We are IntechOpen,
the world's leading publisher of Open Access books
Built by scientists, for scientists

6,900
Open access books available

186,000
International authors and editors

200M
Downloads

Our authors are among the

154
Countries delivered to

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

CLARIVATE ANALYTICS
BOOK CITATION INDEX
INDEXED

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Data Mining and Intelligent Agents for Supporting Mass Customization in the Automotive Industry

Efthimia Mavridou[1,3], Dimitrios Tzovaras[1], Evangelos Bekiaris[2],
Pavlos Spanidis[2], Maria Gemou[2] and George Hassapis[3]
*[1]Informatics and Telematics Institute, Centre for Research and Technology Hellas, 6th km
Charilaou – Thermi Rd., P.O. Box: 60361, P.C.: 57001, Thermi, Thessaloniki,
[2]Hellenic Institute of Transport, Centre for Research and Technology Hellas, 6th km
Charilaou – Thermi Rd., P.O. Box: 60361, P.C.: 57001, Thermi, Thessaloniki,
[3]Department of Electrical and Computer Engineering, Faculty of Engineering, Aristotle
University of Thessaloniki, P.C.:54124 , Thessaloniki,
Greece*

1. Introduction

Mass customisation has been said to be the new frontier in business competition (Pine, 1992). The objective of mass customisation is to deliver goods and services that meet individual customers' needs with near mass production efficiency (Tseng & Jiao, 2001). Currently, only few automotive industries have deployed mass customisation systems in their product design and manufacturing processes. In the current paper, we present such a mass customization system, designed as an agent-oriented architecture which proposes to the vehicle customers (of car and truck segments) personalised vehicle configurations according to their personal affective needs.

Design for performance (i.e. functional design) and design for usability (i.e. ergonomic design) no longer empower a competitive edge because product technologies turn to be mature, or competitors can quickly catch up (Khalid & Helander, 2004). Affective design has become very important in prescribing that designed objects have a meaning that goes beyond their functional needs (Khalid et al., 2006). Customers actively seek design features that are important for their emotional satisfaction, and vehicle design must therefore address customer affective needs. Affective needs are defined as user requirements for a specific product, driven by emotions, sentiments and attitudes (Khalid et al., 2006). Understanding customer affective needs is important to ensure a good fit of affective and functional requirements to design parameters.

Several pieces of research have been presented for supporting affective design such as Kansei engineering which has been well recognized as a technique of translating consumers' subjective impressions about a product into design elements (Nagamashi, 1989). (Ishihara et al., 1995) apply neural network techniques to enhance the inference between Kansei words and design elements in Kansei design systems. (Matsubara & Nagamachi. 1997) propose to

develop hybrid expert systems for Kansei design support. (Jiao, 2007) proposes an affective design framework based on ambient intelligence techniques to facilitate decision-making in designing customized product ecosystems. In the current paper, a new research focus and perspective that integrates cognition/thinking and emotion/affect in uncovering customer needs is deployed, the Citarasa Engineering (CE) (Khalid et al., 2006). It is developed for the purpose of supporting affective design as an alternative to existing methods such as Kansei Engineering (Nagamashi, 1989). Citarasa refers to a Malay word which means emotional intent or a strong desire for a product. For the purpose of discovering the mapping relationship between customers' affective needs, defined by their citarasa, and the design parameters that characterize the design elements of vehicles, data mining techniques were deployed.

Data mining (DM) enables efficient knowledge extraction from large datasets, in order to discover hidden or non-obvious patterns in data (Witten et al., 2005). Our motivation for using DM was based on the hypothesis that the application of the appropriate DM technique on customer surveys could form a suitable mechanism for the knowledge extraction representing the correlation between customer affective needs and design parameters related to the various design elements of vehicles. The extracted knowledge was then used for the provision of personalised recommendations to customers in collaboration with the agent-based framework developed and via the web and VR based interfaces developed in the context of the CATER – STREP project (Annex I-"Description of Work", 2006). The latter constitutes the second part of the work held. The agent – based system developed interacts with different modules of the overall integrated system developed in CATER, in order to support the mass customisation supply chain including suppliers, factories, subcontractors, warehouses, distribution centres and retailers.

2. Mining of customer survey data

2.1 Data mining process

The aim of the data mining process was to identify the mapping relationship between customer affective needs and vehicle configurations, with final goal to propose to new customers' vehicle configurations according to their personal affective needs. Affective needs are described by the use of citarasa descriptors (*Cd*), which are keywords extracted through probe elicitation surveys and semantic based methods conducted in the scope of CATER (Annex I-"Description of Work", 2006).

We consider a vehicle configuration V as a set of design elements: $V = [de_1, de_2, ..., de_n]$. The term design element (de_i) refers to the customizable vehicle parts such as steering-wheel, wheel-rim, mirrors etc. Each design element de_i is characterized by a set of design parameters (dp_{ij}) such as color, shape etc. Thus, a design element de_i is represented as a set of design parameters, $de_i = [dp_{i1}, dp_{i2}, ..., dp_{in}]$. Each dp_{ij} has a set of possible values. For example the $dp_{11} = material$ of the $de_1 = steering - wheel$ has the set of values: $[vinyl, alu\min ium, wood]$. Different values of the design parameters result in different versions of the design elements, and consequently in different vehicle configurations. We construct a classification mechanism for predicting the values of each of the design parameters that satisfy customer affective needs. Specifically, we construct a classification mechanism for each of the design parameters (dp_{ij}). Then, by the assistance of the agent-based framework (section 3) we can propose to the customer vehicle configurations that correspond to the predicted design parameters, and therefore to the customer affective

needs. We deploy a classification approach based on association rules. Association rule discovery refers to the discovery of the relationships among a large set of data items (Agrawal et al., 1994), while classification focuses on building a classification model for categorizing new data. Let $I = [i_1, i_2, ..., i_n]$ be a set of items and let D be a set of records, where each record R is a set of items such that $R \subseteq I$. An association rule is an implication of the form $X \rightarrow Y$, where $X \subset I$, $Y \subset I$ and $X \cap Y = \varnothing$. X is the head of the rule and Y is the body. The confidence c of a rule is defined as the number of records that contain X and also Y ($count(X \cap Y)$) divided by the number of records in D that contain X ($count(X)$):

$$c = \frac{count(X \cap Y)}{count(X)}$$ (1)

Confidence can be interpreted as an estimation of the probability of $P(X | Y)$. The support s of a rule is defined as the number of records that contain X and also Y ($count(X \cap Y)$) divided by the total number of records in D ($count(R)$).

$$s = \frac{count(X \cap Y)}{count(R)}$$ (2)

Classification based on association rules (also known as associative classification, AC), is a relatively new classification approach integrating association mining and classification. Several studies (Li et al., 2001; Yin & Han, 2003 & Sun et al., 2006) have provided evidence that AC algorithms are able to extract classifiers competitive with traditional classification approaches such as C4.5. The main steps of an AC classifier are the following (Thabtah, 2007):

Step 1.   Discovery of all frequent rules.

Step 2.   The production of all class association rules (CARs) that have confidences above the minimum confidence threshold from frequent rules extracted in Step 1.

Step 3.   The selection of one subset of CARs to form the classifier from those generated at Step 2.

Step 4.   Measuring the quality of the derived classifier on test data objects.

In our framework we deploy a variation of the CBA (Liu et al., 1998) algorithm, which is a typical associative classifier. CBA first generates as candidate rules all the class association rules exceeding the given support and confidence thresholds using the A-priori algorithm (Agrawal & Srikant, 1994). After the rule generation, CBA prunes the set of rules using the pessimistic error rate method (Quinlan, 1987). More specifically if rule's pessimistic error rate is higher than the pessimistic error rate of rule then the rule is pruned. In the testing phase, the best rule whose body is satisfied by the test object is chosen for prediction. We use a variation of the CBA presented in (Coenen, 2004, b) which replaces the Apriori algorithm with the Apriori-TFP (Coenen et al., 2004, a) which utilizes a tree structure for more effective mining of the association rules.

In the following section, we present a case study on the application of the presented data mining process on data of car customer surveys.

2.2 Case study on car customers

The customer surveys which were conducted in the context of CATER project provided the data for our study. Those included interview surveys of 140 truck drivers and 261 car drivers from Europe and Asia (China, Finland, France, Germany, Greece, India, Italy,

Malaysia, Netherlands, Singapore, Sweden, Switzerland, the UK). We present a case study on the car customer surveys data.

Each individual car customer was asked to select among different versions of various design elements. The case study focused on the 4 design elements that the car customers were more interested to customize. Table 1 includes the design elements (de_i (1st column) and their related design parameters (dp_{ij}) (2nd column) that were included in this case study.

Design elements	Design parameters
de_1 = wheels	dp_{11} = material, dp_{12} = number of spokes
de_2 = seats	dp_{21} = material, dp_{22} = shape
de_3 = steering – wheel	dp_{31} = material, dp_{32} = number of spokes
de_4 = side mirror	dp_{41} = shape

Table 1. Design elements and their related design parameters

For each customer we were provided the citarasa descriptor (*Cd*) that described his/her affective needs, information regarding his/her selections on specific versions of design elements (and thus in specific values of design parameters) and demographic information such as the gender, the age, and the geographic region which according to the citarasa method should also be taken into account. Table 2 includes the respective variables. A snapshot of our complete dataset is presented in Table 3. Each row corresponds to an individual car customer response. For example, row 1 corresponds to a male car customer who comes from Asia, his age is above 55 and his affective needs are described by the

Name	Values
Region	Europe, Asia
Gender	Male, Female
Age	18-24, 25-54, 55-above

Table 2. Demographic information variables for car customers

Region	Gender	Age	Cd	dp_{11}	dp_{12}	dp_{21}	dp_{22}	dp_{31}	dp_{32}	dp_{41}
Asia	Male	55-	Classic	Aluminium	Five	Polyester	Flat	Wood	Three	Angular
Asia	Male	55-	Classic	Aluminium	Five	Polyester	Flat	Wood	Four	Angular
Asia	Female	25-54	Modern	Aluminium	Multiple	Canvas	Wide	Aluminium	Three	Curvy
Asia	Female	25-54	Cool	Aluminium	Multiple	Canvas	Curved	Vinyl	Three	Rectangular
Europe	Female	25-54	Cool	Alloy	Six	Canvas	Curved	Vinyl	Multiple	Rectangular

Table 3. Snapshot the car customers data set

citarasa descriptor (Cd) *Classic.* The rest of the columns correspond to his selection on specific design elements and design parameters. For example, in column 5 and row 1 the customer's selection on the material of the wheels (*Aluminium*) is included.

For each design parameter dp_{ij} a classification based on association rules was constructed. As a result, 7 classification mechanisms were constructed to provide a mapping between customers' affective needs and the specific design parameter of a design element. Towards this direction, the customer survey data set was divided to 7 subsets, each one related to a design parameter, which were provided as training data to the CBA algorithm. The support s and confidence c thresholds were set to 10% and 50% respectively. Table 4 includes the number of rules generated by the CBA algorithm for each design parameter dp_{ij}. The 2nd row refers to the whole set of the generated rules while the 3rd row to number of rules that above the support and confidence thresholds.

Design parameter	dp_{11}	dp_{12}	dp_{21}	dp_{22}	dp_{31}	dp_{32}	dp_{41}
Numbers of rules generated	141	97	144	84	123	44	110
Number of rules above thresholds s=10% and c=50%	27	31	24	27	27	19	24

Table 4. Number of rules generated for each design parameter

Besides the classification purposes, the rules generated provided also a meaningful overview of the associations among data. Table 5 includes the rules generated for the dp_{32} (which refers to the number of spokes of the steering-wheel) that were above the support

No. rule	Rule	Confidence
1	Region=*Europe* and Gender =*Female* and Cd =*Classic* -> *Three*	100.0%
2	Region=*Europe* and Gender=*Female* and Cd=*Sporty* -> *Three*	100.0%
3	Region=*Asia* and Gender=*Female* and Cd=*Classic* -> *Four*	100.0%
4	Region =*Europe* and Age =*18-24* and Cd =*Cute* -> *Three*	100.0%
5	Region =*Asia* and Gender = *Male* and Cd =*Cool* -> *Three*	100.0%
6	Region=*Asia* and Age =*18-24* Cd =*Classic* -> *Four*	100.0%
7	Region =*Asia* and Gender=*Male* and Cd= *Modern* -> *Multiple*	100.0%
8	Region=*Asia* and Age =*18-24* and Cd =*Sporty*-> *Multiple*	100.0%
9	Age=*55-above* and Cd=*Classic* -> *Three*	100.0%
10	Age =*55-above* and Cd=*Sporty* -> *Three*	100.0%
11	Age =*55-above* and Cd =*Cute* -> *Multiple*	100.0%
12	Gender =*Male* and Age=*18-24* and Cd =*Cute*} -> *Three*	100.0%
13	Region=*Europe* and Cd =*Classic* -> *Three*	91.66%
14	Region =*Europe* and Cd= *Sporty* -> *Three*	83.33%
15	Region =*Female* and Age=*25-54* and Cd =*Cool* -> *Four*	83.33%
16	Region =*Europe* and Age =*18-24*} -> *Three*	80.0%
17	Region=*Europe* and Gender =*Female* and Cd =*Cute* -> Three	80.0%
18	Region=*Asia* and Gender=Female and Age=*18-24* -> Four	80.0%
19	Default -> *Three*	0.0%

Table 5. Rules generated for the design parameter dp_{32}

and confidence thresholds. For example, rule 1 implies that a female customer who comes from Europe, and her affective needs are described by the citarasa descriptor *Classic* she would be satisfied with a steering-wheel with three spokes.

2.3 Evaluation

The accuracy of the classifiers was assessed by a k-fold cross validation (Kohavi *et al.* 1995) process. According to this method, the dataset is divided into k subsets. Each time one of the k subsets is used as the test set and the other $k-1$ form the training set. The advantage of this method is that it does not depend on how the data gets divided as each one of the data instances takes part in the test set once and in the training set $k-1$ times. The most commonly used value for k, which is used in our study, is 10. The accuracy (AC) of the classifiers is measured by the proportion of the total number of items that were correctly classified. It is determined using the equation (3):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

The *TP* (*True Positive*) is the number of positive cases that were correctly classified. And the *FP* (*False positive*) is the number of negatives cases that were incorrectly classified as positive. In proportion, the *TN* (*True negative*) is defined as the number of negatives cases that were classified correctly and the *FN* (*False negative*) is the number of positives cases that were incorrectly classified as negative. Figure 1 includes the calculated predictive accuracy of the classifiers generated for each design parameter dp_{ij}.
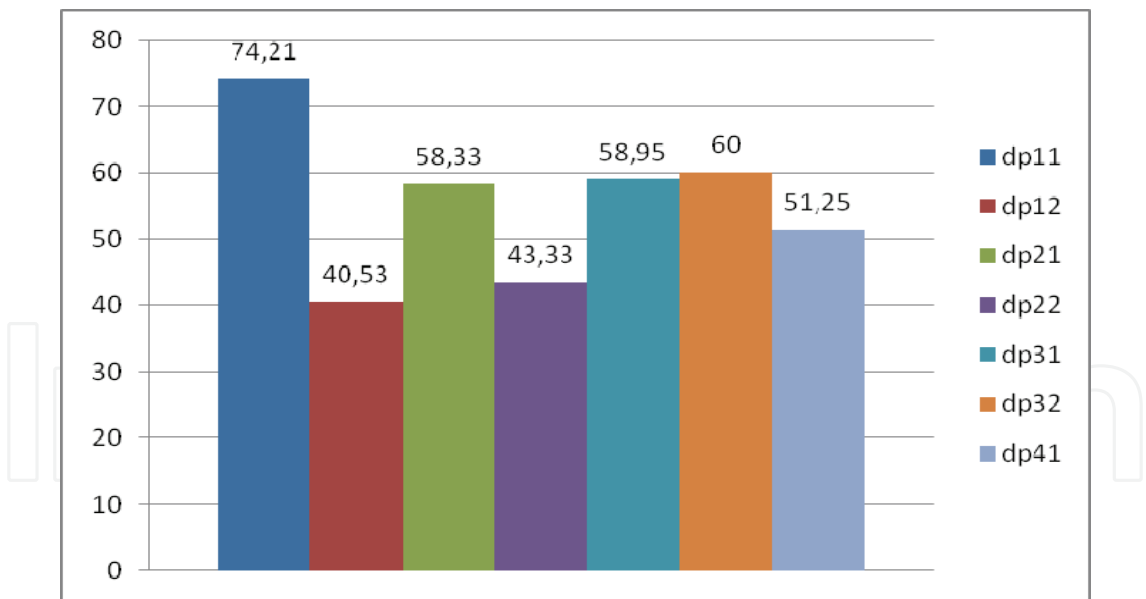

Fig. 1. Predictive accuracy of classifiers

As it is depicted in Figure 1, most of the classifiers have achieved a level of predictive accuracy above 50%. The average accuracy of all classifiers is 55,23%. The generated classifiers form the prediction mechanism which generates for each design parameter a specific prediction based on the generated rules. Table 6 shows the predicted values for an individual customer. The example refers to a female car driver from Europe, who belongs to the age range of 25-54 and would like to have a "Cool" car.

Design parameter	Predicted Values	Design parameter	Predicted Values
dp_{11}	Aluminium	dp_{31}	Wide
dp_{12}	Multiple	dp_{32}	Four
dp_{21}	Aluminium	dp_{41}	Angular
dp_{22}	Canvas		

Table 6. Predicted design parameters for a customer

The predicted values are provided as input to the agent-based framework developed (see following Chapter) and are "interpreted" to configuration elements by the use of the configuration ontology. Finally, the complete vehicle recommendation is then presented visually to the user via web and VR based user interfaces.

3. Agent-based framework

3.1 Agent technology

The agent – based system has been developed with a new technology of JADE which is called Web Service Integration Gateway (WSIG). The objective of WSIG is to expose services provided by agents and published in the JADE framework as web services, though giving developers enough flexibility to meet specific requirements. The process involves the generation of a suitable WSDL for each service-description registered with the Data Framework and also the publication of the exposed services in a UDDI registry. The Web Services are becoming one of the most important topics of software development and a standard for interconnection of different applications.

The WSIG add-on of JADE supports the standard Web Services stack, consisting of WSDL for service descriptions, SOAP message transport and a UDDI repository for publishing Web Services using Models (Jade WSIG Guide 2008). As shown in Figure 2, WSIG is a web application composed of two main elements:

- the WSIG Servlet, and,
- the WSIG Agent.

The WSIG Servlet is the front-end towards the internet world (Jade WSIG Guide 2008) and is responsible for:

- Serving incoming HTTP/SOAP requests;
- Extracting the SOAP message;
- Preparing the corresponding agent action and passing it to the WSIG Agent Moreover once the action has been served;
- Converting the action result into a SOAP message;
- Preparing the HTTP/SOAP response to be sent back to the client.

The WSIG Agent is the gateway between the Web and the Agent worlds (Jade WSIG Guide 2008) and is responsible for:

- Forwarding agent actions received from the WSIG Servlet to the agents actually able to serve them and getting back responses.
- Subscribing to the JADE DF to receive notifications about agent registrations / de-registrations.
- Creating the WSDL corresponding to each agent service registered with the DF and publishes the service in a UDDI registry if needed.
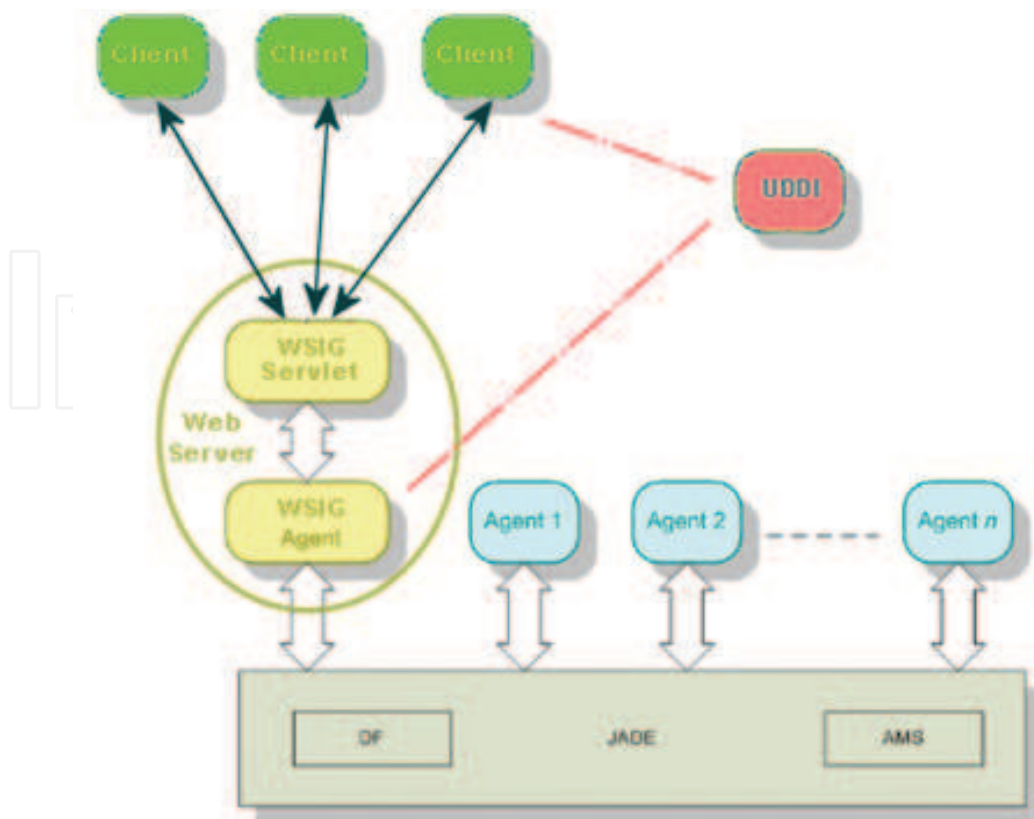
Fig. 2. WSIG Architecture (Jade 2008)

Two main processes are continuously active in the WSIG web application:

i.   The process responsible for intercepting DF registrations/de-registrations and converting them into suitable WSDLs. As mentioned, this process is completely carried out by the WSIG Agent.

ii.   The process responsible for serving incoming web service requests and triggering the corresponding agent actions. This process is carried out jointly by the WSIG Servlet (performing the necessary translations) and the WSIG Agent (forwarding requests to agents able to serve them).

The FIPA (Foundation for Intelligent Physical Agents) compliant JADE/LEAP platform (Jade 2008) adopted allows for an architecture that is:

• Distributed (different platforms);
• Standards based (FIPA, HTTP, XML, RDF);
• Process centric (agents);
• Widely used in ICT (Information and Communication Technologies);
• Open source (possibility of features addition);
• Cross-platform (Operating System, e.g. Linux);
• Variety of message transport protocols.

JADE (Java Agent DEvelopment Framework) is a software framework fully implemented in Java language (Jade 2008). It aims at the development of multi-agent systems and applications confirming to FIPA standards for intelligent agents. It includes:

• A runtime environment where JADE agents can "live" and that must be active on a given host before one or more agents can be executed on the host.
• A library of classes that programmers can use to develop their agents.

- A suite of graphical tools that allows administrating and monitoring the activity of running agents.

Each running instance of the JADE runtime environment is called a 'Container' as it can contain several agents. A set of active containers is called a 'Platform'. A single special Main Container should always be active in a platform and all other containers register with it when they start. The Main Container differs from normal containers in the ability of accepting registrations from other containers. This registration can be done by the two special agents that start when the main container is launched. These are:

- The Agent Management System (AMS) that provides the naming service and represents the authority in the platform. The Agent Communication Channel (ACC) is the agent that provides the path for basic contact between agents inside and outside the platform.
- Standards The Directory Facilitator (DF) that provides a Yellow Pages service by means of which an agent can find other agents providing the required services. The standard specifies also the Agent Communication Language (ACL). Agent communication is based on message passing, where agents communicate by formulating and transmitting individual messages to each other.

3.2 Agents in the overall CATER architecture

As it has already been mentioned, the CATER architecture is based on agents. Figure 3 shows the connectivity of the agents with the rest modules of the system. More analytically, the agent is interconnected with three main modules. These are namely: a) the Web interface, b) the Citarasa engine and c) the DIYD engine of the system. On the Web interface, the agent allows the user to register and/or login him/herself to the system. Specific entries are requested by the user, such as the name and surname of the user, desired username and password and also the occupation, the region, the age and the gender.

The occupation, the region, the age and the gender in specific, constitute the input that is required by the *Citarasa* engine in order to predict a vehicle configuration, customized to the specific user, classified also per *Citarasa Descriptor* (i.e. "Cute", "Cool", "Classic", etc.). The prediction of the most suitable vehicle configuration is performed through the classification
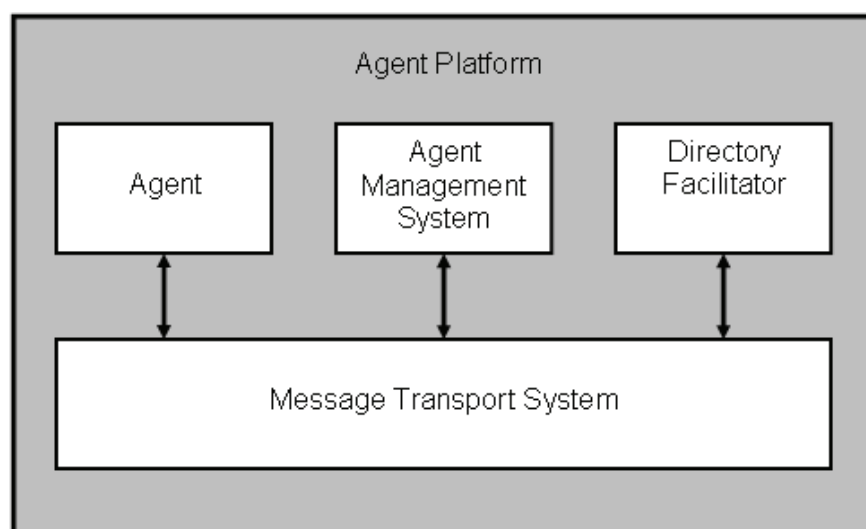
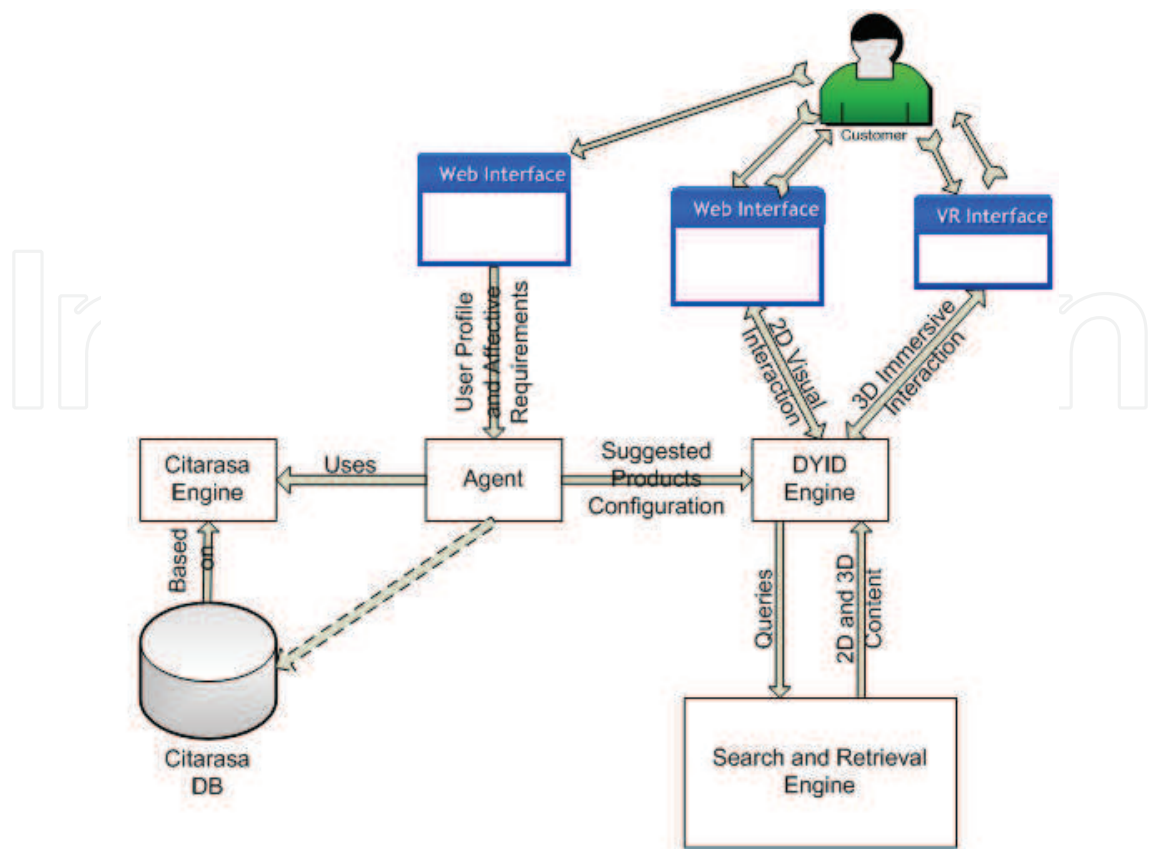

Fig. 3. Agent Platform internal diagram

Fig. 4. Agent's conceptual architecture

models generated by the data mining process (as described in section 2) which constitute the knowledge base of the Data Mining module of the *Citarasa* engine. All requested entries by each registered user are collected in the *Citarasa* engineering database.

The agent is interconnected with the DIYD engine that constitutes the interface of the user with the Citarasa engine. The DIYD engine requests from the user (via the web interface) to choose among a list of *Citarasa Descriptors* (i.e. "Cool", "Cute", "Classic", etc.) (Figure 5) that according to his/her opinion characterise in the most felicitous way his/her overall preference regarding the vehicle s/he wishes to view and further configure. The DIYD engine, utilising the output of the *Citarasa* engine, finally provides to the user a suggested vehicle configuration, customised to his/her profile and declared preference, by the means of web or VR based interfaces (Figure 6).

The agent – based system consists of several functions. Each function is responsible for a particular activity and these activities are accessible through a special XML file, the WSDL file. In this file, the client is able to find all the available activities that the agent can perform. Table 7 below contains the list of the major actions that the CATER agent performs.

These functions are available through the World Wide Web. Any module that needs to interact with the CATER system has to follow the rules of the above functions in order to retrieve the required/requested results.

It should be noted that the agent has been designed in such a way so as to support also the self training of the system. Every time a user completes his/her vehicle configuration process, the CATER agent stores this information. A specific number of new entries on the database trigger the update of the knowledge base of the DM module that is responsible for the vehicle configuration prediction recommended to the user.
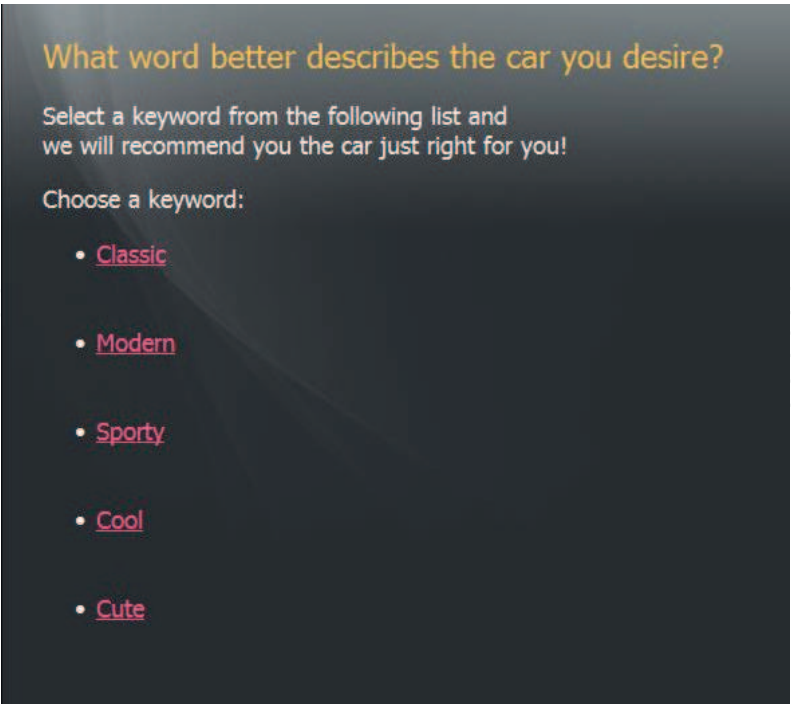
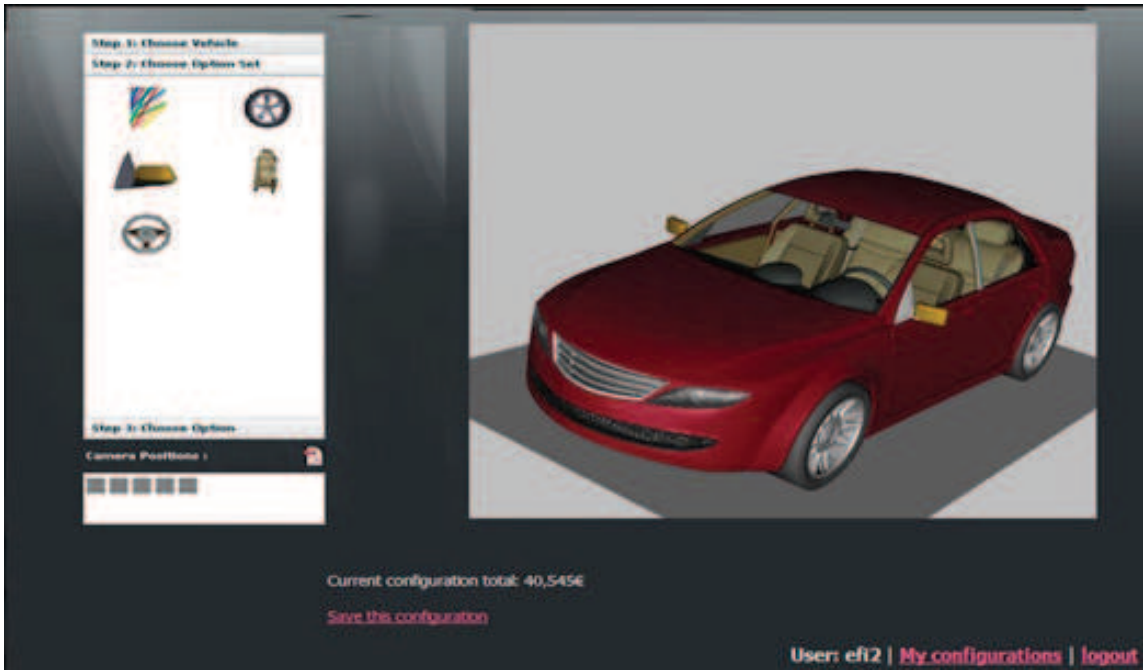Fig. 5. Selection among a list of Citarasa Descriptors via the web interface

Fig. 6. Proposed configuration via the web interface

Activity	Function	Description
Registration	setUser( )	This function has a list of attributes as input (name, surname, username, password, region, occupation, age, gender) and outputs "0" or "1" (false or true) which indicates the successful addition of the data in the database.

Activity	Function	Description
Registration	getUsernameExistance( )	This function examines if a specific username already exists in the database. It has one attribute as an input, the username and it outputs "1" or "0" for true or false respectively.
Log In	getUserId( )	This function provides the ID number of the user. It has two attributes as input (username and password) and outputs the ID number of the user when the log in is successful or "1" if there is an error with the username and/or password.
Log In	updateUser( )	This function is responsible for the user profile update. It gets one value as input (the username) and it returns "0" or "1" (false or true) which indicates the successful addition of the data in the database.
Accessing CATER list	setComponentValue( )	This is a function that stores the user's history. It keeps the CATER components database updated depending on the choices-selections of the user. The function stores the user's updates on a specific component with input attributes user ID, region, occupation, descriptor, component, component ID, attribute and outputs "1" or "0" (false or true) indicating the successful addition of the data in the table.
Accessing CATER list	getUserAttributes( )	This function collects all the attributes of a user. It requires the ID number of the user as input and it outputs a vector (an array of data) with the name, surname, username, password, region, occupation, age, gender.
Accessing CATER list	getComponentId( )	A function that returns the ID number of the vehicle-component combination according to the vehicle type (i.e. car or truck) and the component name (i.e. mirror, steering wheel, etc.).
Accessing CATER list	getActualAttribute( )	This function uses semantics (guided by ontology) for the mapping of predicted design parameters to actual elements which are available in the DIYD engine. It has two input attributes (the component ID and the extracted output) and returns the corresponding element of the DIYD Engine.
Accessing CATER list	getStatistics( )	This is a function that provides the percentage of the available choices of a descriptor according to the entered input (region, gender, age range and descriptor).

Table 7. List of functions of the agent – based system of CATER

4. Conclusion

This paper presented a data mining and agent-based framework based on *citarasa* principles. The methodology followed provided a mapping mechanism of customer affective needs described by their *citarasa* to design parameters related to vehicle design elements. Results derived on the application of the methodology on customer survey data showed that the framework is capable of providing recommendations to the customers based on the generated mechanism. However, the need for more customer data and larger training datasets will be always a desirable option because it results in improvement of the data mining outcome and hence accuracy of user recommendations. Future experiments will be conducted in order to evaluate the generated mechanism and measure the improvement introduced, compared to the initially evaluated rules.

In addition, the design and the development of a specific module of the CATER integrated system, namely the agent – based system of CATER which is responsible for the interconnection and interface of different modules of the system, aiming, finally, at proposing a personalised vehicle configuration to the customer is being presented in the current paper. It should be noted that the customer is able to further elaborate the proposed by the system vehicle configuration through the CATER configurators, if wishes so.

The agents' technology deployed is a FIPA compliant JADE/LEAP platform technology which has been indicated as the best solution for Client – Server communications (Jade 2008). The functionality of the agent required the use of another add-on application of JADE which is called WSIG (Jade WSIG Guide 2008). This add-on transformed the agent's functionality to web service in order to be available to anyone through the World Wide Web and made feasible the interface of CATER engines output through a web interface.

The personalisation enabled by the CATER agent lies in the output of the data mining process described in this paper, and associates in practice the user profile, in terms of age, region, gender and the user needs (reflected through the *Citarasa Descriptors*) in order to predict the most suitable vehicle configuration per se (user).

The communication of this result to the user, via web and VR interfaces, is again a responsibility of the CATER agent system. Finally, a valuable advantage of the CATER agent system is the ability to store the history of each user vehicle configuration tried. The history records are then utilised for the update of the prediction rules, and as such, of the progressing improvement of their accuracy.

5. References

Agrawal, R. & Srikant, R. (1994). Fast algorithms for mining association rules. *Proceedings of the 20th International Conference of Very Large Data Bases*, pp. 487-499, Santiago de Chile, Sept. 1994, Morgan, Santiago de Chile

Annex I-"Description of Work", CATER project , CN. 035030, Sixth Framework Programme, Priority 2-IST, Information Society Technologies (2006). [Online].Available at: http://www.cater-ist.org

Coenen, F.; Leng P. & Ahmed S. (2004). Data structures for association rule mining: T-trees and P-trees, *IEEE Trans. Knowl.,Data Eng*., Vol. 26, No 6, June 2004, pp. 774-778, 1041-4347

Coenen, F. (2004). The LUCS-KDD Group, Department of Computer Science, The University of Liverpool, UK [Online].Available at: http://www.cSc.liv.ac.uk/~frans/KDD

Cross, N. (2000). Engineering design methods: Strategies for product design (3rd ed.).Wiley, 978-0471872504, Chichester, UK

Jade Agent Development Framework – an Open Source platform for peer-to-peer agent based applications (2008). [Online] Available at: http://jade.tilab.com

Jade Web Services Integration Gateway (WSIG) Guide (2008). [Online] Available at: http://jade.tilab.com (add-ons area)

Jiao, R.J.; Xu Q.; Du J., Zhang Y.; Helander, M.; Khalid, H.; Helo, P. & Cheng, N. (2008). Analytical affective design with ambient intelligence for mass customization and personalization. *International Journal of Flexible Manufacturing Systems*, Vol. 19, No 4, February 2008, pp. 570-595, 0920-6299

Ishihara, S.; Ishihara, K.; Nagamashi, M., & Matsubara, Y. (1995). An automatic builder for a Kansei engineering expert system using selforganizing neural networks. *International Journal of Industrial Ergonomics*, Vol. 15, No. 1, January 1995, pp. 13–24, 1936-6590

Khalid, H. M. & Helander, M. G. (2004). A framework for affective customer needs in product design. *Theoretical Issues in Ergonomics Science*, Vol.5, No. 1, January 2004, pp. 27–42, 1463-992X

Khalid, H.M. and Helander, M.G. (2006). Customer emotional needs in product design. *International Journal on Concurrent Engineering: Research and Applications*, Vol. 14, No. 3, pp. 197-206, 1531-2003

Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection, *Proceedings of fourteenth International Joint Conference on Artificial Intelligence*, pp. 1137-143, Montréal, Aug. 1995, Morgan Kaufmann, Québec, Canada.

Li, W.; Han, J. & Pei, J. (2001) CMAR: Accurate and efficient classification based on multiple-class association rule, *Proceedings of the International Conference on Data Mining (ICDM'01),* pp. 369–376, San Jose, November 2001, IEEE Computer Society Press,San Jose California

Liu, B.; Hsu, W. & Ma, Y. (1998). Integrating Classification and Association Rule Mining, *Proceedings of the 4rd International Conference Knowledge Discovery and Data Mining (KDD-98),* pp. 80-96, New York, Aug. 1998, AAAI Press, New York USA

Nagamashi, M. (1989). *Kansei Engineering*, Kaibundo Publisher Co Ltd, Tokyo

Matsubara, Y. & Nagamachi, M. (1997). Hybrid Kansei engineering system and design support. *International Journal of Industrial Ergonomics*, Vol. 19, No. 2, pp. 81–92, 0169-8141

Quinlan, J. (1987). Simplifying decision trees. *International Journal of Man–Machine Studies, Vol. 27*, pp. 221–248.

Sun, Y.; Wong, A. & Wang, Y. (2006). An overview of associative classifier, P*roceedings of the 2006 International conference on Data mining,* pp. 138-143, Las Vegas, June 2006, Nevada

Thabtah, F. (2007). A review of associative classification mining, *The Knowledge Engineering Review*, Vol 22, No.1, pp. 37-65, 0269-8889

Witten, I.H. & Frank, E. (2005). *Data Mining: Practical Machine Learning Tools and Techniques (Second Edition)*, Morgan Kaufmann, 0-12-088407-0, San Francisco, CA, USA

Yin, X. & Han, J. (2003). CPAR: Classification based on predictive association rules, *Proceedings of the Third SIAM International Conference on Data Mining*, pp. 331–335, San Francisco, May 2003, SIAM, CA USA

Proceedings of the Third SIAM International Conference on Data Mining, pp. 331–335, San Francisco, May 2003, SIAM, CA USA
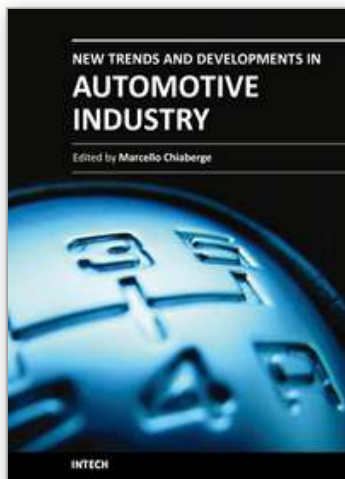
New Trends and Developments in Automotive Industry

Edited by Prof. Marcello Chiaberge

This book is divided in five main parts (production technology, system production, machinery, design and materials) and tries to show emerging solutions in automotive industry fields related to OEMs and no-OEMs sectors in order to show the vitality of this leading industry for worldwide economies and related important impacts on other industrial sectors and their environmental sub-products.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Efthimia Mavridou, Dimitrios Tzovaras, Evangelos Beakiaris, Pavlos Spanidis, Maria Gemou and George Hassapis (2011). Data Mining and Intelligent Agents for Supporting Mass Customization in the Automotive Industry, New Trends and Developments in Automotive Industry, Prof. Marcello Chiaberge (Ed.), ISBN: 978-953-307-999-8, InTech, Available from: http://www.intechopen.com/books/new-trends-and-developments-in-automotive-industry/data-mining-and-intelligent-agents-for-supporting-mass-customization-in-the-automotive-industry

INTECH
open science | open minds