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IMPROVING THE QUALITY OF MARKETING ANALYTICS SYSTEMS

Abstract*: This review aimed at providing a systematic review of the current status of marketing analytics systems, and identifies possible areas of improving their quality. A total of 49 papers were shortlisted and reviewed under different sections. The following general trends could be noted. Marketing analytics involves complex processes of analysing large volume of qualitative and quantitative data over a period of time to evaluate the success of marketing activities in terms of firm performance. Many successful firms have used this technique and this is one reason behind their improved performance. Many leading business organisations are using marketing analytics, the full potential is yet to be realised in spite of continuous arrival and further development of new software technologies and processes of marketing analytics. Especially, big data analytics offer more precise measurement and prediction of customer engagement and buying behaviour. At the same time, there are also challenges and barriers of top management support, lack of funds and resources, lack of enthusiasm, lack of skills and above all how to take decisions based on the results of marketing analytics. Addressing these challenges can improve the quality of marketing analytics systems and the ultimate results. This research has practical implications for firms which use marketing analytics systems.*

Keywords: *Marketing; Analytics Systems; Quality; Review.*

1. Introduction

Marketing analytics is a subject dealing with the processes and technologies of evaluation of success of marketing activities by marketers. As marketing activities expanded in its scope and technological applications over time, evaluating its effectiveness based on the data from one or two of the marketing channels became insufficient. A holistic picture integrating the data from all channels became necessary. Marketing analytics evolved from this requirement (SAS, 2020). Examples of Netflix, Spotify and EasyJet were given as the firms using marketing analytics successfully for enhancing their performance by Aeroscop (2019).

There is no doubt that marketing analytics contributes to the financial performance of firms, the extent of which is positively influenced by competition in the industry and rapid consumer behavioural changes. The factors determining effectiveness of deployment of marketing analytics are support from the top management team, a supportive analytics culture, appropriate data, information technology support, and analytics skills (Germann et al., 2013). This paper reviews the research done on the development, methods and outcomes of using marketing analytics, and identifies possible areas of improving their quality.

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2. Methodology

The methodology used for this paper is a systematic review. The title of the paper was used the keyword. To select the papers, the first five pages of Google Scholar was searched with ‘Any time’ as the period of search and the process was repeated using time frame of 2016 and later. Only English language papers were selected. Abstracts were also included if they contain important information and full text is not available. A total of 61 papers were yielded using the above mentioned approach, out of these 49 papers of various types were shortlisted to be reviewed after removing duplicate and irrelevant papers. The selected papers are discussed under the following sections.

3. Result

3.1 History of marketing analytics

The history of marketing analytics was traced by Wedel and Kannan (2016). Systematic use of data by Charles Coolidge Parlin for the Curtis Publishing Company in Boston in marketing started in 1911. The data gathered by Parlin was used by advertising and publishing firms. Many companies established commercial research departments as a result. In 1919, Duncan stressed on both internal and external data. Questionnaire surveys were already popular in 120’s as Gallup used it for opinion polls. This was found extremely useful in marketing research. Psychological concepts also were introduced with the attention-interest-desire-action model of Starch in 1923. This was followed by many copy research. A.C. Nielsen established the first marketing research company in 1923. Nielsen started measuring product sales in stores and in the 1930s and 1950s, started evaluating radio and television audiences in the 1930’s to 1950’s. Another firm, Burke was set up in 1931 and it began with product testing research for Proctor & Gamble. GfK was established in Germany in 1934. Field experiments and telephone interviews and surveys were popular in the next decade. Panel data was found increasingly useful for various types of marketing research. Recency, frequency and monetary metrics introduced by George Cullinan became the forerunner of CRM. Companies started using their own data in 1961. Warehouse withdrawal data was measured by Selling Areas marketing Institute from 1966. Use of computers was also started around the same time. From late 1970s, Claritas started gathering geo-demographic data in a large way by sourcing from government databases and credit agencies based on the work of Charles Booth, a sociologist, around 1890.

Universal Product Code and IBM’s computerized point of-sale scanning devices in food retailing were the first automated data capture systems for retailers introduced in 1972. Nielsen took advantage of these quickly. Loyalty cards enabled traceability of individual customers. Scanner panel data (1983) and in-home bar coding system of IRI (measuring television advertising fromm1979) in 1995 followed. Introduction of personal computers in 1981 by IBM use of internal customer data. In 1990, CRM software was released in 1990 based on the earlier work on sales force automation at Siebel Systems. Personal computers also helped in survey research using personal and telephone interviewing. Large amounts of marketing data became available with the introduction of World Wide Web in 1995. Now, clickstream data could be extracted from server logs to track page views and clicks using cookies. These data facilitated measurement of effectiveness of online advertising. CRM systems were developed by Oracle as the internet facilitated it. Salesforce first delivered CRM systems through cloud computing in 1999. Coming of Google started the search engine methods for data search using computer keyboard. A file transfer protocol search engine, Archie, was developed by McGill University. User-generated content, including online product reviews, blogs, and video, resulted in increasing volume and variety of data were some of the data trends that followed. Introduction of Facebook in 2004, Twitter in 2006 and any other similar sites and YouTube in 2005 marked the beginning of social networking data in large volumes. Introduction of smartphones, especially global positioning system in Apple iPhones, enabled capture of consumer location data.

These were the data generation, storage in databases and its acquisition by firms. The analytics part was pioneered by Ford Foundation and the Harvard Institute of Basic Mathematics for Applications in Business during 1959-1960. Statistical methods preceded econometric methods as decision making tools through the efforts of Marketing Science Institute since 1961. Many other analytical methods and software for automation followed in quick succession and is still continuing. Similarly models and frameworks, models of customer psychological behaviour are being developed continuously to increasingly facilitate marketing analytic methods and strategic decision making. However, while some surveys indicate positive perceptions and high levels of applications of marketing analytics by firms, others find lower enthusiasm among firms due to lack of knowledge and enthusiasm and top management support to implement marketing analytics. From the above details, it can be seen that most of the marketing analytics developments took place in USA.

Six areas of marketing analysis- strategic evaluation of investment projects, profitability of products, contribution of marketing programmes to margins, sales reporting and analysis, sales planning and forecasting and pricing- were discussed by Petti (2012). A comprehensive review of marketing analytics was provided by Iacobucci et al. (2019).

3.2 Methods of marketing analytics

There are many sources which describe methods of marketing analytics. Some of the recent ones are Rackley (2015), France and Ghose (2019), Hemann and Burbary (2013). Highlights of marketing analytics has been provided in the book by Rackley (2015), which are given briefly below.

Analytics dashboards help marketing engines run effectively. He demonstrated the importance of true marketing analytics in a number of ways. An example of how marketing analytics of various digital tools can achieve good results was explained in detail. The analytics process consists of-

a) Identify the metrics using objective, efficiency and effectiveness as the guiding factors.
b) Analysis of metrics using web analytics, CRM and marketing automation tools. Compare the current state with the desired state to determine the root cause of to explain why these two are different. Historical and benchmark data are very helpful.
c) Take actions to improve by examining and selecting the option closest to achieving the objective. Methods like A/B testing can help to identify the most desirable action.
d) Repeat the above steps as many times as possible to confirm conclusions.

To start marketing analytics, its need, readiness and organisational context should be assessed. Capabilities and skills of various types for analytics need to be built up. The required data and analytical tools and systems need to be in place. The metrics can now be firmly established. Then the whole arrangement needs to be reviewed and corrected if necessary, before launching marketing analytics. Return on investment made on marketing (MROI). But ROI cannot measure the soft benefits like increased brand awareness due to a campaign etc. Many other challenges exist in measuring MROI. Apart from ROI, other metrics like market share, customer lifetime value, retention rate, and cost of customer acquisition are also important. MROI needs to be read along with these metrics. A dashboard or a score card score board is required for regular and continuous monitoring of progress in meeting the marketing objectives. There are multiple sources of data for marketing analytics including web analytics data, CRM systems, social media, email marketing systems, Excel spreadsheet data, sales transaction data, marketing automation systems, accounting systems, external demographic data and ERP systems listed in the decreasing order of the extent of using these tools. Software is available to handle these data and create the dashboards. The dashboards need to have the facility to continuously updating the data. A series of dashboards with the details required at various levels of management is ideal.

- Technology: the base platforms, systems, or clouds of technology that enable core marketing processes and results tracking.
- Tools: focused software solutions that enable specific functions, such as the dashboard functionality.

Various tools based on well-known methods of data analysis are available. There could be some barriers of implementing marketing analytics in organisations like lack of support from the top, lack of enthusiasm among people in the marketing department as well as in the organisation itself. Marketing department may not have the freedom to use creative freedom to explore new innovative solutions. Instead they may be forced to follow a certain reporting format always. This also affects motivation and enthusiasm among marketing department staff. Many frontier level applications are springing up rapidly. Big data, predictive modelling and advanced attribution to properly and precisely allocate fractional conversion credit for the ultimate outcome to the firm across the entire media stream that customers are exposed to on their buying journeys.

In their article, France and Ghose (2019) observed that global market for business intelligence guided by marketing analytics was estimated to be around $200 billion in 2020, increasing from $130 billion four years ago. This growth was made possible by data. There had been information explosion caused by many corporate databases, mobile-apps, web analytics data, social media and sensor data. Data analysis has been used widely in marketing. The main objective of firms in using data analytics had been to improve customer relationships. The main challenges in this respect are identifying relationships between diverse data spread among many sources, predicting the customer behaviour, and predicting sales of the product or service. The authors identify data mining, expert systems, marketing science, operations research and statistics as core disciplines of marketing analytics. The business areas covered are branding strategy, acquisition, insight and retention of customers, digital marketing, product development and positioning and promotion strategy. The authors describe the concepts and methods related to visualisation of data, segmentation and grouping and class prediction aspects of analytics with some mathematical treatments and listing of useful software.

The book by Hemann and Burbary (2013) deals solely with digital marketing analytics. The principles, methods and practices of analysing data from various digital sources to understand the customer behaviour, predict and devise marketing strategies are explained. According to Hair (2007) predictive analysis in marketing contributes to conversion of information to knowledge. Methods of accessing and analysing big data were discussed by Wedel and Kannan (2016). The taxonomy of knowledge fusion occurring when traditional marketing analytics is used for application in big data was explored by Xu (2016) and noted that deliberate strategic options are required to achieve the intended benefits from such a knowledge fusion. A big data analytical framework for gaming in real world situation was developed by Nair et al. (2017). The framework was implemented and evaluated for casino operations in MGM Resorts International group. Individual transaction data were fitted to empirical models of consumer responses to the marketing efforts. The estimates were used for optimised targeting and segmenting the market.

The increasing profits resulting from its implementation was $10 million to $15 million per campaign equivalent to 20 cents per dollar spent. Erevelles et al. (2016) advocated inductive rather than deductive reasoning in big data analysis. Risk based testing, ignorance, radical innovation and creative intensity were listed as useful factors for deriving full benefits of big data analytics in marketing research. In the case of luxury brands also, Liu et al. (2019) used big data from Twitter accounts of five years of July 2012 to June 2017, consisting of 3.78 million tweets on 15 luxury brands having the highest number of Twitter followers. The results indicated customer engagement to be more important than customisation. Important dimensions of customer engagement that increased social media marketing were entertainment value, brand interaction, and trendiness pf the luxury brand.

In a review of big data analytics, discussed the key concepts and issues regarding social big data, their features, technologies used in marketing, an operative methodology which may provide useful insights from social big data, some recent use cases, issues and further research. There is exponential increase by several billions of posts in social media. Kauffmann et al. (2019) used a framework to automatically analyse consumer rating reviews, in which, negative and positive opinions were transformed into a quantitative score. Sentiment analysis was employed to analyse online reviews on Amazon. A Fake Review Detection Framework (FRDF) was used for detecting and removing fake reviews using Natural Language Processing (NLP) technology. Brands were rated according to consumer sentiments. The framework was found useful more comprehensive decision-making, especially with the use of FRDF to rank best products by price, their respective sentiment value and a 5-Star score.

Inductive fuzzy classification system developed by Kaufmann (2012) can be applied to customer analytics on existing data using attribute selection and visualization of inductive membership functions provide insights into different customer classes. Product analytics can be improved by evaluating likelihood of product usage in the data for different customer characteristics with inductive membership functions. Transforming customer attributes into inductive membership degrees, which are based on predictive models, can optimize target selection for individual marketing and enhance the response rate of campaigns. A case study of a Swiss online service marketing firm was used for validating the model. Implementation of prototype and experimental study were also done.

Deep learning offers promise with impressive results in AI applications. Examples are Apple Siri conversion of human voice into computer commands to answer questions of Apple users, automated driving through highways and development of DNA-based medical products. In this respect, Urban et al. (2020) obtained better results with use of deep learning software than the traditional regression methods for prediction of credit card preferences of customers from online customer sessions of NerdWallet site. Demographics and card attributes were used as the variables. However, the authors cautioned against economically unworthy use of deep learning as benefit to cost ratio may not be high enough to support investment in this technology. The scope of AI and machine learning in enhancing marketing performance of firms was discussed by Even (2019).

Although the software, SmartPLS provides a frictionless design, permitting quick specification and estimation of partial least squares (PLS) path models, it focuses more on the complicated setup of the model and statistical analysis rather than the interpretation of results and theoretical meaning for a project. Complicated interface of a software is need not make it rigorous. Mechanistic attention to the software and data does not lead to useful results. Access to both big data and software to analyse them are important. Data, empirical models and results are not theory, but descriptions of specific observations of empirical patterns. Theory is still required to explain the observed patterns. Risk of confirmation bias may occur when confirmatory approaches to analytics and data mining are done. Such problems can be avoided using comparative approaches to judge the applicability of theories with many working hypotheses or explanations. Thus, rigor of data analysis and theoretical relevance are simultaneously important (Petrescu & Krishen, 2019).

Copulsky et al. (2017) dealt with the progressive shifts from access to tools to automation of activities to real-time predictive analytics. Increased attention on marketing technology solutions supporting embedded analytics leading to marketing attribution will be the next focus in future. The next-best-action marketing solutions will be sought here. However, Success of organisations in integrating and harmonising customer data in real time will determine the success of such efforts.

Monte Carlo Stimulation (MCS) is useful for integration of different components in marketing analytics. Usefulness of MCS for integrating customer behaviour models, market/customer segmentation levels, customer service, CRM software testing were explained in the form of case studies. However, certain issues like verification and validation problems and heavy computational requirements exist. Software available for MCS are costly (Furness, 2011).

As digitization of the retail industry has been rapidly evolving, there is an equally growing wealth of event-based tracking data on consumer behaviour in terms of online clickstreams and offline sensors tracking the movement of shoppers etc. On the other hand, stronger regulations on data privacy and increasing consciousness of consumers about protection of their privacy imply availability of data restricted to an anonymized and fragmented form sans exact identify individual consumers. A methodology for analysing anonymised and fragmented event-based (AFE) data was proposed by Kakatkar and Spann (2019). It allows to approximate recovery of heterogeneity at individual-level and derive important variables from the raw data. To validate the methodology, representative data were collected by deploying sensor-enabled shelves in a field experiment within a store and analysed by the authors.

The combined use of marketing analytics, social media and brand communities have contributed to more innovative methods of customer engagement across various industries. Further integration of marketing analytics with artificial intelligence (AI) has further enhanced the capabilities of marketers to understand customer engagement better (Nagaraj, 2020).

In a review, Järvinen and Karjaluoto (2015) noted that the benefits of marketing performance measurement for any firms depends upon the nature and extent to which the organization exploits the metrics system under any specific circumstances. Web analytics will be particularly useful for companies having complex selling processes to enhance their business performance.

In digital marketing (DM), web analytics (WA) and Key Performance Indicators (KPIs) are required for the devising marketing strategy. In this connection, Saura et al. (2017) surveyed the different DM metrics to determine the most relevant metrics and KPIs to increase the effectiveness of their DM strategies. Lists of these have been presented in the paper.

The advantages of machine learning methods to handle and process large volumes of marketing related data were discussed by Booth (2019). Firms can improve their performance by implementing marketing analytics, as the insights from implementation provided by Kumar and Sharma (2017) reveal.

The most important use of marketing analytics is social media analysis. However, one important method has not been utilised fully yet. It is the analysis of customers' affective experiences appearing in the social media content. Jussila et al. (2017) used action design research, to develop a framework for analysis of the affective experiences from social media content. In this framework, different emotional categories and their intensities in terms of affective experience is measured. It is an advanced method of the generally used sentiment analysis method used for analysis of social media content. Marketers can use this framework to evaluate even the weak emotional signals of the customers and devise strategies to lead the customer to an emotional path of higher value. The framework was pilot tested with an intention to use more widely. A systematic review of literature on social media analytics and metrics for marketing purposes was published by Misirlis and Vlachopoulou (2018).

3.3 How firms use marketing analytics - examples of firms

Wedel and Kannan (2016) mention the Wal-Mart as an example of big data analytics, Netflix as an example of a highly centralised and AT & T as an example of decentralised marketing analytics. In the case of big data analysis at Walmart, the company built a capability to process 2.5 petabytes of data per hour through its own cloud. A state-of-the-art analytics hub, Data Café has been created for this purpose. The facility handles about 200 streams of internal and external data, which includes 40 petabytes of recent transactional data. Walmart uses over 200 external sources of information including meteorological data, economic data, Nielsen data, telecom data, social media data, gas prices and local events databases. All these data can be modelled, manipulated and visualized. Teams from any business unit anywhere in the world can seek solutions to their problems from the analytics experts. The solutions will be displayed within short time spans of minutes on the touch screen smart boards of the centre. Quick processing of big data saved a lot of money for Walmart by preventing any loss of sales. The analytical algorithms enables the quick processing of all data. However, separate data silos also exist at sore levels to manage inventories, customer loyalty and price comparisons. The ability of analysing such vast amounts of data from hundreds of sources very fast is matched by the ability to take decisions and implement them also fast (Marr, 2017).

A marketing mix profiling of big data analysis was provide by Fan et al. (2015). Data requirement, methods of analysis and applications for the five P's of marketing mix (people, place, product, promotion and price) were considered in this framework. Using multi-industry dataset, Hallikainen et al. (2020) analysed the effects of customer big data analytics on performances in terms of customer relationship and sales growth of 417 B2B firms and both were significantly improved by customer big data analysis and structural equation modelling.

According to Benoit et al. (2020), although there are threats and obstacles, challenges and opportunities to create value also co-exist. These opportunities need to be explored and exploited by implementing marketing analytics.

In a review, 11 types of uses of web analytics by companies were identified by Chaffey and Patron (2012). Although these tools have been widely adopted, their usage rates were low, especially in customer journey analysis and segmentation. However, all surveyed companies recognised the need to improve on their usage in identifying "key performance indicators (KPIs), funnel analysis, mining internal search data and integrating user testing and analytics”. Barriers identified were lack of resources, funds, strategy and ownership, organisation culture, inter-departmental conflicts, siloed organisation, poor technology, poor integration among various systems and dependence on third parties. Suggestions to improve the situation have been given.

Use of mobiles among consumers is increasing rapidly causing customer behaviour changes. Some questions in this respect, are whether meaningful advertisement is possible considering the small screen size of mobiles, whether mobile advertising becomes intrusive or invisible to customers and are these possible to be scaled. For firms, the important question is the financial performance outcome (ROI) per unit of currency spent on mobile marketing. To answer these questions, Mobile Marketing Association (MMA) conducted an industry-wide research program, SMoX, the details of which were reported by Bakopoulos et al. (2016). The first SMoX studies were done on the in-market campaigns with AT&T, Coca-Cola, Walmart and MasterCard. Real life campaigns were used for collection of data. The collected data were analysed using experimental design and statistical modelling conducted. The collection and analysis of data were done continuously throughout the campaign duration. All media exposure data were collected. New technological innovations were used to measure mobile’s value even in situations of low allocation to mobile media. This is usually a problem in many other methodological approaches. Variables measured were sales behaviour, foot traffic to stores and brand impact to obtain a comprehensive picture of advertising ROI. The results showed strong contribution of mobile on campaign effects even to the extent of double that of campaign average. Reallocation to mobile campaigns did not require additional investments. ROI from mobile increased by 100-160%. The company-wise results were as follows-

AT&T aimed their campaign to maximise the awareness of their new handset (Motorola Moto X) and achieved twice the awareness (number of people who became aware) per dollar spent in comparison with television and digital modes.

The goal of MasterCard was to increase the link of the card with travel. In this case, mobile was 1.7 times more efficient in terms of driving image (‘Good Card to Carry When Travelling’) compared to the campaign average.

Walmart evaluated its annual Back to School campaign and found mobile as the most efficient channel, driving almost twice the sales in comparison with the campaign average and more than twice compared to television. It also increased verified foot traffic as location ads produced a significant improvement compared to control.

Coca-Cola obtained 25% of increased awareness, 9% increase in its image of ‘Home Brewed Taste’ conversions and 6% increase in sales with 5% of budget with mobile marketing first ever national campaign for Gold Peak tea in North America.

Coca-Cola in China tested a campaign for the Chinese New Year and found mobile producing almost double the ROI over television. It was also twice as efficient in driving sales compared to the campaign average. Out of the total, 8% of the sales generated by the CNY campaign was due to mobile, which constituted only 4 % of the total marketing mix.

Bhandari et al. (2014) cited a successful example of a property-and-casualty insurance company in the United States increasing its marketing productivity by more than 15 percent each year from 2009 to 2012 consecutively. At the same time, marketing cost was the same for the entire period. But the spending across the industry increased by 62 percent. The company attributed its success to marketing analysis helping in decision making better.

In UK, a survey of 221 firms led Cao et al. (2019) to conclude that the dynamic capability to perform marketing analytics, along with marketing decision making, enhances their competitiveness. This finding endorsed the dynamic capability theory of Teece et al. (1997). The 221 firms represented manufacturing, retail, wholesale, professional, financial, technology and many other sectors.

Marketing performance and predictive analytics was used by Dasan (2013) to evaluate the current and potential international competitiveness of some high performance SMEs in different countries, with some studies on Czech and Russian SMEs. A significant proportion of them were exporting. SMEs in BRICM (Brazil, Russia, India, China and Mexico) and G7 countries had more partners in developed countries.

There were difficulties in establishing contacts and customer base in export destination countries for these SMEs. Logistics was a strong point for these SMEs. Mean revenue per invoice was steady for Russian SMEs and increasing for Czech SMEs and the trend was projected to continue in the future. The usefulness of marketing analytics to measure customer behaviour in SMEs was assessed by Miles (2014). Three significant marketing analytics on customer behaviour (customer turnover/frequency; velocity of profit/payment for services), marketing behaviour (potential of product/services; economic conditions), and economic behaviour (pricing adjustment; market barriers) of 198 SMEs were done. The results showed moderately significant predictability of customer behavioural patterns by marketing behaviour analytic. The economic impact of National Football League's Super Bowl events in term of the largest consumer spending event is very high. Consumer spending in this staggering event is in the range of $10-15 billion over the last decade. Indianapolis won the bid to host this event in 2012, The city used social media analytics to evaluate the perception of the public on its Super Bowl marketing efforts. The city wanted to project hospitality and accommodation as two strong points as a promotion campaign for consumer spending in Super Bowl as well as a tourism attraction as its long-term objective.

Vorvoreanu et al. (2013) used the contents of Facebook and Twitter which were available publicly for customer sentiment analysis. A total of 71063 tweets and posts were collected over the five day period of the Superbowl event. Majority of the public sentiments were neutral. But only very few were negative. Issues related to negative sentiments were identified by further analysis through word clouds to take immediate actions. Post-event, the media chats were very positive about hospitality. There were more negative sentiments about accommodation especially limited expensive lodges, large crowds and limited parking space.

In their work, Branda et al. (2018) studied on the factors of marketing analysis organisation (MAO) in B2B firms with the assistance of subject matter experts. It was found that marketing analysis orientation of business organisations depended upon funding, top management support, how analytics is understood and recognised in the organisation, professional experts in marketing analytics department, favourable risk environment in the organisation and extent to which the results of marketing analytics is used by the company.

Social media analytics was used by Kefi et al. (2017) to evaluate cultural effects on Facebook brands of a French beauty and cosmetics firm operating in both France in French and Saudi Arabia in Arabic. It was found that the company is publishing both global and culture specific content on its French and Saudi Arabian Facebook brand pages, which leads to two different types of reactions from these communities according to their culture. In Saudi Arabia, ‘big smoky dark eyes’ is one significant female aesthetic ideals in the Arab culture, along with an amber fragrance and a darkened skin.

Moreover, in the Muslim tradition, women are veiled; so, it is permissible to highlight the face, especially the eyes.

In French branded content, augmentation-focused product specialities are highlighted. In Arabic content, more visual and ludic contests are stressed. This difference due to the differences of individualistic culture of France and collectivist culture of Saudi Arabia. Cultural targeting of brands have been very successfully applied a few other companies like McDonald and KFC. Social media appears to be the best way to communicate such targeting to the concerned audience selectively.

The online survey results from 289 Chinese firms by Cao and Tian (2020) showed that use of marketing analytics was associated with CRM and brand management capabilities in a positive manner and in turn, were related with marketing performance.

Some novel technological trends currently used by retailers to obtain consumer data and marketing analytics were discussed by Petrescu and Krishen (2018). They included IP addresses, geo-fencing data, beacons, behavioural data from the Internet of Things, automated facial recognition data, and radio frequency identification (RFID) tags. Specifically geo-conquesting is a method of competitive locational targeting done by sending mobile promotions to consumers located near competitors.

In the current data environment, tolerance towards the diversity of methodologies and methods has been instrumental for understating, explaining and predicting marketing phenomena. This is especially relevant in the context of rapid growth of global datasphere from 33 zettabytes in 2018 to 175 zettabytes by 2025 and about 30% of the world's data requiring real-time processing, of which, about 80% will be unstructured. Using and processing such voluminous data will require diverse technologies and methods. This is the reason for advocating tolerance towards the diversity of technologies and methods and considering their availability as strength rather than as weakness (Petrescu & Krishen, 2019). The issue of data privacy becomes relevant here. Citing the example of Facebook Cambridge Analytica episode, this issue was discussed in detail by Petrescu and Krishen (2018) as marketing analytics using big data and internet of things can amplify these problems even for those whose data were not collected. Too much privacy and security of personal data can hamper market analytics. So, a balanced approach is required.

Cognitive computer systems are still rapidly developing. They can transform the way in which information is used in business applications. Cognitive system has the advantage of collecting the relevant data of interest by itself based on pre-set criteria. The data so collected is analysed for frequency of references to certain brands and how everyone perceived about it.

Demographic and geographical spread of awareness about brands and products can also be measured using this method. Cervenka et al. (2016) used IBM Watson Analytic tool to analyse unstructured data found on social media to measure the price perception among university students (18-25 years age) of a new Samsung product (Samsung Galaxy S7) during the first two months from its launch covering the period of 3rd January 2016 to 4th March 2016.

4. Conclusions

Although many leading business organisations are using marketing analytics, the full potential is yet to be realised in spite of continuous arrival and further development of new software technologies and processes of marketing analytics. Especially, big data analytics offer more precise measurement and prediction of customer engagement and buying behaviour. At the same time, there are also challenges and barriers of top management support, lack of funds and resources, lack of enthusiasm, lack of skills and above all how to take decisions based on the results of marketing analytics. Addressing these challenges can improve the quality of marketing analytics systems and the ultimate results. This research has practical implications for firms which use marketing analytics systems.

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