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# INTELLIGENTPERSONALIZATION APPROACHESFORCOMPLEX CUSTOMER BEHAVIOUR: AN OVERVIEW

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***Abstract*****:** *Intelligent techniques have been used in the marketing and sales sectors of business to improve analysis, increase revenues and save time. In customer-centric institutions, one of the areas in which intelligent techniques and data mining algorithms have been used is the personalization for enhanced CRM (customer relationship management) performance. However, with a growing number of customers, the diversity of products on offer, the complex behavior of customer groups and the continuous change of personalization parameters, the production of a tailored personalized recommendation and the prediction of future needs are a challenging task. Within these institutions, personalization that is more true to the customer needs leads to better targeted marketing campaigns and enhances customer satisfaction with the ultimate aim of increasing the rates of customer retention, and improving competitive advantage. Intelligent techniques and data mining algorithms have been used to produce a more accurately tailored action or service to individual customers or segments of customers. However, many limitations still exist in the CRM personalization lifecycle that undermine the scope of personalized actions that follow; especially in evaluating of effectiveness of targeting, ensuring the coverage of a large segment customers and the control on the decision making process.*

*In this paper, we explain the large dimensionality of the problem, categorize the main business objectives of the personalization process, and survey representative works for each objective. Through the survey of these representative works, we identified the successes of intelligent techniques in the personalization process as well as the limitations that still exist,in addition to some areas of possible further improvement.*

***Keywords:****Personalization, Intelligent DSS, Dimensional Modeling,Clustering,Association Rules, User Profile, Group Profile, Object Profiling, Recommendation, Business Intelligence, Customer Churn, Data Mining*

## 1. Introduction

Personalization is the ability to provide items, services or actions that are tailored to individuals' needs in the right time based on knowledge about their preferences and past behavior. Hence, using the information generated to predict their next activity or building an intelligent decision support system are considered focus points of researchesin various business domains; like banking, telecom, education and others, as well as for data scientists. Building a personalized recommendation engine is considered a big challenge in both computer science and CRM fields. CRM is a process used to learn more about customers' preferences and behaviors in order to develop stronger long-term relationship with them. The process involves the use of continuously refined profile of current and potential customers in order to anticipate and respond to their needs. It draws on a combination of business process and intelligent techniques to discover the knowledge about the customers and answer questions like, "who are the customers?", "what do they do?" and "what do they like?" Answering these questions is central to any business in their quest to find competitive advantages to acquire new customers, develop and retain existing ones.

This paper aims to categorize the various core objectivesof applying personalization analysis and survey representative works for each objective as shown in Figure 1. The personalization generated from the multidimensional analysis of data is utilized afterwards to enhance the CRM performance.

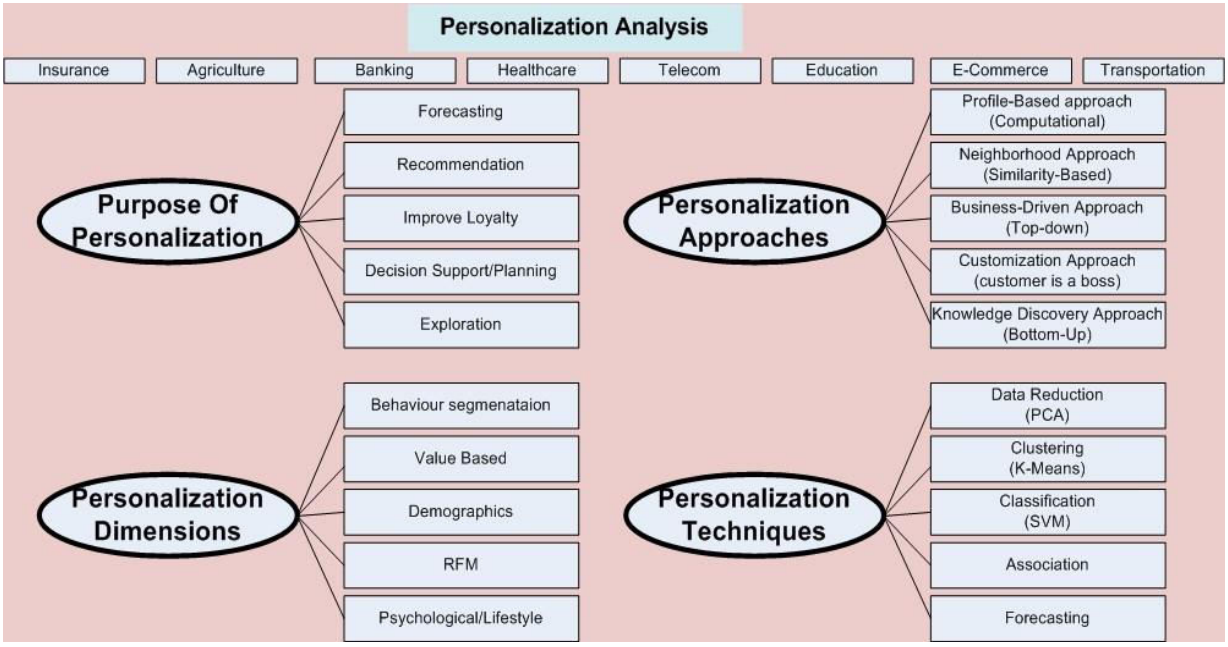


**Figure 1: Personalization analysis form different focusing perspective**

## 2. The Technical Personalization Process

The personalization implementation process are illustrated in Figure 2 and achieved through the execution of the following steps:

1. Define dataset to work on.
2. Identify dimensions of segmentation.

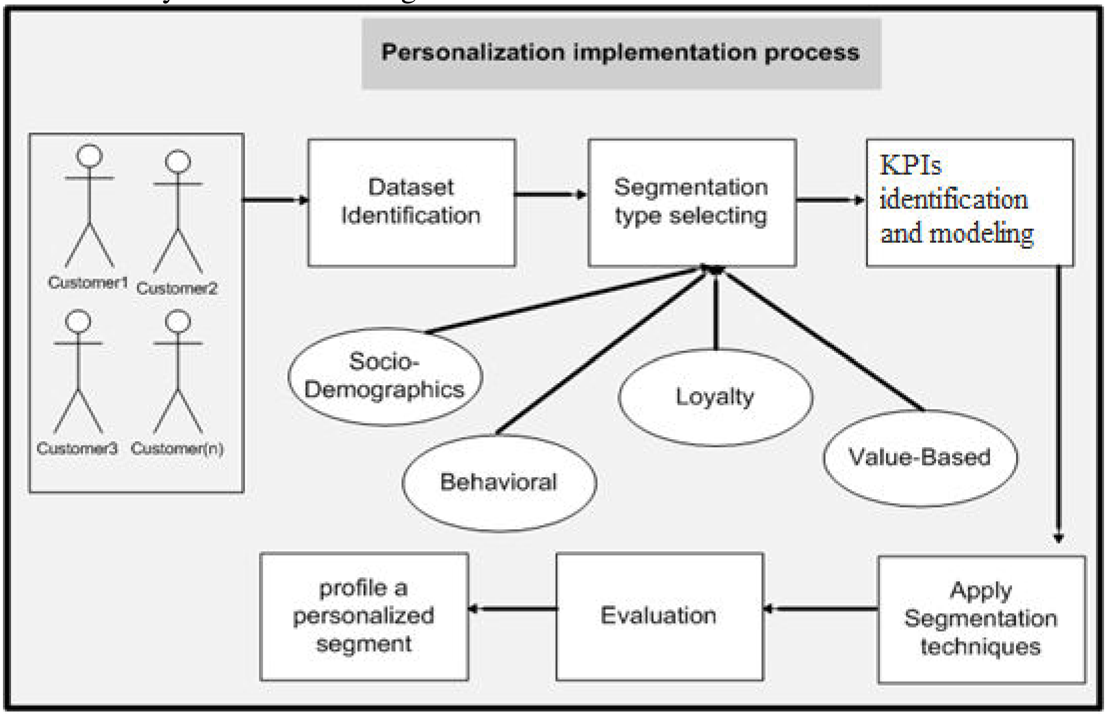


**Figure 2: Personalization Implementation process**

3. Identify KPIs (Key Performance Indicators); these are the effective statistical measures that have the ability to indicate the criteria that can helpto better understand the customer.

4. Generate segments by using clustering modeling techniques.

5. Evaluate the framework segments as the data miners inspect the clustering solutions and seek guidance from the marketers for selecting the most effective segmentation.

6. Profile revealed segments to support the business evaluation of the segments as well as the subsequent development of effective marketing strategies tailored for each segment.

## 3. The Personalization Approaches

Personalization approaches aim to deliver a tailored action or service to individual customers. There are many personalization approaches developed where each approach has a different set of steps and different logic to be implemented and, accordingly, leads to different results. The process of selecting a specific technique is done based on the content availability and business needs. The following subsections explain the differences between the main five personalization approaches.

### 3.1 Profile-Based approach

Profile-based approach is a computational approach that needs a complete model of customers' behavior, actions, and customers' reactions based on information stored in a data set. Data mining and optimization models can be used here to discover and analyze the stored profile of the customer. Profile-based approaches guarantee the full automation in generating the action.Consider the following scenario "a retail bank is considering a new credit card marketing campaign and the reaction of customers towards this new product". The success of the profile-based model is based on the completeness of the data. For example if a group of customers didn't respond to the campaigns, the mining algorithms couldn't be used to generate a personalized action.

One of the benefits of the computational approaches is the automation of actions based on the customer profile, as no human interference is needed. One limitation of those approaches is that the success of an action is based on the reaction;generatinga personalized action requires the customer'sresponse to the promotion campaign first. The full coverage of customers is an important missed factor here, having not all customers respond to the campaign leads to unknown behavior and incomplete profile.

### 3.2 Neighborhood Approach (Similarity-Based Pattern Recognition)

Similarity-based pattern recognition methods or neighborhood approaches are usually used by recommender systems and web content personalization methods. Thismethodis based on customer preferences extracted from customer profiles assuming that the unknown preferences of a customer can be derived by identifying the similarity with other customers. Accordingly a "similarity-based" approach does not require storing as much information as theprofile-based approach.

The similarity-based method has been used in different researches. One work used it for banking retention model for the churn of customers. The marketers faced the issue of how personalized actions should be part of a marketing campaign. The financial advisor decides that the actions to be delivered to each customer should be based on studying the individual customer's behavior. There are two main factors considered by the managers in choosing the most proper approach (1) Keeping high control on the marketing process, (2) Achieving better targeting with respect to prior marketing campaigns.The level of targeting did not increase as much as expected because the scope of actions in a "similarity-based" approach is quite limited, as it reduces the level of targeting. [10]

### 3.3 Business-Driven Approach (Top-down)

Business-driven approaches include the direct marketing approaches. Here the decision of what actions to deliver is made before the definition of customers' profiles. The top-down approaches do not cover the whole customer base. It satisfies the effectiveness of targeting factor like in reducing customer churn. In these approaches, supervised data mining techniques can be applied for the classification process. Business-driven approach is another definition for that approach in which the business experts define the input and output factors before customer's preferences are defined. For example, the marketing manager can define a specific service like offering a discount on credit cards purchasing then start to extract the target customers by building the most convenient profile.

The limitations of the business-driven approach appear clearly in the fact that the level of targeting did not increase as much as expected, because of the complex behavior of the customers, as the customer's decision of leaving or remaining loyal only depends on the offered products without considering any other effective dimensions. The supervised models which require a predefined input and output based on the top down approach mainly depend on human inputs and expectations which miss some existing facts. Lack of coverage measuring factor is another limitation of using the top-down approach as a personalization method. Business-driven approach doesn't cover the entire customer base to personalize all cases, but it focus on specific cases instead. [10]

### 3.4 Customization Approach (Customer is the Boss)

Customization approaches offer customers many different options and let the customers choose the suitable one. In these approaches, action is taken from customers' choices. For instance, a retail bank can propose customers to choose one option among many credit card options. The association between the marketing activity and the profile is done by the customer. The control over the process is low and the resulting actions are expensive. However, the targeting is expected to be quite effective.Some of business sectors use the customization approach when the user can personalize his product online. Considering the Nike website as an example [13], the customer can add his name on the product or customize the parts design and colors. Many business owners changed their point of view by shifting from focusing on shareholder value to focusing on the consumer [14].

Moving from mass production to mass customization and then to personalization produces a great efficiency in customer satisfaction. The visualization tool for the customization process is highly needed for customer understanding between different models for the effective personalization [12].Personalization based on customization clearly shows that the targeting is effective but expensive and the customers' coverage is totally missed.

### 3.5 Knowledge Discovery Approach (Bottom-Up)

Knowledge discovery approaches arebottom-up approaches that use front office personnel. These approaches can be implemented in two steps: 1. Build customer profiles, 2.Decide on the proper action. It is worth to mention that the first step has to precede the second step. On one side, the knowledge discovery approaches cannot be fully automated, so these approaches are typically not very efficient. On the other side, targeting can be very effective because each profile is thoroughly analyzed before generating a proper action, so the knowledge discovery approach is suitable for financial advisors.In mobile knowledge discovery, a lot of information can be captured from mobile device holders like family, friends, wakeup time, job, feelings (from social network), preferred items (through search engines), health status (through health check apps), financial statement, locations (through GPS) and the future plans (through the notes). “Now I Know You Well” is what the analysis can say to the mobile holders [16].

The big limitation in mobile knowledge discovery is penetrating the privacy of mobile holders.Moreover, offers may annoy the customers as for every model,an execution message could be sent. Another limitation is that not all people have a smartphone and even if they have, they may disable the sharing personal information feature which leads to incomplete knowledge model and miss targeting offers.

## 4 Effective Dimensions in Segmentation for Personalization

Segmentation for personalization is the ability to segment single entities in groups which have same characteristics to be targeted in personalized actions. There are many dimensions that could possibly be used for segmentation to improve the personalized targeting and ultimately get the one-to-one customer manipulation. The various categories of dimensions are illustrated in Figure 1. The following subsections provide an overview on the most effective dimensions for representative segmentation and present a list of factors and example research for each dimension.

### 4.1 Socio-demographics segmentation dimension

Socio-demographics dimension is considered base factor in defining a customer’s behavior; factors that describe the social positioning of a customer and their geographical location. These factors include attributes like age, gender, income, employment, and city or region. The use of attributes help in providing personalized service since customers sharing the same values for these attributes (age or gender) tend to be interested in the same products. Residence or region is used because they may indicate the culture of the customer towards a certain activity [1, 5, 6].

### 4.2 Behavioral segmentation dimension

The behavioral segmentation dimension describes the segmentation based on customers’ purchasing metrics, examples of these factors include:

- RFM (Recency, Frequency, and Monetary) factors. These factors not only describe the shopping behavior of customers but are also measures of their loyalty. Recency metric indicates when the customer made his latest transaction; Frequency metric shows the frequent shopping in stores and Monetary metric defines the amounts of customer spending[3].
- Payment metric. This factor describes the regularity of the customer in making payments.

- Usage dimension. This factor enables the model to follow up the customer usage[8].

### 4.3 Value-Based segmentation dimension

Value-based segmentation dimension is one of the most important segmentation types since it can be used to identify the most valuable customers, and to track value changes over time.In value-based segmentation, customers are grouped according to their value to the vendor or institutionas shown in Figure 3. This segmentation methodis used to differentiate the service delivery strategies and to optimize the allocation of resources in marketing initiatives. Usually in research that uses this type of segmentation, the total spending of the customer on a monthly basis is utilized to categorize the customer in three baseline segments that defines the customer's value for the organization [7, 1].

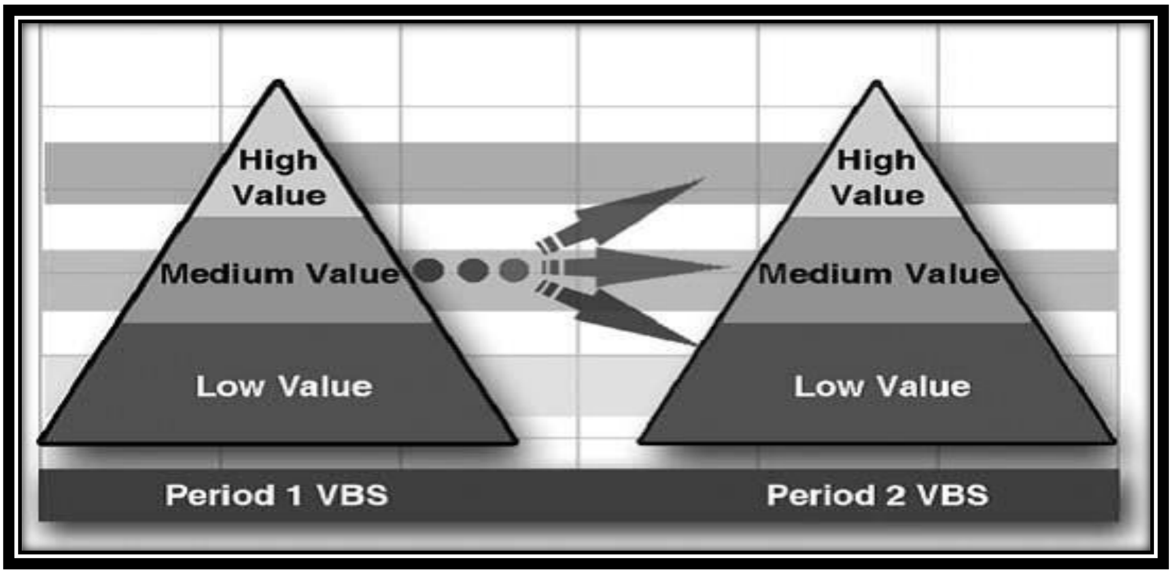


**Figure 3: Value-Based Segmentation**

Customer Lifetime Value (CLTV) is an application for customer value. CLTV presents value of the future cash flows attributed to the customer during his entire relationship with the company. It is used to predict the most profitable group of customers, understand those customers' common characteristics, and focus more on them rather than on less profitable customers. Thisparticular use of a customer value for segmentation was the basis for research in [4, 9].

### 4.4 Time Series Analysis Dimension

Time dimension is proved to be an effective dimensionin segmentation. For example,identifying the time in the year or the time of the day when an activity tends to increase or a surge in payment amounts tends to occur. Some researchersusedthis dimension in segmentation to predict the next best activity to be presented to specific customer groups throughout the year's intervals [16]. The approach proposed in their research used time series analysis and was able to answer the questions of: Who? Goes where? and When do they go? Henceforth, the patterns discovered were used to personalize the actions for specific customer groups based on the place and time dimensions [11].

### 4.5 Life-Stages Segmentation

Life-stages present opportunities for promoting products and services that address the particular needs of customers in different stages of their life. Theorganization recognizes the important life-stage events and associates them to consuming behaviors. For example, in retail bankinglife-segmentation framework can recommend a specific banking products or services for customers that match their needs as per life-stage segment as shown in Figure 4.The limitation of life-stage segmentation is the difficulty in identifying the life stage, since the life-events arenot usually stored in the customer'sdatabase and the organization may not know the updates of customer's life events to be segmented in an automated way. To overcome this limitation, the age of customersis usually used as a proxy for life-stageidentification instead [20].

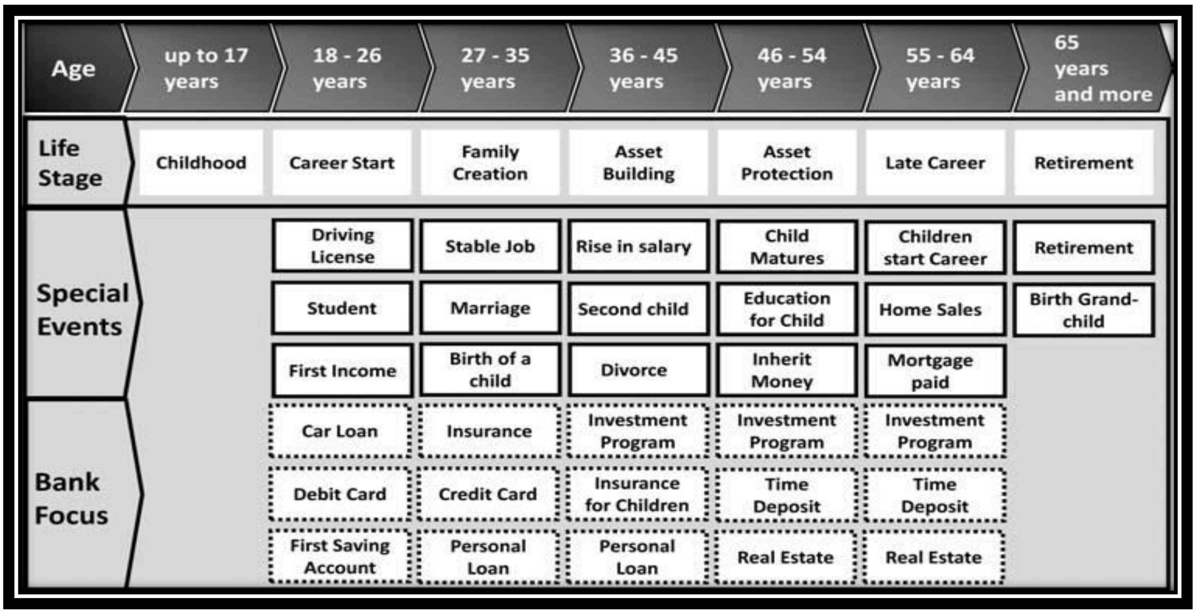


**Figure 4: An example from the banking industry for Life-Stage segmentation**

## 5 Objectives of Personalization Approaches

Personalization is considered for marketing and data analysis in many business domains, but the objective sought out of the personalization varies. This section surveys the different perspectives of applying the personalization approaches ina number of domainsand highlights the value realized from the implementation.

## 5.1 Forecasting

Forecasting, in this context, is usually concerned with predicting the customer’s Next Best Activity (NBA). A predictive model can be built for use in marketing campaigns to attract new customers, provide a new service to existing ones, or decrease the customer’s churn rate. With the increased use of mobile devices, Mobile Personalized Marketing (MPM), which is the personalized marketing via mobile devices,is becoming an increasingly important marketing tool. The research applied on Nokia context data aimed to get better prediction of customers' preferences by studying a set of correlations between contexts of mobile users and their activities[16].
Churn prediction problem is an important analytical CRM application of in-time identification of customers shifting loyalties from one service provider to another. In [18],the authors used rules extracted from a hybrid approach of SVM(Support Vector Machine)and NBTree (hybrid classifier) between Naive Bayes and decision trees as shown in Figure 5. Authors applied the analytical CRM through enterprise wide repositories, sales data (purchasing history), financial data (payment history and credit score), marketing data (campaign response, loyalty scheme data) and service data. The results show that anexisting ‘loyal’customer is likely going to churn out in the near future with the best sensitivity of 91.85%.

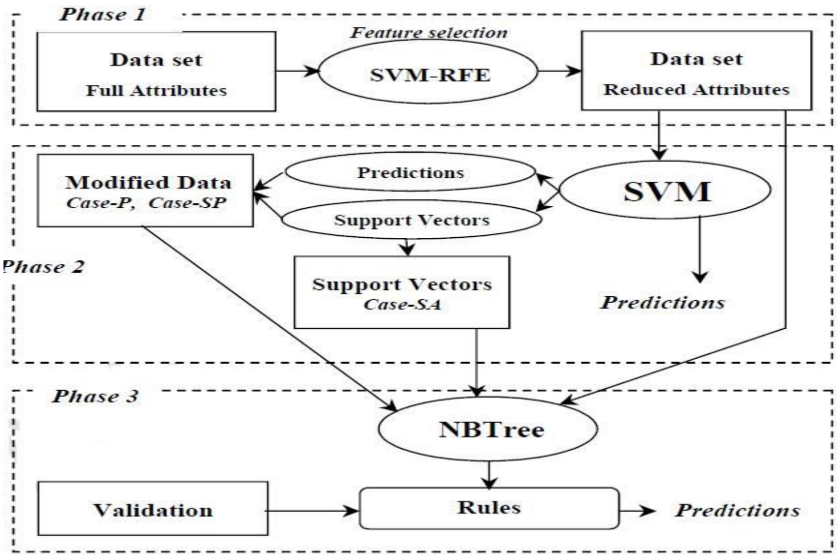


**Figure 5: Rule extraction using selected attributes of data [18]**

## 5.2 Recommendation

Recommender systems have become extremely common in recent years; especially with the large overtake of e-commerce websites. The recommendation engine is a solution that has the ability to generate a set of items to be recommended to a customer through an automated intelligent analysis of historical data. Evident examples are recommendations to customers on movies, books, and electronics websites. In addition to recommendations on news websites, research articles, services and products in general. The main idea is to recommend a personalized item to a customer to match his needs after analyzing hisprofile,In addition to the purchase history. Hence, a similarity between future and past behaviors of one customer is assumed. Generally, ifa similar behaviorbetween groups of customers is observed, other similar behaviors can also be anticipated.

Some researchers used the similarity-based approach to generate recommendations of products for bank customers [10]. The researchers used data from a medium-sized Italian retail bank facing the issue of increased customer churn rate. A redemption rate of 78.5% was observed, meaning that 1062 customers out of 1353 contacted customers responded positively to the marketing action proposed and did not leave the bank, thus reducing the overall churn rate. The main limitations of the proposed approach are the low degree of targeting level, and lack of automation.

### 5.3 Decision Support and Planning

The efficient decision support and planning system is built based on accurate personalization approaches.An Intelligent Decision Support System (IDSS) is a decision support system that uses an intelligent data mining techniques to support decision makersin the area of Management Information System (MIS). The aim of personalization is to use the segmented customer groups to create customized marketing strategies through a stable DSS in order to satisfy clients' needs better, and increase profitability. In the field of insurance, a DSS is built based on PCA (Principle Component Analysis) to reduce the number of variables and to detect structure in the relationships between variables that classifies variables to optimize customer claims experience and provide convenient fast claims service [2].

### 5.4 Loyalty Improvement

Analyzing user preferences through their purchase history is usually an importantstep in the personalization process. Online shopping process becomes more convenient when the vendor automatically knows the customer's name, shopping history and mailing address [19]. Then, the real key to ensure customer satisfaction is to know your customer. Vendors can use the customer's information to tailor the customers' needs.This will help improvethe customer's experience while shopping and improve their loyalty to this particular vendor.

In the education field, an effective Personalized Creativity Learning System (PCLS) was developedto optimize the learning quality through tailoring the learning experience to meet the learners' needs [15]. PCLS was developed by integrating personalized learning theories, hybrid decision trees technique, and game-based learning(as shown in Figure 6) to make learning enjoyable. PCLS improved the limitations of traditional creativity learning systems as well asincreasing the learner interaction, satisfaction and loyalty which led to enhancement of learning motivation and outcomes.

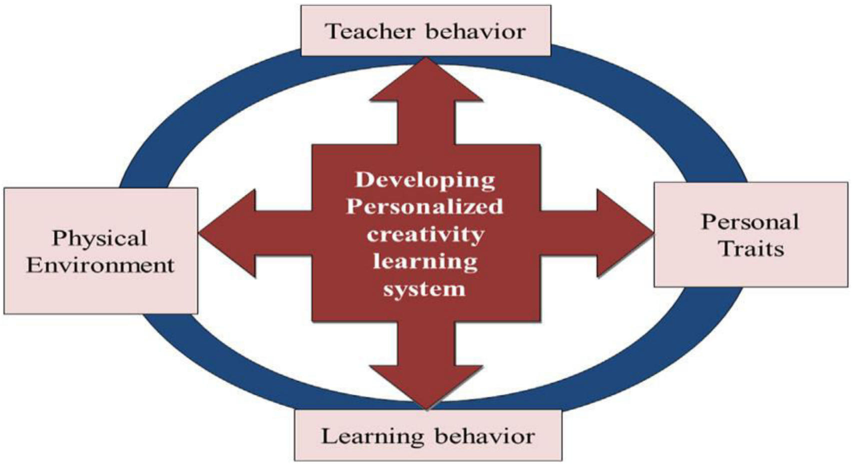


**Figure 6: The critical values of the PCLS**

## 5.5 Exploration and Discovery

To explore and discover large amount of complex data, the personalized patterns should be extracted. Sometimes the objective of the personalization process is purely to provide a deeper understanding of customers and market behaviors. The objective of this area of research is to understand the data, evaluate it and model it.

An advanced analytics approach was proposed and implemented in [17]to explore customer complex behavior during sales' campaigns through a visual, data-driven and efficient framework for customer-segmentation and campaign-response modeling. The researchers applied SOM (Self-Organized Map) data mining technique to group customers by their purchasing behavior. To enable the visual monitoring of the customer base and to track customer behavior before and during the sales campaign,a link segment-migration pattern using feature plane representations was createdas shown in Figure 7.

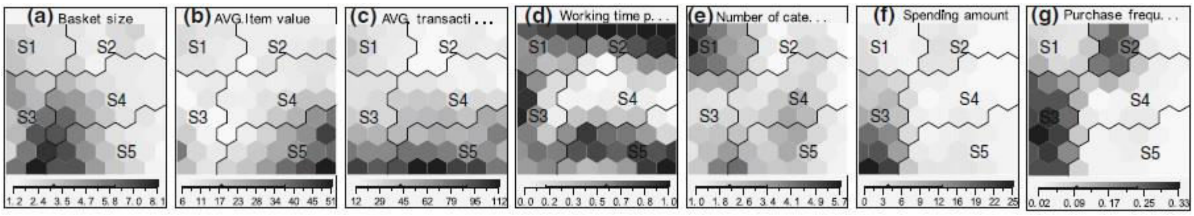


**Figure7: Daily purchasing behavior profile [17]**

## 6 Conclusion

This papersurveyed the needs for and approaches to personalization in different domains.The competition in the CRM field has increased to get a competitive advantage to interact with customers effectively.Many approaches have been used to provide customers with personalized service/experience through the full CRM lifecycle from the beginning of customer acquisition to development and retention. Many intelligent techniqueswere explored and used to allowpersonalized actions tailored to individual needs.The paper foundremarkable results in the personalization area as it was clear that the level of customer satisfaction and loyalty improved which leads togreater understanding of customers to support the identification of new marketing opportunities, design and development of new products/services tailored to each segment characteristics. The personalization approach leads to design customized product, offering tailored rewards and incentives, selecting the appropriate advertising and communication message and channel and differentiation in customer service according to each segment's importance. Finally, resource allocation became more effective according to the potential return from each segment, increase in overall profitability and setting a long-term relationship with the customer to retain and develop them. Limitations to existing research were found to be related to the level of targeting, full coverage of customer base and automation of the process. Further work in the area of personalization would include enhancing the effectiveness of targeting by considering additional effective dimensions and handling the automation of personalization approaches.

## References

[1] Yang,X. , Chen, J. , Hao, P. and Wang,Y. (2015) Application of Clustering for Customer Segmentation in Private Banking, in: Seventh International Conference on Digital Image Processing ,ICDIP 2015, Proceedings of SPIE. Bellingham, WA 2015, 96311Z , Vol. 9631

[2] Zhou, L. and Zhang, N. (2015) Customer Segmentation and Optimal Insurance Compensation Ratio: Decision-making Analysis in Financial Institutions, International Journal of Multimedia and Ubiquitous Engineering, Vol.10 , No. 8 , pp.161-170.

[3] Azadnia, A.H.; Ghadimi, P.; Aghdam, M.M. (2012) A Hybrid Model of Data Mining and MCDM Methods for Estimating Customer Lifetime Value ,in: Proceedings of the 41st International Conference on Computers & Industrial Engineering, Los Angeles, CA, USA, 23–25 July 2012; pp. 80–85.

[4] J. Cuadros, V.E. Domínguez (2014), Customer segmentation model based on value generation for marketing strategies formulation, EstudiosGerenciales ,Volume 30, Issue 130, January–March 2014, Pages 25–30.

[5] Hamka, F., Bouwman, H., De Reuver, M., &Kroesen, M., (2014) Mobile customer segmentation based on smartphone measurement ,Telematics and Informatics, Volume 31, Issue 2, May 2014, Pages 220–227

[6] Javalgi, R. G., Jr,J.J.B., Prasad,V. K. and Rao,S.R. (2015) A Life Cycle Segmentation Approach to Marketing Financial Products and Services : Proceedings of the 1988 International Conference of Services Marketing, Springer International Publishing, Pages 11-22, ISBN: 978-3-319-17316-0 (Print) 978-3-319-17317-7 (Online)

[7] Hu, C., Shu,H. and Qiao, X. (2014) Customer Segmentation Model Research Based on Organizational Customer Life Cycle in Telecom Operator: Advances in Social Science, Education and Humanities Research, icetss-14 © Atlantis Press, November 2014

[8]Sung-Shun Weng1*, Shang-Chia Liu2 and Tsung-Hsien Wu3, (2011), "Applying Bayesian Network and Association rule analysis for product recommendation", International Journal of Electronic Business Management, Vol. 9, No. 2, pp. 149-159.

[9] Tabaei,Z. and Fathian,M. (2012) Using Customer lifetime Value Model for Product Recommendation: An Electronic Retailing Case Study, ,IJEEEE 2012 Vol.2(1), pp. 077-082, Feb. 2012, ISSN: 2010-3654

[10] Gorgoglione, M. and Panniello, U. (2011) Beyond Customer Churn: Generating Personalized Actions to Retain Customers in a Retail Bank by a Recommender System Approach, Journal of Intelligent Learning Systems and Applications, Vol. 3 No. 2, 2011, pp. 90-102.

[11] Galal, M., Hassan, G. and Aref, M.(2016) Developing a Personalized Multi-Dimensional Framework using Business Intelligence Techniques in Banking, In Proceedings of the 10th International Conference on Informatics and Systems, May 2016, PP. 21-27, ACM.

[12] Hu, S.J. (2008) Evolving Paradigms of Manufacturing: From Mass Production to Mass Customization and Personalization, in: Forty Sixth CIRP Conference on Manufacturing Systems 2013, Procedia CIRP, Volume 7, 2013, Pages 3–8

[13] http://www.nike.com/us/en_us/c/nikeid[Accessed 30 September 2017].

[14] Lafley, A.G. andCharan,R. (2008) The Game-Changer: How You Can Drive Revenue and Profit Growth with Innovation, Crown Publishing Group, April 8th 2008

[15] Lin,C., Yeh,Y., Hung,Y. and Chang,R. (2013) Data mining for providing a personalized learning path in creativity: An application of decision trees, Computers & Education, Volume 68, October 2013, Pages 199–210

[16] Tang, H., Liao,S. and Sun,S. (2013) A prediction framework based on contextual data to support Mobile Personalized Marketing, Decision Support Systems, Elsevier B.V ,Volume 56, December 2013, PP. 234–246

[17] Yao, Z., Sarlin, P., Eklund, T., Back, b. (2012) Combining visual customer segmentation and response modeling, ECIS 2012 Proceedings. Paper 143, http://aisel.aisnet.org/ecis2012/143 [last accessed Dec. 2015]

[18] Farquad,M., Ravi,V. and Raju,S. (2014) Churn prediction using comprehensible support vector machine: An analytical CRM application. Appl. Soft Computing, Volume 19, June 2014, Pages 31

[19] Jaeger, O. (2014) Creating Customer Loyalty With Personalization, http://www.chiefmarketer.com/creating-customer-loyalty-personalization/ [ last access Dec 2015]

[20] Tsiptsis, K., Chorianopoulos,A. (2009) Data Mining Techniques in CRM: Inside Customer Segmentation, WILEY, ISBN-13: 978-0470743973 , ISBN-10: 0470743972