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Design and Development of a Mobile APP for Multichannel Sales Systems based on Artificial Intelligence

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Abstract— **In this paper the authors propose a mobile application oriented on mobile multi-channel marketing. The multi-channel model consists of enabled mobile channels of sellers linked to a central node which is managed by a system administrator. The study case is related to an industrial project concerning an intelligent sales system allowing that a customer who enters in a store can always find available a requested product: the customer which asks a specific product into a store always can receive it by means of the mobile application managed by the same store behaving as a master node. The administrator will send the request to other vendors by using the different mobile communication channels by receiving quickly a response. The proposed system is upgraded by means of a Rapid Miner data mining engine able to improve business intelligence (B.I.) and strategic marketing by means of artificial intelligence (A.I.) algorithms. The implemented A.I. algorithms are artificial neural network (ANN), Decision Tree, and K-means. These algorithms will provide information about strategies concerning warehouse management, brands and sellers classification and B.I. based on sales prediction. In the proposed paper will be discussed the prototype system design, the framework of implementation, and the A.I. results. This prototype system is suitable for the innovation in new marketing services and processes.**

Keywords— **Multichannel Marketing System, Mobile Marketing, Artificial Intelligence, Data Mining, Rapid Miner.**

I. INTRODUCTION

Different studies focused attention on multi-channel concept for the strategic marketing [1]-[15]. The study discussed in [1] aims to understand how social networks [4] can influence consumer behavior [5] in a multichannel sales involving physical stores and electronic commerce. In [2] some authors analyzed the price behavior in online stores helping to understand how online sales can influence store sales in a business intelligence (B.I.) view. In the food sector, many retailers have become multi-channel retailers, through the opening of an alternative online store [3], thus proving that the multi-channel retailing could be a good concept for strategic marketing model [7]. Other researchers studied in [6] the state of the art about works on channel choice between store, internet, catalog, branch, call center and self-service terminals. Some results demonstrate that the integration of multiple channels within a single point of sale handled by one retailer is feasible and successful [8], thus suggesting the idea to concentrate the multi-channel management to an unique node. In any case, the difficulty of translating physical experience into an online store is one of the main reasons why the fashion industry has been slower than other sectors to adopt E-commerce [9]. In this direction authors would like to enhance the importance of the physical experience of the consumer by improving a multi-store connection by means of mobile application.

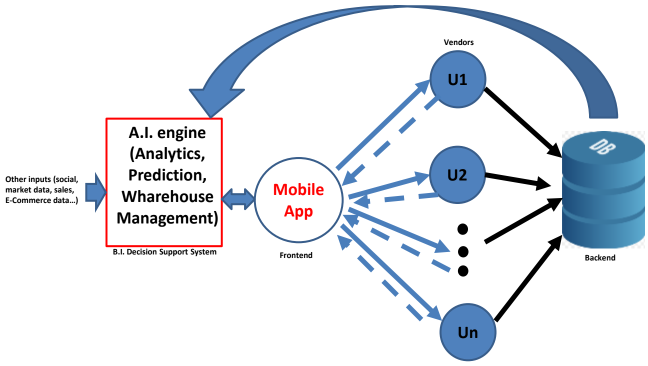

Fig. 1. Main functional diagram of the proposed multi-channel model.

Some results showed that even if brand differentiation effectively relieves competition and conflicts between channels, it is generally not sufficient to achieve complete channel coordination [10]. In any case the advent of the online channel and new additional digital channels such as mobile channels and social media have changed retail business models, the execution of the retail mix, and shopper behavior [11]. For this purpose it is important to add to the multi-channel system more facilities such as Artificial Intelligence (A.I.) Decision Support Systems (DDs). Other important research topics are related promotions in multi-channel [12], effects of channel performance [13], and channel competition [14]. A.I. could improve content marketing processes [15], besides A.I. clustering algorithms has been adopted in literature for dynamic pricing by means of a mobile application [16], thus confirming that A.I. engine implementation is necessary to improve an advanced business intelligence (B.I.). More specifically Sales prediction [17] and sentiment analysis [18] by A.I. are important B.I. issues. These topics could be implemented by data mining tools such as Rapid Miner used in literature for B.I. in market basket analysis (MBA) [19]. Following the state of the art we propose in Fig. 1 an innovative model based on the multi-channel concept and on the application of an A.I. engine as DSS suitable for strategic marketing: the proposed model consists of a mobile application coordinated by a vendor node enabling a multi-channel system able to find products unavailable in the store by sending the request to other vendors indicated in Fig. 1 by U_i. The A.I. engine will support the marketing decisions by analyzing other information such as market indices, E-Commerce data, and social sentiment data by optimizing warehouse management and predicting sales of defined products. According to these topics has been developed the conceptual model of Fig. 1, which is summarized in the following main requirements:

1) a consumer requires a product in a store;
2) the system administrator (node of the system) provides the product if it is available in the store, otherwise will ask by means the mobile application to other sellers the required product; the sellers are classified for product marks thus allowing to the engine to suggest the true seller;
3) the selected seller will notify the possible product availability, and the transaction will be executed by storing data in the database of the backend system;
4) sales data are collected and the A.I. algorithms will provide a Decision Support System (DSS) about the best sellers cluster, the best price to adopt, and the best warehouse stock management also according with processing of other information (social network, market data, customer segmentation, sales data, E-commerce data, open data, etc.).

As shown in Fig. 1, the prototype system is structured in the following three main parts:

1) a frontend interface (mobile APP);
2) a backend system enabling the multi-channel data flow;
3) a data mining (A.I.) engine for B.I..

We will discuss in the next sessions the system design, the main backend and frontend specifications of the prototype system, and finally different simulations of the A.I. engine.

II. Prototype System Design

In this section we discuss the whole design sketched in the basic architecture of Fig.1. In order to propose a full design scheme, different layouts of diagrams will be illustrated. Unified Modeling Language (UML) has been used for the design layouts (UMLet tool). The following three main actors participate to different use cases of the prototype system:

- actor System Administrator (ASA): this actor manages the entire system and the input data, the data processing and the output phases; in addition ASA interacts with the customers, checks the availability of the requested product in the warehouse database of the store (brand, model, size, etc.), and checks the external product availability by means of the multi-channel system; finally ASA will use the A.I. engine by evaluating the output results in order to undertake business intelligence operations (B.I.);
- actor User A (different vendors connected to the prototype system related to U_i of Fig. 1): this actor will upload on the backend system different information concerning products;
- customer: this actor requires a specific product and makes the payment or reservation interacting with ASA.

The design is developed in the following five layouts:

- use case diagram (UCD) of the whole prototype system (Fig. 2);
- ASA Activity Diagram (AD of Fig. 3);
- user A activity diagram (Fig. 4);
- customer activity diagram (Fig. 5);
- sequence diagram (SD of Fig. 6).

In the UCD diagram of Fig. 2 are enhanced the relationships between all the actors and the following data processing phases:

- input phase, data access and data entry: this phase represents the acquisition and retrieval phase related to all input data such as customer request (product request), user A data entry (data entry process of the mobile application) and data stored in the database;
- data processing phase: in this phase are performed analytics operations concerning a first level data processing related to statistical analysis and to trend visualization, and a second level data processing through A.I. and application of data mining algorithms such as neural networks, clustering, and Decision Tree; the processing also includes the check of the product availability performed by queries applied to the database system;
- output phase: this phase represents the graphical reporting of the output results (dashboards) useful for B.I. operations.

ASA actor participates to all the functions, besides customer and user A actors participate only to the input data process related to product request and to join use of the mobile application, respectively.

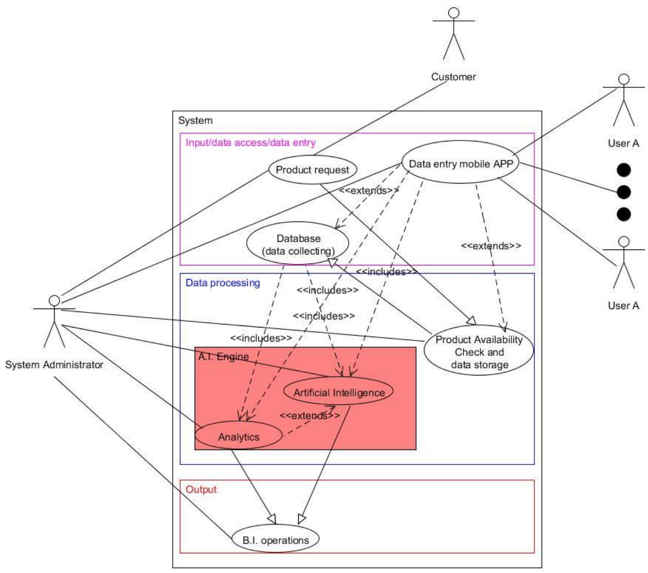

Fig. 2. Use Case Diagram of the project (UCD).

According with AD of Fig. 3, ASA actor checks the product availability of the customer request, and, in the case of unavailability in the store, uses the mobile application by visualizing all the seller linked channels. The data request is stored in the database, and the product is ordered after the seller notification. ASA can use the A.I. engine independently from the multichannel system in order to optimize the warehouse management, to improve the customer relationships or to analyze B.I. outputs which will be described in section III.

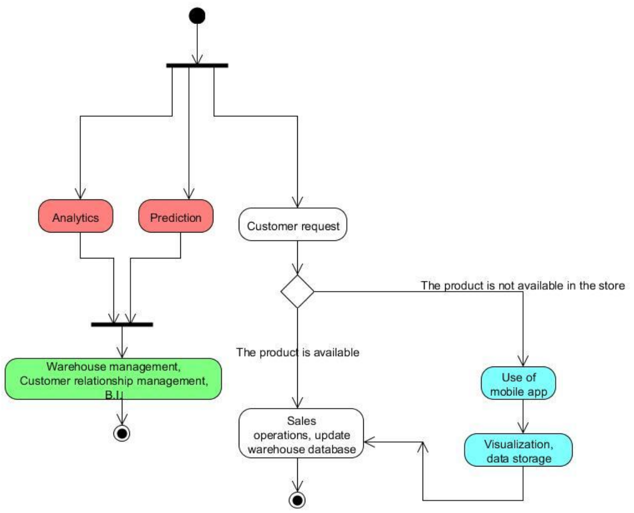

Fig. 3. ASA Activity Diagram.

In Fig. 4 is illustrated the AD related to the seller actor: initially the User A actor uploads in the backend system his credentials (necessary for the login) and the list of available products through the frontend of the mobile application, then he checks the ASA request by sending a notification. In Fig. 5 is illustrated the Customer AD which is characterized to two main activities: the product payment or the purchase renunciation.

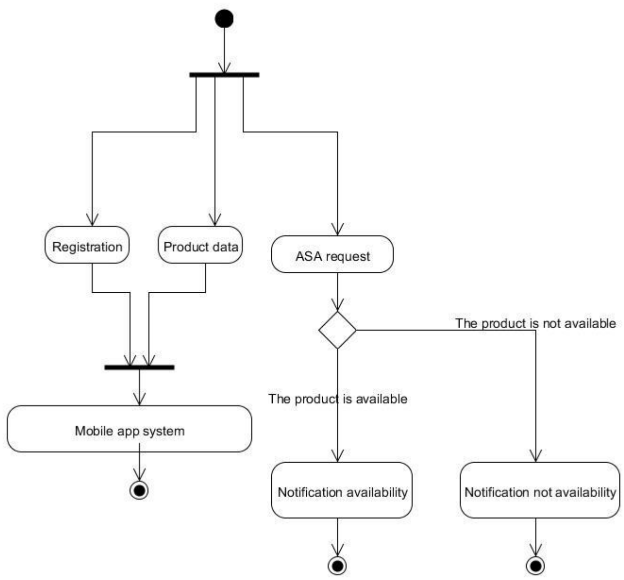

Fig. 4. User A Activity Diagram.

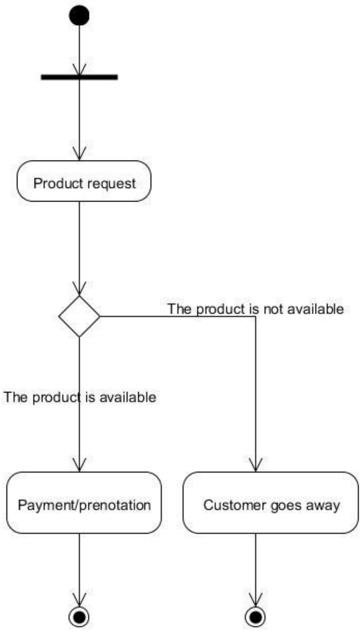

Fig. 5. Customer Activity Diagram.

In Fig. 6 is shown the SD merging all the functions reported in all the activities diagrams and in the UCD, by providing the timing of all the involved processes.

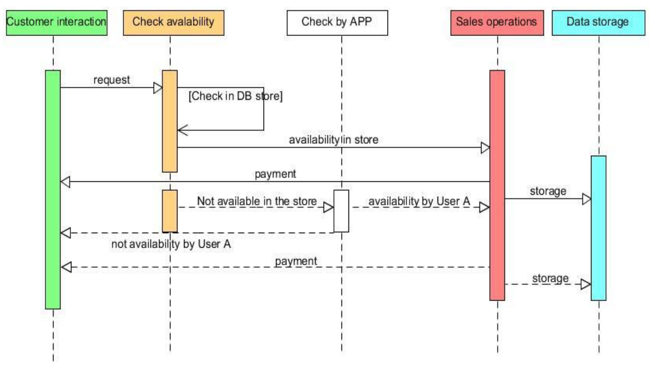

Fig. 6. Sequence Diagram (SD).

We list below the main requirements of the mobile application (Android and iOS native applications):

- user registration;
- login process;
- recovery password procedure;
- product request procedure creation;
- procedure to add request details;
- management of the requests;
- request list;
- list of the sent requests,
- list of the received requests;
- push notifications: by means of this specification will be possible to disable the notifications altogether or to receive them only for the brands of interest.

The framework used for the development is based on the following technologies:

- PHP 5.5+;
- GD Graphics Library;
- Imagick (PHP extension to create and modify images using the ImageMagick library);
- OpenSSL: full-featured toolkit for the Transport Layer Security (TLS) and Secure Sockets Layer (SSL) protocols;
- MySQL 5.5.

Summarizing, the mobile application allows to insert in the network all the users U_i which treat clothes, make requests for any finished items and put in communication all the involved actors. By means the application it will be possible to easily identify both the requests sent and those received regarding the treated products. When the User A user will launch the application for the first time, he must register by filling in a defined profile field his company data and his treated brand data, in this manner the ASA actor will receive notifications only in case of requests inherent to the treated brands. In the backend there will be all the lists of requests and of user profiles. All data will be stored in a database and will be processed for analytics and B.I.. In Fig. 7 is illustrated the mockup related the graphical user interface (GUI) of the product request panel.

Fig. 7. A mockup of the mobile application related to the request GUI.

The backend manages three main tables: notification table, request table, and users table. All tables contain the following attributes:

- User A Name;
- User A Surname;
- User A E-mail;
- Last access (date-time);
- Request title;
- Sender;
- Recipient;
- Date of the e-mail sent ;
- Date of the e-mail read;
- Push sent (date-time);
- Open push (date-time).
- Business name;
- Requested title;
- Date of the created istance;
- Date of the closed istance;
- Gender;
- Size;
- Brand;
- Product code.

A beta testing has been performed for the mobile application performance evaluation by solving faults and bugs.

III. Artificial Intelligence Results

In order to improve the A.I. implementation, we have added to the backend database system other information related to a specific product such as: quantity of product sold in the last month, social network rating, market index. All these values are normalized in a scale ranging from 0 to 100 and are exported into a csv file which will be processed as an input database data file. The Rapid Miner Studio Version 8.1 has been adopted for A.I. processing. In Fig. 8 (a) we illustrate the workflow implemented for neural network data processing which is structured by the following objects:

- Read CSV (it read the input csv file);
- Multiply (it switches the input dataset in both the training and testing branches);
- Filtering (it applies logical and numerical conditions applied to the input dataset where the testing dataset will consist of the last 20 requests besides the training dataset will consist of all 115 records;
- Neural Net (this operator learns a model by means of a feed-forward neural network trained by a back propagation algorithm named multi-layer perceptron MLP [20]; training cycles = 500; training rate = 0.8, momentum = 0.2, error epsilon 1E-5, 1 hidden layer , local random seed = 1992);
- Performance (model scoring).

In Fig. 8 (b) is shown the applied neural network.

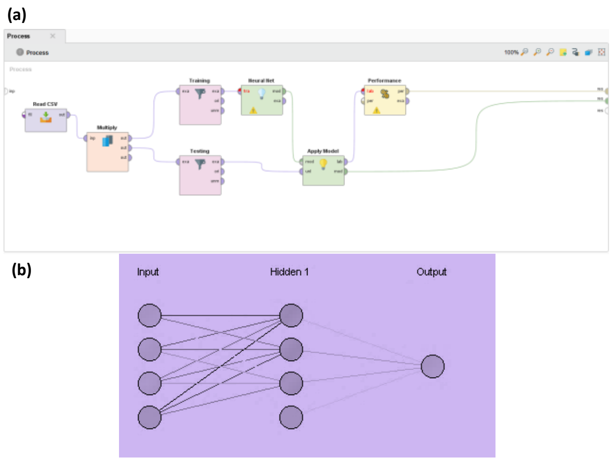

Fig. 8. Rapid Miner: (a) neural network algorithm workflow; (b) applied neural network graph.

About neural network results, in Fig. 9 are plotted the graphs related the quantities of some products sold in the last month together with the predicted quantities of the some products by crossing and processing different data such as social sentiment and market trend. The results confirms the sales trend behaviour, by observing a prediction of less sold quantities for the last products (product code 15, 17, 18, 19 and 20). This result could support the warehouse management of stocks by planning in advance the supply of stocks of specific products on the basis of the forecast calculation.

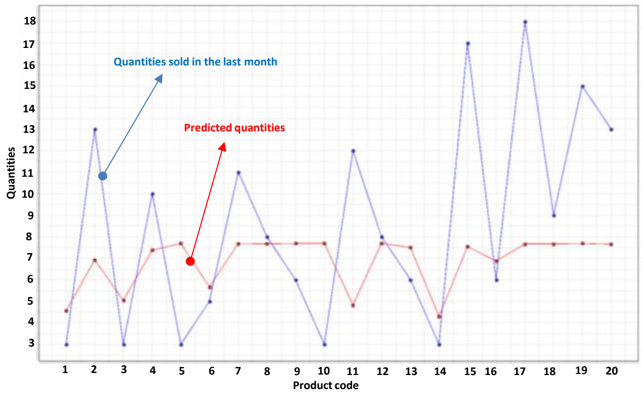

Fig. 9. Rapid Miner: sales prediction in the next month of some products.

Another typology of A.I. processing is provided by data clustering. Specifically we have applied the k-Means algorithm [21], which is modeled by the workflow of Fig. 10. In Fig. 11 and Fig. 12 are illustrated the scattering plots related the data dispersion of five clusters (k =5 generating Cluster 0, Cluster 1, Cluster 2, Cluster 3, Cluster 4) versus social sentiment score and market index, respectively. In order to visualize better data dispersion the jitter plot modality has been used: jittering is the act of adding random noise to data in order to prevent overplotting in the output graphs.

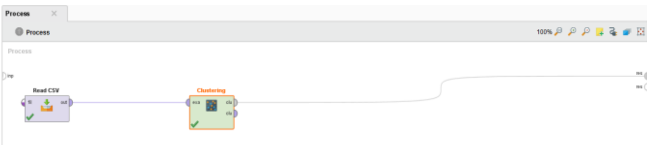

Fig. 10. Rapid Miner: workflow of the clustering k- Means algorithm.

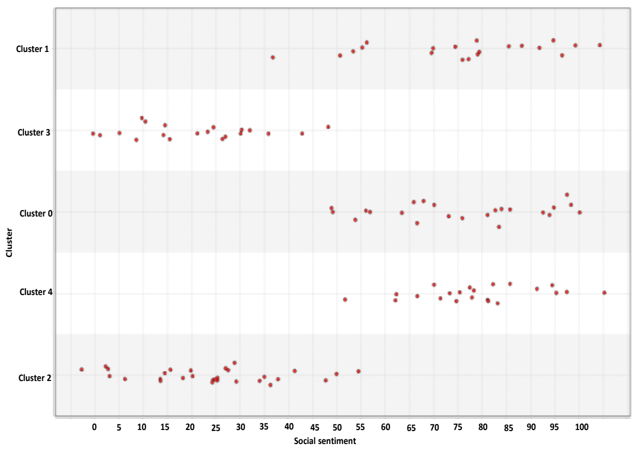

Fig. 11. Rapid Miner scatter plot: product clusters versus social sentiment.

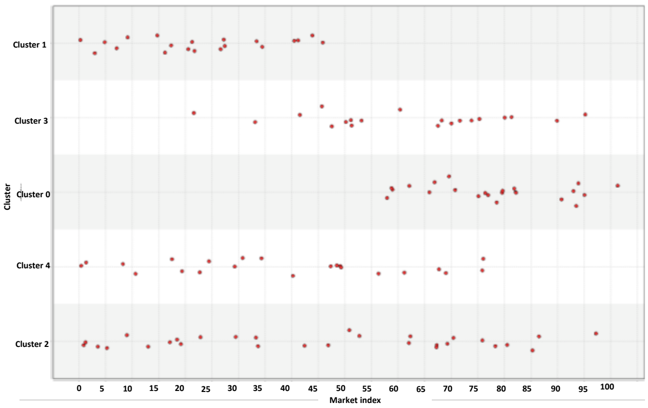

Fig. 12. Rapid Miner scatter plot: product clusters versus market index (an high index means a good market).

We observe that the used data mining tool provides information about each data point indicated in plot of Fig. 11 and Fig. 12. The clustering analysis is useful in order to apply B.I. by following a defined marketing strategy of the store oriented on market or on social trend. The last A.I. application concerns Decision Tree algorithm [22]. Figure 13 illustrates the Decision Tree object named as ID3 (Dichotomiser Iterative 3 algorithm) [23], and used for the data processing. The algorithm is executed by setting the following parameters: gain ratio criterion type, minimal size for split = 5, minimal leaf size = 2, minimal gain = 0.1. The tree graph of Fig. 14 is convenient in order to classify all the linked sellers U_i by taking into account their brands. The automatic classification it is important to accelerate the searching process.

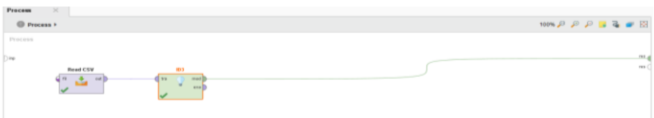

Fig. 13. Rapid Miner: Decision tree ID 3object.

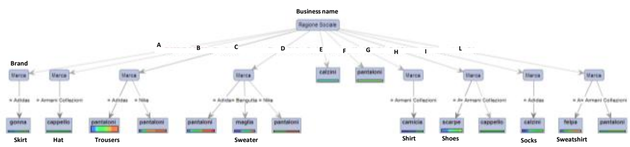

Fig. 14. Rapid Miner: Decision Tree output.

IV. Conclusion

The main goal of the proposed work was to provide a mobile application useful to find by a multi-channel mobile system a requested product unavailable in the store. The proposed mobile application is able to switch the request into different communication channels linked to other registered sellers. The prototype system permits to apply different artificial intelligence algorithms by processing the backend data together with other data such as social sentiments, market index and sold quantities associated to a defined product. The Rapid Miner outputs of the neural network, k-Means, and Decision tree algorithms provided important information about strategic marketing, warehouse management and business intelligence. A full automatic A.I. processing could furthermore improve the proposed decision support system. E-commerce integration in the automatic data processing will upgrade the prototype system and the B.I. facilities.

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REFERENCES

[1] Y. T. Jang, S. E. Chang, P. A. Chen, “Exploring Social Networking Sites for Facilitating Multi-Channel Retailing. Multimedia Tools and Applications,” 2015, Vol. 74, No. 1, pp. 159-178.

[2] T. Fang-Fang; X. Xiaolin; “Will the growth of multi-channel retailing diminish the pricing efficiency of the web?,” Journal of Retailing, 2001, vol. 77, No.3, pp. 319-333.

[3] M. Kristina, et al., “The Impact of the Multi-Channel Retail Mix on Online Store Choice: Does Online Experience Matter?,” Journal of Retailing, 2015, Vol. 91, No. 2, pp. 272-288.

[4] T. Ioan, et al. Sesa “A Scalable Multi-Channel Communication and Booking Solution for E-Commerce in the Tourism Domain,” E-Business Engineering (ICEBE), 2013, IEEE 10th International Conference on. IEEE, 2013. p. 288-293.

[5] T. Kollmann, A. Kuckertz, I. Kayser, “Cannibalization or synergy? Consumers' channel selection in online–offline multichannel systems,” Journal of Retailing and Consumer Services, 2012, Vol. 19, No. 2, pp. 186-194.

[6] D. Hummel, S. Schacht, A. Maedche, “Determinants of Multi-Channel Behavior: Exploring Avenues for Future Research in the Services Industry,” Thirty Seventh International Conference on Information Systems, Dublin 2016, pp. 1-12.

[7] G.-W. Bock, et al., “The Progression of Online Trust in the Multi-Channel Retailer Context and the Role of Product Uncertainty,” Decision Support Systems, 2012, Vol. 53, No. 1, pp. 97-107.

[8] E. Pantano, M. Viassone, “Engaging Consumers on New Integrated Multichannel Retail Settings: Challenges for Retailers,” Journal of Retailing and Consumer Services, 2015, Vol. 25, pp. 106-114.

[9] M. Blázquez, “Fashion Shopping in Multichannel Retail: the Role of Technology in Enhancing the Customer Experience,” International Journal of Electronic Commerce, 2014, Vol. 18, No.4, pp. 97-116.

[10] R. Yan, “Managing Channel Coordination in a Multi-Channel Manufacturer–Retailer Supply Chain,” Industrial Marketing Management, 2011, Vol. 40, No. 4, pp. 636-642.

[11] P. C. Verhoef, P. K. Kannan, J. J. Inman, “From Multi-channel Retailing to Omni-Channel Retailing: Introduction to the Special Issue on Multi-Channel Retailing,” Journal of Retailing, 2015, Vol. 91, No. 2, pp. 174-181.

[12] E. Breugelmans, K. Campo, “Cross-Channel Effects of Price Promotions: An Empirical Analysis of the Multi-Channel Grocery Retail Sector,” Journal of Retailing, 2016, Vol. 92, No. 3, pp. 333-351.

[13] M. Van Birgelen, A. De Jong, K. De Ruyter, Ko, “Multi-channel Service Retailing: the Effects of Channel Performance Satisfaction on Behavioral Intentions,” Journal of Retailing, 2006, 82.4: 367-377.

[14] P. I. Jeffers, B. R. Nault , “Why Competition from a Multi-Channel E-Tailer does not always Benefit Consumers,” Decision Sciences, 2011, Vol. 42, No. 1, pp. 69-91.

[15] U. Kose, S. Sert, “Improving Content Marketing Processes with the Approaches of Artificial Intelligence,” 2017, Ecoforum, Vol. 6, No. 1.

[16] A. Massaro, A. Galiano, G. Fanelli, B. Bosshael, V. Vitti, “Web App for Dynamic Pricing Modeling in Automotive Applications and Data Mining Analytics,” (IJCSIT) International Journal of Computer Science and Information Technologies, 2018, Vol. 9, No. 1, pp. 4-9.

[17] K. N. Mahanjan, A. Kumar, “Business Intelligent Smart Sales Prediction Analysis for Pharmaceutical Distribution and Proposed Generic Model,” (IJCSIT) International Journal of Computer Science and Information Technologies, 2017, Vol. 8, No. 3, pp. 407-412.

[18] S. Kulkarni, N. Prabhune, V. Sathe, “Sentiment Analysis of Product Reviews,” (IJCSIT) International Journal of Computer Science and Information Technologies, 2018, Vol. 9, No. 1, pp. 19-22.

[19] A. Massaro, A. Galiano, D. Barbuzzi, L. Pellicani, G. Birardi, D. D. Romagno, L. Frulli, “Joint Activities of Market Basket Analysis and Product Facing for Business Intelligence oriented on Global Distribution Market: examples of data mining applications,” (IJCSIT) International Journal of Computer Science and Information Technologies, 2017, Vol. 8, No. 2, pp. 178-183.

[20] M. M. A. Mia, S. K. Biswas, M. C. Urmi, A. Siddique, “An Algorithm For Training Multilayer Perceptron (MLP) For Image Reconstruction Using Neural Network Without Overfitting,” International Journal of Scientific & Technology Research, 2015, Vol. 4, No. 2, pp. 271-275.

[21] A. Siddharth, K. Parneet, A. Prachi, “Economical Maintenance and Replacement Decision Making in Fleet Management using Data Mining” The SIJ Transactions on Computer Science Engineering & its Applications (CSEA), 2013, Vol. 1, No. 2, pp. 36-48.

[22] R. C. Barros et al., “Automatic Design of Decision-Tree Induction Algorithms,” SpringerBriefs in Computer Science, 2015.

[23] H. Bhatt, S. Mehta, L. R. D’mello, “Use of ID3 Decision Tree Algorithm for Placement Prediction,” (IJCSIT) International Journal of Computer Science and Information Technologies, 2015, Vol. 6, No. 5, pp. 4785-4789.