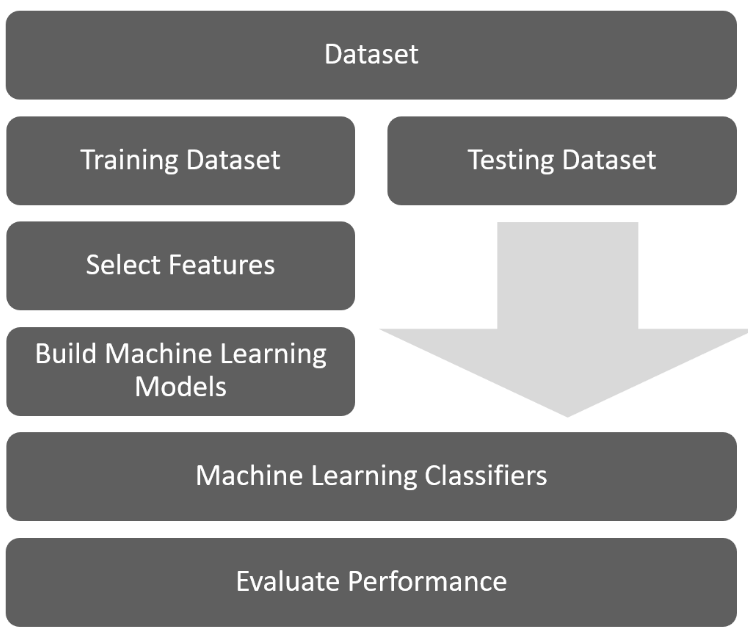


Figure 49**:** Machine Learning Prediction Approach for Post Engagement

4.5.1. Data Pre-processing

Each tweet consists of several attributes, where the types of these attributes are mainly string and numerical numbers. To perform the experiments using a machine learning model, the user data must be only numerical values, since any other input type is not acceptable by any machine learning model Thus, in this step, we begin by processing the tweets to originate only numerical types attributes. The text attributes that are converted to numerical values is the day of the tweet, the type of the tweet, and the text of the tweet.

The post day of the tweet attribute (Sunday to Saturday) is converted to numerical value by mapping each day to its corresponding numeric value (1-7). For instance, Sunday is mapped to 1, Monday is mapped to 2, and Tuesday is mapped to 3 and so on. With respect to the post type of tweets, the values of this attribute are Photo, Status, and Video. Accordingly, the tweets types are mapped to one, two, and three; respectively. The text conversion of the tweets is conducted by performing the tokenization process followed by the text vectorization process.

4.5.2. Tokenization

In the tokenization process, we start by converting the text into lowercase. Then, we proceed by converting each word to its root. For instant "computing" and "computation" are converted to "compute". This aim to reduce the number of the words in the used vocabulary, and reduces the computational complexity, since each word is mapped to a unique value in the vectorization process. Next, we reduce the size of the input text by eliminating the punctuations and the "stopwords". Stop words are those words that are commonly used and do not have significant impact to change the meaning or change the context. The filtration of these stop words has significant impact on the performance of the NLP tasks. For instance, in the English language, the words “an”, “the”, “you”, “he”, “they”, “however”, “as” and “by” are recognized as common stop worlds, wherein the Arabic language, the words “الى”, “في”, “هو”, “هي”, “بينما”, “كان” and “خلال” are examples of common stop words.

4.5.3. Text Vectorization

Further to the text tokenization, the vectorization process aims to assign a numerical value for each word in the available text. Based on the employed vectorization process, a word numerical value represents the importance of the word in the document. The output of this process is represented as a matrix, where each row matrix represents the numerical weight values (importance) of a tweet. To obtain this matrix, several methods can be used to calculate the weights for the tweet values, where two of the most well-known methods to perform this calculation are the world count and the Term Frequency-Inverse Document Frequency (TF-IDF). The word count method (also known as bag of words) works by counting the number of times each word appeared in the text. This method is typically applied in situations where only the number times a word appears in the text (tweet) plays an important role in the classification process (Alqaryouti et al. 2019).

The TF-IDF method aims to determine the importance of each word in the tweets. Accordingly, words appear in small number of tweets are expected to have higher weight compared to words that appear in most of the tweets. This method has great advantage in situation where relatively unique words are expected to help in the classification process. Therefore, in this work, we adopt this method as part of the pre-processing step. The TF-IDF starts by calculating the frequency of each word appearance. The term frequency for word w_i ((w_i)) is calculated by dividing the number of times a word appeared in the text over the total number of words in the text (TF). Then, this method proceeds by calculating the IDF for each word. This inverse is calculated as follows:

$$IDF(w_i) = \log(\frac{NT}{NTw_i})$$

Where NT refers to the total number of documents (tweets), and NTw_i refers to the number of documents (tweets) that has the word w_i. The IDF is typically used to scale down the weight of the words that appear in a high percentage of the tweets. Then, then the TD-IDF score for a word w_i is calculated as follows:

$$TD\text{-}IDF(w_i) = TF(w_i) \times IDF(w_i)$$

As we can see from the equation, the process of $TD\text{-}IDF$ aims to increase the weight of the words that appear in small percentage of tweets (Alqaryouti et al. 2018).

4.5.4. Experiments Settings and Results

In this section, several sets of experiments were performed. These experiments aim to address the proposed research questions. In these experiments, the pre-processed input tweets have been divided into training and testing sets. The training set consists of 77% of the tweets, and the testing set has 33% of the tweets. The engagement level of the tweet (high:2, low:1) is used as the class label. Whereas the tweets features represent the text, day, time, category of the tweets.

To analyze the relationship between the tweets features and the expected engagement level, the following machine learning models were adopted and implanted: K-nearest Neighbour, Support Vector Machine (SVM), Multilayer Perceptron, Random Forest, Decision Tree, and Naïve Bayes. The performance metrics that are used to capture the performance of the used models are the following:

Precision: for each class label (low and high), precision refers to the percentage of correctly classified tweets from this class. For example, for the high engagement label class, precision refers to the percentage of correctly classified high engagement level tweets, and it is calculated as follows:

$$P = \frac{TP}{TP + FP}$$

Where TP (True Positive) refers to the number of tweets that are classified as high engagement level, where FP (False Positive) refers to the number of low engagement level tweets that are misclassified as high-level engagement tweets.

For each classification engagement level, the **recall** score represents the percentage of correctly classified tweets of this level. For example, the recall score for the high engagement label class refers to the percentage of correctly classified high engagement level tweets, and it is calculated as follows:

$$R = \frac{TP}{TP + FN}$$

Where in this situation, FN (false negative), refers the high-level engagement tweets that are misclassified as low-level engagement tweets.

The **F1-score** is used to analyze the quality of the classification, and it is calculated as follows:

$$F1 = 2 \times \frac{R \times P}{R + P}$$

Where the higher the F1 score, the better the classifier quality. Next, we divide the performed experiments based on the used classifiers.

Accuracy: refers to the percentage of the correctly classified tweets. The accuracy can be calculated as per the formula below:

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)}$$

4.5.4.1. K-nearest Neighbour

In this section, we present and discuss the performance of the k-nearest neighbours' classifier. In this classifier, tweets features are represented as points in multidimensional Euclidean space. Additionally, each point (tweet) is labelled by the tweet engagement level (low or high). Once a new tweet (point) is submitted to the classifier, the k-nearest neighbours for this unique point will be identified. Then, a voting process will be followed to determine the label of the new point, where the label of the majority neighbours points will be assigned as the label of the new point. In the presented experiments, we have noticed that algorithm performance reaches stability once the value of k reaches ten, and therefore in this section, we have used $k = 10$. Table 40 shows the results for this experiment. From the results, we can see that the accuracy of the k-nearest neighbours' classifier is relatively low (65%). This classifier uses distance to interpret the similarity between the tweets (points), and in the presented experiments, the number of used dimensions is relatively high, and this reduces the efficiency of using distance to interpret the relationship between the points (tweets).

Table 40: Performance Evaluation for K-Nearest Neighbor

Class	**Precision**	**Recall**	**F1-score**
Low	67%	70%	68%
High	64%	62%	63%
Accuracy	65%		

4.5.4.2. Linear Support Vector Machine (SVM)

Table 41 shows the results for the SVM classifier. SVM is a discriminative classifier that aims to determine the optimal location for a hyperplane, which will be used to categorise the new point. In binary classifier, the hyperplane is a line that will be used to separate the two classes, where each class will be located at a different side of the line. In this classifier, the main mechanism aims to determine the location of the line such that the distance between the line and the nearest point on each is maximised (margin). From the results we can see that the SVM classifier achieves significantly higher accuracy 78% compared to the k-nearest neighbours' classifier. This is mainly due its objective of maximising the margin.

Table 41: Performance Evaluation for Linear Support Vector Machine

Class	Precision	Recall	F1-score
Low	78%	81%	80%
High	78%	75%	77%
Accuracy	78.2%		

4.5.4.3. *Naïve Bayes*

The results for the Naïve Bayes classifier are shown in Table **42**. Naïve Bayes classifier is a probabilistic classifier, which works by mainly calculating the probability of each factor, and assumes that the input features are independent. For any given new tweet, this classifier starts by calculating the conditional probabilities that this tweet belongs to a class label given each input feature. Then, the label for the new tweet is selected based on the highest probability. From the results we can see that the Naïve Bayes classifier achieves higher accuracy compared to the k-nearest neighbour classifier, and lower accuracy compared to the SVM classifier. This highlight that each of the class labels tweet sets has unique words that help in the classification process. Additionally, compared to the other two classifiers, in Naïve Bayes classifier, the precision and recall values are not identical for each class label, and this is due to the probabilistic nature of this classifier.

Table 42**:** Performance Evaluation for Naive Bayes

Class	Precision	Recall	F1-score
Low	72%	81%	76%
High	75%	64%	69%
Accuracy	73%		

4.5.4.4. *Multilayer Perceptron (MLP) Classifier*

MLP classifier is recognized as feedforward neural network model, which eventually aims to map set of inputs to set of outputs. This classifier consists of at least three layers, where the backpropagation technique is used for training purposes. Training is established by modifying the weight of the connection between the nodes (neurons) in order to minimize the gap between the expected results and the actual results. Table **43** shows the results for the MLP classifier experiments, were to reduce the computational complexity, we sat the number of optimization iterations to 200. From the results we can see that with regard to the low-class label, the MLP classifier is able to achieve higher precision score compared to the high-class label. This suggest that used data from low-level engagement class have more distinct features, which simplify their classification.

Table 43: Performance Evaluation for Multilayer Perceptron

Class	Precision	Recall	F1-score
Low	74%	69%	72%
High	69%	75%	72%
Accuracy	71.9%		

4.5.4.5. Decision Tree

Decision tree classifier represents the historical training data as a tree. Whereas starting from the root, the nodes that will be located in each level are considered as the "best" available input feature. In this context, best refers to the impact of the feature on the classification process. For instance, assume that we have a binary classification problem (labels high and low) with three binary input features (A, B, and C). In this example, assume that feature *B* has the most impact on the classification process, where 80% of the training data has *B=1*, and 20% of the training data has B=0 (the highest percentage of the other labels is less than 80%). In this example, feature *B* will be selected as the root of the decision tree, since it has the most impact on the classification process. Table **44** shows the results for this classifier experiments. From the results, we can see that the decision tree classifier is able to achieve 76% classification accuracy. The accuracy of this classifier is 1% less than the SVM classifier, and significantly higher compared to the rest of the classifiers. The results of this classifier suggested that the solution space has an organized structure, where there is a direct relationship between the values of the features and the classes points locality. Additionally, from the results we can that the percentage of the other performance metrics (precision, recall, and F1-score) is lower by less than 1% in the decision tree classifier compared to the SVM classifier. This is due to the fact that this classifier is expected to have difficulties correctly classifying the points located near the decision boundaries. Whereas in SVM, the representation of the points in higher dimensional space can help in addressing this problem.

Table 44**:** Performance Evaluation for Decision Tree

Class	Precision	Recall	F1-score
Low	77%	80%	78%
High	76%	73%	74%
Accuracy	76%		

4.5.4.6. Random Forest

Random forest classifier is an ensemble learning technique, in which a set of decision trees is created at random from the training data, and a voting mechanism is applied for these decision trees results in order to determine the classification process outcome. Table **45** shows the results for the Random Forest classifier, where the number of used decision trees is sat to 20. It is clear that this classifier outperforms the previously discussed classifiers. This is mainly due to the mechanism of employing several decision trees since this has the advantage of determining efficient boundaries for the classes.

Table 45**:** Performance Evaluation for Random Forest

Class	Precision	Recall	F1-score
Low	77%	84%	80%
High	80%	72%	76%

Accuracy	78.3%

According to the achieved performance results of the implemented machine learning models, **Hypothesis 2** is supported as these adopted models were able to predict the citizens' engagement level with minimum accuracy of 65% for K-Nearest Neighbor and maximum accuracy of 78.3% for Random Forest.

4.5.4.7. Most Impactful Keywords

To further analyze the behavior of the classifier, we ran the experiments to extract the most common words in the high engagement level tweets.

Figure 50 and

Figure 51 show the results of these experiments. The result shows that classifier relatively identified that same words as the most common ten words. This suggests that the used input tweets have distinct features that are being captured by all classifiers. In addition, the presented results suggested that the tweets that have the most impact are related to the public services. Additionally, the results show the tweets related the ruler of Dubai sheikh Mohammed Bin Rashid and his vision of improving the public and private sectors have achieved the highest engagements. From these figures, it is clear that citizens are more to be engaged with those tweets that talks about Dubai emirate, the influence of the leadership, the government entities' services, the digital transformation, the Pioneership of the emirate on the global level. Thus, **Hypotheses 3** is supported as the machine learning models were able to identify the most impactful keywords that are part of tweets with high engagement levels.

Figure 50: Word Cloud for Keywords in Arabic Tweets with Highest Engagement

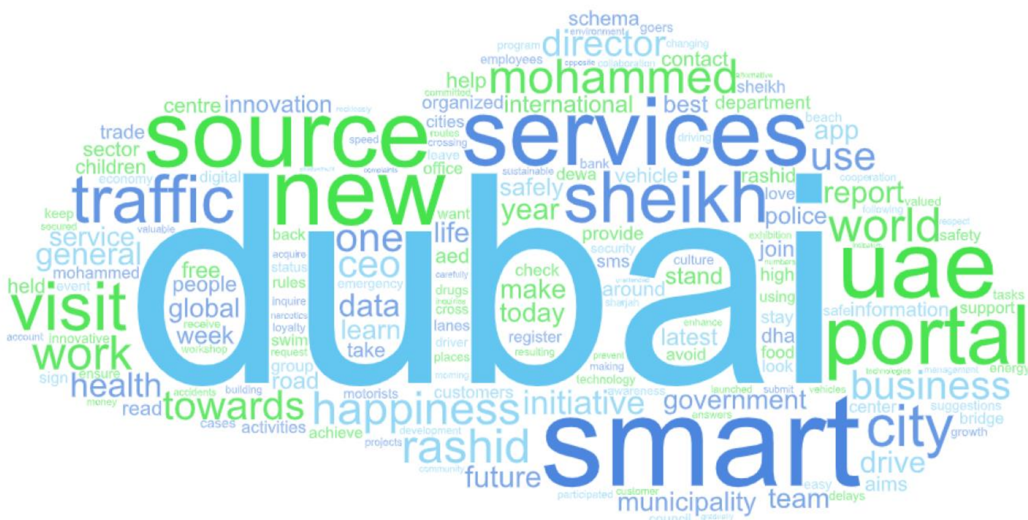


Figure 51: Word Cloud for Keywords in English Tweets with Highest Engagement

5. Chapter Five: Discussion

This study aims to determine the level of citizen engagement in Dubai government's Twitter. Through the use data mining techniques, results indicated that the post variables such as post type, post time, post day, links, mentions, hashtags and tweet language have a significant effect on citizen engagement, thereby supporting all the hypotheses. The main findings showed that: (1) photo and video posts have higher engagement than status posts; (2) engagement is higher during weekdays than weekends; (3) posts with links have higher engagements than posts without links; (4) posts with mentions have higher engagements than posts without mentions; (5) posts with hashtags have lower engagements than post without hashtags; and (6) posts in English and Arabic languages have higher engagements than posts in English and other languages.

In line with these primary findings, the study also emphasizes the increased interaction and engagement in Dubai government's Twitter which consequently entails the effectiveness of the said social media platform in enhancing citizen engagement. Furthermore, the study has revealed the content of the posts that have higher engagements, denoting that the citizens tweets talk more about the services, leadership and overall efficiency of the Dubai government. This means that social media platforms such as Twitter are primarily used by citizens to know and discuss more about the relevant activities of the government which are of direct importance to them. Needless to say, Twitter is an effective tool for enabling communication, interaction and engagement between the public and the government.

This study aims to determine the level of citizen engagement in Dubai government's Twitter. Through the use data mining technique, results indicated that the post variables such as post type, post time, post day, links, mentions, hashtags and tweet language have a significant effect on citizen engagement, thereby supporting all the hypotheses. In response to the study's research questions, the following are noted:

- Do post characteristics impact the users' engagement in Dubai Government Twitter accounts?

The results of the study indicate that post characteristics have a significant impact on the level of citizen engagement in Dubai Government's Twitter. For one, it was revealed that: (1) photo and video posts have higher engagement than status posts; (2) engagement is higher during weekdays; (3) posts with links have higher engagements than posts without links; (4) posts with mentions have higher engagements than posts without mentions; (5) posts with hashtags have lower engagements than post without hashtags; and (6) posts in English and Arabic languages have higher engagements than posts in English and other languages.

- Can we predict the user's engagement based on post characteristics?

Based on the results achieved from using the machine learning models, post characteristics can be used as indicators in predicting user engagement. As a matter of fact, post variables including post day, links, mentions and hashtags, among others having an effect on citizen engagement, Dubai Government can then make use of these attributes to increase eParticipation, underpinning the notion that Twitter is an effective platform for making conversations and for monitoring interactions (Siyam et al. 2910).

- Can we identify the main keywords resulting in higher engagement?

According to Al-Badi et al (2013), social media platforms such as Twitter enable the public sector to create discussions with the citizens regarding specific issues and at the same time, obtain feedback. This can be associated with the results of the study which point out that citizens show higher engagement in discourses relevant to government services. Keywords such as leadership, government services, digital transformation, and ruler of Dubai sheikh Mohammed Bin Rashid receive higher citizen engagements.

Similar to what has been said about posting updates and relevant information regarding government services, leadership, and the efficiency of the entire public sector, Dubai Government should also take note of post attributes that receive higher engagement. Understanding the three stages of eParticipation will also be of huge help. As mentioned by Siyam et al. (2019), these three stages, namely information stage, consultation stage, and decision-making stage, could help the Dubai Government have a more thorough and a more effective approach in motivating increased eParticipation among citizens.

6. Chapter Six: Conclusion and Future Prospects

The study, through the use of data mining, reveals the role of Twitter in increasing engagement between the citizens and the Dubai government. It is noted that post attributes have a significant effect on citizen engagement and that citizens are more actively engaged on topics including services, leadership and government transformation. The significance of this study is reflected on how the information provided can help governments enhance their citizen engagement by following Dubai government's approach. To accomplish this, we collected, prepared and processes 74,037 tweets, representing all tweets for Dubai Government's Twitter in 2018. Through the use of statistical analyses of the impact of post characteristics on the level of citizen engagement and of the various machine learning models, results indicate that citizen engagement level in Dubai Government's Twitter is significantly impacted by all post characteristics. It is also revealed in the study that citizen engagement is higher during weekdays compared to weekends. Furthermore, the machine learning models achieved promising results to predict the citizens' engagement with highest accuracy for Random Forest and Linear Support Vector Machine of 78.3% and 78.2% respectively. This study can be used for future research especially relating to the impact of citizen engagement in Twitter on the improvement of government services. It can also be used to explore strategies in improving citizen engagement on social media.

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