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Sentiment Analysis And Text Mining Of Online Customer Reviews For Digital Wallet Apps Of Fintech Industry

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Abstract - With the use of emerging technologies, the finance sector has proved to be a significant part of our everyday lives. Fintech firms are attracted by the need to improve the financial services already offered by various financial institutions. The digital wallet is the newest financial technology innovation, and it's a fantastic tool for making our payment transactions simple and fast. Many digital wallet apps have also been created and used in payment transactions. Because of the large number of cyber-threats aimed at the financial sector, security has become a critical component of banking. The main goal of this paper is to propose a method for evaluating the mood of Digital Wallet Apps feedback. Messages from Facebook pages, blogs, and other channels like g2.com, mouthshut.com, and trustpilot.com are collected. This were then labelled as positive or negative reviews in NVivo 12 using the auto code function. Very negative 24% Moderately negative 40.83% Moderately positive 25.65% Very positive 9.52% User preferences for Digital Wallet Apps in the FinTech Industry Market should be determined using the findings. This will help the aforementioned industries figure out what works and what doesn't. As a consequence, they'll be able to further improve their products and react to customer demands.

1. INTRODUCTION

In today's environment, cell phones are an integral part of daily life. Because of technical advances, smartphone consumers may now use their phones to perform financial transfers or make purchases through multiple apps built on their phones. We may also store receipts, vouchers, and cards, as well as bills, in the mobile. When a smartphone may double as a pocket, it is referred to as a mobile wallet or digital wallet. According to Ambarish Salodkar et al. (2015), there are various apps such as Paytm, freecharge, and mobiquick. These software may be downloaded and used for a range of uses, including bill paying, online shopping, and phone recharging. People may load a certain sum of money into their mobile wallet, which is a virtual wallet service offered by certain service providers. People may not have to pay cash or swipe their debit or credit card at offline retailers by using the wireless payment app, which is a cashless payment service. Roopali et al. (2016) investigated whether digitalization of payments can be deemed a boost to a country's economic development. The authors have undertook a detailed study of adoption practises. Demonetization has provided another incentive to already creating use of modernised portions in a country like India, where E-exchange and electronic shopping are increasing fundamentally. E-wallets are the most juvenile of the different wireless payment strategies. Digital India is an effort spearheaded by the Indian government to ensure that the government's resources are available to countries through electronic means, either via a stronger online foundation and improved Internet connectivity, or through having the nation digitally powered in the field of revolution. Pinal Chauhan (2013) explained how e-Wallets would make money transactions more convenient for consumers. People who use smartphone devices just have to pay at the point of sale when making a purchase. The author often discusses server-side and client-side e-wallets.

Sentiments are a reflection of an individual's feelings, opinions, and experiences that serve as the foundation for establishing and nurturing narratives framing the mentality of inundated methods of understanding and comprehension. Any person in today's world who has their own perception and understanding seeks to improve it by professing it to others, so that the subject or matter will thrive by the input of the subject or matter. As a part of a society dominated by feelings and expectations, it is essential to be able to interpret and draw lessons from mutual emotions and perceptions, as all about the world that people revere is the result of a group's collective conviction. To execute sentiment research, related text must be retrieved from the internet using a site scraping method. Messages from Facebook pages, blogs, and other channels including g2.com, mouthshut.com, and trustpilot.com are collected. Following that, the document must be examined to see whether it contains some sentiment. On a famous Digital Wallet Apps' extraction of Twitter posts Using NVivo 12's auto code function This study focuses on the online reviews commonly exchanged by customers of Digital Wallet Apps, which represent the experience and satisfaction through sentiments such as positive, negative, or neutral to measure the customer's opinion in the Indian market.

2. LITERATURE REVIEW

To classify negation expressions, Xing et al. (2015) proposed a study using Amazon product feedback. For data obtained from February to April 2014, sentence level and examination level classification is done. According to a survey performed by Sharef (2014) utilising the Scopus database, the number of publications on sentiment analysis has been gradually growing over the last decade. While the bulk of these research concentrate on social networking sites like Twitter, Facebook, and MySpace, there have also been a variety of important studies on other datasets. Aashutosh Bhatt et al. (2015) proposed a rule-based extraction of product attribute sentiment analysis using feedback of the iPhone 5 obtained from the Amazon website. The POS methodology is used at any step of the statement, with the effects shown in graphs. Terrana et al. (2014) & C.kathiravan (2019) investigated the social relationships of Facebook users using sentiment analysis techniques. According to He, et al. (2017), advanced statistical approaches such as sentiment analysis are becoming common for processing large volumes of data written by social network users. While sentiment analysis, also known as opinion mining, is the study of exploring people's views, feelings, and viewpoints on different topics. S. Yordanova et al. (2017) & C.kathiravan (2019) found that sentiment analysis may be done at three stages, depending on the granularities required, such as whether the study goal is a whole text or paper, one or more composite sentences, or one or more individuals or features of those entities. V. K. Bongirwar is the author of the book V. K. Bongirwar (2015) Text stage, sentence level, and function level are the three different stages that will determine the sentiment analysis tasks. S. Behdenna et al. (2018) S. Kolkur et al. (2015) P. Patil (2016)

3. METHODOLOGY

We used qualitative analysis tools named QSR NVivo 12 to retrieve messages and comments from Facebook pages, as well as other blogs and channels like g2.com, mouthshut.com, and trustpilot.com (QSR International, 2016). NVivo is a programme that allows you to analyse unstructured data. Hilal and Alabri (2013) demonstrated how to do qualitative analysis with NVivo. In order to download the necessary details from the public Facebook group ‘Opposing Views,' we installed the NCapture for NVivo add-on in our browser (Opposing Views, 2016). It is a page where members of Facebook and the aforementioned pages, as well as other blogs and forums such as g2.com, mouthshut.com, and trustpilot.com, post and debate contentious topics. A total of 1500 Posts and comments have been downloaded. After that, the dataset was imported into NVivo for further study. To determine if a comment was positive, negative, or neutral, the following measures were taken.

3.1. Data Clean-Up

The PostID, CommentID, the identity of the person or individual creating the message, the actual text of the post or comment, the date and time the post or comment was made, and the amount of likes are all instances of meta-data derived from Facebook and other sites such as g2.com, mouthshut.com, and trustpilot.com. Only the original posts and comments field texts were used for this study. Extra characters had to be omitted from this area as well. Hu and Liu are two Chinese people (2004)

3.2. Tokenisation

A string is used to store each post or comment. This string must be separated into individual terms in order to be processed further. The method of tokenization divides a string into one or more phrases. 2007 (Feldman & Sanger)

3.3. Stemming

Many phrases in English have several definitions. The terms ordered, ordering, orders, position, placed, positions, putting, put, selection, rate, rank, and saying g all share the same core. As a result, all such terms are stemmed to their source, making the quest procedure more thorough.

3.4. Query Augmentation

We may also use NVivo to search for synonyms of the keywords found in the posts/comments. For instance, if the search term is fear, terms like best, bests, better, and so on would come up. It can also handle terms like delivery brings, delivery saves, and saved saves.

3.5. Classification

Using the auto code functionality in NVivo 12, the posts and comments are eventually labelled as positive, negative, or neutral emotions. Positive and negative sentiment lexicons are built-in to the auto coder. Other networks such as g2.com, mouthshut.com, and trustpilot.com utilise sentiment analysis from Facebook and other websites. In NVivo 12, Automatic Coding was used to make Comments. Positive terms include happy, smile, hope, and others, while negative words include sad, fear, dislike, guilt, remorse, rage, and others. Neutral words are those that are neither positive nor negative.

4. ANALYSIS AND RESULT

For the review of the comments, we used NVivo 12. The automated labelling of sentiments to text is a feature in NVivo 12. Moderately positive, extremely positive, moderately negative, and very negative feelings will all be coded. Each of these divisions has its own lexicon in NVivo. Furthermore, word modifiers such as really, more, or slightly will modify the emotion's class.

The world cloud is a figure made up of the most often reviewed and most relevant words for our analysis, which pertains to review, collected, payments, helpful, Digital, application, technology, and online the specific domains that the Reviews for Digital Wallet Apps, allowing us to determine which words are relatively more relevant than others in order to comprehend the Wallet Apps.

Using Nvivo 12, the sentiments derived as features are viewed in a word cloud. The count is proportional to the scale of the term shown in the Word cloud. Figure 1 depicts all of the sentiment terms that were derived as opinion features.

Figure: 1 Word cloud of all sentiment words

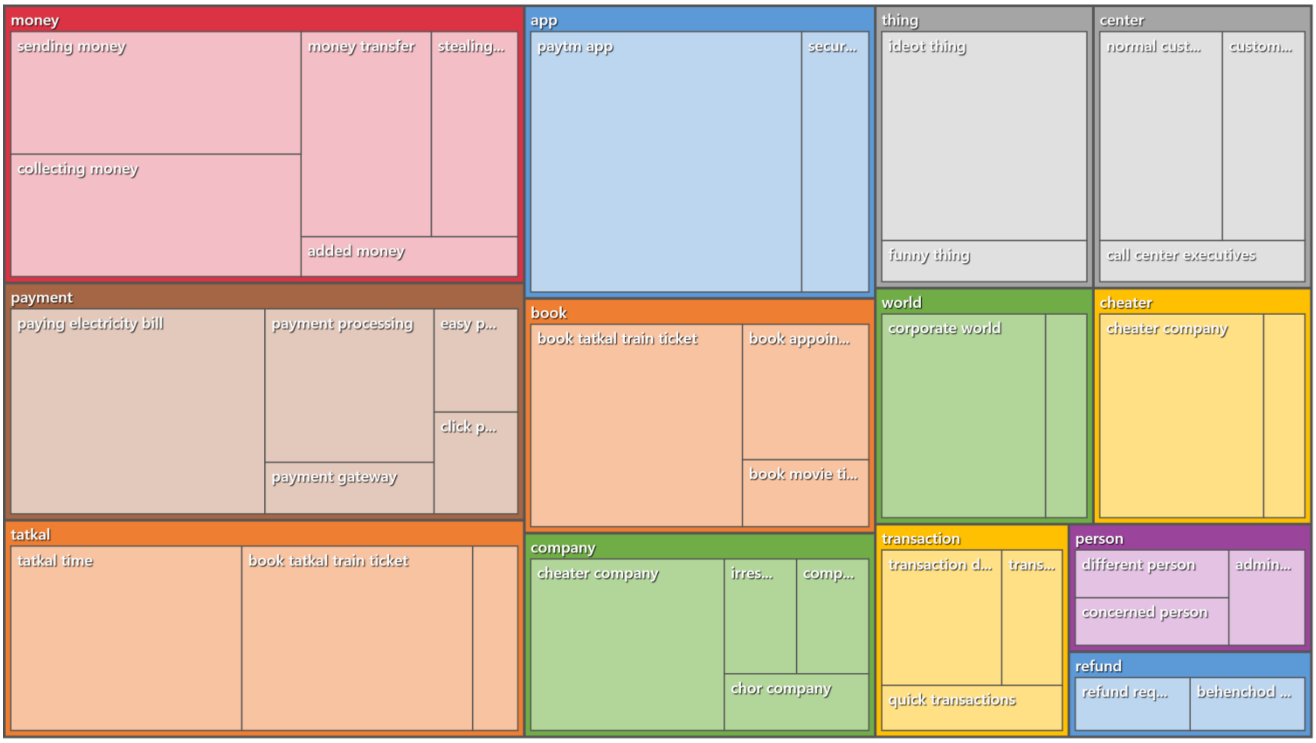

Figure 2: Word trees visually display

Figure 2: Word trees visually display the connection of words in the dataset, providing some context to their use. Words that show up more frequently in combination with the preselected word.
Money:- *Sending Money, Collecting Money, Added Money, Money transfer*
Payment:- *Paying Electricity bill, Payment Gateway, Payment Processing*
Book:- *Book takal train ticket, Book Movie ticket,*
Time: - *Order time, Delivery time etc.,*
Application: - *Fine application, User friendly app*

We have used NVivo 12 for the analysis of the comments. NVivo 12 has a feature for the automatic tagging of sentiments to text. Sentiments can be coded as moderately positive, very positive, moderately negative and very negative. NVivo maintains separate lexicons for each of these categories. Furthermore, word modifiers like very, more or somewhat can change the class of that emotion.

Table 1: Sample of Positive Emotions

Word	**Count**		**Word**	**Count**
app	12		transferring	1
excellent	9		trusted	1
describe	8		trustworthy	1
provider	8		update	1
best	7		using	1
good	7		wallet	1
money	7		want	1
stars	7		paying	1

time	7		perfect	1
application	6		paying	1
make	6		without	1
reviewer	6		world	1
source	6		worthy	1

Table 1 shows a sample list of words that are considered to carry positive emotions. NVivo almost maintains a list of words that are similar to the keyword. For example, the word app can occur in several counts. All these will be stemmed or normalised to the word promise and will count as occurrences of that emotion.

Table 2: Sample of Negative Emotions

Word	**Count**		**Word**	**Count**
bad	39		incorrect	2
time	15		insulting	2
worst	11		invalid	2
money	9		hopeless	2
fraud	7		irresponsible	2
never	7		issue	2
unresolved	4		fool	2
unsatisfied	4		frauds	2
unsuccessful	4		defective	2
useless	4		mistake	2
wrong	3		defective	2
lost			authentically	2
unprofessional	2		avoid	1

Table 2 shows a sample list of words that are considered to carry negative emotions. Figure 3 and Figure 4 show the most frequent positive and negative words that have been used in the comments.

Figure 3: Most Frequent Words Describing Positive Emotions.

Figure 4: Most Frequent Words Describing Negative Emotions.

Table 3: Sample Results after Automatic Coding

REF NO.	COVERAGE	Comment	Emotion
1	0.57%	It helps me on the daily basis, in sending money to colleague, paying electricity bill, recharging mobile etc. It is very secure and fast in any payment processing.	Positive
2	0.21%	very easily and user friendly App	Positive
3	0.78%	This App is good platform	Positive
4	0.22%	The company respect and value for your customer Services	Positive
5	0.36%	I am using this app from really a very long time, so I can say that it is the best security and the transactions are done very authentically.	Positive
6	0.49%	I have already paid post-paid bill and still not clear payment status and i have complain 3-4 times but not response from Customer care	Negative
7	0.58%	APP is good but worst customer care ever.	Negative
8	0.50%	Please do not shop with Mall. Invoiced for one product and sent different product. Really wasting time for Replacement	Negative
9	0.29%	Poor and pathetic service Poor, here was no reminder sent for the Min KYC expiry,	Negative

Table 4: Results of Automatic Coding Different Categories

A : Very negative	B : Moderately negative	C : Moderately positive	D : Very positive
610	1038	652	242

Out of 1500 comments, 603 have been coded as very negative, 783 as moderately negative, 848 as moderately positive and 457 as very positive. Comments which are not coded into these four categories are considered to be neutral. The auto code feature in NVivo does not attempt to classify a whole comment as either positive or negative, instead it looks at words in isolation. This is why we will notice from Table 3 that some comments are tagged as both moderately positive and moderately positive or both very negative positive and very negative. These results are shown graphically in Figure 4 below

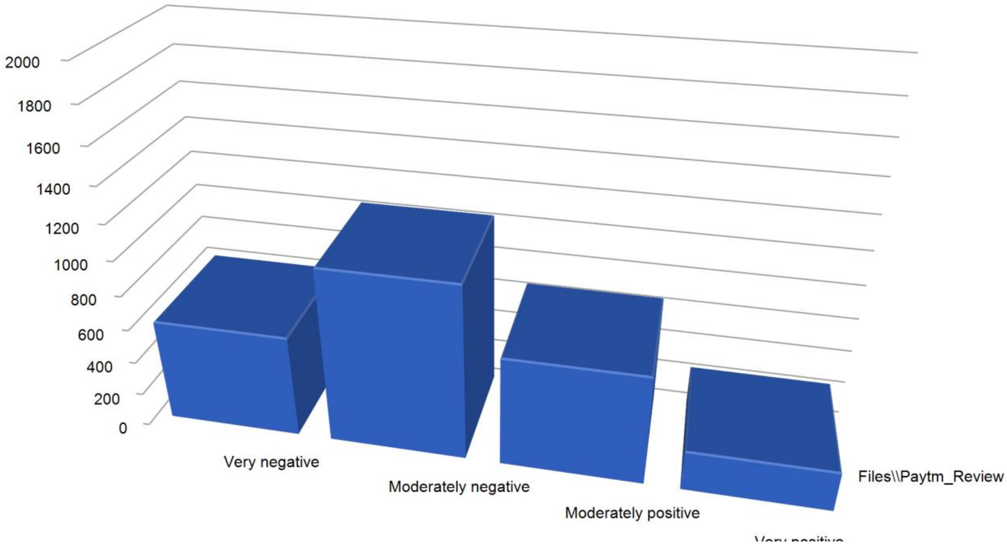

Figure 5: Summarised Results after Automatic Coding.

Table 5: Items clustered by word similarity

Code A	Code B	Pearson correlation coefficient
Sentiment\\Positive	Sentiment\\Positive\Moderately positive	0.926165
Sentiment\\Negative	Sentiment\\Negative\Moderately negative	0.921841
Sentiment\\Negative\Very negative	Sentiment\\Negative	0.874918
Sentiment\\Negative\Very negative	Sentiment\\Negative\Moderately negative	0.618846
Sentiment\\Positive\Very positive	Sentiment\\Positive	0.602022
Sentiment\\Positive	Sentiment\\Negative	0.274424
Sentiment\\Negative	Sentiment\\Positive\Moderately positive	0.260878
Sentiment\\Positive\Very positive	Sentiment\\Positive\Moderately positive	0.256449
Sentiment\\Negative\Very negative	Sentiment\\Positive	0.256198
Sentiment\\Positive\Moderately positive	Sentiment\\Negative\Moderately negative	0.241133
Sentiment\\Positive	Sentiment\\Negative\Moderately negative	0.24009
Sentiment\\Negative\Very negative	Sentiment\\Positive\Moderately positive	0.227442
Sentiment\\Positive\Very positive	Sentiment\\Negative\Very negative	0.175071
Sentiment\\Positive\Very	Sentiment\\Negative	0.150988

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positive		
Sentiment\\Positive\Very positive	Sentiment\\Negative\Moderately negative	0.104799

Figure 6: Items clustered by word similarity

Pearson correlation coefficient is a measure of linear correlation between two sets of data Code A & Code B. It is the covariance of two variables, divided by the sentences of their standard deviations; thus it is essentially a normalised measurement of the covariance, such that the result always has a value between −1 and 1. As with covariance itself, the measure

5. CONCLUSIONS

We explain how to retrieve and analyse posts and comments from Facebook pages, blogs, and other channels like g2.com, mouthshut.com, and trustpilot.com in this article. At the moment, our dataset only contains text data (emoticons, photographs, etc.). NVivo 12's auto code function was used to identify the comments with the required sentiment. We can see that the proportion of negative comments on the forum ‘Opposing Views' is significantly higher than the amount of positive comments. The bulk of the positive comments are in support of It assists me on a regular basis, such as sending money to a colleague, paying my energy bill, and recharging my phone. In every payment processing, it is extremely safe and fast.

There are a few negative comments that attract a lot of coverage. The app is fine, but the customer support is the worst I've ever experienced. Customer service does not coordinate with consumers and does not respond to any questions. The app is great, but the customer service is the worst I've ever seen. This obviously indicates that the business practises employed by Digital Wallet Apps players recognise the market's negative voice and respect it, as well as have timely solutions. Businesses who concentrate on interpreting consumer psychology have more intuitive service and provide greater customer loyalty. 2014 (Isah, Trundle, & Neagu)

Customers' expectations may be evaluated using these methodologies. Hutto and Gilbert (2014) review Sentiment analysis, which is easier than conventional marketing testing. It is an important way for advertisers to obtain instant input on their products or services, and will help them determine how their product can do in the market or make mid-course changes if appropriate. According to the sentiment study performed on Digital Wallet Apps, there were marginally more negative than positive responses in the Indian sector for Digital Wallet Apps. As a result, this method will provide marketers with simple, preliminary insights into the minds of their customers, which can then be followed up with conventional market analysis techniques.

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