Virtual Reality based Conjoint Analysis for Early Customer Integration in Industrial Product Development

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Abstract
Disruptive innovations of products and production systems have the potential to provide a leap in value for existing and new customers. However, companies in industrial markets face two major problems when bringing innovations to markets. First, companies often lack systematic customer integration in the product development process. Second, disruptive innovations break with existing technologies and are therefore regularly beyond the scope of customers' imagination due to its complexity and level of novelty. Hence, when customers evaluate new product concepts, they often cannot fully capture its benefits. By addressing these two problems, companies can promote the efficiency of the product development process and thereby the success of disruptive innovations.

Keywords:
Virtual Reality, Product Development, Conjoint Analysis, Customer Integration, Business-to-Business Marketing, Disruptive Innovation

1 INTRODUCTION
Already in 1961, Schumpeter stated that innovations are a key for a company’s long-term success [1]. Since then, innovations have become one main source for companies to sustain competitive in their markets and are essential for their survival [2] [3] [4] [5]. Further, companies need to build new products that perfectly meet customers’ requirements [6] [7]. Therefore, several methods have emerged to integrate customers at an early stage of the development process. Examples include empathic designs [8] [9], creativity techniques [10] or quality function deployment [11] [12]. The number of innovations across industries increases while the time span under which innovations are launched is shrinking. This puts managers under pressure to pursue an efficient product development process while keeping resource spending at the minimum. In meta-studies, the failure rate of new product development ranges between 20% and 96% [13]. This rate can be reduced by integrating customers in an early stage of the product development [2] [5].

However, companies in industrial markets face two major problems when bringing innovations to markets. First, companies often lack systematic customer integration in the product development process [15]. Second, disruptive innovations break with existing technologies and are therefore regularly beyond the scope of customers’ imagination due to its complexity and level of novelty. Hence, when customers evaluate new product concepts, they often cannot fully capture its benefits. The need to “revitalize themselves through new products” [14] have let companies explore new ways in the product development process. One promising new path for early customer integration is the use of virtual prototypes in the development process of disruptive innovations [15]. Evaluating highly complex innovations in B2B markets help to generate a clear picture of consumer preferences. The advantages of virtual prototypes are that they can be developed earlier, more quickly and more cost effectively than real prototypes [14]. In addition, virtual representations of highly complex products facilitate the information transfer by visually presenting the features and benefits of the new products to potential clients.

This paper aims to develop a systematic procedure for early customer integration by means of efficiently generated virtual prototypes. We developed a method and a software tool enabling companies to integrate customers at an early stage of product development with the help of virtual prototypes to facilitate customers’ imagination of disruptive innovations. Combining the knowledge of business scientists and engineers, a multi-stage limit conjoint analysis with an embedded virtual reality (VR) application helps overcoming the two mentioned problems, as will be shown in this paper. To this end, the paper is divided into two main parts. First, the developed statistical method and the underlying procedure of early customer integration are described. Second, the technical implementation is discussed by focusing on efficient modeling and automated generation of multiple VR stimuli to present innovative product features.

2 EARLY CUSTOMER INTEGRATION IN INDUSTRIAL PRODUCT DEVELOPMENT WITH MELIMCA
At early stages of a new product development (e.g. idea generation and concept phase [16]), companies often cannot estimate the impact of alternative product attributes and levels on customers’ purchase decision [3]. However, new product ideas should be derived based on target customers attribute and level requirements [17] [18]. Therefore, companies need to determine relevant attributes and levels from a customer’s perspective [19]. This information serves as a foundation to conduct concept tests and develop consumer oriented products [20]. Preference measurement techniques thereby yield a detailed analysis regarding the impact of different product attributes and their relative importance on the purchase decision. Although there is a variety of preference measurement techniques [21], the conjoint analysis is the most used method [22] [23]. Conjoint analysis can be used for analyzing consumer preferences in both, business-to-consumer (B2C) markets and business-to-business (B2B) markets. One of the main differences between B2C and B2B markets is that in a B2B-setting the buying decision is taken by a group of people rather than by individuals [24]. This group can be defined as the buying center [17] [25]. In B2B literature, several models have discussed the group decision making process, whereby most of these models assume two consecutive
steps in the decision making process [26] [27]. In the first step, each individual builds his own preference regarding the decision. In the second step, these individuals form a collective decision based on individual preferences [28]. This collective decision varies depending on the influence and bargaining power of buying center members [29]. Therefore, when integrating B2B-customers in the product innovation process, both steps need to be considered separately.

Against this background, Voeth and Hahn have modified the conjoint analysis in a way that allows for estimating individual preferences in a first stage estimating the influence (e.g. bargaining power) of each buying center participant on the group decision in a second stage [30]. Finally, both stages can be combined to simulate the final decision of the group. This method is defined as multiple stage limit conjoint analysis (MELIMCA) and is a systematic approach to integrate customers at an early stage in the product development process. In the following sections, all three stages of the MELIMCA will be discussed in more detail.

2.1 First Stage: Measurement of Individual Preferences

In a first step, individual customer preferences need to be measured. This can be achieved with the help of a traditional conjoint analysis (TCA) [31] [32]. Even though there are several more advanced types of conjoint analysis available, the TCA is used for this study because it requires a limited number of stimuli, which means at the same time, lower efforts for the costly generation of VR stimuli. In a TCA, respondents rank, rate or trade-off a number of different product profiles (stimuli), whereby each stimulus consists of a number of different attributes and levels [33]. However, the TCA is often criticized as being unrealistic because the choice task only generates preference data without incorporating a respondent’s purchase decision [33]. This often leads to the non-realistic assumption that each respondent will buy any of the presented product alternative [33]. Voeth and Hahn have addressed this issue by means of limit conjoint analysis (LCA) [34]. The limit conjoint analysis is an extended version of the traditional conjoint analysis, and has its roots in the group-psychology work of Thibaut and Kelley [35]. In an LCA respondents not only rate or rank their order of preference, but also specify to which ranking position they would still buy the presented product alternative [26]. Usually, respondents are requested to place a limit-card after the last stimulus they would consider worth buying. This procedure helps to differentiate acceptable and non-acceptable combinations of several levels of product attributes (e.g. product alternatives) in two groups [33] as shown in Figure 1.

![Figure 1: Limit-Card](image)

In the example (see Figure 1), the respondent has placed the limit-card between product alternative three and five to declare that he or she would only purchase five of the nine given product alternatives (e.g. product 7, 4, 2, 9 and 1).

Generally, in a TCA for stimulus $i$, the processing of ranked data $\rho_{k*}$ in the total utility value $U_k$ for respondent $i$ is:

$$
\rho_{ki}^* = (K + 1) - \rho_{ki}
$$

(1)

where $K$ represents the total number of stimuli presented to the respondent. With the help of a simple scale transformation, the additional information retrieved from placing the limit-card can be integrated into the TCA-algorithm [36]:

$$
\rho_{ki}^* = \rho_{ki}^* - (K - L_i + 0.5) = (K + 1) - \rho_{ki} - (K - L_i + 0.5) = L_i - \rho_{ki} + 0.5
$$

(2)

After the scale transformation, each attribute suggests that respondents are willing to buy if the benefit $U$ for a stimulus is $U \geq 0$. Conversely, respondents would reject to buy if the benefit $U$ for a stimulus is $U < 0$. The same logic applies to the total utility for each product alternative.

The results of a limit conjoint analysis are three-folded. First, for each product attribute level, the utility, also known as part worth, can be estimated [32]. The part worth provides information about the desirability of each attribute level to the respondent [37]. Second, the relative importance of each attribute can be determined [36]. This helps to uncover the attribute of a product alternative that is of highest importance for the respondent. Finally, a demand function can be derived for each respondent, given that ”price” is one of the included attributes [33]. Thereby, the respondents’ willingness to pay for each of the different product alternatives is revealed.

2.2 Second Stage: Influence Measurement

In a second stage, the bargaining power (e.g. influence) of each buying center group member is measured. This is accomplished with a second limit conjoint analysis, similar to the approach described in section 2.1. However, there is one critical exception: instead of combining different product attributes and levels into product combinations, different possible decision situations are generated [30]. In other words, each buying center member dictates as an attribute and her decision behavior as the respective level. These levels (e.g. decision behaviors) can take the following three scale manifestations: (1) against the purchase, (2) indifferent and (3) in favor of the purchase [36]. For instance, one decision situation could be that buying center member (BCM) 1 is against the purchase, BCM 2 and 3 are indifferent and BCM 3 is in favor of the purchase. For this example, with a buying center size of four members, there are 81 (3$^4$) possible decision situations. In general, for a buying center with a size of $U$, $U^2$ different decision situations exist (full plan). When applying an orthogonal main-effect plan [38], the full plan can be reduced to receive only a limited number of decision situations. The resulting decision situations are ranked for instance by an external expert (e.g. sales force) similar to the procedure described in Figure 1. In particular, the expert ranks the different decision situation of the buying center according to his expected probability that the buying center as a group will decide in favor of the underlying product. Furthermore, the expert also places a limit-card after the last decision situation where he expects that the buying center as a group will no longer come to a decision in favor of the purchase [30].

The scale transformation and its implementation into the TCA algorithm are analogous to the procedure described in section 2.1. Thus, the results from the second stage of the MELIMCA are the same as generated in the first stage [30]. Nevertheless, the interpretation is somewhat different: the most meaningful outcome is the
relative importance of each “attribute”, which in this case is the relative importance of each buying center member. In other words, the relative importance provides a measure for the influence each buying center member has with regard to the group decision.

2.3 Third stage: Estimating the Group Decision

After having estimated the individual preference of each buying center member (see section 2.1) and the relative influence each buying center member has for the group decision (see section 2.2), both stages need to be linked with an integration model. For a limit conjoint analysis, upward- and downward integration models are feasible [39].

In an upward integration model, the individual preference information of the first stage is integrated into the second stage. The upward integration is achieved by “translating” the total utilities (e.g. preferences) of the product alternatives of the first stage into the following decision criteria [30]:

- Total utility is negative = against purchase (-)
- Total utility is not negative but is exceeded by any other utility = indifferent (0)
- Total utility is not negative and not exceeded by any other utility = in favor of purchase (+)

For each buying center member, this “translation” can be applied for all different product alternatives. Hence, for each product alternative, a statement can be made if the BCM is against the purchase, indifferent or in favor of the purchase. From the second stage (see section 2.2), part-worth utilities are known for each buying center member if her decision is (1) against the purchase, (2) indifferent and (3) in favor of the purchase [20]. Linking this information, a total group utility can be estimated for each product alternative by adding up the part-worth utilities (resulting from the second stage) of each buying center member for the respective product alternative. The higher this total group’s utility, the more likely the buying center will decide in favor of the respective product alternative. This group total utility has the advantage that it takes into account both, individual preferences of each buying center member and bargaining power (e.g. influence) each member has within the group decision. However, the disadvantage of this upward integration approach is the loss in information content due to the “translation” of metric data into ordinal data [40]. For instance, two product alternatives with a positive total utility, but a large range get the same decision alternative (e.g. “0”) as two positive alternatives with a rather small range.

Therefore, the downward integration model is the preferred choice of linking both stages [30]. Here, the influence values of the second stage are integrated into the first stage. This is accomplished by weighting the relative influence of each buying center member (e.g. result of the second stage) with the total utility of the respective product alternative (e.g. result of the first stage). The total group utility can therefore be estimated with the following formula:

$$ u_c = \sum_{i=1}^{n} u_{ic} \cdot w_i $$

(3)

where:

- \( u_c \) = estimated total utility for product alternative \( c \) on a group level.
- \( u_{ic} \) = estimated total utility for product alternative \( c \) for individual \( i \)
- \( w_i \) = relative influence of individual \( i \)

The disadvantage of the downward integration model is that the total utility level for each respondent can vary due to the placed limit-card and the resulting scale transformation. However, the advantage lies in incorporating preference differences, which classifies the downward integration model as the preferred choice for this study [30] [39].

2.4 Advancements of MELIMCA

Attempts for further developments of the MELIMCA can either be application oriented or methodological. Regarding the former, no software-tool has yet been developed that incorporates all three steps described in the previous sections. We have therefore set up a web-based software tool that allows for conducting a multi-stage limit conjoint analysis. This tool is the first to provide a systematic approach for early customer integration in complex product innovations. Concerning the latter, two methodological improvements with regard to MELIMCA have been implemented.

First, in most studies, the LCA was conducted using a rating scale, where customers had to rank product alternatives according to their order of preferences [41] [39] [28] [30]. However, several studies have come to the conclusion that using metric data within a conjoint setting is preferred due to the higher information content [42] [43]. Therefore, in the developed software-tool, respondents not only rank but also rate different product alternatives on a 100-point rating scale. Using a 100-point scale implies higher differentiation nuances and thereby higher validity of conjoint results [42].

Second, the MELIMCA need to include alternative stimuli presentations as the stimuli presentation form has a high influence on the validity of the conjoint results [44]. New communication and information technologies, faster processors and rich media computing open the potential to build conjoint stimuli with a much higher degree of realism [44]. “A realistic representation...allows consumers to ‘understand’ the product much more quickly and thus behave as they would at the real point of sale” [45]. Therefore, enriching the stimulus with more information and thereby achieving a high degree of realism is a promising way to optimize customer integration for new product developments. Therefore, in order to test if virtual realities are an alternative to real prototypes within the product development process, the efficient modeling and automated generation of multiple VR stimuli need to be tested. Only in case of efficient VR programming, virtual prototypes present a useful alternative when integrating customers in product developments. Thus, the following section shows how a number of virtual prototypes can be generated efficiently based on two real case innovation projects.

3 APPLICATION OF VR STIMULI IN MELIMCA

MELIMCA offers alternative stimuli presentations: Traditional text based stimuli are used for easy-to-explain products for daily demands like e.g. home appliances etc. Innovative products with features that are difficult to understand for customers are presented with virtual reality (VR) based stimuli. Especially the features of high-tech products, based on the close interaction of mechanics, electrics/electronics, control engineering, software technology and new materials often overwhelm the customer’s imagination power. The advantages of VR stimuli lie in a better customer understanding of the new products benefits which lead to the fact that they can give more reliable answers in the conjoint task. Thus, the following section shows how VR stimuli can be generated efficiently based on real case innovation projects that are part of the German technology network “Intelligent Technical Systems-OstwestfalenLippe (it’s OWL)”. The network it’s OWL is part of the leading-edge-cluster program of the German ministry of science and technology. It is encompassing economy and science about to set world standards for intelligent products and production systems.

3.1 Virtual Reality in Product Development

Virtual reality (VR) is a key technology of virtual prototyping. It stands for an easy-to-understand user interface to a virtual design space and facilitates an interactive exploration of the functionality of a new product. VR means a fully computer generated, three-
dimensional environment, in which the user can interact with and manipulate a realistic representation of the product in real time. VR stands for a realistic rendering of the product appearance (material, surface, colors) and behavior. Secondly, VR makes use of advanced display technologies like projection walls, big screens or head mounted displays that allow the engineers to experience the virtual prototype like a real one. Therefore, VR facilitates an optimal understanding of the features and benefits of the new products in a conjoint analysis.

Virtual prototyping means to build and analyze computer models of products being developed in order to reduce time and cost intensive manufacturing and testing of prototypes to a minimum. A perfect virtual prototype represents all aspects of a product (see figure 2). 3D-CAD systems are basically used to model the shape of parts. The breakdown of the product to its parts and assemblies is represented by the product structure. Therefore, it is necessary to set up a Product Data Management (PDM). The shape of individual parts in conjunction with product structure is used to develop a shape-based design of the product, what we call Digital Mock Up (DMU). It represents the spatial composition of all parts and assemblies of the product. A DMU can be used to carry out experiments such as clash detection, checking assembly and disassembly sequences. As Figure 2 illustrates, we consider a virtual prototype as an extension to DMU since it covers additional aspects such as kinematics, dynamics, and stress. A virtual prototype represents not only shape but also functional features and behaviors [46] [47]. Therefore, it is the basis for a realistic representation of product features in a conjoint analysis with virtual reality based stimuli (VR stimuli).

In a traditional conjoint analysis, respondents rank, rate or trade-off a number of different product profiles (stimuli), whereby each stimulus consists of a number of different product attributes and values [33]. For the generation of VR stimuli, we developed a procedure consisting of three phases:

In the first phase, in a workshop with participants from product development, marketing and sales, the key product attributes are determined. The number should not exceed four attributes (including price) with three values per attribute (e.g. the product is a car; the attributes are color, brand, engine power and price; the attribute color has three values red, blue and yellow). Each combination of attributes describes a stimulus (e.g. stimulus one: color=red, brand=Porsche, Engine Power=200 kW, Price=120 k€). From all possible stimuli, 12 to 15 are selected for conjoint analysis. Result of the first phase is a list with a textual description of selected stimuli with attributes and values.

In the second phase, the descriptions of the stimuli are analyzed and a storyboard for the VR presentation for all attributes and stimuli is developed. The storyboard contains a detailed description of the 3D scene, necessary 3D models (with shape, behavior, material, color, texture etc.) and a description of the user interface. The 3D scene represents the virtual stage for the product presentation (e.g. a racetrack for cars); the different stimuli are represented by 3D models (e.g. a red Porsche racecar with 200 kW); user interface means the necessary input and output devices (e.g. 72” flat screen, steering wheel, keyboard and mouse) and the interaction between user and VR stimulus (e.g. user starts/stops engine by pushing enter button etc.). Result of the second phase is a storyboard for all VR stimuli.

In the third phase, the VR stimuli are generated. Here, the existing data from the development process is analyzed. 3D CAD-models, kinematic models, etc. are converted and prepared for a real-time presentation in a 3D scene. Finally, the application logic and the user interaction are implemented to complete the VR stimuli.

Each VR stimulus is an independent VR application. For a conjoint analysis, a minimum of 9 stimuli are necessary. A stimulus consists of at least 4 attributes with 3 different values, which involves a high effort for modelling and programming. The clue for a cost efficient VR stimuli generation - even with a high number of varying attributes - lies in the smart modeling of the attributes. For each attribute value we design a short 3D sequence. The seamless transition between each attribute in a single stimulus is realized by using the same camera position at the end of one attribute to the beginning of the following attribute. This allows an (semi-) automatic generation of VR stimuli and reduces the manual modelling efforts.

For developing the VR stimuli we used Unity 3D, a game engine with an editor that is capable to generate executable programs for almost every computer platform including desktop operation systems like Windows and Mac OSX as well as mobile Operating systems like Android and iOS. The integration of the VR stimuli in the MELIMCA tool was carried out using the Unity 3D web player plugin.

### 4 CASE STUDIES

#### 4.1 Case Study 1: Self-adjusting Car Headlights

The automotive supplier HELLA KGaA Hueck & Co. develops an intelligent self-adjusting car headlight, which analyzes environment and vehicle data and independently controls the optimal headlight settings for the illumination of the street in front of the car. With a conjoint analysis, customer preferences for different technical approaches should be analyzed. The results should give decisive hints for further development. In a first step, in several workshops four key product features (= attributes) each with 3 values have been determined, as depicted in Table 1.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Level A</th>
<th>Level B</th>
<th>Level C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. User Interaction</td>
<td>No Interaction</td>
<td>Interaction necessary</td>
<td>Interaction optional</td>
</tr>
<tr>
<td>2. Adjustment Scenario</td>
<td>On a wall</td>
<td>On street ground in front</td>
<td>On a rear of a car in front</td>
</tr>
<tr>
<td>3. Light-dark boundary</td>
<td>Symmetric line</td>
<td>Asymmetric Z-shape</td>
<td>L-shape</td>
</tr>
<tr>
<td>4. Price</td>
<td>Price 1</td>
<td>Price 2</td>
<td>Price 3</td>
</tr>
</tbody>
</table>

Table 1: Attributes and levels for HELLA

![Figure 2: The virtual prototype: Representing shape, functional features and behaviors in a computer-internal model [47].](image-url)
In the next step, a storyboard for each attribute and value was developed. The basic approach was to let customers experience the different stimuli during an interactive night drive simulation (see Figure 3): The respondent sits on a motion platform in front of a 72”-LCD display and steers his virtual car interactively through a city by night.

Depending on the stimuli, respondents are asked to initiate the adjustment of the headlights (attribute 1, value B) or it starts automatically (attribute 1, value A). Then he experiences the different adjustment scenarios and adjustment markers (See Figure 4).

When the presentation ends after ca. 30 sec., the price for the stimuli is displayed on the screen and the respondent ranks it in the MELIMCA tool. This procedure ends when the respondent has tested all VR stimuli. The overall duration is about 15 minutes.

### 4.2 Case Study 2: Intelligent Harvesting System

With CLAAS Selbstfahrende Erntemaschinen GmbH, a VR-based conjoint analysis for an innovative software system for the optimization of the harvesting process is performed. By means of intelligent networking of agricultural machines the software system allows an optimized coordination of technical resources and relieves the machine operators.

In its conjoint analysis, CLAAS wants to find out if a set of new technology aspects in its self-propelled forage harvester series JAGUAR correlates to the customer requirements and if the creation of value is worth the development of such technology. Therefore a set of four attributes was selected for the VR-based conjoint analysis, as shown in Table 2.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Level A</th>
<th>Level B</th>
<th>Level C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Type of harvest measurement</td>
<td>No weight or dry substance measurement (weight measurement at weight station)</td>
<td>Weight and dry substance measurement</td>
<td>Weight and dry substance measurement and ingredients determination</td>
</tr>
<tr>
<td>2. Allocation of harvest data</td>
<td>Printout in harvester cockpit</td>
<td>Data transfer using a storage medium (e.g. USB)</td>
<td>Data transfer to land owner with automatic land assignment</td>
</tr>
<tr>
<td>3. User interaction</td>
<td>Manual start/stop harvesting measurement and calibration</td>
<td>Manual start/stop harvesting measurement and automatic harvesting calibration</td>
<td>Full automatic harvesting calibration</td>
</tr>
<tr>
<td>4. Price</td>
<td>Price 1</td>
<td>Price 2</td>
<td>Price 3</td>
</tr>
</tbody>
</table>

Next, a storyboard for each attribute and value was developed. The basic approach was to let customer experience the different stimuli during an interactive harvesting simulation (see figure 5) where the customer takes over the role of the JAGUAR driver harvesting a cornfield. Depending on the stimuli, respondents are asked to start the calibration of the harvesting measurement and calibration (Attribute 3, Value A) or it starts automatically (Attribute 3, Value C) (see figure 5). In the first case, the customer has to input the measured harvesting weight, which is communicated from the weight station by telephone, into the console. After harvesting the cornfield the weight data are either printed out (attribute 2, value A) or digitally transferred using a storage medium (e.g. USB stick) (attribute 2, value B) or a wireless connection to a server (attribute 2, value C).
Unlike the HELLA case, the CLAAS case is more sequential, meaning that the attributes have a strict display order. For example in the HELLA case the attribute 2 and 3 (adjustment scenario and marker) are always displayed together, contrary to the CLAAS case, where every attribute is displayed after another, also having a similar display time. This makes the realization of the short 3D sequences a lot faster and easy to implement in parallel with different teams.

Like in the HELLA case, after the stimuli ends the price is displayed and the respondent ranks it in the MELIMCA tool.

Having tested the MELIMCA tool with about 40 respondents for the HELLA case, it implies that VR stimuli enhance customer’s understanding of the advantages and benefits of product features. Overall, when having VR as an additional description, respondents had a better understanding of the product features in comparison to a verbal description.

5 CONCLUSION

Companies often lack a systematic approach to early integrate customers early in the product development process. This paper shows a step-by-step approach of early customer integration my means of a multi-stage limit conjoint analysis (MELIMCA), which has been programmed into a web-based tool. In addition, complex innovations are often beyond customer’s imagination. Therefore, this paper showed how the conjoint analysis can be extended by integrating cost efficient virtual realities as a stimulus. Nevertheless, the evaluation of the VR stimuli in a conjoint analysis tool is still in its infancy stage. Regarding the approach, future studies should analyze the internal and external validity of the conjoint analysis when comparing textual and virtual stimuli. A comprehensive comparison between the two stimuli should show the pros and cons of the method. Concerning the MELIMCA tool, future studies should elaborate on the question, what “better” means in the context of customer integration in early product development. Are customers more secure when making their decision? Is there a higher product understanding or reduction in complexity when having a virtual reality as a stimulus? In addition, the MELIMCA tool might facilitate the analysis of the underlying processes regarding the purchasing behavior of an organizational buying center. Here, future studies should give deeper insights.

Overall, a conjoint analysis with VR-based stimuli presentation may help companies to find out the market needs, secure market success and prevent failed product developments. Future studies should empirically proof MELIMCA with integrated virtual realities to verify the results.

6 REFERENCES


