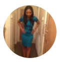
Big Data Analytics and its Application in E-Commerce



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Using Case studies of

Adidas, Walmart and Amazon.com

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***Abstract*-This era unlike any, is faced with explosive growth in the size of data generated/captured. Data growth has undergone a renaissance, influenced primarily by ever cheaper computing power and the ubiquity of the internet. This has led to a paradigm shift in the E-commerce sector; as data is no longer seen as the byproduct of their business activities, but as their biggest asset providing: key insights to the needs of their customers, predicting trends in customer's behavior, democratizing of advertisement to suits consumers varied taste, as well as providing a performance metric to assess the effectiveness in meeting customers' needs.**

This paper presents an overview of the unique features that differentiate big data from traditional datasets. In addition, the application of big data analytics in the E-commerce and the various technologies that make analytics of consumer data possible is discussed.

Further this paper will present some case studies of how leading Ecommerce vendors like *Amazon.com*, *Walmart Inc*, and *Adidas* apply Big Data analytics in their business strategies/activities to improve their competitive advantage. Lastly we identify some challenges these E-commerce vendors face while implementing big data analytics.

1 INTRODUCTION

Over the past years, the capacity of the world to exchange and generate information has increased from 0.3 Exabyte in 1986 (20 % digitized) to 65 Exabyte's in 2007 (99.9 % digitized) (Manyika et al., 2011). Figure 1 illustrates the growth in data from 1986 to2007

For instance, in 2012 Walmart's transactional databases were estimated to contain over 2.5petabytes of customer related data.

The growth of data is fed by the availability of cheaper computing and ubiquity of the internet. Nowadays, virtually everything is done electronically; people exchange information over the internet and engage in buying and selling via the internet (Assuncoa et al., 2013). Ecommerce vendors have taken advantage of the use of the internet to market goods and services, improve revenue and brand awareness. In the year 2012 a survey carried out on businesses in the United Kingdom revealed the following:

- Sales on Website totaled £164 billion, which represented 6% of business turnover (This is a 1% increment from 2011).
- 82% of businesses had a website, while 95% broadband Internet.
- 43% of businesses had social networks accounts, with 23% using social media to respond to customer opinions and questions.

This survey evidences the fact that exchange of electronic information via social media site has positively impacted Ecommerce in terms of revenue and brand awareness.

However, with the advent of big data analytics there will be more informed/ data driven strategies for businesses communicate with consumer. Such that E-commerce vendors/businesses, can harness/analyze the tremendous data (Big Data) generated from Electronic Data Interchange (EDI), in order to gain better understanding of consumer behavior. Such unique insight can be applied to improve customer service, guide business strategy, and provide democratized services to customers. Fig. 2 below illustrates further, the importance of big data analysis to organizations (based on a survey carried out by Mckinsey on 115 leading organizations) (Wielki, 2013)

A practical example of such E-commerce business is Amazon.com –by utilizing special software to analyze cookies and clickstream on consumer browsers, the Company can identify patterns in consumers' shopping habit and hence can provide customized/democratized offers, advertisements and discounts to such consumer (Mosavi & Vaezipour, 2013).

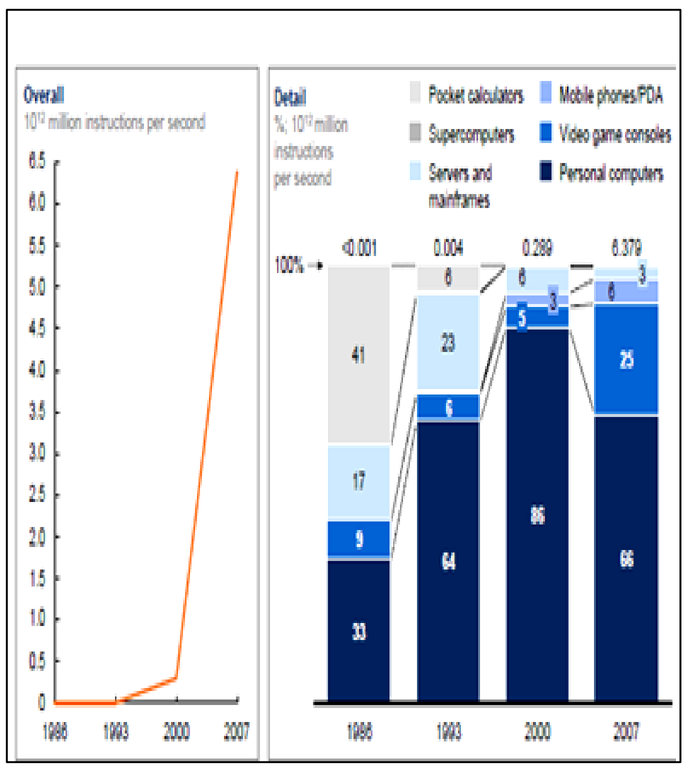

Figure 1: Data growth between 1986 and 2007 (Manyika et al., 2011)

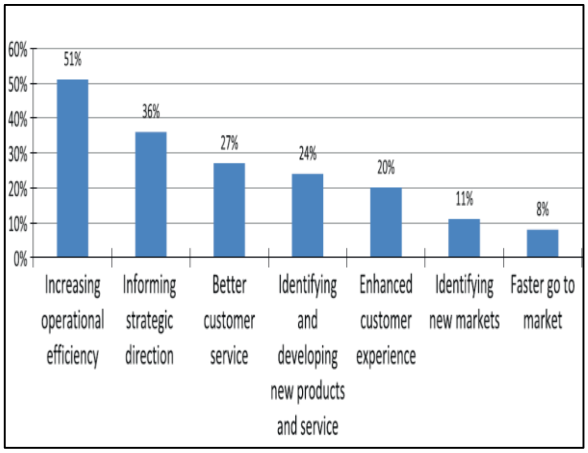

Figure 2: Benefits of Big Data Analysis to Businesses (Wielki, 2013)

1.1 DEFINITION OF BIG DATA ANALYTICS

Presently, there is no unified definition for the term “Big Data", however, the most widely accepted definition of Big data is in terms of 3 characteristics, **volume**, **velocity** and **variety** also referred to as 3 V’s – **V**ariety refers to the heterogeneous nature (made up of structured and unstructured datasets), **V**elocity depicts the speed at which data is captured, and **V**olume refers to the size of data (usually in Petabytes, Exabyte and Terabytes) (Russom, 2011) (Edosio, 2014).

Due to these characteristics, it is impossible to effectively manage and analysis big data using traditional databases. However, using special tools and technologies (such as: Hadoop Distributed files system) Big data effectively managed (management of big data includes process, storage, real-time/near real-time analysis). In addition, when special data mining algorithms (such as: machine learning and clustering algorithm) are introduced to the big data analytical framework, one can derive insight from data (Fan et al., 2013).

For the purpose of this study, we will limit the study of big data analytics to three categories as follows:

1. **Social Media Analytics**: Refers to analysis of large volume of data generated from social media applications/sites (Hea et al., 2013)
2. **Predictive Analytics**: Refers to use of historical data to forecast on consumer behavior and trends (Mosavi & Vaezipour, 2013).
3. **Mobile Analytics**: This refers to the analysis of large volume of data generated from mobile phones, tablets and mobile gadgets (Li & Du, 2012).

2 BIG DATA ANALYTIC TECHNIQUES AND ITS APPLICATION IN E-COMMERCE

2.1 Social Media Analytics and E-Commerce

Social media analytics (SMA) involves the collection of data from social media sites/applications (such as, wiki, Facebook, Twitter, GooglePlus, blogs etc) and evaluating such data to gain insights/knowledge. Social media data can be classified as big data as it bears the 3V characteristics. (For instance each day there is about 35 million status updates, and over 100,000 tweets per minute on Twitter) (Assuncoa et al., 2013).

Social media sites are not just networks of interconnected people, but virtual community, where people interact, exchange information and share opinions. These activities are capable of influencing consumer’s perception on a particular brand. This is

Based on a survey carried out on 6,000 social media users, it was revealed that:

- Almost 40% of social media users have bought an item after “favoriting” or sharing it on a social media site
- 71% of social media users are more likely to purchase based on referrals.
- 74% of consumers depend on social media networks when making decisions on what to purchase.
- Facebook influences 30.8% of social media users purchasing habits, while LinkedIn and YouTube influence 27% of social media site users respectively (Seave, 2013).

As a result of the above statistics, a lot of Ecommerce vendors are adopting social media analytics for the following reasons:

- To gain competitive advantage and business values
- Drive customer traffic,
- Boost customer loyalty and retention,
- Improve sales and revenues, improving customer satisfaction; and most importantly to create brand awareness and build reputation (Hea et al., 2013) (Melville et al., 2009).

Fig 3 below illustrates how various organizations utilize social media sites in their business activities.

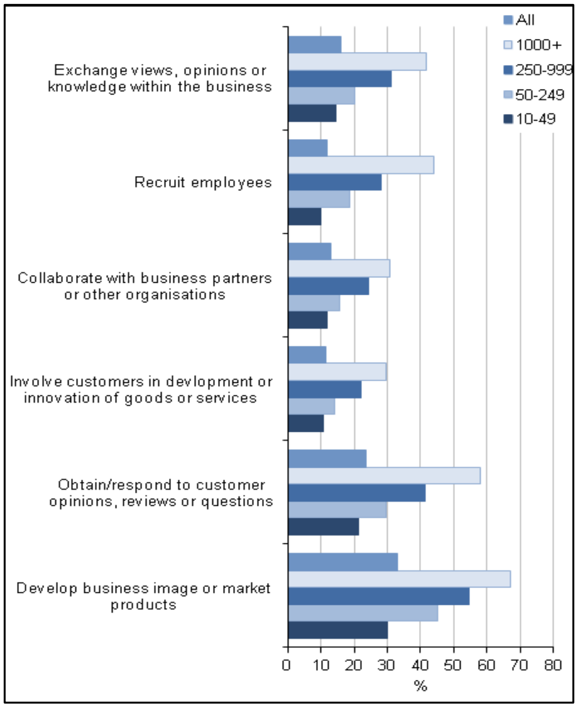

Figure 3: How Organizations use Social Media Sites (Office for National Statistics, 2013)

2.1.1 Technology behind Analysis Social Media Data

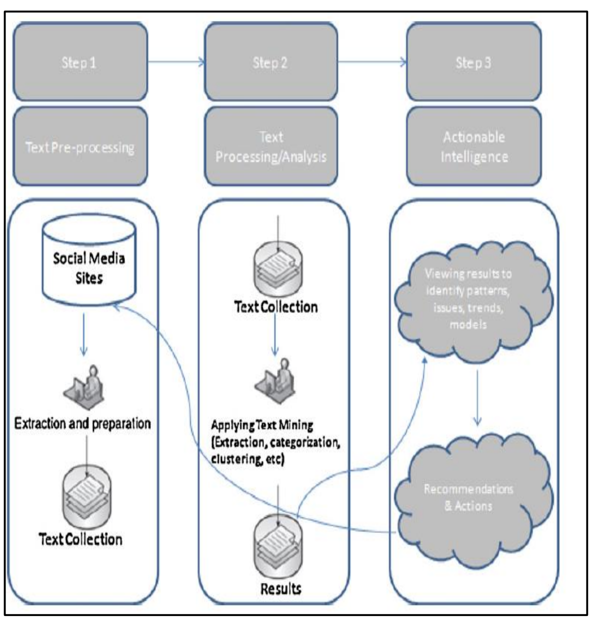

Figure 4: Analysis of Social Media Data (Tan et al., 2013)

Basically there are two common techniques for analyzing social media data, they include: T**ext mining**, and S**entiment analysis** (using machine learning) (Tan et al., 2013)

2.1.2 Text Mining:

This technique is highly dependent on the use of text based content from blogs and social media sites to make judgment on the relevance of an issue. As illustrated in the Fig 4, Text collected is filtered using a keyword filter to retrieve relevant knowledge. The Ecommerce marketer generates list of keywords pertaining to the product being monitored. These key words can be used to identify sentiments about a product (Melville et al., 2009).

2.1.3 Sentiment Analysis (Based on Machine Learning Algorithm):

This technique of analytics works using either a machine learning algorithm or artificial intelligence, to detect sentiments about a particular good on service. Basically each words obtained from the big data is analyzed and tagged, after which it is referenced with a predefined word, or synonym which interprets whether the opinion is positive or not. (Yi & Niblack, 2005)

For instance if a text from a Facebook post says "iphone5 is awesome"

MLP Sentiment Analysis= iphone5 + is+ awesome

Each of these statements is then analyzed (using a predefined sentiment database) to predict the emotions of each word. The term "awesome" is predicted to be positive hence this statement is positive publicity for iphone5.

2.2 Case Study: Walmart Inc. Social Media Analytics

Walmart (referred to as ASDA in the United Kingdom) is an American multinational retail corporation (The Center for Media Justice, 2013).

In April 2011, Walmart purchased Kosmix, a social media start-up focused on e-commerce. Kosmix developed a software application which had the ability to search and analyze social media applications (like Twitter, Facebook, Blog spots) in real-time in order to provide personalized insights to users. Kosmix was also developing a knowledge base application called the "Social Genome" which had the capacity to capture information and relationships about people, events, topics, products, locations, and organizations. When Walmart purchased the company they changed the name to @WalmartLabs.

The Walmart's Social Genome (publicly referred to as Walmart Shopycat) software constantly captures data

from social media sites in real-time with billions of entities and relationships.
The software performs a semantic analysis of social media and feeds its output to a custom built e-commerce applications for Walmart (The Center for Media Justice, 2013).

In January 2013, the Company reported that its social media analytics software project is capable of indexing and searching 60 billion social media documents and in turn help its marketers to understand sentiments, trends, and popular products on a real time basis. The software also has the capacity to see sentiments based on geographic locations and predict trends in all Wal-Mart stores as well as ecommerce stores (The Center for Media Justice, 2013).

3 Big Data and Predictive Analysis

Predictive analytics is the use of past/historical data to predict future trends. This analysis makes use of statistical models and machine learning algorithm to identify patterns and learn from historical data (Shmueli & Koppius, 2011). Figure 8 below has the details. Predictive analytics can also be defined as a process that uses machine learning to analyze data and make predictions (Puri, 2013).

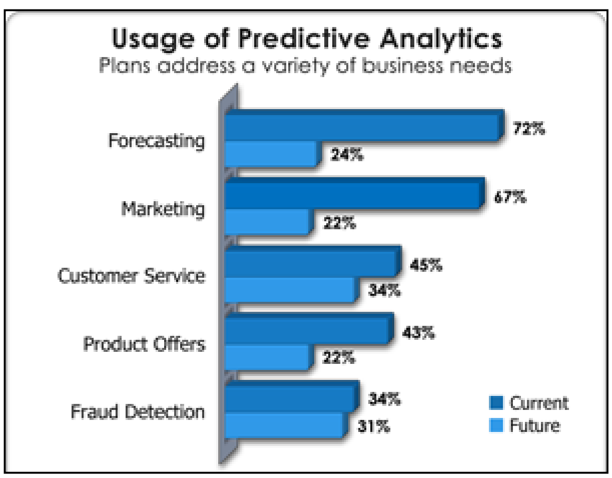

Figure 5: Uses of predictive analytics in an organisation (Millard, 2013)

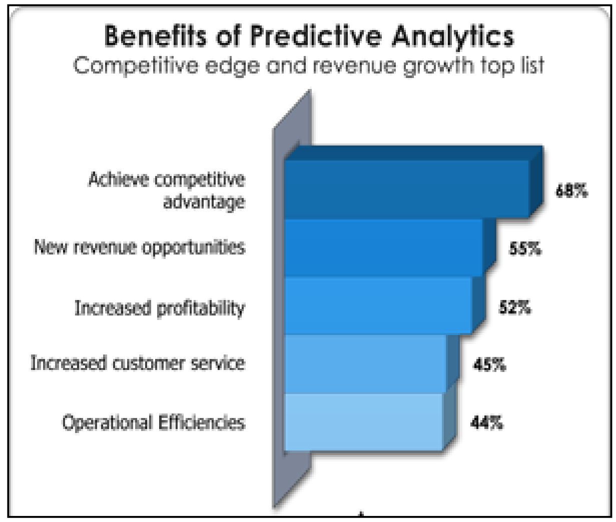

Figure 6: Benefits of predictive analytics (Millard, 2013)

In summary, predictive analytics based on the definitions above, deals with use of data to determine and identify possible future events. This technology has been around for a while, though the adoption has been low because of the complexity and costs. Using the Big data analytical platform to analyze these data (alongside data mining and machine learning algorithm), E-commerce vendor can efficiently predict consumer behavior faster, more efficiently and at more effective cost (Mosavi & Vaezipour, 2013).

There are various applications of predictive analytics to an organization Fig 6 and Fig 7 illustrate the benefits and usage of predictive analytics in organizations. 67% of businesses aim at using predictive analytics to create more strategic marketing campaign in future, and 68% sight competitive advantage as the prime benefit of predictive analysis (Millard, 2013).
Broadly speaking, predictive analytics can be applied in Ecommerce in the following ways:

- Product Recommendation
- Price Management
- Predictive Search

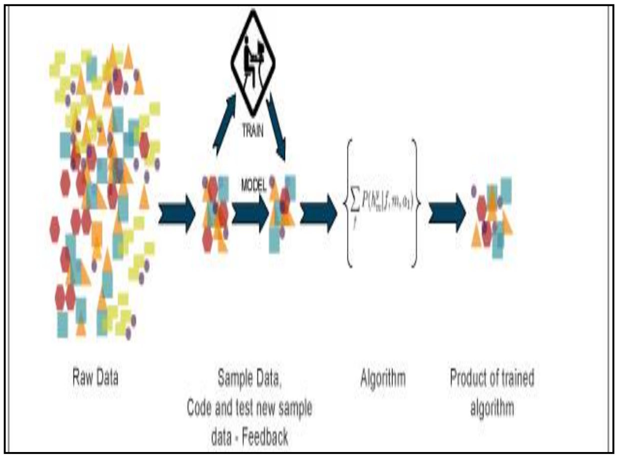

Figure 7: Steps involved in Predictive Algorithms

3.1 Technology behind Product Recommenders on E-Commerce Websites

Typically a large e-commerce site offers thousands of product and services for sale. Navigating and searching for a product out of thousands on a website could be a major setback to consumers. However, with the invention of recommender system, an E-Commerce site/application can quickly identify/predict products that closely suit the consumer's taste (Sarwar et al., 2002). There are two main algorithms/technologies that support the recommendation system:

1. Collaborative Filtering
2. Clustering Algorithm

3.1.1 Collaborative Filtering:

Using a technology called Collaborative Filtering (CF), a database of historical user preference is created. When a new customer access the ecommerce site, the customer is matched with the database of preferences, in order to discover a preference class that closely matches the consumers taste. These products are then recommended to the new consumer (Sarwar et al., 2002).

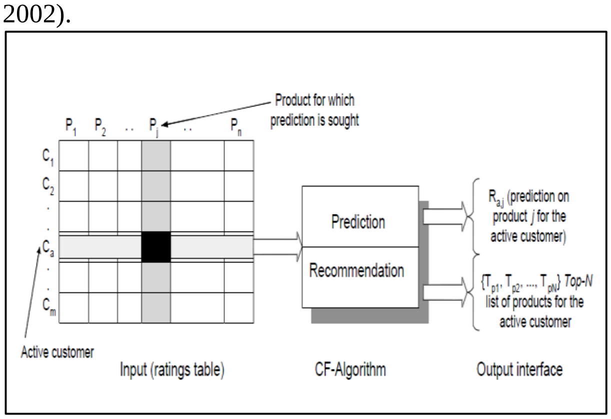

Figure 8: Collaborative Filtering Algorithm based on (Sarwar et al., 2002)

3.1.2 Clustering Algorithm

Clustering Algorithm technique works by identifying groups of users that have similar preferences. These users are then clustered into a single group and are given a unique identifier. New customers cluster are predicted by calculating the average similarities of the individual members in that cluster. Hence a user could be a partial member of more than one cluster depending of the weight of the user's average opinion (Sarwar et al., 2002).

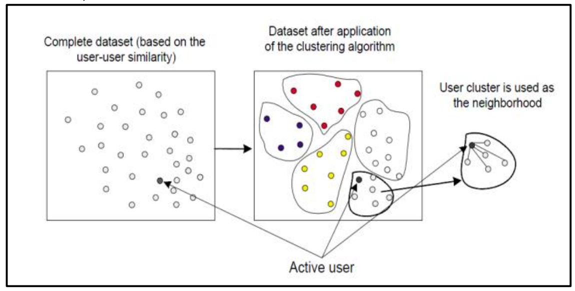

Figure 9: Clustering Algorithm based on (Sarwar et al., 2002)

3.1.3 Case Study: Use of Product Recommender in Amazon.com

Amazon.com is currently the world's largest online retail store. Amazon started off as an online book store and rapidly diversified into production and sales of consumer goods, electronics, and house hold items amongst others.

In Amazon product recommenders are used to personalize each customers experience on the online store. Products are adapted to suits each customers taste (on a real time basis). This is a Big Data challenge as Amazon captures millions of customer's data.

Amazon makes use of clustering algorithms and collaborative filtering to group customers based on preferences. Their product recommender system group's customers into clusters/groups based on:

- Similar search
- Item to Item collaborative filtering.

3.1.3.1 Search based Product Recommender at Amazon.com

Search based (also called content based search) utilizes a consumers purchase history and rated item to create a search query which find other items (such as author or similar genres) similar to consumers taste. For example: if a customer purchases a DVD called the "*God Father*". The product recommender will recommend movies either from similar authors, similar genres, and similar directors (Linden et al., 2003).

3.1.3.2 Item to Item collaborative filtering at Amazon.com

Amazon.com not only uses its product recommendations on its e-commerce store, but also it is used as a Marketing tool in form of email campaigns.

By clicking on the link *"Your Recommendations"* customers can filter product by product recommendation based on items currently in their shopping carts.

- Item to Item collaboration at Amazon.com works by matching each of the users purchased or rated items to an item that is similar.
- The algorithm builds a similar items table by and finding items that customers tend to purchase.
- The algorithm also builds a product-to-product matrix by iterating through item pairs and computes a similarity metric for each pair (Linden et al., 2003).

3.2 Price Management / Dynamic Pricing:

It involves the use of historical data such as: previous purchases, clickstream, cookies, enterprise resource planning systems to dynamically set prices of an item or offer customized discounts. This technology customizes the price/ discount for a particular good to suit a particular customer in real time. Hence, it is possible to two different customers to purchase the same item from an online store at two different prices (Grewala et al., 2011). Whilst this technology has it benefits, customers may get aggravated or feel sense of discrimination due to the price variation.

3.3 Case Study of Amazon.com Dynamic Pricing

Several consumers are becoming increasingly aware of price discrimination in Amazon.com. For instance in September 2000, CNN reported that some customers of Amazon where aggravated over price discrimination on the price of a particular DVD. One the buyers reported that the price of a DVD after deleting cookies on his computer, differed by $2.50 margin. Also figure 10 illustrates a practical example of price discrimination of a particular product by Amazon.com. In another instance, CNN reported that Amazon.com made use of dynamic pricing algorithm while selling a product called "Diamond Rio MP3 Player" for $51 less than its original price (Ramasatry, 2005)

Figure 10: Dynamic Pricing at Amazon.com- The same product has two different prices for two different users

3.4 Wal-Mart: Prioritizing the Point of Sale

In 2013, Wal-Mart Labs purchased a company called Inkiru. Inkiru is a startup that uses predictive analytics in analyzing big data. The predictive technology was designed to capture data from diverse sources and help Walmart create personalized marketing/ merchandising campaigns to targeted customers (Puri, 2013).

4 Mobile Analytics and E-Commerce

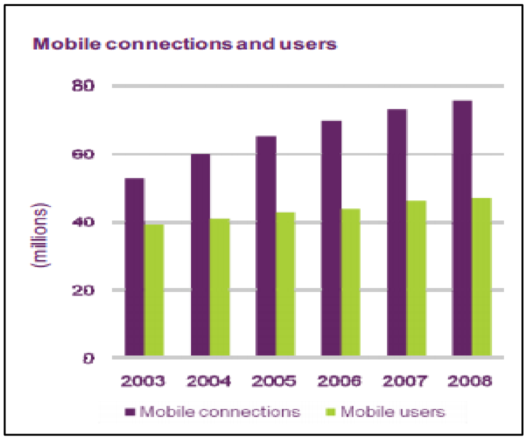

Figure 11: Growth of Mobile users in the UK between 2003 and 2008 (Ofcom, 2009)

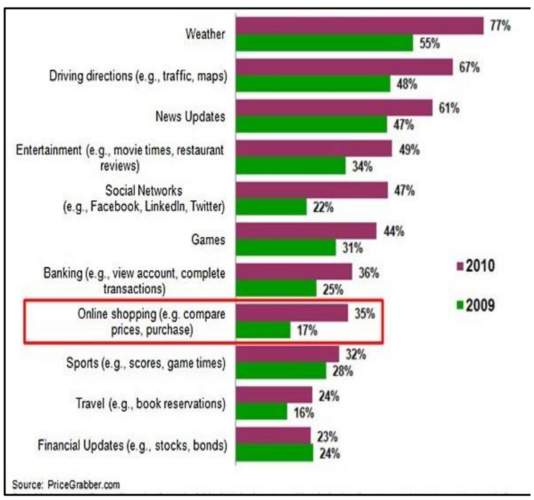

Figure 12: Uses of Mobile phone (Ofcom, 2009)

Over the years there has been massive growth in the number of mobile phone users. The size of mobile phone users in the UK grew from about 40 million in 2003 to over 78 million in 2008(See figure12 for details above) (Ofcom, 2009).

In like manner, there has been radical change in the uses of mobile phones, previously mobile phones where just utilized as a mere tool for communication, however in this era mobile phones are used to perform variety of functionalities such as: send emails, games, track people (using GPS), perform banking transactions , online shopping amongst others etc. Figure 13(above) illustrates the uses of mobile phone (35% of smart phone users admitted to using their mobile phones for online shopping (Ofcom, 2009) (Tao et al., 2012) (Ververidis & Polyzos, 2002). Hence mobile phones can serve as a medium to propagate e-commerce activities.

By analyzing big data generated from mobile phone data exchange, ecommerce companies can provide value added services such as: Geo advertising: Location based discounts. E-commerce vendors can also identify location patterns using existing customer data to convey prospects customized messages to customers in a timely manner (Ofcom, 2009).

Some of the benefits of using mobile phone analytics include:

- It is a much cheaper, effective and timely platform to promote products and services to consumer (Ververidis & Polyzos, 2002).
- Advertisement can be sent in real time based on their locations, and proximity from a store, by leveraging on data mined for GPS information from customers mobile phones (Li & Du, 2012)

4.1 Technologies behind Mobile Phone Analytics

Location-based services aims at offering personalized mobile transactions to some specific individuals at a particular location, by using knowledge of their current location (Li & Du, 2012). Basically the technologies that foster location based marketing include the use of RFID tags, Bluetooth and GPS to identify user’s proximity to a particular location.

Bluetooth location Based Advertiser: This location based system makes use of Bluetooth to target users with special offers at a specific time of the day. For example: Based on studies of users of a particular supermarket, discounts can be offered to targeted consumers. Such discount can be conveyed in- store using the Bluetooth location based service system to target such customers when they are around the e-commerce store (Li & Du, 2012).

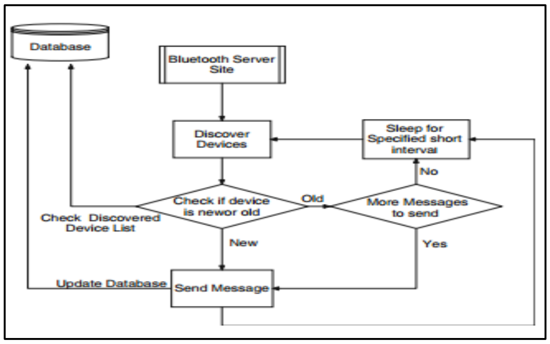

Figure 13: Flowchart of a Bluetooth enabled location based advertisement system based on (Li & Du, 2012)

4.2 Case Study: Adidas "Light You Up" Mobile Campaign

To launch a new product called the "Adizero F50 soccer cleat" Adidas partnered with Mullen's media hub (Mullen is a media and advertising company), the major target for this campaign was mobile users across multiple mobile platforms (Android, Windows, iOS). The aim was to invite them to Adidas' light show, which introduced the Adidas new product (Mullen, 2012).

Using location-based targeting, the Company was able to target users within a three-mile radius of Penn Station and push mobile advertisements in relevant mobile applications (like Facebook) and in some cases SMS. The advertisement read: "Adidas and Messi — After Dark Tonight." Customers where redirected to a landing page which displayed the promotional video describing the event, the location and the time (Mullen, 2012).

This feat was achieved using big data analytics to filter customer's locations and streamlining (in real time) manner the locations of thousands of to push advertisement notifications to them.

The outcome of this campaign was a huge success

- it reached 7.3 million users,
- there were 45,856 clicks to the Adidas shop,
- Over 15,000 shares on social media sites.
- 7.6 million People watched it live.

5 CONCLUSION

In as much as big data analytics hold much promises for providing business insights, analyzing consumer behavior- it is not without its unique challenges. According to research, the largest obstacles to big data analytics are staffing and training , followed by privacy constraints. Majority of consumers are concerned about how their personal identifiable information is used. Privacy expert believe that Big Data analytics is an infringement on privacy of our daily lives.

Despite these challenges a lot of companies are moving ahead to adopt big data in their e-commerce strategies. According to Mckinsey in (Manyika et al., 2011), majority of the top five business organizations in the USA claim to yielding tremendous growth. Hence, noting the promises big data analytics holds for e-commerce there is need to train necessary skills and build good governance framework for big data analytics.

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