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Data Analytics in CRM Processes: A Literature Review

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Abstract – **Nowadays, the data scarcity problem has been supplanted by the data deluge problem. Marketers and Customer Relationship Management (CRM) specialists have access to rich data on consumer behaviour. The current challenge is effective utilisation of these data in CRM processes and selection of appropriate data analytics techniques. Data analytics techniques help find hidden patterns in data. The present paper explores the characteristics of data analytics as the integrated tool in CRM for sales managers. The paper aims at analysing some of the different analytics methods and tools which can be used for continuous improvement of CRM processes. A systematic literature has been conducted to achieve this goal. The results of the review highlight the most frequently considered CRM processes in the context of data analytics.**

Keywords – **Analytical CRM, data analytics, data mining.**

I. Introduction

Data analytics research has its origins in the 1970s. However, it has experienced a recent explosion of publications since 2008, chiefly, due to improvement of computing technologies. The data analytics literature has been growing over the past few years, attracting a steady stream of research and journal publications. Today many companies that consider themselves market driven are still organised around their products. In the era of rapidly changing, globalised economies, and highly competitive markets, transformation from a product-centric focus to a more customer-centric view is required. Customers expect personalised products and services because they know that companies have data about them and the opportunity exists to provide customisation. Nowadays, the ability to generate useful information from data is essential for CRM specialists. This can be achieved by using data mining (DM) techniques to find the hidden and unknown customer information from customer data and, thus, achieve effective CRM. According to the 2016 Digital Trends in Financial Services study, 62 percent of respondents indicate a single customer view is a top priority in the advancement of digital maturity [1].

Demographic, socioeconomic or geographic characteristics of the customers are the traditionally and widely used variables for the customer analysis. Customer intelligence data mining models may be the most powerful and simplest technique for generating knowledge from CRM data [2]; however, this approach does not consider the customer behaviour data [2]. Data analytics provides an opportunity to transform from a product-centric focus to a more customer-centric view [3]. Data analytics, supported by CRM, can be used throughout the organisation, from forecasting customer behaviour and purchasing patterns to identifying trends in sales activities. Data analytics needs to be used to form responses to real time shifts in customer actions and behaviour.

Effective CRM using data analytics has many stakeholders, including data mining practitioners and consultants, data analysts, statisticians, and CRM officers. Historically, business intelligence and data warehouses have been associated with back office employees. Over time, knowledge workers got directly involved in data analysis and developed abilities to perform rich and diverse analytical activities. Pervasive BI is the ability to deliver integrated right-time DW information to all users, including front-line employees, suppliers, customers, and business partners [4]. As usage matured, requirements to include predictive analytics, event-driven alerts, and operational decision support have become the norm [4].

The present paper provides a systematic review of literature related to application of data analytics techniques in CRM published in academic journals and other reports between 2013 and 2017. The specific research questions addressed are: 1) used data mining techniques in each phase of the customer lifecycle, 2) used CRM functional solutions in each phase of the customer lifecycle, 3) used data mining technique in CRM functional solutions. It builds on earlier work by Ngai et al. [5] focusing solely on data mining in the context of CRM systems.

The paper is organised as follows. Section II describes the research methodology used in the study. Section III reviews data analytics in the customer life cycle and data analytics techniques. In Section IV, articles about data analytics in CRM are analysed and the results of the classification are reported, and, finally, conclusions, limitations and implications of the study are discussed.

II. Research Methodology

Bibliographical databases are used for searching research articles in the survey. A review of articles related to the topic was done within SCOPUS, which is one of the largest abstract and citation databases of peer-reviewed literature. The literature search was conducted using terms “customer relationship management” and “data analytics” which resulted in 62 articles.

TABLE I
Summary of Funded Publications

Year of Publication	Publications Count
2013	10
2014	14
2015	17
2016	11
2017	10

The abstract or/and full text of each article were reviewed to eliminate those that were not actually related to data analytics techniques in CRM. The selection criteria were as follows:

- only articles published in business intelligence, data mining, knowledge discovery or customer management related journals were selected, as these were the most appropriate outlets for data analytics in CRM research and the focus of this review;
- only articles of Computer Science, Engineering, Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Mathematics and Materials Science were selected;
- only articles clearly describing usage of data analytics techniques in CRM processes were selected;
- unpublished working papers were excluded;
- publication duplicates were excluded.

Each article was carefully reviewed and separately classified according to the four categories of CRM dimensions, nine CRM functional solutions and seven categories of data mining models.

III. Data Analytics in the Customer Life Cycle

Customers' data may be found in enterprise-wide repositories, sales data (purchasing history), financial data (payment history and credit score), marketing data (campaign response, loyalty scheme data) and service data. All of these data create new opportunities to extract more value. As shown in Fig. 1, enterprise CRM supports all aspects of the customer life cycle. Ideally, CRM is "a cross-functional process for achieving a continuing dialogue with customers, across all of their contact and access points, with personalised treatment of the most valuable customers, to increase customer retention and the effectiveness of marketing initiatives" [9].

From the business planning perspective, the CRM framework can be classified into operational and analytical. Operational CRM refers to the automation of business processes, whereas analytical CRM refers to the analysis of customer descriptive, attitudinal, interactive and behavioural information so as to support the organisation's customer management strategies [5].

Analytical CRM builds on the foundation of customer information. The role of analytical CRM continuously increases in enterprises. Analytical CRM is the use of data to develop relationship strategies.

The ability to access, analyse, and manage vast volumes of data while rapidly evolving the information architecture has long been a goal at many enterprise institutions. An integrated approach to data analytics management requires a broad business perspective not just slamming in another software package. Typically, data analytics involves integration with the following infrastructure and tools [5]:

- analytical CRM (customer information storage and business rules and decision automation engine. Predictive models can be integrated with a business rule engine, which drives the workflow);
- predictive analysis, data mining, and statistical modelling tools;
- visualization tool (business intelligence).

Typically, there are four phases of the customer lifecycle: Customer Identification, Customer Attraction, Customer Retention, and Customer Development. These four dimensions can be seen as a closed cycle of a customer management system. In order to gain a deep understanding of Data analytics in CRM processes, this section will introduce CRM functional technologies that are closely related to data analytics. Table I outlines some of the most widely used CRM functional solutions, their definitions and their implementation benefits.

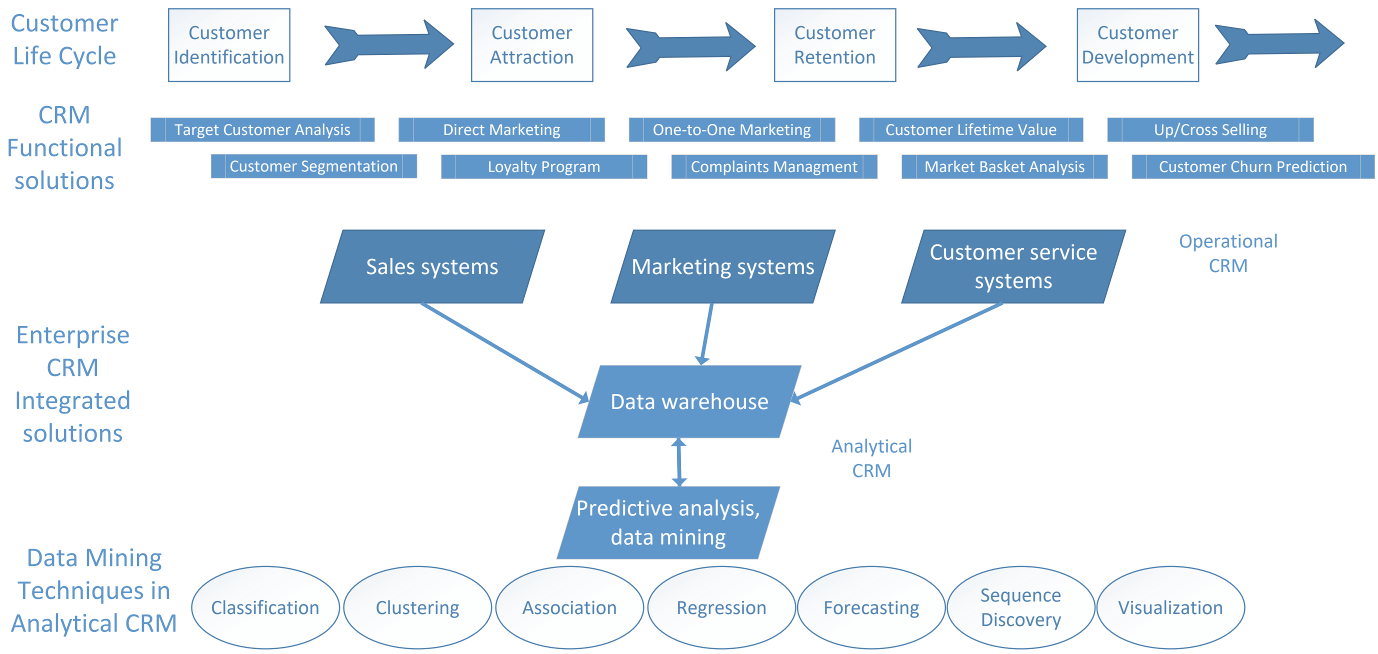

Fig. 1. CRM supports the customer life cycle.

TABLE II
CRM FUNCTIONAL SOLUTIONS

#	CRM Functional Solution	Definition
1	Target customer analysis	A target market analysis is a systematic and comprehensive assessment that allows identifying important characteristics about target markets and grouping them into categories based on those characteristics
2	Customer Segmentation	Customer segmentation divides a customer base into groups of individuals that are similar in specific ways relevant to marketing, such as age, gender, interests and spending habits
3	Direct Marketing	Direct marketing is a form of advertising which enterprises and organisations use to communicate directly to customers through a variety of media, including cell phone text messaging, e-mail, websites, etc. [39]
4	Loyalty Program me	Loyalty programmes are structured marketing strategies designed by merchants to encourage customers to continue to shop or use the services of businesses associated with each programme. These programmes exist covering most types of business, each one having varying features and reward schemes [15]
5	One-to-one marketing	Personalised marketing is a marketing strategy by which companies leverage data analysis and digital technology to deliver individualised messages and product offerings to current or prospective customers [54]
6	Complaint management	Complaint management re-establishes the satisfaction of the person who has lodged a complaint and reinforces the customer relationship
7	Customer lifetime value	In marketing, a customer lifetime value is a prediction of the net profit attributed to the entire future relationship with a customer [41]
8	Market basket analysis	Market basket analysis (also called an association analysis) analyses purchases that commonly happen together
9	Up/Cross-selling	Cross-selling is a practice of selling an additional product or service to the existing customer. In practice, businesses define cross-selling in many ways. It is often combined with cross-selling and up-selling techniques to increase revenue [12]

Table II outlines the existing CRM functional solutions and its concepts and scenarios which make some impact on specific operation management industrial business use cases. There are nine existing examples of data analytics applications in industries which enhance operation processes to some extent.

IV. DATA ANALYTICS TECHNIQUES

Methods for querying and mining big data are fundamentally different from traditional statistical analysis on small samples. Firstly, data mining requires integrated, cleaned, trustworthy, and efficiently accessible data, declarative query and mining interfaces, scalable mining algorithms, and big-data computing environments. At the same time, data mining itself can also be used to help improve the quality and trustworthiness of the data, understand its semantics, and provide intelligent querying functions [13].

Each data mining technique can perform one of the following types of data modelling or even more: Association, Classification, Clustering, Forecasting, Regression, Sequence Discovery and Visualisation [11].

A. Association

Association or association rule learning is method that is used to discover unknown relationships hidden in big data. Rules refer to a set of identified frequent itemsets that represent the uncovered relationships in the dataset. The underlying idea is to identify rules that will predict the occurrence of one or more items based on the occurrence of other items in the dataset. There are different algorithms used to identify frequent itemsets in order to perform association rule mining. The most known algorithm is the Apriori algorithm, but the Eclat and the FP-growth algorithm are also often used [5].

B. Classification

In data mining, classification is considered an instance of supervised learning, i.e., learning where a training set of correctly identified observations is available. Classification is the problem of identifying to which of a set of categories a new observation belongs, on the basis of a training set of data containing observations whose category membership is known. An example would be assigning a customer into “high risk” or “low risk” classes or assigning a diagnosis to a given patient [10], [14].

C. Clustering

In data mining, clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters). Big data clustering techniques are classified into two categories: single machine clustering techniques and multiple machine clustering techniques, the latter have been drawing more attention recently because they are faster and more adapt to the new challenges of big data [5], [14].

D. Forecasting

Forecasting is the process of making predictions of the future based on past and present data and most commonly by analysis of trends. A commonplace example might be estimation of some variables of interest at some specified future date [4], [5].

E. Regression

Regression analysis is widely used for prediction and forecasting. In data mining, the regression analysis is a statistical process for estimating the relationships among variables. Most commonly, the regression analysis estimates the conditional expectation of the dependent variable given the independent variables, i.e., the average value of the dependent variable when the independent variables are fixed [4], [5].

F. Sequence Discovery

Sequential pattern mining is a topic of data mining concerned with finding statistically relevant patterns between data examples where the values are delivered in a sequence. It is usually presumed that the values are discrete, and thus time series mining is closely related. Sequential pattern mining is a special case of structured data mining [6].

G. Visualisation

The purpose of data visualisation is to communicate information clearly and efficiently via statistical graphics, plots and information graphics [7]. Effective visualisation helps users analyse and reason about data and evidence. It makes complex data more accessible, understandable and usable. Data visualisation combines technical and artistic aspects of data analysis. It is viewed as a branch of descriptive statistics by some researchers, and as a grounded theory development tool by others [8].

The prediction model can have varying levels of sophistication and accuracy, ranging from a crude heuristic to the use of complex predictive analytics techniques.

V. Classification of the Articles

The distribution of articles classified by the CRM dimension is shown in Table III. Among the four CRM dimensions, customer development (19 out of 51 articles, 37.3 %) is the most common dimension for which data analytics is used to support decision making.

TABLE III

THE DISTRIBUTION OF ARTICLES CLASSIFIED BY THE CRM DIMENSION

CRM Dimension	Amount	Percentage	Papers
Customer Identification	9	18 %	[16], [18], [27], [40], [46] , [47] ,[50], [55], [67]
Customer Attraction	16	31 %	[19], [20], [29], [34], [37], [44], [45], [49], [52], [53], [57],[59], [61], [65], [66], [68]
Customer Retention	7	14 %	[17], [21], [24], [26], [28], [35], [64]
Customer Development	19	37 %	[3], [22], [23], [25], [30], [31], [32], [33], [36], [38], [42], [43], [48], [51], [56], [58], [60], [62], [63]

The distribution of articles classified by the CRM functional solution is shown in Table IV. Among the nine CRM functional solutions, direct marketing (10 out of 51 articles, 20 %) is the most common CRM functional solution for which data analytics is used to support decision making.

The distribution of articles classified by the data mining technique is shown in Table V. Among the seven data mining techniques, clustering (7 out of 51 articles, 14 %) is the most common data mining technique for which data analytics is used to support decision making.

TABLE VI

THE DISTRIBUTION OF ARTICLES CLASSIFIED BY THE CRM FUNCTIONAL SOLUTION

CRM Functional Solution	Amount	Percentage	Papers
Target customer analysis	9	18 %	[16], [18], [29], [45], [53], [59], [63], [50], [47]
Customer Segmentation	6	12 %	[18], [27], [40], [46], [55], [67]
loyalty programme	9	18 %	[21], [24], [28], [35], [38], [42], [48], [58], [60]
Direct marketing	10	20 %	[34], [37], [44], [49] ,[52], [57], [61], [65], [66], [68]
One-to-one marketing	2	4 %	[31], [33]
Complaint management	2	4 %	[17], [35]
Customer lifetime value	8	16 %	[25], [26], [30], [51], [56], [60], [62], [64]
Market basket analysis	2	4 %	[34], [37]
Up/Cross-selling	7	14 %	[3] ,[20], [22], [23], [32], [36], [38]

TABLE V

THE DISTRIBUTION OF ARTICLES CLASSIFIED BY THE DATA MINING TECHNIQUE

Data Mining Technique	Amount	Percentage	Papers
Association	3	6 %	[3], [34], [37]
Classification	6	12 %	[18], [3], [21], [22], [27], [35]
Clustering	7	14 %	[3], [27], [40], [46], [55], [67], [71]
Forecasting	2	4 %	[23], [30]
Regression	4	8 %	[24], [58], [65], [68]
Sequence Discovery	2	4 %	[26], [63]
Visualisation	6	12 %	[25], [35], [42], [51], [55],[59]

Full list of reviewed publications with classification is available at https://drive.google.com/open?id=0Bwp9RlyV--pwcFg1dC1kSzlMNG8

VI. Conclusion

Application of data analytics in CRM is an emerging trend in the industry. It has attracted the attention of industry practitioners and academics. This literature review has identified 51 articles related to data analytics in CRM, published between 2013 and 2017. This paper has provided a detailed review based on four CRM dimensions, seven CRM functional solutions and nine data mining techniques.

This study have some limitations. First of all, this literature review has only surveyed articles published between 2013 and 2017, which were extracted based on a keyword search of “customer relationship management” and “data analytics”.

Enterprise CRM supports all aspects of the customer life cycle. The Role of analytical CRM continuously increases in an enterprise. Analytical CRM is the use of data to develop relationship strategies. The clustering model is the most commonly applied model in CRM processes for predicting future customer behaviour.

References

[1] Econsultancy and Adobe, *Digital Trends in the Financial Services and Insurance Sector*, 2016.

[2] D. Sasikala, S. Kalaiselvi, and M. Phil Scholar, "Data Mining for Business Intelligence in CRM System," *International Journal of Multidisciplinary Research and Development*, vol. 3, no. 3, pp. 198–200, Mar. 2016.

[3] P. Gončarovs and J. Grabis, "Using Data Analytics for Continuous Improvement of CRM Processes: Case of Financial Institution," *New Trends in Databases and Information Systems*, pp. 313–323, 2017. https://doi.org/10.1007/978-3-319-67162-8_31

[4] J.Markarian, S. Brobst and J. Bedell, *Critical Success Factors Deploying Pervasive BI*, 2007 [Online]. Available: https://pdfs.semanticscholar.org/b66b/05e9231eb70c9554f668da67b4f3cdd9a078.pdf

[5] E. W. T. Ngai, L. Xiu, and D. C. K. Chau, "Application of Data Mining Techniques in Customer Relationship Management: A Literature Review and Classification," *Expert Systems with Applications*, vol. 36, no. 2, pp. 2592–2602, Mar. 2009. https://doi.org/10.1016/j.eswa.2008.02.021

[6] N. R. Mabroukeh and C. I. Ezeife, "A Taxonomy of Sequential Pattern Mining Algorithms," *ACM Computing Surveys*, vol. 43, no. 1, pp. 1–41, Nov. 2010. https://doi.org/10.1145/1824795.1824798

[7] M. Friendly, *Milestones in the history of thematic cartography, statistical graphics, and data visualization*, 2009 [Online]. Available: http://www.math.yorku.ca/SCS/Gallery/milestone/milestone.pdf

[8] M. Aparicio and C. J. Costa, "Data visualization," *Communication Design Quarterly Review*, vol. 3, no. 1, pp. 7–11, Jan. 2015. https://doi.org/10.1145/2721882.2721883

[9] J. F. Tanner Jr., M. Ahearne, T. W. Leigh, C. H. Mason, and W. C. Moncrief, "CRM in Sales-Intensive Organizations: A Review and Future Directions," Journal of Personal Selling and Sales Management, vol. 25, pp. 169–180, Mar. 2005.

[10] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 2nd ed. Prentice Hall, 1995.

[11] H. Zhao and S. Zhao, "Applications of Data Mining in the Enterprise Customer Relationship Management," *Proceedings of the 2012 International Conference on Information Technology and Management Science (ICITMS 2012)*, pp. 55–60, Dec. 2012. https://doi.org/10.1007/978-3-642-34910-2_7

[12] F. Harding, *Cross-Selling Success: A Rainmaker's Guide to Professional Account Development*. Avon, MA: Adams Media, 2002.

[13] A. Labrinidis and H. V. Jagadish, "Challenges and Opportunities with Big Data," *Proceedings of the VLDB Endowment*, vol. 5, no. 12, pp. 2032–2033, Aug. 2012. https://doi.org/10.14778/2367502.2367572

[14] B. Zerhari, A. A. Lahcen, S. Mouline, "Big Data Clustering: Algorithms and Challenges," *International Conference on Big Data, Cloud and Applications BDCA'15, At Tetuan, Morocco*, May 2015 [Online]. Available: http://docplayer.net/35109043-Big-data-clustering-algorithms-and-challenges.html

[15] B. Sharp and A. Sharp, "Loyalty Programs and Their Impact on Repeat-Purchase Loyalty Patterns," International Journal of Research in Marketing, vol. 14, no. 5, pp. 473–486, Dec. 1997. https://doi.org/10.1016/s0167-8116(97)00022-0

[16] J. S. Johnson, S. B. Friend, and H. S. Lee, "Big Data Facilitation, Utilization, and Monetization: Exploring the 3Vs in a New Product Development Process," *Journal of Product Innovation Management*, vol. 34, no. 5, pp. 640–658, Jun. 2017. https://doi.org/10.1111/jpim.12397

[17] G. S. Erickson and H. N. Rothberg, "Healthcare and Hospitality: Intangible Dynamics for Evaluating Industry Sectors," *The Service Industries Journal*, vol. 37, no. 9–10, pp. 589–606, Jun. 2017. https://doi.org/10.1080/02642069.2017.1346628

[18] A. Oztekin, "Creating a Marketing Strategy in Healthcare Industry: A Holistic Data Analytic Approach," *Annals of Operations Research*, May 2017. https://doi.org/10.1007/s10479-017-2493-4

[19] C. M. Gordon, "Four Eras of CRM Selling," *Decision Management*, pp. 939–957, 2017. https://doi.org/10.4018/978-1-5225-1837-2.ch041

[20] B. Ahmed, F. Amroush, and M. L. Ben Maati, "The Implementation Trends of Intelligence E-CRM in Business Process," *2016 4th IEEE International Colloquium on Information Science and Technology (CiSt)*, Oct. 2016.https://doi.org/10.1109/cist.2016.7805080

[21] G. Jipa, "Employees Opinion Mining: Value of Structured and Unstructured Content Analytics in Bank," *29th IBIMA Conference*, 2017.

[22] T. G. K. Vasista and A. M. AlAbdullatif, "Role of Electronic Customer Relationship Management in Demand Chain Management," *International Journal of Information Systems and Supply Chain Management*, vol. 10, no. 1, pp. 53–67, Jan. 2017. https://doi.org/10.4018/ijisscm.2017010104

[23] C. I. Papanagnou and O. Matthews-Amune, "Coping with Demand Volatility in Retail Pharmacies with the Aid of Big Data Exploration," *Computers & Operations Research*, Aug. 2017. https://doi.org/10.1016/j.cor.2017.08.009

[24] G. Rajini and D. V. Sangamaheswary, "An Emphasize of Customer Relationship Management Analytics in Telecom Industry," *Indian Journal of Science and Technology*, vol. 9, no. 32, Aug. 2016. https://doi.org/10.17485/ijst/2016/v9i32/98646

[25] B. Magee, D. Sammon, T. Nagle, and P. O'Raghallaigh, "Introducing Data Driven Practices into Sales Environments: Examining the Impact of Data Visualisation on User Engagement and Sales Results," *Journal of Decision Systems*, vol. 25, no. 1, pp. 313–328, Jun. 2016. https://doi.org/10.1080/12460125.2016.1187403

[26] S. Chen, Y. Huang, and W. Huang, "Big Data Analytics on Aviation Social Media: The Case of China Southern Airlines on Sina Weibo," *2016 IEEE Second International Conference on Big Data Computing Service and Applications (BigDataService)*, Mar. 2016. https://doi.org/10.1109/bigdataservice.2016.51

[27] L. Kumari, S. Dhamnani, A. Bhatnagar, A. R. Sinha, and R. Sinha, "Audience Prism: Segmentation and Early Classification of Visitors Based on Reading Interests," *Proceedings of the 3rd IKDD Conference on Data Science, 2016 – CODS'16*, 2016. https://doi.org/10.1145/2888451.2888459

[28] L. Xu, H.-C. Chu, "Big Data Analytics Toward Intelligent Mobile Service Provisions of Customer Relationship Management in E-Commerce" *Journal of Computers*, vol. 26, no. 4, Jan. 2016 [Online]. Available: http://www.csroc.org.tw/journal/JOC26_4/JOC26-4-7.pdf

[29] R. T. Bedeley, M. Benbow, and L. S. Iyer, "An Analytic-Based Strategy for College Sports Ticket Sales and Management," *Emergent Research Forum*, 2016.

[30] S. Palanimalai and I. Paramasivam, "Big Data Analytics Bring New Insights and Higher Business Value – an Experiment Carried Out to Divulge Sales Forecasting Solutions," *International Journal of Advanced Intelligence Paradigms*, vol. 8, no. 2, p. 207, 2016. https://doi.org/10.1504/ijaip.2016.075728

[31] A. Kumar, R. Bezawada, R. Rishika, R. Janakiraman, and P. K. Kannan, "From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior," *Journal of Marketing*, vol. 80, no. 1, pp. 7–25, Jan. 2016. https://doi.org/10.1509/jm.14.0249

[32] R. K. Bagla and A. B. Singh, "Integration of Personalized Service Delivery with Information Technology: Future of CRM in Indian Banking," *Prabandhan: Indian Journal of Management*, vol. 9, no. 12, p. 19, Dec. 2016. https://doi.org/10.17010/pijom/2016/v9i12/107007

[33] P. C. Verhoef, E. Kooge, and N. Walk, "Creating Value with Big Data Analytics: Making Smarter Marketing Decisions," Jan. 2016. https://doi.org/10.4324/9781315734750

[34] B. Suvalka, S. Khandelwal, and C. Patel, "Revised ECLAT Algorithm for Frequent Itemset Mining," *Information Systems Design and Intelligent Applications*, pp. 219–226, 2016. https://doi.org/10.1007/978-81-322-2752-6_21

[35] A. Cook, P. Wu, and K. Mengersen, "Machine Learning and Visual Analytics for Consulting Business Decision Support," *2015 Big Data Visual Analytics (BDVA)*, Sep. 2015. https://doi.org/10.1109/bdva.2015.7314299

[36] O. Boujena, K. Coussement, and K. W. de Bock, "Data-Driven Customer Centricity," *Advances in Marketing, Customer Relationship Management, and E-Services*, pp. 157–174, 2015. https://doi.org/10.4018/978-1-4666-8459-1.ch008

[37] M. Yang, W. H. Hsu, and S. T. Kallumadi, "Predictive Analytics of Social Networks: A survey of tasks and techniques," *Business Intelligence*, pp. 1080–1116, 2016. https://doi.org/10.4018/978-1-4666-9562-7.ch056

[38] A. Ayanso and D. Visser, "Analytics and Performance Measurement Frameworks for Social Customer Relationship Management," Social Media and Networking, pp. 252–280. https://doi.org/10.4018/978-1-4666-8614-4.ch014
[39] Direct Marketing Association (U.S.), Global Insight, Inc., The Power of Direct Marketing: ROI, Sales, Expenditures, and Employment in the US, 13th edition, 2009.
[40] M. F. Clarke, "The Work of Mad Men that Makes the Methods of Math Men Work," *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems – CHI' 15*, 2015. https://doi.org/10.1145/2702123.2702493
[41] G. Fripp, "Guide to CLV," Guide to Customer Lifetime Value, 2014.
[42] G. Mastorakis, N. Trihas, E. Perakakis, and I. Kopanakis, "E-CRM in Tourism Exploiting Emerging Information and Communication Technologies," *Anatolia*, vol. 26, no. 1, pp. 32–44, Apr. 2014. https://doi.org/10.1080/13032917.2014.902767
[43] F. Chiang and S. Sitaramachandran, "A Data Quality Framework for Customer Relationship Analytics," *Web Information Systems Engineering – WISE 2015*, pp. 366–378, 2015. https://doi.org/10.1007/978-3-319-26187-4_35
[44] J. Huang, P. Guo, Q. Xie, and X. Meng, "Cloud Services Platform Based on Big Data Analytics and Its Application in Livestock Management and Marketing," *Proceedings of science*, Dec. 2015.
[45] G. Phillips-Wren and A. Hoskisson, "An Analytical Journey Towards Big Data," *Journal of Decision Systems*, vol. 24, no. 1, pp. 87–102, Jan. 2015. https://doi.org/10.1080/12460125.2015.994333
[46] C.-B. Chen, D. Agrawal, and S. Kumara, "Retail Analytics: Market Segmentation Through Transaction Data," Retail Analytics, pp. 15–46, Oct. 2015. https://doi.org/10.1002/9781119205340.ch2
[47] J.-P. Tres, "Optimizing Marketing Resource Allocation Through Web Analytics" Annual Technical Conference – ANTEC, Conference Proceedings .2013.
[48] I. Russo, I. Confente, and A. Borghesi,"Using Big Data in the Supply Chain Context: Opportunities and Challenges," *The 16th European Conference on Knowledge Management ECKM 2015*, 2015.
[49] A. Asllani and D. Halstead, "A Multi-Objective Optimization Approach Using the RFM Model in Direct Marketing," *Academy of Marketing Studies Journal*, vol. 19, pp. 49–62, 2015.
[50] B. Kawas, M. S. Squillante, D. Subramanian, and K. R. Varshney, "Prescriptive Analytics for Allocating Sales Teams to Opportunities," *2013 IEEE 13th International Conference on Data Mining Workshops*, Dec. 2013. https://doi.org/10.1109/icdmw.2013.156
[51] A. H. Holmbom, S. Ronnqvist, P. Sarlin, T. Eklund, and B. Back, "Green vs. Non-Green Customer Behavior: A Self-Organizing Time Map over Greenness," 2013 IEEE 13th International Conference on Data Mining Workshops, Dec. 2013. https://doi.org/10.1109/icdmw.2013.103
[52] M. Nagarajan, D. Contractor, S. Dill, J. Ajmera, H.-I. Ahn, A. Verma, and M. Denesuk, "Content Analytics System for Social Customer Relationship Management," *Proceedings of the Seventh International AAAI Conference on Weblogs and Social Media*, 2013.
[53] I. R. Keck and R. J. Ross, "Exploring Customer Specific KPI Selection Strategies for an Adaptive Time Critical User Interface," *Proceedings of the 19th international conference on Intelligent User Interfaces - IUI'14*, 2014. https://doi.org/10.1145/2557500.2557536
[54] A. Chandra, "AdobeVoice: Why Personalization Is Key to the Future of Marketing," Forbes, 2014 [Online]. Available: https://www.forbes.com/sites/adobe/2014/05/12/why-personalization-is-key-to-the-future-of-marketing/#4f321dbfccd8.
[55] Z. Yao, P. Sarlin, T. Eklund, and B. Back, "Combining Visual Customer Segmentation and Response Modeling," *Neural Computing and Applications*, vol. 25, no. 1, pp. 123–134, Jul. 2013. https://doi.org/10.1007/s00521-013-1454-3
[56] A. Persson and L. Ryals, "Making Customer Relationship Decisions: Analytics V Rules of Thumb," *Journal of Business Research*, vol. 67, no. 8, pp. 1725–1732, Aug. 2014. https://doi.org/10.1016/j.jbusres.2014.02.019
[57] J. K. von Bischhoffshausen and H. Fromm, "Sales Force Analytics for the Solution Selling Firm: A Predictive Model for Assessing the Impact of Sales Team Assignments," 2014 [Online]. Available: https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1545&context=amcis2014
[58] A. Faed, O. K. Hussain, and E. Chang, "A Methodology to Map Customer Complaints and Measure Customer Satisfaction and Loyalty," Service Oriented Computing and Applications, vol. 8, no. 1, pp. 33–53, Oct. 2013. https://doi.org/10.1007/s11761-013-0142-6
[59] J. H. Black, *A New Era in Mill Analytics: Easy and Effective Ways to Improve Production Management Decisions*, 2014.
[60] R. T. Rust and M.-H. Huang, "The Service Revolution and the Transformation of Marketing Science," *Marketing Science*, vol. 33, no. 2, pp. 206–221, Mar. 2014. https://doi.org/10.1287/mksc.2013.0836
[61] L. Xu, J. A. Duan, and A. Whinston, "Path to Purchase: A Mutually Exciting Point Process Model for Online Advertising and Conversion," *Management Science*, vol. 60, no. 6, pp. 1392–1412, Jun. 2014. https://doi.org/10.1287/mnsc.2014.1952
[62] D. Hladky, S. Maltseva, D. Ogorodniychuk, G. Drobyazko, M. Voigt, and J. J. Le Grange, "Return on Investment in Linking Content to CRM by Applying the Linked Data Stack," *Communications in Computer and Information Science*, pp. 76–89, 2014. https://doi.org/10.1007/978-3-319-11716-4_7
[63] M. Oliveira, A. Guerreiro, and J. Gama, "Dynamic communities in evolving customer networks: an analysis using landmark and sliding windows," *Social Network Analysis and Mining*, vol. 4, no. 1, Jun. 2014. https://doi.org/10.1007/s13278-014-0208-2
[64] R. Cognini, F. Corradini, A. Polzonetti, and B. Re, "Five Factors That Make Pervasive Business Intelligence a Winning Wager," *2014 IEEE International Conference on Industrial Engineering and Engineering Management*, Dec. 2014. https://doi.org/10.1109/ieem.2014.7058712
[65] E. Suh and M. Alhaery, "Maximizing Player Value Through the Application of Cross-Gaming Predictive Models," *International Journal of Contemporary Hospitality Management*, vol. 26, no. 8, pp. 1243–1269, Nov. 2014. https://doi.org/10.1108/ijchm-05-2013-0221
[66] D. A. Ostrowski, "Semantic Filtering in Social Media for Trend Modeling," *2013 IEEE Seventh International Conference on Semantic Computing*, Sep. 2013. https://doi.org/10.1109/icsc.2013.78
[67] H. S. Miranda and R. Henriques, "Building Clusters for CRM Startegies by Mining Airlines Customer Data," *2013 8th Iberian Conference on Information Systems and Technologies (CISTI)*, 2013.
[68] P. Baecke and D. Van den Poel, "Improving Customer Acquisition Models by Incorporating Spatial Autocorrelation at Different Levels of Granularity," *Journal of Intelligent Information Systems*, vol. 41, no. 1, pp. 73–90, Nov. 2012. https://doi.org/10.1007/s10844-012-0225-4

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