An Investigation of Attitudes towards Mobile Payments.

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Declaration

I declare that the work described in this dissertation is, except where otherwise stated, entirely my own work, and has not been submitted as an exercise for a degree at this or any other university. I further declare that this research has been carried out in full compliance with the ethical research requirements of the School of Computer Science and Statistics.

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Abstract

The worldwide mobile payment market is expected to have over 448 million users and $617 billion U.S. dollars in transaction value by 2016. Since it is a rapidly growing industry, it is imperative to investigate society's perceptions on mobile payments. Such an examination may be invaluable to facilitate further expansion, market adoption, and also help to improve the existing systems and platforms. The amount of academic research concerning individuals' attitudes towards mobile payments is limited.

This research investigates society's sentiment towards mobile payments. It seeks to find any patterns and concerns that may be helpful in establishing an implementation strategy in order to facilitate further adoption.

The method of data collection for this study is social media research using Twitter data. The sentiment analysis revealed a majorly positive attitude towards mobile payments. However, it is also observed that issues concerning mobile payment security may have an impact on further acceptance of mobile payments technologies.

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1. Introduction

1.1 Background to Study

Mobile payments (often referred to as m-payments) are becoming progressively prevalent with the development of information and communication technology (ICT) and ubiquitous internet access. “Mobile payments can also be regarded as the electronic payment transaction procedure that enables a payer to use a mobile device to initiate, authorize or confirm a payment” (Yoris, et al., 2008). In other words, mobile payments enable the direct purchase of goods or services as well as the transfer of funds between the bank accounts of the purchaser and merchant.

An increasing amount of businesses are introducing various mobile payment options for consumers. Services such as Apple Pay, Google Wallet and PayPal are becoming increasingly widespread across society, and are slowly replacing traditional methods of payment. This rapid expansion will revolutionise how society transfers and receives funds, which may lead to a cash-less world.

Mobile payment technologies allow for a swift, simple and relatively low cost transfer of funds. Nowadays, people are able to purchase goods, book flights, pay bills, and pay for endless services using their mobile phones or tablets. Various companies and organizations are rapidly tapping into the mobile payments market for the unparalleled advantages it offers consumers and businesses alike. Its benefits include the convenience of 24/7 access to payments, the speed at which users can buy goods online or transfer funds in a matter of a few clicks and at a relatively inexpensive cost.

There are many advantages associated with mobile payments, although the switch from cash to mobile requires time. It is crucial to investigate how the society perceives mobile payments and what expectations service providers and business owners must meet in order for users to adopt mobile payments.

There are two distinct types of mobile payments: mobile applications and Near Field Communication (NFC).

Mobile applications act as a mobile wallet, allowing users to process payments through the internet network. This type of payment must have the ability to access account information, payment origin, and payment processing. An example of such a payment method is an online wallet service provider such as PayPal, or alternatively, simply a bank.

Near Field Communication (NFC) is a technology in which smartphones and other devices establish radio communication with each other by being touched together or being brought within proximity (Rushabh, 2015). The specification details of NFC can be found in ISO 18092 (ISO/IEC, 2013). The main characteristic of NFC is that it is a wireless communication interface with a working distance that is limited to about 10 cm (Haselsteiner & Breitfuß, 2011). “To a certain extent, NFC is the fusion of a contactless smartcard (RFID) and a mobile phone. Mobile phone can therefore be used like a contact-less card” (Ondrus & Pigneur, 2007). Unlike mobile applications, NFC payments are not reliant on internet network access in order to complete the transaction.

Rapid ICT development revolutionised the payments industry, transforming how consumers and businesses carry out transactions and receive funds. The days of cheque books and bank drafts are gone. The mobile payment industry is continuing to grow and advanced smartphones are becoming the wallets of the future in what could soon be a conceivably cashless world.

The classification of mobile payments can be described as follows: Point of Sale (POS), contactless, and remote mobile payments (OECD , 2012). This first requires the seller and buyer to be present to finalize the transaction. This can be completed by utilizing Near Field Communication, Bluetooth or infrared technology. The latter describes payments that use SMS or WAP technology.

According to reports, smartphone data traffic will grow seven times between 2013 and 2019. “The amount of data used on each active smartphone subscription will substantially increase from an average of 0.8 GB per month in 2013, to a forecast average of around 2.8 GB per month in 2019” (Ericsson, June, 2014). Smartphone penetration in Europe is set to reach 765 million subscriptions in the next five years (Ericsson, June, 2014).

Along with rapidly increasing smartphone usage penetration, mobile payment statistics are also escalating. The worldwide mobile payment market is expected to have over 448 million users and $617 billion U.S. dollars in transaction value by 2016 (Shen, 2012).

1.2 The Research Questions

The objective of this research is to explore society’s attitudes toward mobile payments. To address this objective, the following research questions are examined:

- What sentiment is expressed by Twitter users towards mobile payments?
- Are there any frequently arising topics discussed by Twitter users with regards to mobile payments?

- What are the possible limitations that may prevent mobile payments from further adoption?

1.3 Importance of this Research

The future of mobile payments is exceptionally important for users, businesses and organizations around the world. Mobile payments are a significant fragment of every economy, as they encourage user spending and decrease transactional costs. The mobile payment usage is rapidly increasing with an estimated transaction value set to reach $617 billion and 448 million users by 2016. (Shen, 2012)

Since it is a rapidly growing industry, it is important to examine the public's outlook and opinions of mobile payments. Such an examination can be invaluable to facilitate further expansion, market adoption as well as to help improve the existing systems and platforms.

Mobile money ecosystems develop as lower-cost, better-scalable alternatives to traditional banking. Organizations should start looking at leveraging these ecosystems to make corporate payments more efficient and secure. (Jain, 2014). The importance of users' experiences and attitudes, however, cannot be overlooked. It is essential that organizations are aware of the future of mobile payments and also how the society regards them.

The monitoring of user acceptance is crucial to every technological advancement and early action can significantly affect user adoption in the future. This fact is particularly true of emerging technologies. It is vital to identify any gaps, pros, cons, and people's needs and interests, as mobile payment options become a preferred payment solution. To date, an insufficient amount of research has focussed on monitoring.

Although there are more than 120 mobile money projects deployed in about 70 emerging markets (Beshouri, et al., 2010), mobile payment has only taken off in a limited number of countries. This failure to disseminate a service with such huge potential worldwide shows that the reasons behind the successful cases are not clearly understood, and as a result, have not been easily replicated (Diniz, 2011). According to Jette (2015), "Mobile payments have a great promise which has not so far materialized. There's been a lot of hype (…) The promoters of mobile payment services will need to find ways to convince consumers to reach for their phones instead of their plastic–and convince retailers it's worth the equipment investment to accept new forms of payment."

This research aims to clarify society's attitude toward mobile payments. It seeks to find any patterns and concerns that may be helpful to establish an implementation strategy in order to facilitate further adoption of mobile payments.

1.4 Beneficiaries of this research

There is small amount of current available research that examples people’s attitudes towards mobile payments. This research aims to provide a measurement of the attitudes and to explore possible limitations that may prevent mobile payments from further adoption.

This research is pertinent to mobile payment service providers. As service providers seek to attract individual users and businesses to their services, a further understanding of their prospective customers’ attitudes will support them in improving their product, and ultimately, will help them to satisfy the needs of their consumer base.

As there are legal gaps and a lack of clear regulations, legislators may find this research informative to establish criteria for mobile payment service providers. Lastly, academics may find this research of value in the field of social sciences, or furthermore, in the field of technology.

1.5 Dissertation Road Map

Chapter 1 provides background information and the context of this study. It also outlines the research questions.

Chapter 2 reviews existing literature relevant to this research. Topics covered include descriptions of mobile payment systems, security concepts, and adoption issues.

Chapter 3 describes the research methodologies used. It examines the strengths and weaknesses of the methods chosen. It also describes how the data collection was carried out.

Chapter 4 analyses the data gathered and provides insights into findings.

Chapter 5 concludes the findings of this research and recommends further research questions.

2. Literature review

2.1 Introduction

The purpose of this literature review is to asses and analyse academic literature on mobile payments industry that focuses on user experiences and concerns, and additionally, research studies on how mobile payments are perceived that have been carried out to date.

This literature review seeks to describe the current state of mobile payments. It also aims to present prevalent topics on the subject including the security and adoption issues as well as to illustrate different types of mobile payment systems that are currently available on the market.

2.2 Mobile Payment Systems

Broadly speaking, a mobile payment is a payment in which a mobile device is utilised to perform a transaction or a transfer of funds in return for purchases (Karnouskos, 2004).

Mobile payments generally fall into two categories: payments for goods or services and bill payments. Mobile payments commonly provide access to account based funds, such as account transfers, direct online banking, debit or credit cards. The typical usage entails the user choosing to make a mobile payment, connecting to a server via the mobile device to perform authentication and authorization, and subsequently, the user is presented with confirmation of the complete transaction. A mobile payment service comprises of all technologies that are offered to the user as well as all the tasks that the payment service providers perform to commit payment transactions (Rushabh, 2015).

As described by Stiller (2012), there are a number of mobile payment systems that fall into the following categories:

- Mobile as Point of Sale
- Mobile at Point of Sale
- Mobile Payment Platforms

2.2.1 Mobile at a Point of Sale

This method enables the consumer to pay for goods or services using their mobile device. The device must connect with the merchandiser's device to complete the transaction successfully. This type of payment can be carried out utilising the NFC technology (as described in the introduction chapter).

Apple Pay for iPhone and Google Wallet for Android are currently the most popular NFC payment options. They act as e-wallets and provide consumers with instant access to funds in order to complete purchases at merchants that have enabled Apple Pay or Google Wallet. In order to accept NFC payments, merchants must be equipped with a contactless chip device reader.

The advantages of such payment systems are the ease of transactions between customer and merchant and the speed to complete a payment. The limitation of NFC's is the fact that it works only from very short distances. There are also a number of security concerns around NFC payments that will be explored in the following sections.

2.2.2 Mobile as Point of Sale

There are various mobile applications and systems that enable merchants to process credit or debit card payments through the use of a smartphone or a tablet. SumUp is an example of a payment method offering mobile POS. SumUp offers a mobile application and a small chip and pin terminal that enables merchants to process card payments. Through the use of mobile points of sale, merchants can benefit from a quick and simple set up, low transaction costs and a high level of payment security.

2.2.3 Mobile Payment Platforms

Mobile Payment Platforms refer to any other m-payment options and services such as PayPal, Stripe or Realex. PayPal is a web based service. As described by Guadamus (2004), it works by enabling the consumer to send funds to any person by providing their email address and then by placing a sum in an online form. Once the recipient receives the email, he must open a PayPal account; the money then is taken from the sender's bank account or credit card and deposited into a new account in PayPal, acting almost like a viral payment system, which explains the incredible growth of PayPal as a viable online payment method (Guadamus, 2004). PayPal has introduced a smartphone application as well as an SMS payment service.

Mobile Payment Platforms have been extremely popular amongst business and individuals. They are easy to use and have low transactional costs. They also provide a high level of security and fund protection for senders and recipients.

2.3 Mobile Payments in the Past and Future

As smartphones are becoming more affordable, mobile payments are gaining rapid popularity.

The introduction of mobile phones with various functionalities have opened up numerous profitable opportunities for merchants and businesses. In the late 1990s and early 2000s, mobile payment services became a popular topic and remained so even after the burst of the Internet hype. Mobile payments attracted researchers. Hundreds of mobile payment services as well as access to electronic payment and Internet banking were introduced all over the world. (Dahlberg T, 2006).

For a mobile payment system to succeed, it requires a high volume of transaction and a large customer base. If major industries do not sponsor mobile payments, there is almost no chance of success (J & Y, 2007). According to Gartner Inc., the global market for mobile payments will increase to about $720 billion worth of transactions by 2017 with more than 450 million users.

Dahlberg T, (2006) carried out a literature review for the purpose of examining the past, present and future of mobile payments '(…) findings indicate that the business models of mobile payment services need to evolve from limited proprietary solutions towards cooperative and standardized solutions in order to succeed.' The research demonstrated that clear changes are needed to meet market needs.

There have been a number of failed launches and discontinued mobile payment systems in recent years such as Paybox in Germany. Even though mobile payments have gained rapid popularity, there are clear indications that there are concerns arising in terms of their adoption, which the following section will discuss.

2.4 Adoption Issues

One of the main trends observed in studies and publications is in regard to the adoption of mobile payments. It is a concern for service providers, merchants and users alike. A successful adoption of m-payments is dependent on a number of factors from both the user's and service provider's perspective.

In the examination of available research and publications (including peer and non-peer reviewed papers, journal articles and news articles), it is clear that it is somewhat difficult to tailor the 'perfect' mobile payments system that will suit both the user and merchant. There are a number of concerns expressed in regards to adoption issues.

In research based on available literature on m-payments carried out by Diniz H et al., (2011) security, technological limitations, and a lack of standards and trust rank highly on the list presented in table 1 below.

Obstacles to implementation	Papers	%
Technological/security/user interface limitations	16	18%
Lack of infrastructure (mobile coverage etc.)	5	6%
Unwillingness of consumers and merchants to adopt / lack of trust	16	18%
Lack of standards / interoperability	10	11%
Regulations / legal framework	7	8%
Problems of scale / network effect	6	7%
High costs / overhead	8	9%
Lack of cooperation between market players	4	5%
Lack of knowledge of m-payments	10	11%
Low levels of literacy and financial education	3	3%
Other	2	2%

TABLE 2.1 Peer-reviewed papers: obstacles to implementation. Source: Diniz, 2011

The research is based on an analysis of peer and non-peer reviewed practitioner oriented publications – a total of 196 papers. The study addresses the probable limitations of mobile payments that prevent them from being adopted. It also aims to map areas that are frequently researched and the methodologies that were used.

A summary from a Diniz, H study (2012) finds user adoption issues are mainly related to '(…) security, privacy, trust, fraud and risk perception. It also includes psychological inhibitions caused by the technology and new services.'

Another area identified as an obstacle to adoption are business model problems. This is mainly due to the different needs of each merchant. Managing the operations, agents and resellers is problematic due to the lack of an ecosystem facilitating an easy adoption and clear structures with regards to commissions for agents. Diniz, H also identifies the lack of infrastructure in terms of availability and service coverage. The formalised training of agents and the public regulation to facilitate innovate businesses in highly regulated markets is also required.

Price and cost is another major concern. 'On the user side, the constraint may be the cost and price of devices and services; on the supplier side, the problem is the financial sustainability of the initiatives. This category also includes the difficulties of remaining price competitive for low-value transactions.' (Diniz, 2011).

This particular research based on available publications is valuable to help to establish how users, merchants and suppliers feel about the implementation of mobile payments. It is of interest to observe that the patterns are very similar in both peer and non-peer reviewed sources.

Similar trends are also highlighted in the research carried out by Dahlberg T, et al. 2006, which was briefly discussed in the previous section. According to the findings, the impact of mobile payments is also dependent on socio-economic factors such as regulation, legislation, habits and national economy infrastructures. These will influence the performance as well as the actual adoption of mobile payments by the society. This research is based on 73 peer-reviewed publications. The peer reviewed papers addressed two different topics: firstly, consumers and merchants, and secondly, consumers and technological issues. They used a remarkable approach, which provides into each group of users of mobile payments and also focuses on issues from the consumer's perspective. Their approach, however, fails to examine issues faced by merchants and m-payment solution providers.

The similar trends presented in table 1 above are frequently discussed and mentioned in many academic and press articles. Summarizing this chapter – from research carried out to date – it appears that security, costs, infrastructure, reliability and regulations are the main factors that determine the adaptability of mobile payment systems. However, it is important to point out that this is a multifaceted matter and adaptability can be reliant on a variety of factors depending on the merchant, location and other socio-economic factors.

In qualitative research that explored the consumer adoption of mobile payments carried out by Mallat (2007), a number of issues emerged. Focus group interviews carried out by Mallat (2007) revealed that there are compatibility issues associated with larger value orders. Users were concerned about the lack of suitable charging models and security, and as a result, interviewees were happy to pay for purchases up to €100 using their mobile phones at a point of sale.

Users also identified the complexity of mobile payment services as a possible concern that could prevent adoption, SMS services in particular. They complained about the lack of instructions to make payments in the use SMS messages and about the amount of time it takes to enter various payment codes. One of the responses stated *"Well, for example, I* *haven't signed up for the [mobile] parking service because I would have to register somewhere and I haven't bothered to find out where I should register and what it would require from me … they have not made it easy for me"* (Mallat, 2007).

Another issue identified concerned the network externalities and costs. Users observed that there are too few merchants that offer the opportunity to pay with mobile phones. There may also be certain costs involved in using mobile payment services. Users were not willing to incur these charges if there was an option to settle a payment with cash. *"I noticed that I could pay for purchases on a vending machine with a mobile phone, but it was more expensive than using coins and I thought it was totally unnecessary and I used coins"* (Mallat, 2007).

Lastly, Mallat's research once again revealed the issues concerning fraud, unauthorized use, lack of transaction record and documentation, and the vagueness of the transaction. "The findings further indicate that trust in mobile payment service providers and merchants reduced perceived risks of mobile payments. The interviewees were more willing to conduct payments with trustworthy transaction parties and regarded established banks, credit card companies, and telecom operators as reliable mobile payment service providers. Banks were slightly preferred to other providers" (Mallat, 2007).

To summarize this matter, from research carried out to date it appears that security, costs, infrastructure, reliability and regulations are the main factors that determine the adaptability of mobile payment systems. However, it is crucial to point out that this is a multifaceted matter and that adaptability can be reliant on a variety of factors depending on the merchant, location and other socio-economic factors.

2.5 Mobile Payment Security

It the discussion of mobile payments, it is essential to consider the security of mobile payment systems and any concerns that may arise. As highlighted in other research studies, mobile payment security is an imperative requirement that directly contributes to the success and compliance of the system.

"There are new technologies and new entrants as well as a complex supply chain that will increase the security risks. There is no real standard for technology that has captured the market and regulations relative some of the new entrants are non-existent" (Pegueros, 2012).

Mobile payment security must be designed and appropriate for each mobile payment model. In other words, the security of the mobile payment system will be different for online payments (such as paying for goods via transfer of funds using a smartphone app) than it is for NFC or QR code payments.

There are a number of various security systems available on the market today. The credit card is the main preferred and most popular method used to complete transactions using mobile devices. Customers use their credit card numbers that are entered into an app/web browser based system to complete purchases online. The funds are then debited from the customer's bank account and transferred to the merchant or service provider.

Wrona K, et al. (2001), distinguish two main protocols that are used to secure mobile payments completed using a credit card: SSL (Secure Socket Layer) and SET (Secure Electronic Transaction).

2.5.1 Secure Socket Layer (SSL)

SSL is a standard internet security protocol developed by an American computer services company called Netscape. It is not a payment system itself but it is used to secure transport layer connections via the Internet (Wrona, et al., 2001). SSL works first by authenticating the server and client and then by encrypting credit card information and any other confidential payment information. In this way, payments are securely transmitted from the buyer to merchant. Authentication is carried out by an SSL handshake protocol.

The handshake protocol enables the client and server to establish the secret keys with which they can communicate. It involves three phases with a number of messages sent in each direction throughout. As described by Kant K, (1991), the three handshake stages are as follows:

1. **Parameter Negotiation:** initial client hello message that provides challenge data, session-id and the ciphers that can be used by the client. The server then responds with a connection-id, ciphers that it can accept, and then exchanges the key method, authentication algorithm and any other parameters.
2. **Mutual Authentication:** server establishes credentials to the client in a particular way for example with a server certificate (SSL certificate). The server may also request a client certificate.
3. **Secret Key Exchange**: client selects secret key for data exchange, encrypts data using server's public key and sends the encrypted data to the server. Connection-id protocol is sent with the key. The server then verifies by sending encrypted challenge data back to client followed by session-id. Server-id may be cached by the server for future use.

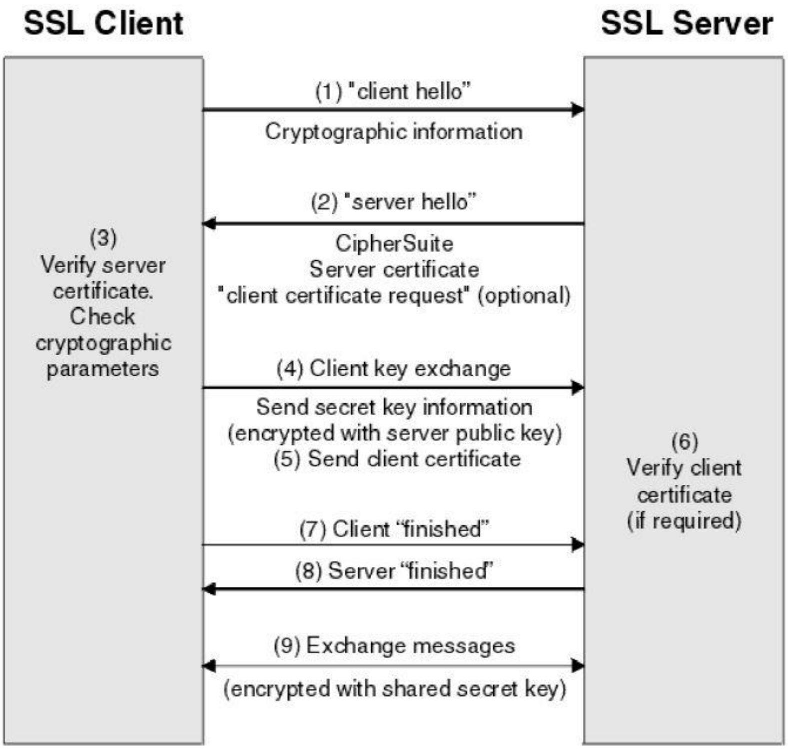

FIGURE 2.1. Overview of the SSL or TSL handshake by IBM Knowledge Center (2015).

The main downside of the SSL protocol is its vulnerability to credit card fraud through servers that pretend to be merchants, the misuse of credit card details sent to merchants or users who pretend to be card holders (credit card/identity theft) (Wrona, et al., 2001).

2.5.2 Secure Electronic Transaction (Set)

Secure electronic transaction (SET) "(…) developed mainly by the credit card industry to secure payment card transactions over open networks. (…) The current version of SET was designed for the common desktop PCs as the typical user terminal, and the Internet as the transport network. SET provides an electronic commerce infrastructure with very robust security model that delivers confidentiality of information, integrity of data, interoperability, and certificate based authentication" (Wrona, et al., 2001). SET failed to meet the high expectations due to high costs to merchants and complicated installation for consumers.

2.5.3 3D Secure

As SSL is vulnerable to fraud and SET has acceptance problems, there are a number of electronic payment systems for credit cards such as 3D (Three Domain) Secure and EMV-based Chip Electronic Commerce (Wrona, et al., 2001).

3D Secure has been introduced by Visa in response to SSL fraud vulnerability called 'Verified by Visa'. MasterCard followed with 'MasterCard SecureCode'. Simply put, it is an additional verification step that minimizes fraud by requesting additional information form the cardholder before authorising the transaction.

Mayes K, (2008) describes the 3D secure massage flow as follows:

1. Consumer selects their purchases from merchant's website and begins the check-out process.
2. Cardholder enters their credit card details such as card number, expiry date, CCV code and billing address. The website then determines whether the user has enrolled in the 3D-Secure system.
3. The Directory Service (DS) forwards the request to the appropriate Access Control Server (ACS).
4. ACS determines whether the user is registered with 3D secure. Then it returns the Verify Enrolment Response to the DS.
5. Response is returned to merchant and decides on an action depending on the response, for example: Cardholder not registered- allow to proceed with transaction or force or suggest to enroll in 3D Secure. If registered, the cardholder proceeds with the transaction.
6. The cardholder is presented with a new browser window, which will request the cardholder to enter additional information such as a username and a password.
7. The ACS verifies the information provided by the cardholder. If the information matches, the transaction is completed. If not, the cardholder receives a message informing them that details provided are incorrect and the transaction cannot be completed.

According to Mayes K, (2008), the success of 3D Secure is dependent on whether users and merchants liked it. He highlights that users may find it inconvenient to remember additional passwords, to receive an unexpected pop up prompting them to register, and also may be wary about providing additional confidential information. It is an additional step for users to complete a transaction. From the merchant's perspective, the user ideally would be able to pay with as little hassle as possible. Mayes also states that 3D Secure is somewhat the opposite of what the industry is moving towards, the 'touch and pay' ways of purchasing.

2.6 Conclusion

There is limited academic literature available regarding the public's perceptions of mobile payments. The majority of academic publications relate to the use, security and adoption issues. Very few publications, however, focus on how society perceives mobile payments.

As outlined in the literature review, existing peer and non-peer reviewed research focuses on case studies, literature reviews, experiments, focus groups, interviews and surveys such as Diniz (2001) and Mallat (2007). This research aims to use social media as a main source of data. This form of exploration into how the society feels about mobile payments may provide more insight and my find new trends, patterns and unbiased results.

3. Methodology

3.1 Introduction

The purpose of this section is to present the research philosophy and methodology used in this research. The rationale behind the chosen methodology is also explained.

3.2 Research philosophy

Saunders et al. (2009) outline research as “The systematic collection and interpretation of information with a clear purpose, to find things out.” According to Burns (2008), research is a process that leads to a new or improved knowledge. Regardless of the method used, the aim is to deliver informed decisions and to generate successful outcomes. For the purpose of this research, a number of methods have been identified and described in the subsequent sections. The selection of the appropriate research philosophy is vital to every research, as “The research philosophy you adopt contains important assumptions about the way in which you view the world” (Saunders et al, 2009).

3.2.1 Positivism

Positivism was chosen as the most suitable philosophy for this research as it is purely objective and relates to the nature of relationships. This study is based mainly on facts and has minimal interaction with subjects. Data gathered for this research was based on already existing tweets, and therefore, subjects were unaware that they were observed. In this research, positivist philosophy led to accurate and objective results.

Positivist researchers are objective and believe that reality is stable. They believe subjects or a phenomenon should only be observed and that the research should never interfere with it. According to the positivist concept, the subject is a unit passively reacting to environmental factors on the principle of stimulus and response. Their behavior is determined, and ‘forced’ by the environment.

The positivist methodology, the primary objective of the research, tries to explore and explain the regularity and prediction of phenomena. These studies seek to discover the general laws or rules that govern the behavior of subjects. According to Eriksson & Kovalainen (2008), “the key approach of the scientific method is the experiment in which the operationalization of issues that are studied is the prevailing idea: only things that are measurable can be dealt with.”

The interprevist approach was also considered, but was deemed unsuitable, due to the nature of the data used in this research. There was no opportunity to influence and be influenced by the research activity.

3.3 Research Strategy

3.3.1 Quantitative

"Quantitative is predominantly used as a synonym for a data collection technique (such as a questionnaire) or an analysis procedure (such as graphs or statistics) that generates or uses numerical data" (Saunders et al. 2009).

In quantitative research, we operate with variables that can be measured: from a simple indication of how many responses we have received to advanced statistical analysis, factor analysis, regression analysis, and multidimensional scaling.

In studies of this type, the principle of the measurement is to compare collected results with each other using statistical knowledge.

The advantages of quantitative research methods are:

- Determining the scale and size of variable data
- Comparing the groups with each other
- Identifying factors affecting the phenomenon studied
- Systematic nature of the study

Burns (2000) highlights that this method of research is precise and reliable. Statistical data allows for the sophisticated analysis and illustration of results. The analysis can be easily replicated and allows for the use of the controlled experiments.

Conversely, Burns (2000) also highlights the limitations of qualitative research methods. He claims that it is difficult to eliminate or control all variables due to the human nature. No research can plans how humans will reacts. Quantitative research fails to take into account how the researcher is subjectively involved in every step of the process and in the interpretation of results, and therefore, is not completely objective. At times, the data gathered does not include an explanation of 'why' and does not provide insights, and therefore, it may be difficult to interpret the results.

3.3.2 Qualitative

"Qualitative research is pragmatic, interpretive, and grounded in the lived experiences of people" (Marshall & Rossman, 1991).

Qualitative research methods are focused on the 'deeper' analysis of the phenomenon. Quantitative research places its main emphasis on researching deeply and with more accurately in order to better understand the phenomenon analysed. The qualitative research does not use quantitation (which is used in quantitative research), but instead, uses techniques that are designed to extract knowledge from the subjects.

As the name suggests, qualitative research is carried out in order to achieve ‘good’ quality of information and to expand knowledge about the already examined phenomenon. Quantitative research studies phenomena and features that are already known and predetermined. Qualitative studies, on the other hand, provide a new quality of knowledge and information, which in turn provides a deeper understanding of the phenomenon.

Qualitative techniques are designed to extract information about subjects’ knowledge or opinion of a given phenomenon. Qualitative research obtains answers from the subjects and the researcher does not assume the findings in advance. As a result, these techniques allow the research to acquire new unique data and enables the analysis to look at the issue from another angle and from another perspective.

According to Hogan et al. (2009) “Generally speaking, qualitative research has ‘traditionally’ been conducted by means of direct observation of a sample, case studies, experiences, introspection, an examination of relevant texts, interviews, focus groups, life stories, and the researcher’s own participation in the settings that she / he is researching.” Burns (2006) clarifies that qualitative research stresses the validity of multiple meanings of events. He claims that reality is not fixed. It is variable and it can only be understood by analysing and examining the experiences and meanings of different people.

The obvious advantage of qualitative methods is the delivery of new and better quality information, which contributes to a better understanding of the examined phenomenon. There are, however, limitations to this method. According to Burns (2006), the two main limitations are problems of generalization and time commitment. It is impossible to generalize and replicate peoples’ actions, contexts and understandings. Moreover, the time required for data collection and analysis presents another major disadvantage. The researcher must spend a considerable amount of time with the subjects and thoroughly record all actions and/or interviews. This presence of the researcher can also effect the subjects’ responses.

As highlighted by Anderson (1998), the quality of the data gathered is heavily dependent on the skills of the researcher. The researcher themselves can have an effect on the results achieved, as rigor is difficult to maintain throughout the process.

3.3.3 Triangulation – Strategy Chosen for This Study

The method of triangulation was considered as the most suitable approach for this study. It is a powerful form of data analysis which produce both quantitative and qualitative results. This approach to research will assist in the general understanding of the quantitative results and will and provide complementary information.

Triangulation is the process of combing two or more perspectives to refine and clarify the findings of the research. Triangulation has a number of different forms such as: triangulation of methodologies, methods, data and theories. The challenge of triangulation is that it can lead to conflicting and controversial results. Triangulation however does allow better results to be reached, with new information, angles, understandings and new research questions (Eriksson & Kovalainen, 2008).

This approach allows various aspects of the test object to be grasped, e.g., to answer questions about the scale of phenomena (through the use of quantitative methods) and a deeper understanding of the specifics of the problems (through the use of qualitative methods). It also allows the strengths of each method to be used through the mutual neutralisation of their weaknesses.

3.4 Research Methods Considered

The data collection methods considered for this research are described in the following sections. Social Media Research was deemed the most suitable method. It enabled an innovative type of data to be gathered, which could produce new and interesting results. Surveys, interviews, experiments, and case studies have already been used as a tool in similar research studies in the past.

3.4.1 Survey/Questionnaire

Method of gathering information from the subjects using a set of questions. They are carried out as 'test' on the basis of a written interview. They are usually used to test a large sample of subjects, which can be done quickly and at a low cost. These studies save time and resources since they do not require the researcher's presence. The role of the researcher in this method is limited only to the development of the survey and the selection of what trends are then tested. The survey has an impersonal and anonymous nature that leads to honest answers.

3.4.2 Interviews

Interviews are carried out as a form of a conversation between at least two or more people. Interviewers ask questions and obtain answers from respondents. The purpose of the interview is to obtain predetermined data relevant to the investigator. The questions are designed by the researcher. Interviews are a long and time consuming processes, which allows for an in depth perspective and ordinarily qualitative data.

3.4.3 Experiment

The purpose of the experiment is to test a hypothesis in order to investigate how a particular phenomenon works. It helps to understand and observe the reactions of people in regards the subject of interest. They allow for the full control and development of situational conditions of a phenomenon or a process.

3.4.4 Social Media Research (SMR)

Research that utilises social media as the primary data set. It works through the gathering of data or by monitoring social media platforms such as Facebook, Twitter, blogs and forums. The data gathered can then be analysed via ethnographic and netnographic methods, sentiment analysis or other means.

3.4.5 Case study

Analysis of a single case that allows conclusions to be drawn as causes and results of its' course. The purpose of the case study is to demonstrate the concepts which are worth learning from and how potential mistakes can be avoided. Case studies contribute to an understanding of a concept or a phenomenon by examining all variables. It involves an interpretation of the results of the study.

3.5 Method Used to Conduct Research

3.5.1 Social media research – Twitter

Twitter is a free social media platform that allows users to create their own profiles and post short messages called 'tweets' that consist of up to 140 characters. Users can post 'tweets' that are visible to everyone online or privately, in which case only users that are their 'followers' can view them.

Millions of people use microblogging platforms to communicate among Internet users. Users write about their opinions, share experiences and discuss current topics and issues. Microblogging sites are becoming a valuable source of people's opinions and sentiments. It is clear that this data can very effective while conducting marketing and social research (Pak & Paroubek 2011).

Social Media Research was chosen as the approach to gather qualitative data, which would be analysed using sentiment and manual analysis. Utilising social media platforms as the source of data is a relatively new concept in academic research. This form of research was deemed suitable for the purposes of this study due to the nature of the research question.

3.5.2 The Rationale for Choosing 'Tweets' as the Data Source

The aim of this research is to observe and investigate the attitudes of the society towards mobile payments. Social media platforms often act as forums for users to express their opinions and to engage in discussions on an endless number of topics.

According to the Twitter website, as of February 2015 the number of monthly active users stands at 315 million with 5 billion tweets sent per day. It is clear that the social media platform provides a wealth of knowledge and data that can be used for academic research.

The goal is to provide unbiased results from existing ‘tweets’ that can be utilised to provide insights into people’s attitudes on mobile payments. As the subjects of the study are observed rather than asked to participate, their ‘responses’ are less likely to be false or biased.

Twitter claims that over 80% of their active users use the service via a mobile application. It may be assumed, therefore, that many of these users may already be familiar with mobile payments and have access to a smartphone and Internet. This fact means that Twitter holds a huge sample size of participants from whom insights can be drawn. In this way, this data is opposed to a survey, which would only targets subjects familiar with mobile payments.

Social media research greatly speeds up the process to gather data for the purposes of this study in comparison to surveys or interviews that can take weeks or months to conclude. Twitter enables researchers to instantly capture required data in the form of conversations and comments on any topic from any date range and demographic.

It also resolves the limitations of other research methods discussed in the preceding section. The data collected using social media platforms is organic. Conversations occur naturally, and therefore the researcher can be assured that the results collected are not altered by their own input or research methods.

3.6 Population selection

For the purpose of this research, the collection of tweets was performed through Twitter search results containing ‘#mobilepayments’ or ‘#mobilepayment’ ‘hashtagged’ keywords. To initially target the appropriate population and relevant data, requirements needed to be set in order to gather specific tweets displaying relevant characteristics.

With the intention to gather tweets that were most likely to contain opinions on mobile payments, the hashtags ‘#mobilepayments’ and ‘#mobilepayment’ were employed. “Users usually use hashtags to mark topics. This is primarily done to increase the visibility of their tweets” (Agrawal et al. 2011). By using appropriate hashtags, harvested tweets were relevant to the research topic and were likely to be in English.

It was decided that the manual search result collection from Twitter would be too time consuming. To rapidly collect and record Twitter search results containing the keywords “#mobilepayments” or “#mobilepayments”, Google Apps Script was used to harvest tweets.

"Google Apps Script is a JavaScript cloud scripting language that provides easy ways to automate tasks across Google products and third party services and build web applications" (Google Apps Script, 2015).

For the purpose of this study, a free online template called TAGS was deemed the most appropriate tool to automatically run and save Twitter search results. Messages were collected by querying the Twitter API and recorded in a Google Spreadsheet. According to Martin Hawskey, the creator of the template "TAGS is a free Google Sheet template which lets you setup and run automated collection of search results from Twitter." The TAGS template is available at https://tags.hawskey.info.

Setting up the TAGS Google Sheet template involves a few steps described below.

1. Go to https://tags.hawskey.info and select 'Get TAGS v6.0' option.
2. To create a customised version of TAGS, a spreadsheet template must be copied as a new Google Spreadsheet.
3. TAGS v6.0 can be customised according to users' needs. As illustrated in figure 2 below, the user may set their own parameters such as keyword search items, period, minimum follower count filter, number of tweets, and type of search.
4. To execute the script, the user must authorise the application to run using their Google credentials followed by the Twitter Authorisation Key and Secret Key tokens. These tokens may be obtained by creating a Twitter Application on their website available at https://apps.twitter.com.
5. Once all necessary authorisations are verified, the script can be set up to run and start harvesting tweets with the indicated keyword into a Google Spreadsheet.
6. As soon as the required amount of tweets were harvested, they were exported into a Comma Separated Value Format (CSV) document.

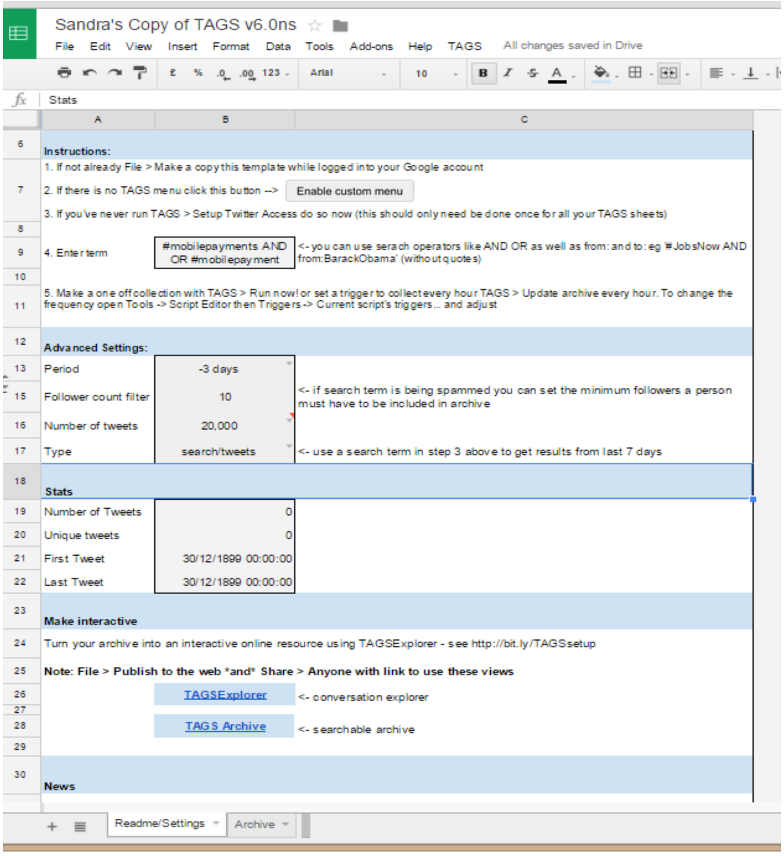

FIGURE 3.1 Customised TAGS template used for this study.

3.7 Sample

According to Satista.com (2015), at the time of research there were an estimated 380 million people using mobile payments to purchase goods and services. The aim of this study is to investigate society's attitudes towards mobile payments, and therefore it is important to select a wide sample of the population.

According to Saunders et al. (2009), “The larger your samples' size the lower the likely error in generalising to the population. Probability sampling is therefore a compromise between the accuracy of your findings and the amount of time and money you invest in collecting, checking and analysing the data.” The size of the sample is almost always a matter of judgement and also depends on time and available resources.

In this research, quota sampling was used to gather representative data from a group of users on Twitter using a hashtag “mobilepayment(s)” to categorise their tweet. This method allows data to be gathered that is representative of the whole group. This sampling method was deemed suitable as this study aims to investigate a certain characteristic.

Twitter allows a large quantity of data to be gathered in a relatively short period of time. The sentiment analysis was executed using a Python script in which the analysis of large volumes of data was not a constraint. To keep these factors in mind, the number of tweets harvested in this research were capped at 20,000. Tweets were harvested once per week over the course of one month in March 2015 to enable randomness. The data collected was sampled as every tweet contained a desired keyword, and therefore the majority of tweets were relevant to the study. With over 80% of people using the platform via a smartphone application, it can be assumed that the majority of the data gathered came from smartphone users. This increases the likelihood of users to be familiar with mobile payments.

3.8 Type of data gathered

The data consisted of qualitative results in the form of short fragments of text of up to 140 characters (approximately 11 words). The triangulation method was used during data analysis, as the data collected could be interpreted in both a qualitative and quantitative way.

TAGS template can collect supplementary information such as usernames and dates. To ensure full confidentiality and to consider ethical and privacy requirements, only tweet text has been used. No personally identifiable information has been used in this research.

3.9 Quantitative analysis - Sentiment Analysis

"Sentiment analysis seeks to identify the viewpoint(s) underlying a text span; an example application is classifying a movie review as "thumbs up" or "thumbs down" (Pang & Lee, 2004).

Sentiment is the summation of feelings, emotions, opinions and attitudes. Sentiment analysis determines whether a piece of text is positive, negative or neutral. Another commonly used term is opinion mining. It is generally used to discover how people feel about a certain subject. According to Agrawal et al. (2011), "sentiment analysis has been handled as a Natural Language Processing task at many levels of granularity. Starting from being a document level classification task (Turney, 2002; Pang and Lee, 2004), it has been handled at the sentence level (Hu and Liu, 2004; Kim and Hovy, 2004) and more recently at the phrase level (Wilson et al., 2005; Agarwal et al., 2009)."

Given the aim of this study, sentiment analysis is a suitable choice to review collected data. Sentiment analysis is becoming increasingly popular in academic, marketing, social and business fields. For example, in 2012 sentiment analysis was used to analyse the real time Twitter sentiment during the U.S Presidential Election Cycle.

A Natural Language Toolkit (freely available at http://nltk.org) was used to carry out the sentiment analysis. "NLTK has been called a wonderful tool for teaching, and working in, computational linguistics using Python, and an amazing library to play with natural language" (NLTK, 2015). According to Bird et al. (2009), technologies based on NTL are becoming increasingly popular with phones equipped with text prediction and hand writing recognition. "By providing more natural human-machine interfaces, and more sophisticated access to stored information, language processing has come to play a central role in the multilingual information society" (Bird, et al., 2009).

3.10 Information Extraction with Python

This section will outline the Python script and how it was used to analyse data, establish sentiments and for data cleansing. The full Python script is available in appendix A.

A number of tweets have been manually removed before the analysis as they were unsuitable for this research. With the help of Microsoft Excel, duplicate tweets as well as tweets from business accounts have been removed from the data set. Duplicate tweets would affect the analysis and give false values for negative and positive tweets. Additionally, any omitted duplicates were removed by the script. Tweets from business and news Twitter accounts were removed in order for the analysis to provide insights from individuals.

Initially, the script imports all necessary libraries (tools) needed for the analysis i.e. a Natural Language Toolkit (NLTK) (used to build programmes operating with human language data), frequency distribution, and wordcloud.

```
import pandas as pd
import nltk
import urllib2
import re
import csv
from nltk import FreqDist
from wordcloud import WordCloud, STOPWORDS
from pylab import *
import matplotlib.pyplot as plt
```

The loop that determines the polarity (positive, negative) each tweet (in a row) and stores them in a list contains values to be written in a file similar to the input file, but with an extra column containing the sentiment value for a particular entry; "ind" is the index, "row" is single entry from the tweets file containing all the provided values.

```
for ind, row in data.iterrows():
    pos_score=0
    neg_score=0
    #text of a tweet
    tweet = row['Tweet text']
```

The removal of exact duplicate tweets consisted of excluding all tweets containing ‘RT’ in the body of the text. ‘RT’ stands for ‘Retweet’, which means the tweet was duplicated from another user.

```
while "RT" not in tweet:
```

The lexicon used for determining sentiments did not include web-derived data (such as emoticons). Therefore, it was necessary to remove them to avoid confusing the script. With the intention of achieving more meaningful and relevant data, a number of symbols and characters were excluded from the data set. Firstly, in order to remove any usernames “@’” signs were changed to “/ “, which were further removed by the script. In the piece of script below, the program unnecessary removes non-meaningful characters i.e. “//”, “_”, “.”. Other items that were removed are English stop words, URLs (the code excluded all characters following “http://”, “/” (usernames) and tweets in languages other than English).

```
sentence_list = [w.lower() for w in sentence_list]
        sentence_list = [w for w in sentence_list if not "/" in w]
        sentence_list = [w for w in sentence_list if not "'" in w]
        sentence_list = [w for w in sentence_list if not "\\x" in w]
        sentence_list = [w for w in sentence_list if not "http" inw]
        sentence_list = [w for w in sentence_list if not
(re.match(r'^\W+$',w) != None)]
        sentence_list = [w for w in sentence_list if not
(re.match(r'^[0-9]+$',w) != None)]
        sentence_list = [w.replace(".","") for w in sentence_list]
        sentence_list = [w for w in sentence_list if not w in
nltk.corpus.stopwords.words('english')]
        sentence_list = [w for w in sentence_list if not "_" in w]
```

The script calculated the positive and negative scores for each token (tweet) and summed it. For each tweet, the number of positive and negative words was counted. If the tweet contained more positive than negative words, then it was assigned a positive sentiment. If the tweet contained more negative words, it was deemed negative. If it contained neither positive nor negative keywords, it was considered neutral.

This was done by cross-referencing words in the tweet with respective words contained in the keyword lexicon. The word lexicon containing the polarity of positive and negative words was developed by Jeffrey Breen. The lists are publicly available online on the GitHub website. The lexicon contained 4,784 negative words and 2,007 positive words (Breen, 2011).

```
pos_overlap=0

        neg_overlap=0
```

```
        for tok in sentence_list:
            for r in pos_list:
                if tok==r:
                    pos_overlap=pos_overlap+1
                    break

            for i in neg_list:
                if tok==i:
                    neg_overlap=neg_overlap+1
                    break

        if pos_overlap>0 or neg_overlap>0:
            pos_score = float(pos_overlap)/(pos_overlap + neg_overlap)
            neg_score = float(neg_overlap)/(pos_overlap + neg_overlap)
```

The sentiment value was assigned according to the positive and negative scores in each tweet. Each row from the list was saved as a CSV file. An example of the finished analysis of positive tweets is shown below on table 3.1.

```
if pos_score>neg_score:
            row_to_write.append('pos')
        elif neg_score>pos_score:
            row_to_write.append('neg')
        else:
            row_to_write.append('neu')
        all_rows.append(row_to_write)
        break
for y in range(len(all_rows)):
    csv_writer.writerow([x for x in all_rows[y]])
```

Tweet text	Sentiment
Whats wrong with mobile money service. Made 2 payments for yaka but not received token numbers. Ps. Got only 1 unit left #mobilepayments	neg
Why hasn't #starbucks #mobilepayments rolled out in #Orlando? Feels stupid going into #Starbucks with only a mobile phone in hand.	neg
#mobilepayments NFC is turned off at most retailers. Lame. #retailpayments	neg
Friday is takeaway night to research payment journeys. Domino's/PayPal was okay last week but Wagamama/V.me tonight = Fail. #mobilepayments	neg
I find it difficult to understand why a shop/vendor will not have card or some sort of mobile payment system #cashless #mobilepayments	neg
It's days like these when I wish mobile wallets be adopted faster! #forgottenwallet #mobilepayments	neg

TABLE 3.1 Examples of tweet text.

3.11 Frequency Distribution

With the intention of enriching the analysis, word frequency graphs were created for each category. The graphs consisted of the 150 most common words in each category. Once again, the symbols and characters that were previously explained were excluded from the analysis.

Additionally, in this part of the analysis, the following words were excluded: 'mobilepayments', 'mobilepayment', 'mobile', 'payments', 'payment', 'via', 'apple', 'pay', 'applepay'. These words do not bring any valuable insights into the analysis and hinder the true results. The reasons for the exclusion of 'ApplePay' will be discussed in the analysis section.

```
print '{}{}'.format('Lexical diversity: ', lexical_diversity(full_pos_tw_list))
pos_tw_freq_dist = FreqDist(full_pos_tw_list)
print pos_tw_freq_dist
```

```
numWords = 0
wordLimit = 30
freq_dist=pos_tw_freq_dist.most_common(150)

for i,w in freq_dist:
    print "%s : %s"% (i,w)

pos_tw_freq_dist.plot(wordLimit)
```

3.12 Wordcloud

Wordcloud helps to illustrate results from the word frequency graph for positive, negative and neutral tweets. Similarly, all characters and words deemed as unwanted were excluded from the word cloud. The size of the font depicts how frequently words were in the text.

```
wordcloud = WordCloud(font_path='/Library/Fonts/Comic Sans MS.ttf',
stopwords=STOPWORDS, background_color='black', width=1800,
height=1400).generate(str(full_pos_tw_list))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```

3.13 Manual Qualitative Analysis

To further aid the quantitative analysis of tweets and to provide a deeper understanding of the results, tweets that contained the top 31 keywords from each category (positive and negative) were manually examined. Additionally, in order to test the effectiveness of the quantitative analysis, manual tweet classification has been carried out. Microsoft Excel was used in order to aid manual examination of tweets.

The manual qualitative analysis had two objectives:

- To verify the effectiveness and precision of the sentiment analysis.
- To gain qualitative insights to enrich the understanding of attained results.

Tweets containing the top 31 positive and negative keywords were manually examined and grouped according to topics or themes.

It is somewhat challenging to test the accuracy of the sentiment analysis. A random sample of 10% of the total tweets, however, has been selected from each data set categorised into positive, negative and neutral tweets.

Tweets were analysed according to the following structure:

1. Check if the tweet has been categorised correctly. If yes enter, 1 in to column C, if incorrect enter 0.

2. Once the manual classification was completed, the incorrect and correct tweet categories were totalled.

The manual classification of tweets produced the following results shown in table below.

	Positive	Negative	Neutral
No. of tweets selected for manual classification	300	71	666
No. of tweets classified incorrectly by the script	27	8	104
Percentage of tweets classified incorrectly	9%	11%	15%

TABLE 3.2 Manual classification results.

It can be observed that 9% of positive tweets, 11% of negative tweets and 15% of neutral tweets were classified incorrectly by the Python script. In total, 13% of selected tweets were categorised incorrectly. There may be several reasons for this error. Upon examining the tweets, it became evident that the script did not understand the use of sarcasm. This was an anticipated finding. To give an example, the script categorised the following evidently negative sarcastic tweet as positive "*Yeah #mobilepayments are super secure… sharing your pin codes is also secure HA".* 15% of neutral tweets were categorised incorrectly, and upon investigation it showed that the lexicon was missing certain positive and negative words. Some of the tweets required more context to be recognised as either positive or negative.

It may be assumed that the script was around 87% accurate in assigning correct sentiments to tweets. This result is satisfying, which led to the relatively high accuracy of the results.

3.14 Ethical considerations

The primary ethical considerations concerned the full anonymity of all subjects chosen for the study. This goes towards ensuring that all the data gathered and published does not reveal the identity of any individuals. In this research, it involved the insurance that all the data gathered did not include usernames or any other personal information. If a Twitter username came up in the body of a tweet, it was erased.

Twitter restricts the amount of data that can be pulled from the API. This study has complied with all Twitter terms and conditions.

3.15 Lessons learned

Sentiment analysis has its limitations. Upon a simple manual inspection, some falsely detected sentiments were found. According to a study on Twitter sentiment analysis carried out by Agarwal et al. (2011), due to the nature of the service, users often use special characters, make grammatical mistakes, and use emoticons to express particular meanings.

As Twitter data is used for this research, it is important to point out that some messages contain emoticons, informal social media dialect and potentially misspelled words. The lexicon used in this study was designed for Twitter text analysis. It did include some of the most commonly misspelled words and internet slang (i.e. LOL, WOW). However, it did not include emoticons. Some useful data may have been excluded during this analysis due to this limitation.

Additionally, some tweets may have been categorised inaccurately due to the use of sarcasm in tweets. Furthermore, a small amount of tweets required that their context were evaluated in order to determine their sentiment.

Ideally, a new lexicon tailored especially for the analysis of social media text data with the inclusion of special characters (emoticons) could have been generated. Regretfully, due to the limited amount of time and resources, such an inclusion was not conceivable.

4 Findings and Analysis

4.1 Introduction

The research intended to explore society's attitudes towards mobile payments through the means of Twitter data. It hoped that the analysis would portray an accurate image of how society currently perceives mobile payments. The knowledge gained from this research may assist in the further development and successful implementation of mobile payment systems and to facilitate a better understanding of issues concerning this technology's adoption.

4.2 Data analysis

Python is a powerful programming language with a robust ability to process linguistic data, and therefore, it was deemed suitable for the purposes of this research.

In this study, a Python Script has been built in order to automatically clear up and analyse harvested tweets. The aim of the analysis was to sort tweets into positive, negative and neutral categories. The script also distinguished between the most frequently occurring words within the positive, negative and neutral categories. Finally, it created wordclouds for each category in order to visualise the results. Both the main functions of the script built and the logic behind them are outlined in the subsequent section.

Qualitative data analysis was carried out after sentiment analysis. 10% of the random tweets from each category were manually analysed to verify the effectiveness of the Python Script. All further observations or patterns were also helpful into the attained outcomes.

4.3 Sentiment Analysis Results

Sentiment analysis categorised tweets according to their 'mood': positive, negative or neutral. Out of 20,000 tweets, close to half of them - 9,661 were eliminated due to being duplicates ('retweeted' tweets) and irrelevant tweets to this study such as advertisements and news headlines from businesses rather than individuals. This figure is overwhelming, but expected. Users often retweet news headlines and announcements, and therefore it can be assumed that the majority of removed tweets were neutral.

The Python script built for the purposes of this study distinguished 3,003 tweets as positive, 719 tweets as negative and 6,617 tweets as neutral.

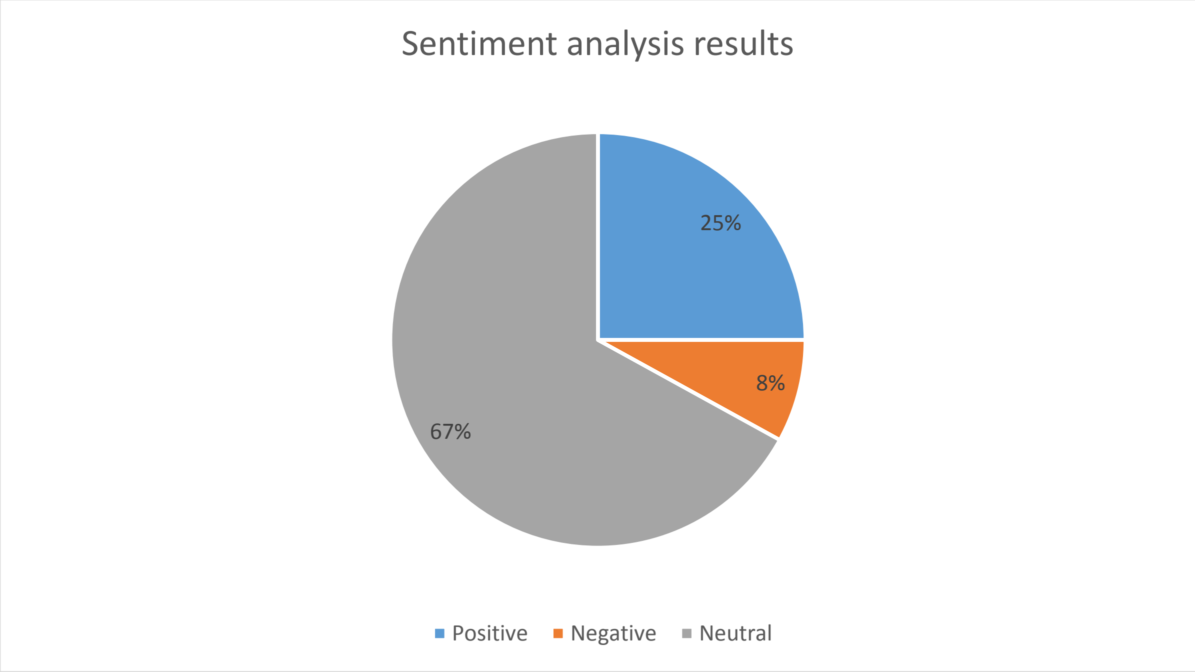

FIGURE 4.1. Sentiment analysis percentage results.

During the qualitative analysis, neutral tweets were excluded due to their irrelevance to this study. Neutral tweets were composed mainly news headlines and neutral announcements, for instance: *“PayPal introduces a QR Code Mobile Payment System #mobilepayments”.*

The result of this analysis (excluding neutral tweets) show that 3,722 out of 20,000 tweets were attributed with either a negative or positive sentiment as illustrated in figure 2.2 below.

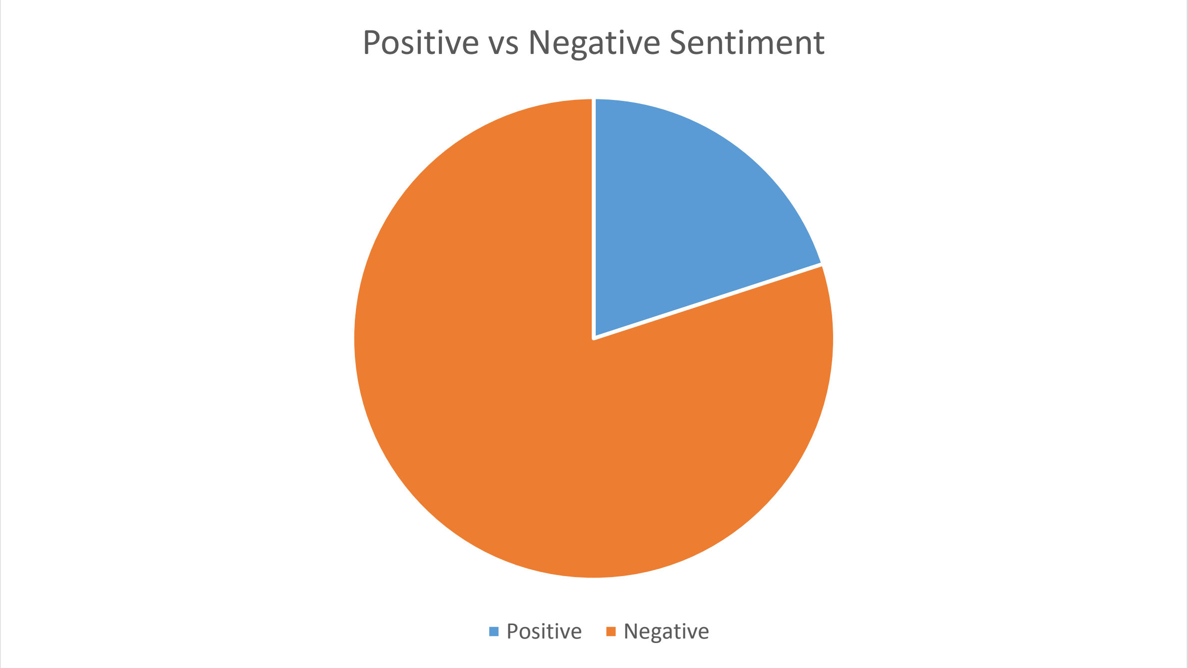

FIGURE 2.2 Positive vs Negative Sentiment.

The findings demonstrate that the general outlook on mobile payments is adequately positive. However, a further examination of the above results was desired to gain a detailed insight into the above results.

4.4 Frequency Distribution Analysis

"Word length frequencies typically investigate the frequency of words of different lengths in syllables. These distributions are common amongst texts and are typically interpreted as a type of negative binomial distribution (Altmann 1988; Wimmer & Altmann 1996) or Hyper-Poisson (Best 1998)" (Smith, 2012).

In order to gain further insights into the sentiment analysis results, a word frequency list of the top 150 words has been compiled from each subset. The full lists of each subset are available in Appendix B and C.

To gain meaningful results, the top eights keywords that emerged in all subsets have been excluded from the list.

Mobile payment(s), mobile – do not provide any meaningful insights to this study as all gathered tweets contained that keyword.

ApplePay/pay/apple – were excluded as they appeared in all subsets as top keywords. While it certainly is an interesting outcome, it obscures other significant results. Apple Pay is a popular topic in the mobile payments field, and its relevance to this study will be discussed in the next chapter. Enhanced insights were gained by excluding Apple Pay from the frequency distribution list.

Via- word frequently appearing in tweets concerning mobile payments i.e. 'payment via mobile'.

4.5 Positive Keyword Distribution Chart

The top 30 positive keywords are illustrated in the chart below. The complete list is available in appendix B. The 30 most common keywords in each category were analysed in detail. Each keyword has been manually analysed through qualitative examination.

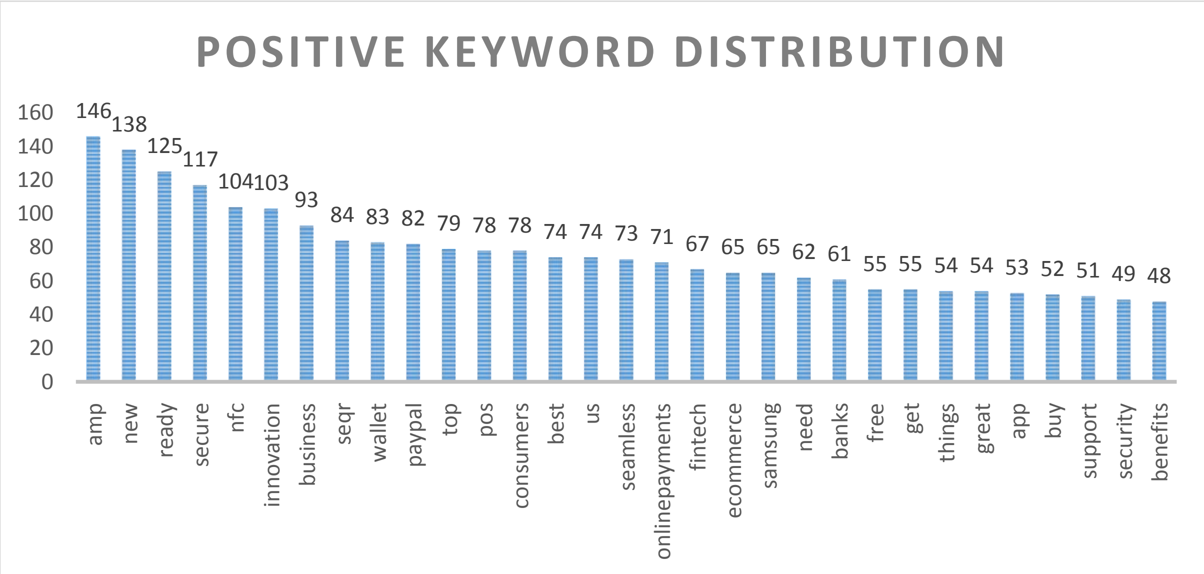

FIGURE 4.3 Positive keyword distribution.

The keyword distribution revealed a number of interesting results.

AMP is the most frequently occurring word in the positive category. Upon manual qualitative analysis of the tweets containing 'AMP' keyword, there were a few trends observed to explain this result:

- AMP stands for Advanced Mobile Payment. It is a Canadian company specialising in providing hardware and software for mobile payment solutions. Their products are reviewed and discussed on Twitter.
- At the time of data collection in March 2015 an Australian financial services company called AMP limited launched NFC mobile payments for their customers on Android devices. The launch was discussed on Twitter.
- AMP can also be used as an acronym for 'Advanced Mobile Payment' to describe a payment solution.

In order to gain better insights into this trend, a further manual qualitative analysis has been carried out on all tweets containing 'AMP'. The analysis revealed that 67 tweets were in reference to the Canadian company, 50 tweets about the Australian bank and 29 were used as a term to describe a payment method.

This results demonstrate a positive attitude towards mobile payment solutions and an enthusiasm for new payment options.

The word, "new", upon examining tweets further revealed a positive interest in new mobile payment systems. In addition, it is clear that there are many new payment solutions appearing on the market. Positive reviews of new and emerging mobile payment technologies and services were a common trend. Users were frequently replying to tweets which announced new mobile payment options. A few examples of tweets containing the keyword "new" are outlined below.

Loved your insight on new @USERNAME!! My startup @USERNAME solves the frustrations behind closing tabs through seamless #mobilepayments
@USERNAME I just completed my first transaction on your new mobile app...kind of exciting, actually. Research for work, of course. ;-) #mobilepayments #nfc
Good to hear about new EMV compliant m-POS devices that are below $70 in #Malaysia #mobilepayments
@USERNAME your new app looks slick! #mobilepayments
Thank you @USERNAME for new HCE support in Windows 10 for phone! #mobilepayments
My favorite new habit is using my mobile to pay for coffee in the morning. #mobilepayments #payments2015

TABLE 4.1 Examples of tweets containing the keyword 'new'.

It is somewhat unanticipated to observe that 'secure' and 'security' are frequent positive keywords. From the literature review, it was clear that mobile payment security is a large theme in the adoption barriers that mobile payments face. According to a study carried out by Diniz, H (2012), issues in user adoption are mainly related to security, privacy, trust, fraud and risk perception. The qualitative analysis of "secure" revealed a significant amount of tweets relating to new more secure mobile payment options and security advancements. This may demonstrate an increased trust in mobile payments with the introduction of new mobile payment options. Also, it comes evident that service providers are working towards closing the security gap and advances in user adoption.

This study shows that consumers and businesses are ready to embrace mobile payment methods. The keyword 'ready' was associated mainly with users discussing that businesses are now ready to provide a mobile payment solution i.e*. “nice, iZettle ready to launch a card reader that works with apple pay and chip and pin”.* Likewise, statements with the keyword ‘ready’ claimed that consumers would like to use mobile payments i.e*. "@USERNAME: Another successful launch. LTC ready for e-ticketing. Congratulations @USERNAME #technology #mobilepayments.”*

As outlined in the literature review, NFC payments are on the increase. It is encouraging to observe the NFC score highly on the positive keyword list. The majority of tweets related to opinions, business announcements, and new advancements in NFC technology i.e. *“If I'm frank, I'm way more excited about #NFC #mobilepayments. People are gonna get over #EMV reeeeal quick.”, “#NFC and #MobilePayments are just awesome.”* Despite a number of security concerns there outlined in the literature review, it appears that the public feels confident about NFC payments. This finding may further be confirmed by increased usage statistics.

Innovation mainly appeared as a “hashtag” people used to categorise positive tweets about mobile payments. This finding advocates that the public identifies mobile payments with optimistic innovation.

“Looks like secure #Payments are key to success of #mobilepayments in #India #authentication #innovation”

“Mobile payments are the future! #technology #innovation #mobilepayments #mobile.”

The presence of SEQR, PayPal and Samsung further endorses the concept that the public is enthusiastic and positive about mobile payment solutions and services. “SEQR is Sweden’s and Europe’s most used mobile wallet in stores and online. SEQR enables anybody with a smartphone to pay in stores, at restaurants, parking lots and online, transfer money at no charge, connect loyalty programs, store receipts digitally and receive offers and promotions directly through one mobile app” (SEQR, 2015). Soon, Samsung is launching its own mobile payment solution called Samsung Pay. It is evident that the public is anticipating the launch of this new service. Tweets relating to SEQR and PayPal were mainly reviews of the service.

“SEQR is so seamless it’s the future! #mobilepayments #mobilewallet #innovation”
“*#PayPal is the amazing service that changed my business for the better! #mobilepayment #onthego”.*
“@SEQRbe Keep up the good work #SEQR Belgium! #mobilepayments”

TABLE 4.2 Examples of tweets

Additionally, the keyword 'banks' relates to new mobile payment services that banks are introducing in response to customer demand for such services.

The remaining keywords: seamless, benefits, need, free, buy, app, security, top, great, support, fintech and support are the top words used in tweets to describe mobile payments.

"*Seamless. Just paid with #ApplePay on #Starbucks #Mobile App #MobilePayments #Tokenization #Fintech #DataSecurity Replacing Cash"*

The presence of these keywords is a promising trend, as it further demonstrates that the public considers mobile payments a positive development.

4.6 Negative Keyword Distribution Chart

Similarly to the positive category, 30 negative words are presented in the chart below.

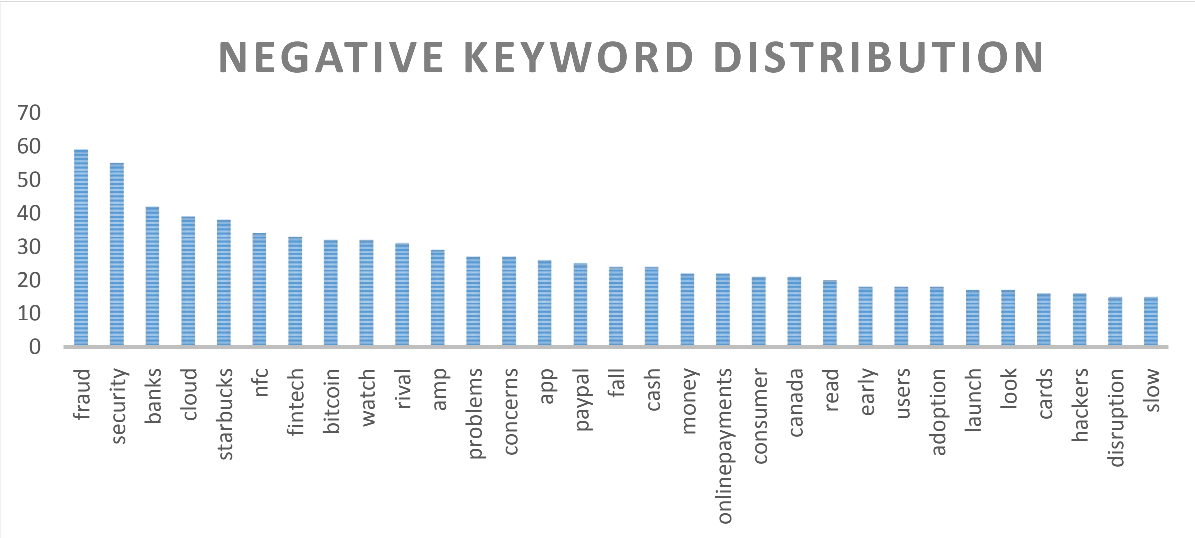

FIGURE 4.4. Negative Keyword Distribution

Unsurprisingly, fraud and security hold the first two places in the negative word list. This is an imperative discovery confirming the trend frequently declared in literature and publications. Fraud and security are the main barriers that prevent mobile payments from adoption. The public is evidently concerned about these issues, and as a result, is apprehensive about using mobile payment services. This discovery is somewhat contradictory to findings explored in the previous section, in which the results show positive associations with mobile payment security.

Tweets show that consumers are anxious about the risk of fraud associated with mobile payment services. The table below demonstrates the main negative views relating to security and fraud in tweets gathered for this study. With regards to keywords, tweets including 'cloud' express concern over security and potential threats associated with carrying out transactions using cloud-based mobile payment services.

The presence of APM and PayPal is also conflicting to positive keyword findings. However, their presence further demonstrates that people have concerns and adverse opinions of these mobile payment services. The majority of negative tweets containing these keywords were in fact associated with fraud and security.

@USERNAME With advancement and innovation in #mobilepayments can we expect reduction of fraud?
Stripe or Realex or Paypal...which is cheaper and safer?! #fraud #mobilepayments #help
#Mobilepayment #fraud is growing, but merchants are falling behind in their efforts to prevent it.
#Mobilepayments: where there's money, there's #fraud
Anyone else anxious about #mobilepayment apps? #fraud #theft #security
#fraud management is not mobile-friendly #mobilepayments
Good point @USERNAME, the big question with #mobilepayments is whether they'll become safer #fraud #security

TABLE 4.3 Tweet examples relating to fraud

It is vital to observe that the count for the 'security' keyword is approximately 50% lower in the negative category in comparison to the positive category. In drawing conclusions from these findings, it is important to differentiate that even though the public does feel positively about the security of mobile payments, it is still a significant concern for some users.

A remarkable pattern was observed in negative tweets containing the keyword "banks". 23 tweets related to consumers considered switch banks if they do not offer a mobile payment solution for their day-to-day banking needs. Users discussed how a lack of mobile banking is a major inconvenience nowadays. Banks tend to compete with each other by offering attractive interest rates and lower banking fees. This finding may suggest that in order for banks to gain a significant competitive advantage and to increase their retention rates they ought to offer mobile banking. This finding is significant as in this day and age, people appear to "shop around" when choosing their bank by evaluating available offers. It is a strong message for banks, as consumers will leave if they fail to cater for their mobile payment needs.

Yes I will defo switch banks if they fail to offer #mobilepayments.
Why do banks move so slow on #mobilepayments? they'll lose customers.
@USERNAME I prefer to look forward, not backwards. Mobile app please #mobilepayments.
I wish my bank offered mobile banking It's such a pain. I will need to look into switching. #mobilepayment #banking
I can't believe @USERNAME does not have a working mobile site where I can make easy #mobilepayments. Wth

TABLE 4.4 Examples of tweets relating to banks.

The remaining tweets associated with the keyword 'bank' are tweets concerning the threat mobile payments pose to banks. It appears that users discuss the fact that banks are worried about becoming redundant in future *"Canadian banks see threat in tech companies offering #mobilepayments"*. A number of tweets referred to concerns about fraud as banks introduce mobile payment options.

During the data collection for this study, there has been a security breach of the Starbucks mobile application. The Starbucks app allows users to add credit card details and make payments using a mobile phone. Hackers gained access to users' accounts and made gift card purchases. Consequently, this was reflected in the sentiment analysis. Twitter users were reporting and discussing the hack as well as criticising Starbucks.

"*Starbucks blaming passwords, victims doesn't fix the problem; burning questions about attack remain #mobilepayments"*

"Sorry Starbucks but the security hack has totally put me off the service #mobilepayments".

Bitcoin is a somewhat controversial virtual currency, which is reflected in tweets. Users are discussing the safety and legal issues with regards to paying online with the Bitcoin currency. From the qualitative analysis of tweets, it is evident that in order for virtual currencies to be viewed positively, more regulation and clarity is needed. Most of the tweets related to users questioning the legality and security of Bitcoin.

The word 'watch' was an interesting observation in the negative category. Upon the qualitative review of tweets containing that keyword, it became evident that the majority of users were discussing the Apple Watch, and more precisely, its mobile payment feature. In general, tweets questioned the security of carrying out transactions using the smart watch. Users felt it was 'too easy' to make payments for it to be safe and that the functions of the watch were limited in terms of payments. Users described the Apple Pay function on Apple

Watch with the following statements: “too easy to steal money”, “limited”, “vulnerable to fraud and theft”.

The remaining keywords: problems, concerns, fail, early, adoption, hacker, disruption, app, and slow were commonly used when discussing mobile payments in tweets with a negative sentiment.

4.7 Wordclouds

In this research, the use of wordclouds facilitated the illustration of trends emerging in mobile payment tweets with positive and negative sentiments. It simplifies the understanding of results by highlighting the 150 top occurring keywords in both categories. The wordcloud creates an image based on the frequency of a given word; the higher the word frequency, the larger the print of the word on the image. The wordclouds below helped to interpret the findings qualitatively, while at the same time, integrating the quantitative

FIGURE 4.5 Positive wordcloud.

importance of the results. The positive and negative wordclouds below reflect the frequency distribution chart. It also provides a wider spectrum on how mobile payments are perceived.

The positive wordcloud below displays encouraging results with regards to the adoption of mobile payments. It may be observed that users perceive mobile payments as secure and innovative. They may be ready to adopt mobile payments and feel enthusiastic about NFC payments.

Negative wordcloud below demonstrates the concerns of the public. As it may be observed, security and fraud stand out from the image, which also reflect the scale of the issue.

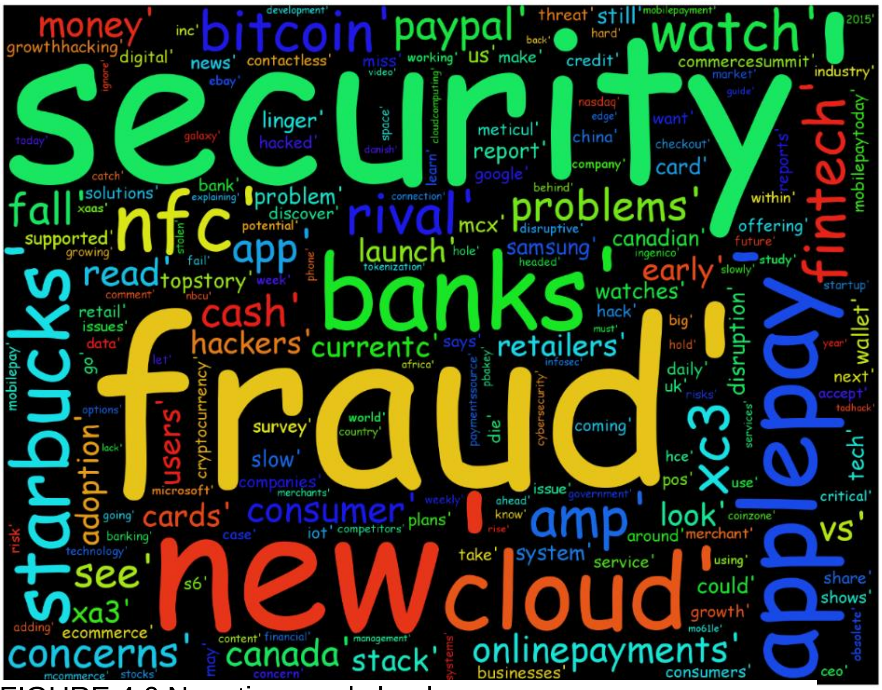

FIGURE 4.6 Negative word cloud.

4.8 Summary

This chapter presented and analysed the results of tweets gathered that contain the mobile payment(s) hashtag. Tweets obtained through Twitter API were subjected to an automated sentiment analysis followed by a manual qualitative examination of tweets.

A number of valuable findings were acquired during this study. It was found that the society views mobile payments positively with 80% of tweets identified as positive and 20% as negative. The keyword frequency distribution chart and the qualitative analysis revealed further insights into attitudes towards mobile payments.

The positive keyword distribution chart showed that users feel enthusiastic about new mobile payment services. With an increasing amount of mobile payment services becoming available on the market, users are ready to adopt them. It was observed that people feel more confident about the safety and security. Mobile payment services provided by SEQR, PayPal and Samsung are positively reviewed and popular amongst users.

While 80% of tweets were found to have a positive sentiment, the remaining 20% of negative tweets revealed the concerns and limitations of mobile payments.

Fraud and security are still significant concerns for users. People are anxious that they are being exposed to theft and other risks while using mobile payments services. It is a main obstacle to prevent mobile payments from adoption. It is evident that further anti-fraud improvements must be developed in order to advance the growth of mobile payments.

It became apparent that clients are willing to switch banks if they fail to provide them with mobile banking options in order to facilitate their technological requirements. This finding suggests that in order for banks to gain a competitive advantage, they ought to facilitate mobile payments.

5 Conclusions and Future Work

5.1 Introduction

The purpose of this chapter is to evaluate the findings and conclusions of this study to answer the research questions. This chapter also outlines important observations and recommendations for future research.

5.2 Conclusions

The purpose of this research was to investigate attitudes towards mobile payments. The following research questions were used to facilitate the understanding of the research: “Does the society feel more positive or more negative about mobile payments?”, “Are there any patterns in relation to how people feel about mobile payments?”, “What are the possible limitations that may prevent mobile payments from further adoption?”

5.2.1 What sentiment is expressed by Twitter users towards mobile payments?

Based on the sentiment analysis, it was found that 80% of individuals feel positively about mobile payments while 20% of individuals feel negatively.

5.2.2 Are there any frequently arising topics discussed by Twitter users with regards to mobile payments? How can they be interpreted?

Patterns were found in relation to what people mention in reference to mobile payments either in a positive or negative manner.

A significant amount of individuals mentioned Apple Pay in their tweets. This finding is expected as it was the most recognised and deliberated mobile payment service at the time of research.

The individuals that discussed mobile payments in a positive manner often referred to businesses offering new mobile payment services, the security of mobile payments and Near Field Communication payments. The most frequently used positive words to describe mobile payments were: seamless, innovative, top, best, benefits, need, support, security and fintech. In general, people conversed enthusiastically about mobile payments, and typically discussed their benefits and advancements. This result demonstrates a positive attitude towards mobile payment solutions and an enthusiasm for new payment options.

People who expressed a negative sentiment towards mobile payments often mentioned security and fraud. Individuals raised concerns about potential risks associated with using mobile payment services. The predominant negative words used were: concerns, fail, early, adoption, hacker, disruption, app, and slow.

These findings show that users still have issues with mobile payments and that these issues mainly relate to fraud and security.

5.2.3 What are the possible obstacles that may prevent mobile payments from further adoption?

The study showed that fraud and security threats are the most apparent factors preventing people from using mobile payments. Another factor that may prevent mobile payments from being adopted is the pace at which mobile payment services are becoming available. The study found that banks and other business ought to introduce mobile payment options at a quicker rate to their customers. There are several reasons why business are slow to introduce mobile payments that were found in data analysis carried out in this study, as well as in previous research studies that were outlined in the literature review. Those are as follows:

- Security threats.
- User interface and technological limitations.
- Lack of infrastructure.
- High costs.
- Lack of knowledge of mobile payments.
- Lack of standards and regulations.

5.3 Additional Observations of Interest

A few interesting trends were observed during this research. The study showed that a number of individuals mentioned that they are prepared to leave their current bank if they fail to provide them with mobile banking services to meet their day-to-day banking needs. This finding is a thought-provoking as many banks compete with one another to acquire more customers and to increase their customer retention. It is evident that by introducing mobile banking options (such as a mobile application), banks may gain a significant competitive advantage.

Another interesting observation in this study was the repeated mentions of the Starbucks mobile application security hack, Bitcoin's legality and security, and the limitations and security of Apple Watch. This insight is a valuable as it displays customer attitudes towards these services and products. This finding identifies in what areas these services failed in meeting consumer expectations and satisfaction. It appears that in order to maintain a successful mobile payment system, it is crucial for businesses to provide clarity on the legal standing of the service or product, as well as to display and maintain high standards of security and safety to users.

5.4 Limitations of This Research

As a result of inadequate resources, time and legal constraints, this study was limited in terms of the amount of tweets that could be collected and analysed. Therefore, the results of this study cannot be considered as adequately representative of society as a whole.

Data cleansing has been carried out manually and also through the use of the Python script. However, it is not certain that all unsuitable tweets for this analysis have been excluded.

With regards to the sentiment analysis, it is challenging to test the performance of the Python script created for the purposes of this study. Additionally, the positive and negative word lexicon did not contain emoticons, which are commonly used on Twitter to express emotions. As a consequence, they needed to be excluded from data analysis. Some useful data may have been excluded as a result of this limitation.

5.5 Opportunities for Further Research

This study examined how people perceive mobile payments. It is hoped that the findings can be used to facilitate further research into this area. There is a small amount of existing academic research dedicated to this particular area. This research raised further questions, including:

- How to minimise security risks associated with mobile payments?
- How to facilitate the implementation of mobile payments for businesses?

These topics are worth exploring, as there is a rapidly growing demand for mobile payments. Mobile payments are changing how people and businesses carry out transactions on a daily basis, and therefore it is vital to explore this topic further. The scope of this research may possibly be further expanded to gain a deeper understanding of how people perceive mobile payments and what may be done in order to increase user adoption and to minimise fraud.

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7 Appendix

APPENDIX A. Python script.

```
# import of all needed libraries

import pandas as pd
import nltk
import urllib2
import re
import csv
from nltk import FreqDist
from wordcloud import WordCloud, STOPWORDS
from pylab import *
import matplotlib.pyplot as plt

# variable "path" - contains url address/path for the text file
containing all the collected tweets
path = "/Users/sandra/Downloads/mobilepayments-3a.txt"

#"data" variable specified for reading csv file by means of "pandas"
library; tab is the delimiter between each entry/value
data = pd.read_csv(path, delimiter="\t")

#"text" variable containing object of a type "file" which is an
output of the open() built-in function; "pos_text" variable contains
the text read from the specified file; "pos_list" contains the output
from the function split(), which divides the text by new lines "\n"
and outputs a list of lines
text = open('/Users/sandra/Downloads/positive_words.txt', 'r')
pos_text=text.read()
text = open('/Users/sandra/Downloads/negative_words.txt', 'r')
neg_text=text.read()
pos_list = pos_text.split()
neg_list = neg_text.split()

#"text_file" contains the "file" object for the file where we're
going to store the output of our code; "csv_writer" variable will
contain the csv file we are writing to, separating the entries by
commas (uses "csv" library); "all_rows" variable contains output rows
we will want to store as csv file; row_to_write -> a list of strings
which is the first row with column titles
text_file=open('/Users/sandra/Downloads/SentimentAnalysisSandra3b.csv
', 'wt')
csv_writer = csv.writer(text_file, delimiter=',')
all_rows=[]
row_to_write=['Date','User','Followers','Follows','Retweets','Favouri
tes','Tweet text','Sentiment']
all_rows.append(row_to_write)

#the loop in which we get pos/neg/nau labels for each row/tweet and
store it in a list containing values to be written as file similar to
the input file but with extra column containing the sentiment value
for particular entry; "ind" is the index, "row" is single entry from
the tweets file containing all the provided values
for ind, row in data.iterrows():
    pos_score=0
    neg_score=0
```

```
    #text of a tweet
    tweet = row['Tweet text']

    #continue the analysis of the tweet only if it is not the retweet
    while "RT" not in tweet:

        #"sentence_list" is a list with words from a single tweet
converted into tokens using nltk library; is will skip the tweet and
jump next tweet if there is UnicodeDecodeError or TypeError thown
        try:
            sentence_list = nltk.word_tokenize(tweet)
        except UnicodeDecodeError or TypeError:
            break

        #get rid of certain tokens from the list
        sentence_list = [w.lower() for w in sentence_list]
        sentence_list = [w for w in sentence_list if not "/" in w]
        sentence_list = [w for w in sentence_list if not "'" in w]
        sentence_list = [w for w in sentence_list if not "\\x" in w]
        sentence_list = [w for w in sentence_list if not "http" in w]
        sentence_list = [w for w in sentence_list if not
(re.match(r'^\W+$',w) != None)]
        sentence_list = [w for w in sentence_list if not
(re.match(r'^[0-9]+$',w) != None)]
        sentence_list = [w.replace(".","") for w in sentence_list]
        sentence_list = [w for w in sentence_list if not w in
nltk.corpus.stopwords.words('english')]
        sentence_list = [w for w in sentence_list if not "_" in w]

# calculate the positive and negative score for each token and sum
it; if the word exists in the pos or neg list of words, add 1 to the
score (count pos and words in the tweet)
        pos_overlap=0
        neg_overlap=0
        for tok in sentence_list:
            for r in pos_list:
                if tok==r:
                    pos_overlap=pos_overlap+1
                    break

            for i in neg_list:
                if tok==i:
                    neg_overlap=neg_overlap+1
                    break

        if pos_overlap>0 or neg_overlap>0:
            pos_score = float(pos_overlap)/(pos_overlap +
neg_overlap)
            neg_score = float(neg_overlap)/(pos_overlap +
neg_overlap)

             #add each value from the entry to a list
        row_to_write=[]
        row_to_write.append(row['Date'])
        row_to_write.append(row['User'])
        row_to_write.append(row['Followers'])
        row_to_write.append(row['Follows'])
        row_to_write.append(row['Retweets'])
        row_to_write.append(row['Favourites'])
```

```
        row_to_write.append(row['Tweet text'])

            # assign the sentiment value according to the pos and neg
scores
        if pos_score>neg_score:
            row_to_write.append('pos')
        elif neg_score>pos_score:
            row_to_write.append('neg')
        else:
            row_to_write.append('neu')
    all_rows.append(row_to_write)
    break

#writing each row from the list to the csv file
for y in range(len(all_rows)):
   csv_writer.writerow([x for x in all_rows[y]])


#the part of code creating the graph for frequencies of most popular words

def lexical_diversity(text):
   return len(set(text)) / len(text)

path = "/Users/sandra/Downloads/positive_tweets.csv"
data = pd.read_csv(path, delimiter=",")
full_pos_tw_list=[]

#positive
#dont_enclude=["mobilepayments","mobilepayment","mobile","payments","apple","pa
y","applepay","payment","via"]
#negative
#dont_enclude=["mobilepayments","mobilepayment","apple","mobile","pay","payment
s","payment","via"]
#neutral
#dont_enclude=["mobilepayments","mobilepayment","mobile","payments","apple","pa
y","payment","via","applepay"]

for ind, row in data.iterrows():
   tweet = row['Tweet text']

pos_tw_list = nltk.word_tokenize(tweet)
   pos_tw_list = [w.lower() for w in pos_tw_list]
   pos_tw_list = [w for w in pos_tw_list if not "/" in w]
   pos_tw_list = [w for w in pos_tw_list if not "'" in w]
   pos_tw_list = [w for w in pos_tw_list if not "\\x" in w]
   pos_tw_list = [w for w in pos_tw_list if not "http" in w]
   pos_tw_list = [w for w in pos_tw_list if not (re.match(r'^\W+$',w) != None)]
   pos_tw_list = [w for w in pos_tw_list if not (re.match(r'^[0-9]+$',w) != None)]
   pos_tw_list = [w.replace(".","") for w in pos_tw_list]
   pos_tw_list = [w for w in pos_tw_list if not w in nltk.corpus.stopwords.words('english')]
   pos_tw_list = [w for w in pos_tw_list if not "_" in w]
   #pos_tw_list = [w for w in pos_tw_list if not w in dont_enclude]
   full_pos_tw_list = full_pos_tw_list+pos_tw_list

print '{}{}'.format('Lexical diversity: ', lexical_diversity(full_pos_tw_list))
pos_tw_freq_dist = FreqDist(full_pos_tw_list)
print pos_tw_freq_dist
```

```
# Print the top X words
numWords = 0
wordLimit = 30
freq_dist=pos_tw_freq_dist.most_common(150)

for i,w in freq_dist:
    print "%s : %s"% (i,w)

pos_tw_freq_dist.plot(wordLimit)


# the code creating the wordcloud

path = "/Users/sandra/Downloads/negative_tweets.csv"
data = pd.read_csv(path, delimiter=",")
full_pos_tw_list=[]

#positive
#dont_enclude=["mobilepayments","mobilepayment","mobile","payments","apple","pay","applepay","payment","via"]
#negative
#dont_enclude=["mobilepayments","mobilepayment","apple","mobile","pay","payments","payment","via"]
#neutral
#dont_enclude=["mobilepayments","mobilepayment","mobile","payments","apple","pay","payment","via","applepay"]

for ind, row in data.iterrows():
    tweet = row['Tweet text']
    pos_tw_list = nltk.word_tokenize(tweet)

    pos_tw_list = [w.lower() for w in pos_tw_list]
    pos_tw_list = [w for w in pos_tw_list if not "/" in w]
    pos_tw_list = [w for w in pos_tw_list if not "'" in w]
    pos_tw_list = [w for w in pos_tw_list if not "\\x" in w]
    pos_tw_list = [w for w in pos_tw_list if not "http" in w]
    pos_tw_list = [w for w in pos_tw_list if not (re.match(r'^\W+$',w) != None)]
    pos_tw_list = [w for w in pos_tw_list if not (re.match(r'^[0-9]+$',w) != None)]
    pos_tw_list = [w.replace(".","") for w in pos_tw_list]
    pos_tw_list = [w for w in pos_tw_list if not w in nltk.corpus.stopwords.words('english')]
    pos_tw_list = [w for w in pos_tw_list if not "_" in w]
   #pos_tw_list = [w for w in pos_tw_list if not w in dont_enclude]
    full_pos_tw_list = full_pos_tw_list+pos_tw_list


wordcloud = WordCloud(font_path='/Library/Fonts/Comic Sans MS.ttf',
stopwords=STOPWORDS, background_color='black', width=1800,
height=1400).generate(str(full_pos_tw_list))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```

APPENDIX B. Positive keyword frequency distribution list.

mobilepayments : 2027
mobile : 558
payments : 433
apple : 285
pay : 275
applepay : 174
payment : 171
via : 160
amp : 146
new : 138
ready : 125
secure : 117
nfc : 104
innovation : 103
business : 93
seqr : 84
wallet : 83
paypal : 82
top : 79
pos : 78
consumers : 78
best : 74
us : 74
seamless : 73
onlinepayments : 71
fintech : 67
ecommerce : 65
samsung : 65
need : 62
banks : 61
see : 60
free : 55
get : 55
things : 54
great : 54
app : 53
buy : 52
support : 51
security : 49
benefits : 48
africa : 47
make : 46
way : 46
easier : 45
work : 44
tech : 44
future : 43
google : 43
online : 42
qr : 42
like : 42
interesting : 41
banking : 41

customers : 41
loyalty : 40
smart : 40
growing : 39
using : 39
leading : 38
use : 38
retail : 38
watch : 37
come : 37
win : 37
lead : 37
improve : 36
market : 36
uk : 36
bitcoin : 35
trust : 35
today : 35
adoption : 35
world : 35
digital : 34
industry : 34
zapp : 33
service : 33
leads : 33
along : 33
take : 33
fast : 33
success : 33
technology : 32
launch : 32
stand : 31
rbte : 30
transactions : 30
emv : 30
boost : 30
partner : 30
contactless : 30
easy : 29
battle : 29
card : 29
money : 29
good : 29
study : 28
still : 28
year : 28
available : 28
tokenization : 28
apps : 28
adds : 27
ceo : 27
starbucks : 26
samsungpay : 26
users : 26
visa : 26

programs : 25
global : 25
first : 25
cards : 25
article : 25
millennials : 25
technologies : 25
coming : 25
succeed : 25
solution : 24
merchants : 24
ways : 24
cash : 24
read : 24
find : 24
next : 24
even : 23
right : 23
company : 23
customer : 23
mobilemoney : 23
gain : 23
driving : 22
consumer : 22
report : 22
pymnts : 22
offers : 22
million : 22
going : 22
mass : 22
program : 22
mastercard : 22
nice : 22
infographic : 22
credit : 21
mcx : 21
helping : 21
options : 21
wearables : 21
customerexperience : 21
coffee : 20
needed : 20

APPENDIX C. Negative keyword frequency distribution list.

mobilepayments : 645
apple : 165
applepay : 158
mobile : 154
pay : 136
payments : 82
payment : 71
via : 60
fraud : 59
security : 55
banks : 42
cloud : 39
starbucks : 38
nfc : 34
fintech : 33
bitcoin : 32
watch : 32
rival : 31
amp : 29
problems : 27
concerns : 27
app : 26
paypal : 25
fall : 24
cash : 24
money : 22
onlinepayments : 22
consumer : 21
canada : 21
read : 20
early : 18
users : 18
adoption : 18
launch : 17
look : 17
cards : 16
hackers : 16
disruption : 15
slow : 15
retailers : 15
currentc : 15
stack : 15
us : 15
still : 14
watches : 14
problem : 14
samsung : 14
canadian : 13
card : 13
report : 13
topstory : 12
tech : 12
news : 12

mcx : 12
wallet : 12
could : 12
system : 12
supported : 12
linger : 12
service : 11
die : 11
mobilepaytoday : 11
ecommerce : 11
google : 11
threat : 11
survey : 11
retail : 11
growthhacking : 11
companies : 10
bank : 10
solutions : 10
offering : 10
daily : 10
may : 10
hack : 10
consumers : 10
share : 10
miss : 10
uk : 10
go : 10
next : 10
iot : 10
china : 9
credit : 9
make : 9
says : 9
plans : 9
coming : 9
businesses : 9
cryptocurrency : 9
growth : 9
reports : 8
want : 8
digital : 8
s6 : 8
hacked : 8
shows : 8
take : 8
pos : 8
ceo : 8
around : 8
industry : 8
issue : 8
discover : 8
commercesummit : 8
issues : 8
meticul : 8
contactless : 8

inc : 8
merchant : 7
risk : 7
study : 7
ebay : 7
mobilepay : 7
obsolete : 7
learn : 7
data : 7
hce : 7
concern : 7
using : 7
critical : 7
case : 7
accept : 7
disruptive : 7
world : 7
big : 7
within : 7
use : 7
hole : 6
hold : 6
competitors : 6
fail : 6
adding : 6
cybersecurity : 6
market : 6
working : 6
growing : 6
space : 6
future : 6
potential : 6
going : 6
behind : 6
technology : 6
week : 6
company : 6
systems : 6
hard : 6