Dam, N., Le Dinh, T. et Menvielle, W. (2019). Marketing Intelligence From Data Mining Perspective – A Literature Review. International Journal of Innovation Management and Technology (Vol. 10, p. 184-190).
doi: 10.18178/ijimt.2019.10.5.859

Marketing Intelligence from Data Mining Perspective — A Literature Review

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***Abstract*—The digital transformation enables enterprises to mine big data for marketing intelligence on markets, customers, products, and competitor. However, there is a lack of a comprehensive literature review on this issue. With an aim to support enterprises to accelerate the digital transformation and gain competitive advantages through exploiting marketing intelligence from big data, this paper examines the literature in the period from 2001–2018. Consequently, 76 most relevant articles are analyzed based on four marketing intelligence components (Markets, Customers, Products, and Competitors) and six data mining models (Association, Classification, Clustering, Regression, Prediction, and Sequence Discovery). The findings of this study indicate that the research area of product and customer intelligence receives most research attention. This paper also provides a roadmap to guide future research on bridging marketing and information systems through the application of data mining to exploit marketing intelligence from big data.**

***Index Terms*—Big data analytics, data mining, literature review, marketing intelligence.**

I. Introduction

The intelligence-based era has opened up incredible opportunities for enterprises to promote the digital transformation via new smart systems and services related to marketing intelligence from big data [1]. Being described as extremely large data sets in volume, velocity, variety, and veracity, big data is considered as a great source for marketing intelligence [2], [3]. Marketing intelligence can be perceived as the process of applying data mining techniques to gather information on customers, competitors, markets, industry and then is applied into strategic marketing plans [4], [5]. Thus, it enables enterprises to accelerate the digital transformation through product innovation, customer identification, and market demand forecasting [6], [7].

Nowadays, marketing intelligence relies on big data and data mining techniques to gather information [7], [8]. However, the challenges related to exploiting marketing intelligence from big data have also arisen. Firstly, enterprises find it challenging to identify relevant sources of data [2], [9], [10]. Secondly, enterprises face the challenge in classifying different components of marketing intelligence as well as their specific functions [8], [11]. Finally, even though the application of big data in marketing has emerged as a trendy topic in many studies, there seems to be a lack of focus on the technical side; for instance, data mining models and techniques to exploit big data [12]-[14]. This stimulates the research motivation and objective of this paper in identifying different data mining models and techniques to demystify marketing intelligence and its specific application.

This study aims at presenting a literature review related to the application of data mining models to exploit marketing intelligence from big data. The first objective of the study is, therefore, to classify different types of marketing intelligence. Accordingly, the second objective is to identify pertinent sources of big data for each type of marketing intelligence. Then the final objective is to propose state-of-the-art data mining models and techniques to uncover marketing intelligence.

The remaining structure of the paper continues with methodology, theoretical background, and the proposed framework. Then this paper will touch upon a literature review of marketing intelligence followed by the classification of marketing intelligence with data mining models and techniques. The last section indicates an in-depth discussion of contributions as well as significant future research directions.

Manuscript received April 20, 2019; revised September 10, 2019.

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II. Methodology, Theoretical Background, and Proposed Framework

A. Methodology

As the nature of research on marketing intelligence and data mining spreads in various databases, this paper builds its own literature review from different academic sources such as Science Direct, Emerald, Business Source Premier, EBSCOhost, ProQuest, Google Scholars, and IEEE Transaction [15]. Different keywords such as “marketing intelligence”, “data-driven marketing”, “data mining techniques”, “big data analytics” and “literature review” are used to search for articles from these reliable databases. As a result, the collected articles are from top marketing journals and management journals with topics in Marketing and Management such as Journal of Marketing, European Journal of Marketing, Harvard Business Review, Journal of the Academy of Marketing, Management Science, Marketing Management, etc. [12]. Furthermore, articles from information systems journals are also synthesized; for examples: Expert Systems with Applications, MIS Quarterly, Decision Support Systems, IEEE, Information and Management, Decision Support Systems, Communications of the ACM, etc. [7]. All the selected journals in marketing and information systems are listed in the Scimago Journal & Country Rank in 2017 [12]. The distribution of articles by journal titles is shown in Table I as follows:

TABLE I: THE DISTRIBUTION OF ARTICLES BY JOURNAL TITLES

Journal title	No	%
Expert Systems with Applications	10	13.16%
Decision Support Systems	7	9.21%
IEEE	6	7.89%
European Journal of Marketing	5	6.58%
Communications of the ACM	4	5.26%
Information and Management	4	5.26%
Journal of Business Research	4	5.26%
MIS Quarterly	3	3.95%
Journal of Marketing	2	2.63%
Management Science	2	2.63%
ACM Transactions on Information Systems	1	1.32%
Marketing Management	1	1.32%
Others	27	35.53%
Total	76	100.00%

According to Table I, the significant proportion of relevant articles comes from Expert Systems with Applications (13.16%, or 10 of the 76 articles), followed by Decision Support Systems (9.21%, or 7 articles), and the IEEE (7.89%, or 6 articles). Other journals, which are also well referenced, are European Journal of Marketing, Communications of the ACM, Information and Management, Management Science, etc. To ensure the validity and reliability of the literature search process, the forward and backward search techniques are conducted to make sure that 76 chosen articles can represent the literature of this domain [16]. The 76 articles are also classified by the year of publication. Fig. 1 shows the distribution of articles by the year of publication from 2001 to 2018. The 18-year duration seems long enough to see the changes and trends in marketing intelligence. In Fig. 1, it can be seen that the number of articles has grown between 2001 and 2018 with the peak in 2013 and 2016. The period from 2009 to 2013 shows a gradual increase in the number of articles in this domain. There is a fluctuation in the number of articles from 2013 to 2018. This can be explained by the research gap between practitioners and researchers. As mentioned in the introduction part, studies on marketing intelligence and data mining really lack papers discussing the technical side regarding algorithms, machine learning techniques, data mining techniques for a specific application in marketing [12], [14]. As a matter of fact, practitioners such as Adobe, Salesforce, or IBM conduct in-depth studies on customer intelligence, product intelligence, and content intelligence. However, these publications are exclusive from academic databases.

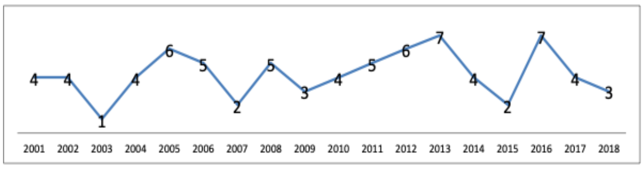

Fig. 1. Distribution of articles by year of publication.

B. Theoretical Background

This study relies on the resource-based theory [17] as this theory is well adopted by many researchers in explaining the key to success for enterprises. Resources such as "all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc." [17] play the most ultimate role in strategic planning for success [18]. Another interesting point is that the resource-based theory not only considers the importance of resources but also highlights the capabilities to exploit them and turn them into sustainable competitive advantages [19]. With that regard, marketing intelligence is considered as significant resources for the service/product enhancement and innovation [4], [6]. Correspondingly, data mining models and techniques play the role as capabilities to turn big data into marketing intelligence [3], [18]. Consequently, it is important to examine the role of marketing intelligence coupled with relevant data mining models and techniques in the success of enterprises. In the next part, this study will discuss components of marketing intelligence as significant resources for the success of enterprises.

C. Proposed Marketing Intelligence Framework

From the perspective of the resource-based theory, enterprises should identify marketing intelligence coupled with data mining models and techniques as significant resources and capabilities for competition [3], [7], [17]. The proposed framework in Fig. 2 is based on the literature review and classification of marketing intelligence from different studies [7], [20], [21]. According to these authors, marketing intelligence, which comprises of market intelligence, product intelligence, customer intelligence, and competitor intelligence, can cover every aspect of the marketing mix. Each component of marketing intelligence will be discussed in detail in the following section. These four components of marketing intelligence belong to the inner layer of the framework. The outer layer of the framework consists of six most typical data mining models to extract different components of marketing intelligence [14], [21].

Fig. 2. A marketing intelligence framework.

A short description of the six typical data mining models with relevant mining techniques is provided as follows [1], [7], [22]:

Classification is used to make a prediction on customer behaviors (Fan *et al.*, 2015) or determine attributes of clusters [23]. Classification mining techniques are neural networks, decision trees, the Naïve Bayes technique, support vector machines, market basket analysis, genetic algorithms, and if-then-else rules [15], [24].

Association is used to find out the relationship among products that customers purchase; thus, enterprises can determine products that tend to be sold together [22], [23] (Bose & Mahapatra, 2001; Seng & Chen, 2010). Association techniques are association rules, statistics and Apriori algorithms [7], [15].

Clustering is used for customer segmentation and user profiling [11], [25]. The most common clustering mining techniques are K-means, the Naïve Bayes technique, RFM analysis (recency, frequency, monetary), market basket analysis, neural networks, and self-organizing map techniques [1], [22], [25].

Regression is used to make a prediction or to find causal relationships among variables [15]. Common regression techniques are linear regression and logistic regression [1], [22].

Prediction is used to predict future values based on historical records [23], [26]. Most common forecasting mining techniques are neural networks, survival analysis, linear regression models, market basket analysis, and logistic model prediction [22], [26].

Sequence discovery is used to identify associations or describe orders of behaviors over time [27]. Sequence discovery techniques are statistics and set theory [15].

III. Marketing Intelligence

In this section, the inner layer of the proposed framework consisting of different components of marketing intelligence is clarified. Literature does not really demonstrate an official definition of marketing intelligence. A revolutionary difference can be seen from the traditional and contemporary definition of marketing intelligence lies in the method to collect information [5], [28]. In the past, marketing intelligence depends on market surveys and internal sources within enterprises to gather information on customers, competitors, markets, industry [5], [29], [30]. Nowadays, the definition of marketing intelligence infers the application of data mining models and techniques to discover marketing insights for strategic decisions [3], [7]. In this sense, marketing intelligence carries the new name as “marketing data intelligence” in which raw data is transformed from internal and external databases to uncover marketing intelligence [27]. Under this approach, marketing intelligence is defined as the process to gather information on customers, competitors, markets, industry through data mining techniques and then is applied into strategic marketing plans [4], [5].

This paper adopts the data mining perspective from many studies to define marketing intelligence as the application of data mining models and techniques to exploit intelligence on markets, products, customers, and competitors [3], [7]. This definition is based on the marketing mix so that it covers all the important aspects that support marketing decisions [3], [11]. As the traditional marketing mix, including product, price, promotion, and place is criticized as product-oriented and lack of customer orientation, this study adopts the fifth P – people with the focus on the customer [3], [11]. Accordingly, marketing intelligence consists of market intelligence (place), product intelligence (product), competitor intelligence (price and promotion), and customer intelligence (people).

A. Market Intelligence

As a broad concept, market intelligence consists of exogenous factors of a potential market such as technology, competition, regulations, and other environmental forces that may influence current and future customer needs and preferences [29]. Market intelligence comprises of a wide range of intelligence from politics and economics to cultures and sociology [6], [28], [31]. Information on the political-economic and social-cultural aspects is crucial for enterprises to make strategic decisions when penetrating new markets [6], [28]. Traditional sources of market intelligence are surveys, reports sales, discussion with customers, market research, and so on [29]. Nowadays, open sources which are referred to unclassified, non-secret, non-indexed sources (e.g.: weblogs, whitepapers, etc.) are also useful to collect market intelligence because they are inexpensive and easy to access [32].

B. Product Intelligence

Product intelligence is usually defined from the perspective of intelligent products [33], [34]. Accordingly, product intelligence includes two dimensions: information-handling and decision-making [33]. This study will reshape the definition of product intelligence from the perspective of data mining. In this regard, product intelligence is the application of data mining techniques to exploit insights on products to increase customer satisfaction and identify business opportunities [11], [20]. The best way to satisfy customers’ needs is to listen to their opinions on products through customer reviews, discussions, attitudes on forums, social media, blogs, and websites [20], [35]. These are considered as great sources to approach customer feedback and needs [11], [20]. Mining user-generated content and web content will allow enterprises not only to develop suitable products for customer needs but also to recommend the right products to the right customers [36], [37].

C. Competitor Intelligence

Competitor intelligence is information on competitors’ products, prices, advertisements, and distribution channels [6]. It is also defined as the ability of an enterprise to understand the strengths and weaknesses its competitors; hence, an enterprise can foresee its competitors’ moves and strategies and improve its performance [38]. With an intent to obtain information on competitors, enterprises can collect log data from e-commerce websites [11]. Data on sale ranks, list price, customer rating, number of reviewers, and days released from e-commerce sites could be used to forecast market demand, estimate cost and price elasticity, and even evaluate the optimality of pricing strategies [11]. Nowadays, not only texts but also images can be mined for competitors’ products reputations [39]. Properties of images such as display formats, image quality, the number of views can affect buyers’ intention, stimulate trust and improve the transaction rate [39], [40].

D. Customer Intelligence

Customer intelligence consists of data and information on needs, preferences, cultures, lifestyle, purchasing power, shopping behaviors, customs and habits of potential customers [6]. In the digital age, customer intelligence is first exploited in the form of web intelligence acquired from

Internet Protocol searches through cookies and server logs [7]. Web intelligence uncovering customers' needs and detecting business opportunities can also be collected from web pages, e-commerce sites, and social media [7], [41]. Marketers can analyze customer clickstream data logs on visit frequency, viewed items, and visit time on a website to understand customers' browsing habits and purchasing behaviors [11], [37]. Enterprises can exploit customer intelligence from internal sources such as billing records, company's weblogs, CRM system, customer surveys, etc. [27]. External sources of customer intelligence are lookups for telephone number and address, social media, competitors' websites, household hierarchies, Fair-Isaacs credit scores, customer reviews, clickstream [8], [11], [27].

IV. Classification of Marketing Intelligence with Data Mining Models and Techniques

A. Data Mining for Market Intelligence

Market intelligence can be divided into two levels: country level and people level [6], [31]. The country level includes political-economic intelligence on legal regulations, economics, technological development, market competitiveness, and public policies [6], [28], [31]. The people level consists of social-cultural intelligence on culture, customs, and habits, purchasing power, customer preference, income, literacy rate, education level, lifestyles, climatic conditions, etc. [6], [28]. Different data mining models such as clustering, prediction, association, classification, and regression are conducted to extract political-economic and social-cultural intelligence [42], [43]. Grounded in these data mining models, a variety of mining techniques are adopted for different purposes. For example, sentiment and effect analysis to scan for market intelligence; decision tree, support vector machines, and logistic regression to predict and discover hidden correlations; genetic algorithms to optimize web searching; generic NLP (Natural Language processing) rules to identify networks of distributors, suppliers, and collaborators; the Bayes technique to classier sentiment in stock markets [42]-[44].

B. Data Mining for Customer Intelligence

Customer intelligence relates to customer relationship management (CRM) in terms of understanding customers and maximizing their values for enterprises. With the help of customer intelligence, CRM will be able to support enterprises to identify and retain the most profitable customers [27]. Based on CRM, customer intelligence consists of four levels: i) Customer identification – how to identify the most profitable customers; ii) Customer attraction – how to attract customers through marketing strategies; iii) Customer retention – how to retain a long-term relationship with customers; iv) Customer development – how to increase customer values [15], [25].

1) Customer identification

Customer intelligence starts with identifying customer segments with similar interests and profitability [15], [21]. Various demographic, psychographic, behavioral or geographic criteria are used for customer segmentation [21], [27]. Accordingly, customer segmentation methods such as clustering and classification are useful in dividing customers into homogenous segments and build customer profiles [11], [12]. Customer profiles should contain information on demography (age, gender), buying behaviors (needs, purchasing power, preferences, lifestyle), purchasing attributes (recency, frequency, size), product category, product mix, and estimated customer lifetime values [21], [45]. In this stage, the decision tree technique in classification and K-means technique in clustering is used to group customer segments with similar characteristics [25]. Then target customer analysis is applied to choose the most profitable segment [46].

2) Customer attraction

With an aim to attract target segments, the classification method takes the lead along with regression and clustering [15]. Taking a closer look at the classification method, Bayesian network classifier, Decision tree, Genetic algorithm, and neural network are the most popular techniques [7], [9], [15]. In addition, RFM analysis in terms of recency, frequency, and monetary of purchases can be applied to comprehend customer behavior and improve direct marketing strategy to attract customers [25].

3) Customer retention

In order to retain customers, it is necessary to customize marketing strategies that suit customer preferences and behaviors [12], [47]. In fact, enterprises normally develop customer profiling, campaign management analysis, credit scoring, recommender systems or loyalty programs to increase customer satisfaction and maintain a long-term relationship [27], [47]. Thus, various data mining methods are applied to support those activities such as classification, association, clustering, sequence discovery, and regression [15]. Accordingly, association rules, decision tree, neural network, logistic regression, and genetic algorithm are mostly discussed by researchers [1], [14], [15].

4) Customer development

With an aim to maximize value creation for enterprises, customer development covers three main perspectives: up/cross-selling, customer lifetime value and market basket analysis [15], [47]. Sequence discovery and association are the data mining methods supporting up/cross-selling along with market basket analysis [45], [48]. To be specific, association rules and neural network are the most common data mining techniques [15]. In estimating customer lifetime value, data scientists apply various mining models, including classification, clustering, forecasting, and regression [15], [22]. Thus, the corresponding data mining techniques are neural network, Bayesian network classifier, association rules, linear regression, survival analysis, Markov chain model [15], [42].

C. Data Mining for Product Intelligence

Based on the proposed definition of product intelligence in the previous part, it can be seen that product intelligence consists of two levels: product development [20], [21] and product recommendation [37], [49].

1) Product development

Product ontologies are built through text mining web content and user-generated content [20], [21]. Product characteristics can be extracted through the text mining method with classification, association, and clustering models [11], [21]. Product characteristics are data on size, weight, color, packaging, and types [4], [49]. Different techniques such as opinion mining, topic modeling, question-answering, information extraction are implemented for different research objectives [7]. Topic modeling is ideal for finding the main theme whereas question-answering is the application of natural language processing to build an ontology supporting human-computer interactions [20], [21]. On the other hand, opinion mining and sentiment analysis techniques are critical for identifying attitudes, emotions, and feelings [50], [51].

2) Product recommendation

This dimension of product intelligence aims to personalize recommendations for each customer through data from clickstreams, customer profiles, mobile call records, and transactions for better customer satisfaction [37]. Among various data mining models, association, classification, clustering, and regression are commonly used for building recommender systems in many studies [52]. In the same vein, the associated mining techniques are K-Nearest Neighbor, Bayesian classifiers, association rules, decision trees, link analysis, neural networks, linear regression [37], [52]. As one of the most important building blocks of recommender systems, k-Nearest neighbor (k-NN) identifies users with similar behaviors through their preference ratings and make recommendations on top products that are likely to be purchased [49].

D. Data Mining for Competitor Intelligence

As mentioned above, the competitor intelligence covers competitors' 4 Ps of the marketing mix including product, price, promotion, and place.

1) Competitors' products intelligence

In order to monitor competitors' product information, data scientists mine web contents with clustering, association model, and product ontology mining [20], [21]. Through the application of association rules, not only product features (design, labeling, brand, guarantee, etc.) but also threats of substitute products can be extracted from customer reviews, product ratings, and product descriptions [6], [20], [21]. Other data mining techniques are latent topic modeling and sentiment analysis that can be used for constructing the product ontology through text mining on social media [20], [21].

2) Competitors' pricing intelligence

Monitoring information on competitors' pricing intelligence includes price strategy, discount policy, margins, credit, secure collection [6]. The most preferred data-mining model to study pricing strategy is the regression model [3], [11]. In particularly, multi-linear regression technique is applied to identify determinants of competitors' price [11]. Along with regression models, association models are also useful to identify potential competitors and their pricing strategy [11].

3) Competitors' promotion intelligence

To acquire intelligence on competitors' promotional strategy, enterprises need to obtain data on promotion time, types (for examples: coupons, bundling, discount, gifting, sampling, etc.), and sales [37]. Regression models, especially linear regression techniques are mostly used to find out the relationships among factors in promotional strategies [3], [11]. In addition, heuristic models place the top position along with clustering, and association models as the most significant tools to develop recommender systems for promotional strategies [37]. Recommender systems will be able to promote suitable products for target customers, especially for movies and shopping industry [27], [47]. The most common data mining techniques to build recommender systems are K-Nearest Neighbor, association rule, link analysis [37].

4) Competitors' place intelligence

Nowadays, data about locations used in the marketing mix can be obtained through location-based service [53]. Location-based data can be traced through mobile devices with GPS, WiFi, GSM, or Bluetooth, vehicles with GPS, smart cards (bank cards or transportation cards), floating sensors (devices with radio frequency identification), check-in from social networks [13], [53]. In terms of location-based marketing, classification, prediction, and regression are the most significant data mining models [11], [13]. Correspondingly, various data mining techniques are conducted such as linear/non-linear regression, the Naïve Bayes technique, neural network, and support vector machine [13], [53].

V. Conclusion

With an aim to promote the digital transformation of marketing via smart services, this paper presents a literature review for exploiting marketing intelligence through the application of data mining on specific functions of marketing. Under this approach, marketing intelligence is classified based on the marketing mix. Relevant data sources, mining models, and techniques are also proposed for each component of marketing intelligence. This paper builds an in-depth literature review of 76 relevant articles from various databases. The research result provides a classification on each component of marketing intelligence with relevant mining models and techniques. The findings of this paper have several important implications.

Through this study, enterprises will be able to make good use of data mining techniques in exploiting marketing intelligence for competition. This will make great practical contributions for enterprises as marketing intelligence can offer certain competitive advantages in approaching potential market, competitors, products, and customers [3], [4]. The proposed framework of marketing intelligence has made a significant theoretical contribution by bridging the gap between information systems and marketing. The framework is promised to be a source of reference for both practitioners and researchers. Researchers can rely on this framework to further their studies.

This paper aims at exploiting marketing intelligence through mining big data to accelerate the digital transformation. Relevant data mining techniques have been identified for specific application in marketing. Marketing intelligence in this paper is classified based on the marketing mix. It is noted that product, customer, and promotion seem to catch more attention than price and place [21]. Therefore, there is a call for further research on marketing intelligence related to price and place. Finally, this paper has proposed specific data mining techniques for different application of marketing. Future scholars can accelerate and deepen this research direction by applying these techniques to solve a practical business problem.

For the time being, we are currently working on the intelligence marketing maturity levels and a framework for marketing intelligence systems. Moreover, an open-source marketing intelligence system for enterprises, especially SMEs (small and medium-sized enterprises) is being developed for experimenting the proposed framework in order to reinforce the practical contributions of this paper.

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