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Abstract

Mass customization and product platform design can exploit the benefits of modularity and provide personalized devices at competitive costs through economies of scope. However, customization-intense platforms can have thousands of potential configurations, whose development and verification must be prioritized. This paper develops a Value analysis methodology that is able to rank alternative platform configurations according to customers' preferences. It introduces Logit Value, a definition of Value based on a well-known stated choice model and explains the five steps of platform-based Value analysis. Since product platforms are complex technical systems, particular attention is given to the gathering of information, the automatic generation of platform architectures and the visualization of results. A case study based on Google ARA's Spiral-2 modular smart phone concept demonstrates an application of the methodology and shows its potential benefits. The case study leverages data from a conjoint analysis and survey of 200 potential customers in Puerto Rico and a generated set of over 21,000 potential configurations of which less than 1% are shown to be non-dominated. The Value analysis identifies module types that are compatible with the modular product platform and appear in a high percentage of Pareto architectures. Knowledge pertaining to non-dominated configurations can provide insights into module development strategy and verification/validation activities.

Nomenclature

$v_j^{\{h\}}$: utility of product j according to agent h

$b_i^{\{h\}}$: part-worth utility of i-th feature according to agent h

u_i : binary variable of i-th feature

$u_c^{\{h\}}(p)$: part-worth utility for price p

P_i : probability of i-th choice

$V_i^{\{h\}}$: Logit Value of i-th choice

$b_{F,i}^{\{h\}}$: part-worth utility of i-th function according to agent h

$b_{P,i}^{\{h\}}$: part-worth utility due to performance level of i-th function according to agent h

$V_0^{\{h\}}$: baseline value according to agent h

$V_{cust}^{\{h\}}$: benefits of customizability according to agent h

$V_{uniq}^{\{h\}}$: benefits of uniqueness according to agent h

$(U_{F,i}^{\{h\}}P_i^{\{h\}})_{emerg}$: benefits of i-th emergent function

$(U_{F,i}^{\{h\}}P_i^{\{h\}})_{md}$: benefits of i-th module function

$U_c^{\{h\}}(p)$: price sensitivity for price p according to agent h

$c_{w,md}$: price of w-th module

c_{core} : price of platform core

1. Introduction and research motivation

Customization in product platforms is both an opportunity and a challenge. It allows entry into different market niches while preserving economies of scope (Meyer and Lehnerd 1997); furthermore, the customization process itself can be highly enjoyable for customers, thus increasing the perceived Value of a product (Tu et al. 2001; Jiao et al. 2003; Franke and Piller 2004; Franke and Schreier 2010). However, platforms are complex systems that require a complex design process (Muffatto and Roveda 2000; Lindemann et al. 2009; Sinha and de Weck 2013; Colombo and Cascini 2014; Cheng et al. 2018) and high front-end investments (Cameron and Crawley 2014); moreover, variety requires sophisticated logistics and a proactive engagement with the market (Wang et al. 2007; Li 2009) and a change in the firm's mindset and culture (Pakkanen et al. 2018). The costs incurred to create, sustain or use a platform might not be worth the customization benefits, as highly modular systems generally show lower performance levels compared to integral ones (Ulrich 1995, Holtta and de Weck 2007). Moreover, the development of modules must match customer's preferences, so that the overall platform is attractive to the market and variety does not increase

complexity in vain. Finally, customers often must be guided through the choice process, e.g. by using bundle strategies or configurators (Derdenger and Kumar 2013; Trentin et al. 2013). Furthermore, the paradox of choice (Schwartz 2004; Piasecki and Hanna 2011) states that the more choice a customer has, the less satisfied he or she may be and choosing over an enormous set of options can be burdensome and tedious, or even intimidating. This can result in a counterintuitive situation where the producer has to deal with high costs due to customization, while the customer becomes increasingly dissatisfied. For example, there is evidence that standardization has more impact on customers' satisfaction than customization in the Far East service industry (Kasiri et al. 2017). These challenges are further aggravated in case of customization-intense devices like Google's Project ARA (McCracken, 2014).

Given all the above, it is clear that the design of highly customizable product platforms must be guided by the preferences of future customers. This paper introduces a method to rank platform configurations according to customers' preferences thanks to a definition of Value that is consistent with stated choice models and Value engineering. This is beneficial for several reasons. First, the Value of a potential platform can be compared against integral products on the market, so that a platform strategy is assessed before making relevant investments in platform development, as observed in (Cameron and Crawley 2014). Then, by highlighting the most valuable combinations, product developers can prioritize module design and variety. Using the customer-based definition of Value, traditional strategies to reduce customers' choice burden like bundles (Derdenger and Kumar 2013) can be derived more intuitively. As shown by Topcu and Mesmer (2018), Value models are able to open the design space to counterintuitive designs and thus can point designers towards better technical solutions. Finally, testing all variants of a customizable platform is an effort-intense, time-consuming activity that can jeopardize the success of the entire project: if too few combinations are tested, the risk of malfunctioning product configuration increases; if too many combinations are

tested, the project may become too expensive or miss the deadlines. Ranking by preferences can help prioritizing the test design and scheduling.

This paper tailors standard Value analysis methodology to meet the specific needs of platform design, by joining in a unique method product marketing, sales strategy and product design, which are usually addressed separately and sequentially. As such, the Value analysis presents three features: it is customer-centered, in that it analyzes the Value provided to customers, it is holistic, since it considers different phases in the product life-cycle, and it is applied to product platforms, i.e. "a set of subsystems and interfaces that form a common structure from which a stream of derivative products can be efficiently developed and produced" (Meyer and Lehnerd 1997). Consequently, the central research questions are: (1) "How to measure the Value of customizable modular product platforms quantitatively?", (2) "How can customer-centered Value analysis be applied to customizable modular product platforms to rank configurations by Value?" and (3) What are the benefits of measuring Value in the early design phases of modular product platforms?. In answering these questions, not only we provide a distinctive perspective on customizability, which can be exploited in platform design processes like the ones in (Jiao et al. 2003); we also follow the suggestion provided in (Simpson et al. 2014), to use customer-perceived Value instead of cost as an objective function in platform design.

The remainder of paper is structured as follows: Section 2 briefly reviews the literature on Value, customization and market-driven platform design; Section 3 introduces the customer-centered Value designated as *Logit Value*. Section 4 describes the Value analysis for customizable platforms, which is applied to a customizable modular smartphone based on Google ARA in Section 5. Finally, Section 6 provides conclusions and future research directions.

2. State of the art

Value is the central measure of the Value analysis, but its definition involves several disciplines, from Economics to Cognitive Sciences and Engineering. This section provides a general overview of fundamental literature on the topic of Value and consists of three parts: Value and customers' choice, Customizability and Market-driven Platform Design.

2.1 Value and customers' choice

Value is one of the main concepts in economic history, dating back even to Adam Smith's "The Wealth of Nations". It is not hard, therefore, to find several definitions and perspectives on the concept of Value; it is much harder to find a synthesis of the various viewpoints. Given the scope of this paper, we will focus on the subset of the literature that explains why customers choose certain products and how this notion can be applied to customizable platforms.

The basic assumption in many stated choice models (Louviere et al. 2000; Chandukala et al. 2007, Kim et al. 2017) is the existence of a scalar measure of consumer preferences called consumer utility, which can be used to rank several choice alternatives. Consumers try to maximize their utility given some form of monetary constraints. The geometrical locus of maximum utility given a constrained budget is called an "indirect utility function". Several choice models can be found in the literature; depending on the goals of the model and the underlying assumptions, some are more appropriate than others (Ben-Akiva 1997). Determining parameters inside these models is the subject of Conjoint analysis (Green and Rao 1971; Ben-Akiva and Lerman 1985; Rao 2014). Conjoint analysis is "a set of techniques ideally suited to studying customers' choice processes" (Rao 2014). A conjoint analysis presents itself as a questionnaire where respondents have to make tradeoffs between product features, including price. Conjoint methods can be subdivided into rating-based methods and choice-based methods. Both categories have strengths and weaknesses; and some

hybrid (Green et al. 1981), adaptive (Johnson 1987) or aggregate (Sylcott and Cagan 2014) methods were developed in order to overcome the limitations of traditional methods.

Economics and marketing focus on the effects of Value on markets and customers; in particular, stated choice models allow capturing customer preferences in a rigorous way, but they do not indicate how to generate Value in a product: this is the goal of engineering design. A set of tools and methods called "Value analysis and engineering" has been developed for the purpose of focusing the Designer attention on Value generation (Miles 1961). Value analysis allows designers to understand what part of a technical system has low Value, while Value engineering increases the Value of a system by identifying solutions to technical problems. Value, in this area, is defined as benefits over costs: "Value is the most-cost-effective way to reliably accomplish a function that will meet the user's needs, desires and expectations" (Dell'Isola 1997). As far as the Value Engineering methodology is concerned, it consists of several phases (Dell'Isola 1997) which are as follows: (1) Information gathering, (2) Alternative generation, (3) Evaluation of solutions, (4) Proposal development and (5) Presentation and implementation.

Stated choice models are a rigorous mathematical tool to measure customer preferences, Value engineering a methodology to design products that satisfy those preferences. These two fields, however, have been developed assuming that products are designed by a single entity and do not change over time. As stated in the introduction, modular customizable products do not respect these assumptions. In order to cover this gap, a Value analysis for customizable modular platform must consider two other relevant aspects: customization and platform design.

2.2 Customization

Customizability can be defined as the systems' lifecycle property that allows customers or users to change a product. System lifecycle properties (also called "Ilities") are properties that belong to the system as a whole and manifest themselves after the system has been put to initial use (de Weck et

al. 2011). Customizability can be seen as a particular aspect of changeability that is manifested when a customer wants to change a product in order to optimally satisfy his or her specific needs (Colombo et al. 2016). Customizability is related to the concept of mass-customization (Pine 1993; Fogliatto et al. 2012): "a product development approach that allows for the creation of goods that minimize the trade-off between the ideal product and the available product […], while maintaining system costs comparable to mass-produced products" (Ferguson et al. 2014).

Customizability and mass customization allow maximizing a customer's Value while reducing the costs relative to a bespoke monolithic product with equivalent functionality. Furthermore, the inherent uniqueness of certain configurations can provide Value on its own (Franke and Schreier 2008). For example, a case study about innovation toolkits showed that customers are on average willing to pay double the baseline price to have self-designed watches (Franke and Piller 2004). Nevertheless, some studies have also underlined that this Value is actually mediated by several factors, like process effort and enjoyment (Franke and Schreier 2010) or the level of insight into customers' own preferences (Franke et al. 2009) and that excessive choice can lead to frustration due to complexity (Valenzuela et al. 2009), post-decisional regret (Zeelenberg et al. 1998), expectations disillusion (Diehl and Poynor 2010) and conflicting desires (Chatterjee and Heath 1996; Gourville and Soman 2005). These aspects need to be taken into consideration when evaluating the Value of a customizable product platform from a customer's perspective.

2.3 Market-driven platform design

A product platform is "a set of sub-systems and interfaces forming a common structure from which a stream of products can be developed" (Meyer and Lehnerd 1997). All platforms may be subdivided into two parts: the core and the periphery (Gawer 2009). The core is composed of those subsystems that remain stable across platform variants, also called platform configurations; while the periphery can change from variant to variant and is usually composed of add-on modules. The core can be used

across several variants with no or only minor modifications; usually, the cost of adapting the core is lower than the cost of designing new product parts de novo.

Addressing front-end issues in platform design is a complex activity, and several researchers have addressed its challenges. (Simpson et al. 2014) subdivides front-end issues into (1) product portfolio and product family positioning, (2) market-driven product family design, (3) product family modeling and (4) platform and product family configuration issues.

Since the goal of the paper is a methodology that joins customer preferences and product design, this literature review focuses on market-driven platform design, which is interested in measuring customers' needs and translating them into technical requirements. (Ferguson et al. 2011) highlights the potential of conjoint analysis in mass customization and underlines strengths and weaknesses of stated choice models for engineering design. In particular, the authors conclude that "Determining a sufficient level of granularity for assessing consumer preferences is a critical issue". (Kazemzadeh et al. 2009) takes advantage of conjoint analysis in order to improve the requirements specification for product families. Stated preferences highlight the most appreciated features of a product, which are translated into requirements thanks to the House of quality matrix. The use of House of quality matrices and indices not only applies to the initial design of a product, but is also relevant for its re-design (Jung and Simpson 2016).

Conjoint analysis has also been employed to determine the "best" product family portfolio. In (Kumar et al. 2009), for example, an advanced market segmentation grid is derived from a nested logit model; the grid is then combined with the product's features and estimated cost, which are given as an input to a commonality optimization algorithm. A general inquiry on commonality optimization from conjoint analyses can be found in (Turner et al. 2011), where bottom-up and top-down methods are compared. The article mentions that top-down methods lead to well-informed

decisions, at the price of more complex analysis. We will employ stated choice models to guide strategic design decisions about modular product platform design.

3. Theoretical framework

In order to integrate conjoint analysis with Value analysis for the design of customizable modular platforms, a common mathematical language must be found. This section (1) proposes a definition of Value that unifies utility models and the definition of engineering Value and (2) instantiates it for customizable modular platforms.

Conjoint analysis is a well-developed methodology to infer customers' preferences through questionnaires. In order to quantify these preferences, a mathematical utility model must be employed, which is usually (but not necessarily) based on the linear combination of part-worth utilities b_i and product features u_i (Ben-Akiva and Lerman 1985; Rao 2014):

$$v_j^{\{h\}} = \sum_{i=1}^{N} b_i^{\{h\}} u_i \qquad (1)$$

Where $v_j^{\{h\}}$ is the utility of product j according to customer h, b_i are numeric coefficients representing the customer's preference, and u_i are binary variables indicating if the i-th feature among the possible N features is present in the j-th product. It must be noted that price sensitivity is included inside the b_i coefficients. However, several studies – for example (Han et al. 2001) – concluded that price sensitivity is not linear and presents thresholds. A more generalized model of utility therefore is:

$$v_j^{\{h\}} = \sum_{i=1}^{N-1} b_i^{\{h\}} u_i + u_c^{\{h\}} \left(\sum_w c_w \right) \qquad (2)$$

where $u_c^{\{h\}}$ is the non-linear contribution to utility $v_j^{\{h\}}$ as a function of the sum of the costs of the w components c_w. Independently from its form, utility can be employed to compute the probability that consumer h chooses a certain product among a set of similar products k:

$$P_i = \frac{\exp(v^{\{h\}}_i)}{\sum_k \exp(v^{\{h\}}_k)} \qquad i = a, b, c, \dots ; \quad k = a, b, c, \dots \tag{3}$$

where P_i is the probability of choosing the product i, $v^{\{h\}}_i$ is the utility given by the customer h to the product i. Equation 3 expresses the probability of choice according to the logit model, a statistical choice model that derives from a logistic distribution (Chandukala et al. 2007).

On the other hand, Value in Value engineering is defined as benefits divided by costs. Benefits are generalized useful functions provided by the product and costs are a generalized measure of resource consumption in order to provide the benefits. As this work is based on a customer-centered view of Value, the costs are the transaction price paid by customers.

Utility and Value seem to be two different mathematical formulations of the same measure. In fact, it is possible to bridge the gap between the two by applying an exponential transformation in Eq. 2 and considering price sensitivity instead of actual costs in Eq. 3. This results in:

$$\exp(v^{\{h\}}_j) = \exp\left[\sum_{i=1}^{N_j-1} b^{\{h\}}_i u_i + u^{\{h\}}_c \left(\sum_w c_w\right)\right] = \frac{\prod_i \exp(b^{\{h\}}_i u_i)}{\exp\left(-u^{\{h\}}_c \left(\sum_w c_w\right)\right)} = \frac{\prod_i U_i P_i}{U_w \left(\sum_w c_w\right)} = V^{\{h\}}_j \tag{4}$$

where the numerator is the positive utility given by the product's features (the benefits' utility) and the denominator is the negative utility given by price (the price utility). We will call this definition of Value, the *Logit Value*.

Eq. 4 is the key to convert the results obtained in a conjoint analysis into a mathematical formulation of Value. This formulation of Value presents two main advantages: first, it gives a solid theoretical background in Value analysis, since Value is not derived from designers' subjective formulations but from a structured analysis of stakeholder preferences; furthermore; this formulation gives a statistical meaning to Value. In fact, the logit model in Eq. 3 can now be written as:

$$P_i = \frac{V^{\{h\}}_i}{\sum_k V^{\{h\}}_k} \qquad i = \text{a, b, c, ...} \; ; \; k = \text{a, b, c, ...} \tag{5}$$

In other words, the probability of choosing a product from a set is given by the ratio between its Value and the sum of the values of all the products present in the consideration set.

This definition of Value can be applied to any product; however, given the scope of this paper, we will focus on the most prominent factors affecting the Value of a modular platform. Based on the literature on the topic, we propose five evaluation parameters:

- The benefits of primary and secondary functions provided by single modules. Purely modular systems present a one-to-one mapping between modules and main functions, but modular platforms usually show a combination of integral and modular aspects (Ulrich 1995; Ulrich and Eppinger 2011);

- The benefits of primary and secondary emergent functions, i.e. emergent functions cannot be attributed to a single module (Corning 2002; Crawley et al. 2015);

- Other intangible factors like branding or prestige (Lassar et al. 1995; Vigneron and Johnson 1999), which define the "baseline" Value of the product;

- The intrinsic benefits of customizability (Bharadwaj et al. 2009; Franke et al. 2009);

- The benefits of product differentiation and uniqueness (Franke and Schreier 2008; Ruvio et al. 2008; Cheema and Kaikati 2010; Liang and He 2012).

The Logit Value of products derived from customizable modular platforms can therefore be defined as

$$V^{\{h\}}_j = \frac{V^{\{h\}}_{md} V^{\{h\}}_{emerg} V^{\{h\}}_0 V^{\{h\}}_{cust} V^{\{h\}}_{uniq}}{U^{\{h\}}_c (\sum_w c_w)} = \frac{\prod_i (U^{\{h\}}_{F,i} P^{\{h\}}_i)_{md} \prod_i (U^{\{h\}}_{F,i} P^{\{h\}}_i)_{emerg} V^{\{h\}}_0 V^{\{h\}}_{cust} V^{\{h\}}_{uniq}}{U^{\{h\}}_c (\sum_w c_{w,md} + c_{core})} \tag{6}$$

where V_{md} is the Value provided by the primary and secondary functions of the modules, V_{emer} refers to the Value-added by emergent properties, V_0 is the Value of intangible factors (such as brand), V_{cust} reflects the benefits of customizability and V_{uniq} represents the contribution of uniqueness. The function $U_c^{\{h\}}$ maps the price sensitivity of customer h to the total price of the product, given by the sum of the prices c_w.

V_{md} and V_{emerg} can be further decomposed in a product between the sensitivity of the customer U to a feature P_i, while the price utility in the denominator now takes into account the price for individual modules $c_{w,md}$ and the price of the platform core c_{core}.

4 Value analysis methodology for customizable product platforms

Section 3 introduced a definition of Value that summarizes the likelihood of choice for a product. This definition alone can be useful to reason about platform design and improvements, but a method is needed to exploit its full potential. This section will apply the Value engineering approach to customizable product platform development, taking advantage of the formulation introduced in the previous sections.

As reminded in Section 2, a traditional Value engineering analysis consists of five main phases: information gathering, alternatives generation, alternatives analysis, proposal development and presentation/implementation of the proposal. The novel methodology presented here (Fig. 1) differs from a standard plan in three aspects. First, the method can be employed for several goals, from prioritizing module development to providing suggestions to customers; for this reason, an initial Goal definition phase is required. Secondly, product platforms are complex technical systems that require significant effort during the design (Sinha and de Weck 2013, Colombo and Cascini 2014). Thus, alternatives generation and evaluation must be supported by (1) computation concept generation methods (M. Mohan et al. 2011), which do not constraint excessively the design space because of the combinatorial complicatedness of the design variants (Colombo and Cascini 2014),

and (2) appropriate visualization techniques, which reduce the cognitive load in the analysis of large datasets (Ware 2008). Finally, the Value considered here is customer-centered, thus it ranks platform configurations from a customer Value perspective. Furthermore, the results of the analysis can also be utilized to set a pricing strategy for modules or to steer customers to the most preferred combinations.

All these activities are iterative in nature. For every new analysis, hypotheses and goals must be laid out clearly and tested. For this reason, the methodology procedure can be associated with scenario analysis (Armstrong 2001).
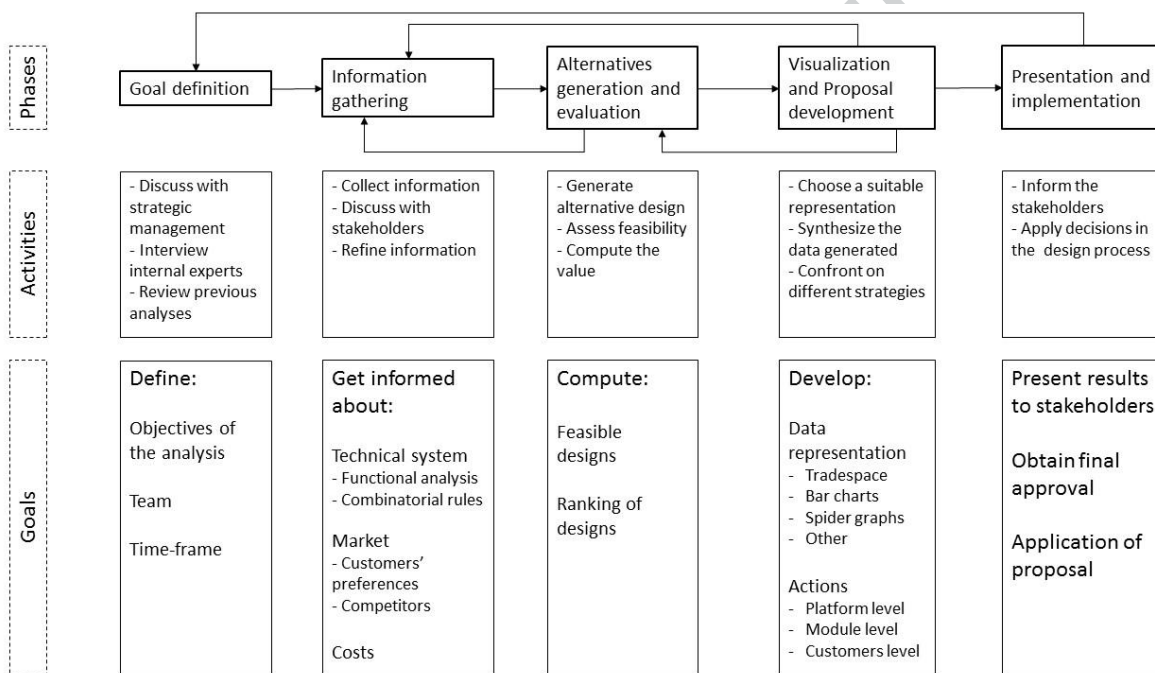
Phases	Goal definition	Information gathering	Alternatives generation and evaluation	Visualization and Proposal development	Presentation and implementation
Activities	- Discuss with strategic management - Interview internal experts - Review previous analyses	- Collect information - Discuss with stakeholders - Refine information	- Generate alternative design - Assess feasibility - Compute the value	- Choose a suitable representation - Synthesize the data generated - Confront on different strategies	- Inform the stakeholders - Apply decisions in the design process
Goals	Define: Objectives of the analysis Team Time-frame	Get informed about: Technical system - Functional analysis - Combinatorial rules Market - Customers' preferences - Competitors Costs	Compute: Feasible designs Ranking of designs	Develop: Data representation - Tradespace - Bar charts - Spider graphs - Other Actions - Platform level - Module level - Customers level	Present results to stakeholders Obtain final approval Application of proposal

Figure 1: Scheme of the Value analysis methodology for customization-intense platforms

4.1 Goal definition

Value analysis allows several studies, depending on the life-cycle stage of the system; thus, the first step in the methodology is the choice of one or more goals.

Value analysis can provide fundamental insights before the beginning of the platform's development. Modularity is a key architectural feature for mass customization, but it tends to reduce performance

because it prevents system-wide optimization of resource consumption (Ulrich 1995). If the drawbacks of modularity are not balanced by the benefits of customizability, a monolithic product may be preferred. This could be true for ultra-high performance markets or markets with uniform customers' preferences.

After a platform architecture has been fixed, designers must evaluate what platform configurations will be offered in the market. As mentioned previously, an optimal number of configurations must be chosen in order to limit the effects of the paradox of choice and to avoid excessive customizability costs. Value rankings may serve this purpose and the preferable configurations may emerge in this way. However, price should also be taken into consideration, as customers' willingness-to-buy usually shows a price threshold (Han et al. 2001). Customers may decide not to buy very valuable configurations because the expense required is too high.

Another outcome of the analysis is the definition of modules' technical requirements and modules' development prioritization. In this case, the focus is on module functions and performance levels. Development, manufacturing and logistics costs are another important issue, as they can influence the final price of the configuration. Moreover, if certain modules show synergistic effects (Corning 2002), they can form bundles. Customer-based Value analyses, if based on price and not on manufacturing costs, can be useful in determining the pricing strategy of the platform. Depending on their price, certain modules can be more or less valuable to the customer; marketing may prefer to increase the price of modules with high benefits, or to decrease the price of non-optimal combinations. Moreover, firms may decide to add a large premium for customizability if the benefits of customizability warrant this; otherwise, they may reduce profit margins or even subsidize modules. Strategic issues related to platforms and markets can be found in (Gawer 2009).

Finally, if the product platform has already been designed and available modules are set, the information provided by the value analysis can be the basis for a configuration tool for customers.

Previous research has shown that customizability benefits arise only if customers can actually enjoy the choice process (Franke and Schreier 2010) and do not feel frustrated (Valenzuela et al. 2009). If individuals' preferences can be inferred, analysis of results can reduce the total configurations considered to the most valuable, thus increasing customers' satisfaction and reducing potential frustration. It could even be imagined that the model is integrated into recommender systems (Ricci et al. 2011) that suggest to the customer/user the most beneficial module substitution based on the device actual use or inferred preferences.

4.2 Information gathering

Information gathering, for example in the form of a market survey, collects the data required for the computation of Value as described in Section 3. Information gathering focuses on three main areas of investigation: the technical system, the market and the costs.

As far as the technical system is concerned, the system must be defined and a functional analysis must be performed. During system definition, designers detail the list of all the potential modules, either already developed or yet to be developed. Functional analysis is necessary in order to specify the functions offered by the system and the relative performance levels. Every function should have one or more technical parameters associated with it. This is needed as a proxy for performance evaluation by customers. The detail of the analysis must be a trade-off between completeness and complexity, as functions will be the input to a subsequent customers' preference investigation. A primary function must be associated with every module, but secondary functions can also be included. Furthermore, system-level functions must be inferred from the combination of the modules. As mentioned earlier, emergent properties are usually the ones associated with the highest benefits.

A market survey provides two important classes of information: customers' preferences and the Value of competitors. Customers' preferences are needed to compute the Value of components, as

highlighted in Eq. 6 and need to be computed through conjoint analysis. While preferences about modules, performance levels, emergent properties and the brand are quite easy to obtain, inferring the benefits of customizability and the Value of uniqueness or price sensitivity can be more challenging. Usually, a cluster analysis (Louviere et al. 2000; Hastie et al. 2009) is performed on the results, so that averaged customer profiles can be mined from the dataset. Technical and functional analysis can also be performed on the competitors, so that competing product values can be quantified. This step is required to inform the decision about whether or not a modular platform concept can be successful against integral products (or other modular products) in the same market.

The last part of the information gathering phase is the platform cost modeling. There exists a wide range of literature on cost modeling that can guide designers and managers through this task (Weustink et al. 2000; Tu et al. 2007).

4.3 Alternatives generation and Alternatives evaluation

Once the set of potential individual modules and their descriptions are known, a list of feasible module combinations must be generated. This can be done manually or automatically. In the manual case, designers' explicit and tacit knowledge is employed. If a configuration database of previous designs exists, it can be used as a starting point for generating feasible combinations.

Since the number of module combinations grows exponentially with the number of modules, automated tools for the generation of feasible combinations are necessary if we wish to examine a significant fraction of the tradespace. Some examples of such tools can be found in (Selva 2012; Zeidner 2010). In this paper, an enumeration tool (developed using Matlab™) was used to generate all possible feasible module combinations (Shougarian 2016). The search tool uses backtracking search subject to compositional constraints to generate the set of feasible configurations. The presence or absence of modules and connections between modules are encoded as vectors of binary decision variables u_i (see Eq. 6). The vectors of binary decision variables are instantiated with design

decisions until all combinations have been enumerated. Constraints are checked every time a design decision is made, meaning that rule violation is checked at every step. In this way, large parts of the binary decision tree are eliminated or "pruned" during search which makes the approach tractable for relatively small problems, O(40) design decisions, with a sparse set of feasible configurations (Shougarian 2016).

Once feasible combinations have been generated, their Value can be computed according to Eq. 7. While the Value associated with the modules' main function and emergent properties is relatively easy to compute, the Value of intangible aspects, such as the Value of customizability and the Value of uniqueness is more challenging, as it requires market insights and close designer-user interaction. To a first approximation, these three aspects can be ignored; however, they can have significant impact on the customers' selection process (Franke and Schreier 2008; Piasecki and Hanna 2011).

4.4 Alternatives visualization and Proposal development

In order to advance a proposal for a new or revised modular product platform and its associated modules, designers must understand which are the most valuable configurations and why. Visualization can be a powerful tool to understand complex systems and design them; several examples can be found in literature, like for example in (Ware 2008). Pareto fronts, in particular, allow comparing the "best" configurations according to several dimensions of evaluation, thus enabling a practical discussion around design trade-offs (Chiandussi et al. 2012, Baylis et al. 2018)

The Proposal development phase consists of a decision-making process aided by analysis results. Depending on the goals defined in Step 1, it can address different aspects of the platform development, like the platform architecture, the modules offered to customers or the pricing strategy. This step can benefit from the involvement of different units in a firm. Iterations between the first four steps may be required either to increase the robustness of the proposal, or to enlarge the scope of the analysis.

4.5 Results presentation and implementation

Once the proposal has been formalized, it needs to be presented to relevant stakeholders and implemented (Freeman and McVea 2001; Garvare and Johansson 2010). Typically, this will involve a review and approval by the firm's executive board.

The Value analysis can bring positive effects only if it is implemented correctly. As the project development proceeds, information becomes less uncertain (McManus and Hastings 2006; de Weck et al. 2007; Wynn et al. 2011); at the same time, market preferences change and the competition landscape evolves; therefore, updating the analysis is fundamental, especially if the final objective is to support the customers' choice process.

5 Case study: Google ARA (modular smartphones)

The methodology proposed in Section 4 will now be applied to a real case study; a customization-intense modular smartphone based on the Spiral-2 concept proposed by Google's Project ARA. This modular product radically changes the architecture of smartphones and follows a technological and strategic trend already observed in personal computers (den Hartigh et al. 2015).

The purpose of this case study is to evaluate the applicability and helpfulness of the methodology by employing it in a real case study. This will be achieved by demonstrating (1) how customer-centered Value analysis can be employed in the context of Google ARA, (2) how unexpected Google ARA configurations are highlighted thanks to this analysis and therefore (3) the benefits of using the methodology proposed. This section can therefore be framed as an Application Evaluation, according to the Design Research Methodology (Blessing and Chakrabarti 2009). A case study of conjoint analysis on smartphones was already proposed in (Okudan et al. 2013), which however focused on off-the-shelf integral smartphones.

The case study presented here is a customization-intense electronic device based on the modular mobile device concept proposed by Google's Project ARA. The details of this case are based on the

Spiral-2 configuration which has provisions for 10 modules attached to an endoskeleton, see Figure 2. The ARA platform consists of an endoskeleton that serves as a central core which modules connect to. The endoskeleton manages information and energy flows between modules using the MIPI M-PHY and UniPro compatible protocols. MIPI is "is a global, collaborative organization comprised of companies that span the mobile ecosystem and are committed to defining and promoting interface specifications for mobile devices" (http://mipi.org/). The M-PHY specification and UniPro technology were specifically developed for mobile devices and enable efficient high bandwidth information transfer.

The results of this case study can inform platform developers about module requirements and help prioritize module development. Whether or not this is done by a captive supply chain or as part of an open two-sided market is outside the scope of this analysis.

5.1 Goal definition

This case study was carried out during the initial concept development phase of project Google ARA, when detailed information did not exist and the level of granularity of the system was quite coarse. The product development team had defined the platform architecture (Spiral-2 configuration), but needed to understand what the *most valuable module combinations* were, so that it could prioritize module development. The analysis therefore highlights the most valuable configurations according to potential clusters of customers. The results also provide insights into the design and behaviour of other customizable smartphones and can be further generalized to customizable modular platforms.

5.2 Information gathering

The objective of the second step of the methodology (see Fig. 2) is to collect information about the technical system, the market and product costs.
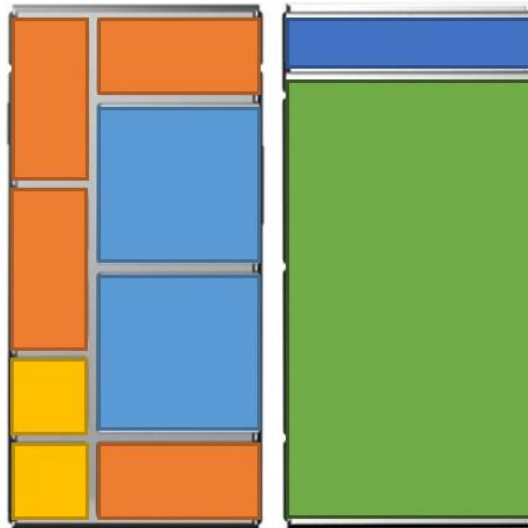
Figure 2: Configuration and layout of the Google ARA platform (spiral-2, left rear, front right)

It is assumed that the system is composed of a set of physical and virtual elements that connect modules together as well as the modules themselves. Different sizes of the device can be imagined. For reference, we assume a Spiral 2 configuration that has ten slots of varying sizes, as shown in Figure 2. These slots (1x1" yellow, 2x1" orange, 2x2" blue and 3x5" green) can be filled by customers with modules such as sensors, batteries, processing units and screens, amongst others. After an examination of components in existing integral smartphones, a list of 21 potential module types was generated (Table 1). Each module type is characterized by its primary function, performance attributes and a normalized price.

Each module has a well-defined primary function and performance attribute. The list of available module types can be expanded, but a trade-off between completeness and complexity was found. Some modules, like the most advanced battery or the highest-capacity memory modules, cannot currently be found on the market, and are here utilized as potential research and development targets.

While Table 1 presents the modules' primary functions, the system is characterized by at least two emerging or system-level performance attributes: battery life and responsiveness. Battery life is the

maximum time a device can be used from a full state of charge to a state of full discharge. It is a function of the battery storage capacity, the number and type of modules installed in the device, the battery management software and the usage profile. Responsiveness is the time lag between an input and a corresponding output. It depends on the processing unit, the available memory, the set of modules in the device, the software manager and the usage of the device. These two features cannot be associated with a single module, even though battery capacity and processing unit clock speed/number of cores have a large impact on these two emergent properties, respectively. Both emergent properties are relevant for the user experience and therefore for the Value of the device, but while computational power is not considered a critical constraint in modern smartphones, battery life is. For this reason, in the remainder of this paper, we will integrate battery life only as part of the analysis, assuming that computational power is always enough to ensure proper responsiveness in the devices.

Table 1: List of module types for customizable modular devices

Type	Primary function	Performance level	Normalized price to customer
Endoskeleton	Supporting and connecting the modules	---	0..83
Processing unit	Processing data	---	0.16
Screen (advanced)	Displaying information Receiving inputs	High resolution	1.00
Screen (basic)	Displaying information Receiving inputs	Mid resolution	0.80
Audio (advanced)	Generating sounds	Hi-fi quality	0.11
Audio (basic)	Generating sounds	Standard quality	0.08
Antenna (advanced)	Communicating data	Optimal reception everywhere	0.23
Antenna (basic)	Communicating data	Good reception	0.17
Camera (advanced)	Taking pictures / video	Professional quality	0.19
Camera (basic)	Taking pictures / video	Amateur quality	0.15

Interface (advanced)	Connecting to other devices	Fast data transfer	0.05
	Connecting to electric plugs		
Interface (basic)	Connecting to other devices	Slow data transfer	0.04
	Connecting to electric plugs		
Environmental sensor	Monitoring environmental conditions	---	0.13
Medical sensor	Capturing health data	---	0.13
Security sensor	Preventing unauthorized access	---	0.13
Memory (advanced)	Storing data	256 GB	0.13
Memory (intermediate)	Storing data	64 GB	0.37
Memory (basic)	Storing data	16 GB	0.30
Battery (basic)	Storing and providing energy	250 mAh	0.23
Battery (intermediate)	Storing and providing energy	500 mAh	0.04
Battery (advanced)	Storing and providing energy	750 mAh	0.06

Customers' part-worth utilities were investigated through a self-explicated conjoint analysis (Rao 2014). The questionnaire was administrated to N=200 people in Puerto Rico, the original Google ARA launch market, through in-person interviews. The sampling was based on gender and age: 49% of the respondents were male, and 51% were female; 36% of the respondents were younger than age 30, 33% were aged 30 to 45 and 31% were between 45 to 64 years old. The questionnaire consisted of 35 questions and took approximately 15 minutes to complete.

In line with previous works on the topic (Chan et al 2012, Ma and Kim 2016), the respondents have been clustered into five groups through the application of Ward's linkage algorithm (Everitt et al. 2001) on customers' part-worth utilities and age.

Details about the five cluster's characteristics are given in Table 2. The analysis of the market survey suggested the existence of five distinct clusters of potential users, each with different preferences for functional utility and price sensitivity. The preferences of each of these five groups are subsequently used to evaluate module combinations associated with the customizable platform in Fig. 2.

Table 2: clusters of customers from conjoint analysis (Puerto Rico, 2015, N=200)

Cluster name	Distinctive feature(s)	Percentage of customers
Cluster 1: Basic-functionality	Main interest in feature phone functionalities	17%
Cluster 2: Price-sensitive	Extremely sensitive to price	8%
Cluster 3: Performance-premium	High preference for high-performance modules	7%
Cluster 4: Balanced	No distinctive features, balanced preference	34.5%
Cluster 5: Enthusiast	High utility for most modules, low price sensitivity	33.5%

The estimated costs of the components were derived from freely available cost breakdowns in integral phones (AppleInsider Staff 2015; Fairphone 2015; Keizer 2015). The cost of components is normalized in order to preserve confidentiality and eliminate the effect of inflation. The module cost considered here is the one-time payment price from independent retailers and not the subsidized device price available from wireless providers.

Finally, as far as the other components of Value are concerned, it is assumed that all the platform configurations have the same intangible Value, the same customizability Value and the same uniqueness Value; for this reason, they are not taken into consideration in this analysis (see Eq. 7).

5.3 Alternatives generation and Alternatives evaluation

The feasibility of module combinations and their emergent properties was evaluated using two numerical approaches. As explained in Section 4, the set of feasible mobile device configurations was generated using architecture enumeration subject to feasibility rules. The system-level property evaluated was the battery life, which depends on both the battery capacity, the classes of modules inside the architecture and the usage profile. The battery life (number of hours the mobile device could function without charging) was estimated for a typical usage-profile, as defined in (Informate 2015).

For the purposes of this work, it was assumed that the platform itself (endoskeleton) contained a 1000 mAh battery. A total of 41 compositional rules placing bounds on the number of connections, the number of modules and constraining total area occupied by modules were used to generate

feasible architectures (module bundles), see Figure 3. The total number of architectures generated was 21,168.
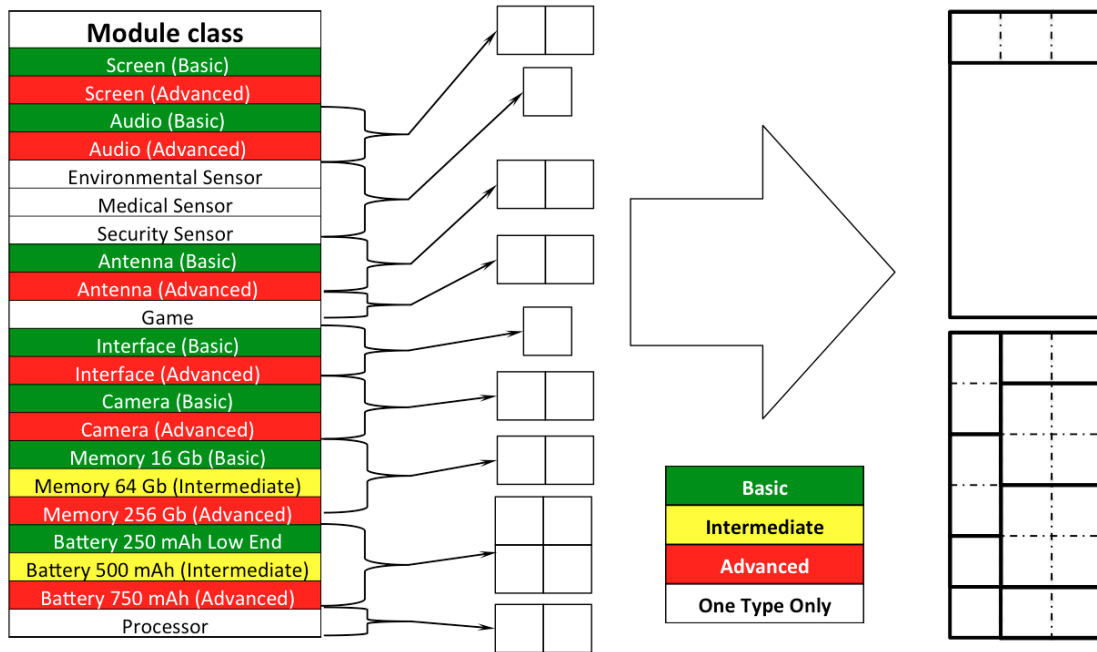

Figure 3: Module type definitions, module sizes (in 1"x1" squares) and customizable platform (left to right). Basic modules are green, intermediate yellow, and advanced modules in red.

The Value of the architectures was computed using Equation 6. At the level of abstraction of the case study, the Value of uniqueness was not measured, therefore it is simply set to unity. Moreover, since only platform architectures will be compared, the baseline Value V_0 and the Value of customizability are the same for all the samples and can be normalized ($V_0 = V_{cust} = 1$). Equation 6 then simplifies to:

$$V_j^{\{h\}} = \frac{\prod_i (U_{F,i}^{\{h\}} P_i^{\{h\}})_{md} \prod_i (U_{F,i}^{\{h\}} P_i^{\{h\}})_{emerg}}{U_c^{\{h\}} (\sum_w c_{w,md} + c_{plat})} \qquad (7)$$

As Table 2 showed, five average user types emerged from the conjoint analysis data. Therefore, the Value defined in Equation 7 must be computed five times for all the feasible 21,168 platform architectures.

5.4 Alternatives visualization and Proposal Development

The Value computed in the previous step of the methodology must be visualized in a comprehensive, but understandable, illustration. First, Figure 4 shows the statistical distributions of Value for each of the five clusters of potential customers (top to bottom).
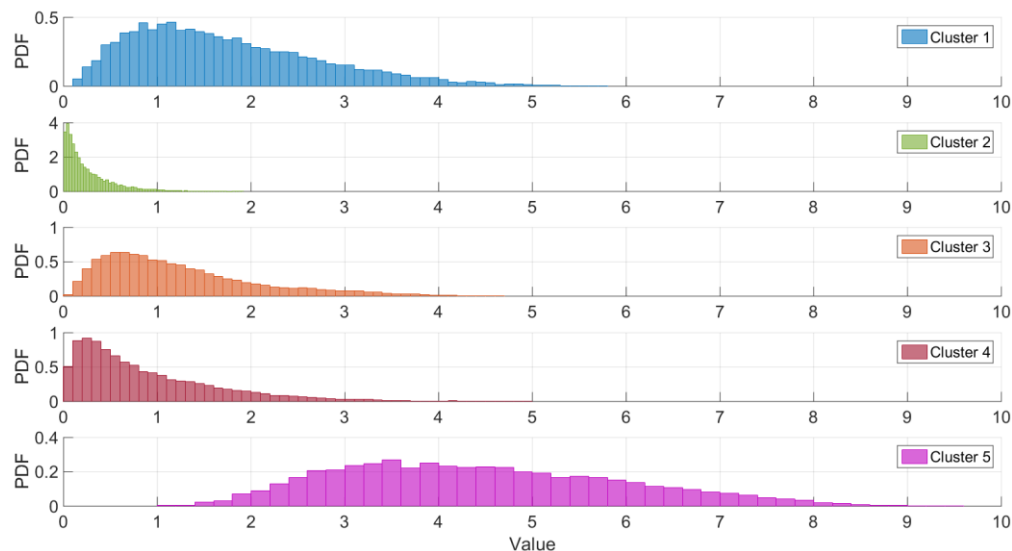

Figure 4: Relative Value distribution for five clusters of potential modular device customers

Cluster 1 (Basic-functionality), Cluster 3 (Performance-premium) and Cluster 4 (Balanced) exhibit similar distributions, even though the mean and the maximum Values are different. Cluster 2 (Price-sensitive) composed of respondents that are particularly price-sensitive, has a very asymmetrical distribution, with rapid decay of the right tail. This suggests that even the most advanced module bundles may not be of high Value to this group. Enthusiasts (Cluster 5), on the other hand, have a distribution with the widest spread, the highest mean and the largest preferences for Value. For all clusters, there are a finite number of architectures that dominate the others, which is an indication that with the assumed module pricing strategy the customizability of the device is not fully exploited. Table 3 summarizes the main features of the best platform architectures according to the Value model.

Table 3: Modules inside the most valuable architectures for each cluster (0 – module not present in the architecture; X – module present in the architecture)

MODULE CLASS	CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4	CLUSTER 5
Architecture code	12706	18178	18178	18106	17404
Benefits	5.3727	2.9117	4.2729	6.8074	14.1353
Price sensitivity	0.9396	1.5221	0.9207	1.3659	1.4971
Screen (basic)	X	X	X	X	X
Screen (advanced)	0	0	0	0	0
Audio (basic)	X	X	X	X	X
Audio (advanced)	0	0	0	0	0
Environmental sensor	0	0	0	0	X
Medical sensor	0	0	0	X	X
Security sensor	X	X	X	0	X
Antenna (basic)	X	X	X	0	0
Antenna (advanced)	0	0	0	X	X
Gaming interface	0	0	0	0	0
Interface (basic)	0	0	0	0	0
Interface (advanced)	X	X	X	X	X
Camera (basic)	0	0	0	0	0
Camera (advanced)	0	0	0	0	0
Memory (16 GB)	X	X	X	X	X
Memory (64 GB)	0	0	0	0	0
Memory (256 GB)	0	0	0	0	0
Battery (250 mAh)	0	0	0	0	0
Battery (500 mAh)	0	X	X	X	X
Battery (750 mAh)	X	0	0	0	0
Processing unit	X	X	X	X	X

The five smartphone architectures have similar features; for example, all of them have a basic screen, basic audio modules and high-performance interfaces; at the same time, the five clusters choose different battery configurations and diverse sensors. The similarity of the most valuable architectures is not easy to explain. On the one hand, it may underline how customers are bound to choose module combinations that resemble the smartphones already on the market because of psychological inertia; on the other, it indicates that a customizable smartphone can radically change the market only with an adequate offer of innovative modules or a well-design pricing strategy. Further investigations about the influence of uniqueness and the user interaction with these devices will further clarify this aspect; still, it is important to highlight that, even if the five configurations are similar, the Logit Value attributed by each cluster is very different, meaning that some clusters consider customizable

smartphone more appealing than others. Note also that Table 3 represents only a single architecture that maximizes Value for each type of user. While Value alone can be a very useful indication of the optimality of individual architectures; the trade-off between benefits and price can be further explored using trade-spaces. We now consider the full set of architectures on Pareto-frontiers in the benefits-price utility tradespace for each user cluster. Figure 5 compares the logarithm of the benefits (the numerator of Eq. 6) with the logarithm of price sensitivity (the denominator of Eq. 6): two architectures are chosen with the same probability if the difference between the two is the same. In Figure 5, the utopia point is in the upper-right corner. The Figure shows only the non-dominated architectures, which are a small percentage (less than 0,5%) of all the total feasible configurations.
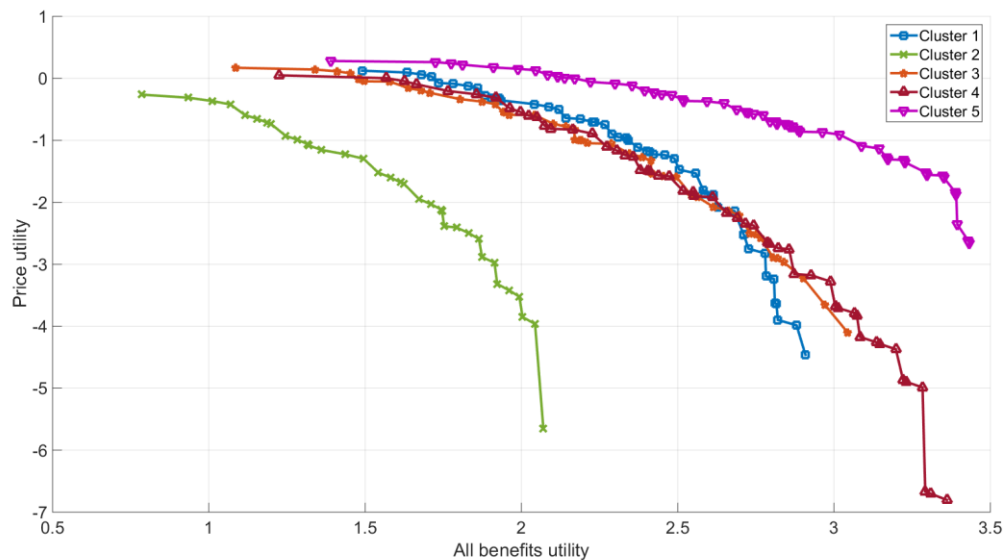

Figure 5: Tradespace utility analysis for smartphone architectures evaluated according to all cluster's part-worth utilities, showing only Pareto-front (non-dominated) architectures.

Even though the platform architectures are the same, they are evaluated differently by each of the five clusters of users. Cluster 5 is the one with the highest evaluations and the mildest price sensitivity function, since the price Value decreases very slowly with an increase in actual price.

Conversely, Cluster 2 is the most difficult to satisfy, due to a very steep price sensitivity function, which decreases the platform Value quickly. Clusters 1, 3 and 4 have similar Pareto frontiers, even though the architectures contained within them may vary. Once the Pareto-front architectures have been found for each cluster, it is possible to analyse what are the most prevalent modules used inside them. Figure 6 shows the ratio of modules to Pareto-front architectures for each Cluster. A ratio of 1 indicates that all architectures on the Pareto-front contain the module in question. A ratio greater than one is possible if on average more than one of the modules is present in each Pareto-front architecture.

The most popular modules are the entry-level audio module, the low-resolution screen, the high-speed interface, the security sensor, and the 750 mAh battery. The modules selected are only partially correlated with their respective part-worth utilities, because the choice process is mediated by the feasibility of platform configurations and the utility of emergent properties. For example, advanced displays are not very popular across the five clusters, but every platform architecture needs one screen to function. Hi-fi audio modules are in theory more valuable than traditional audio modules, but they consume more energy to work; the combination of power usage and the high price makes them rather unpopular in this case study. In other words, Figure 6 indicates that just considering the customers' interest in certain module types in isolation can lead to biased decisions. This highlights the utility of the more integrated Value analysis methodology presented in this paper.

Let us now analyse Figure 5 more closely. When we considered only the highest value configuration for each cluster of users, it seemed that "optimal" architectures were quite similar (Table 3). Figure 5 considers the set of Pareto-optimal architectures for each cluster. Notice that there are significant differences between the frequencies of the same module for different users. A good example is the medical sensor, which comes up very often for some groups, but is rarely present for others. Figure 6 indicates that the medical sensor should be an independent module and that audio and interfaces could be integrated into the platform. It is very important to note however that uncertainty in the

price and preferences of users could significantly impact this result. However, once the model is set up, it is possible to update the analysis along the product cycle, whenever more precise data become available.
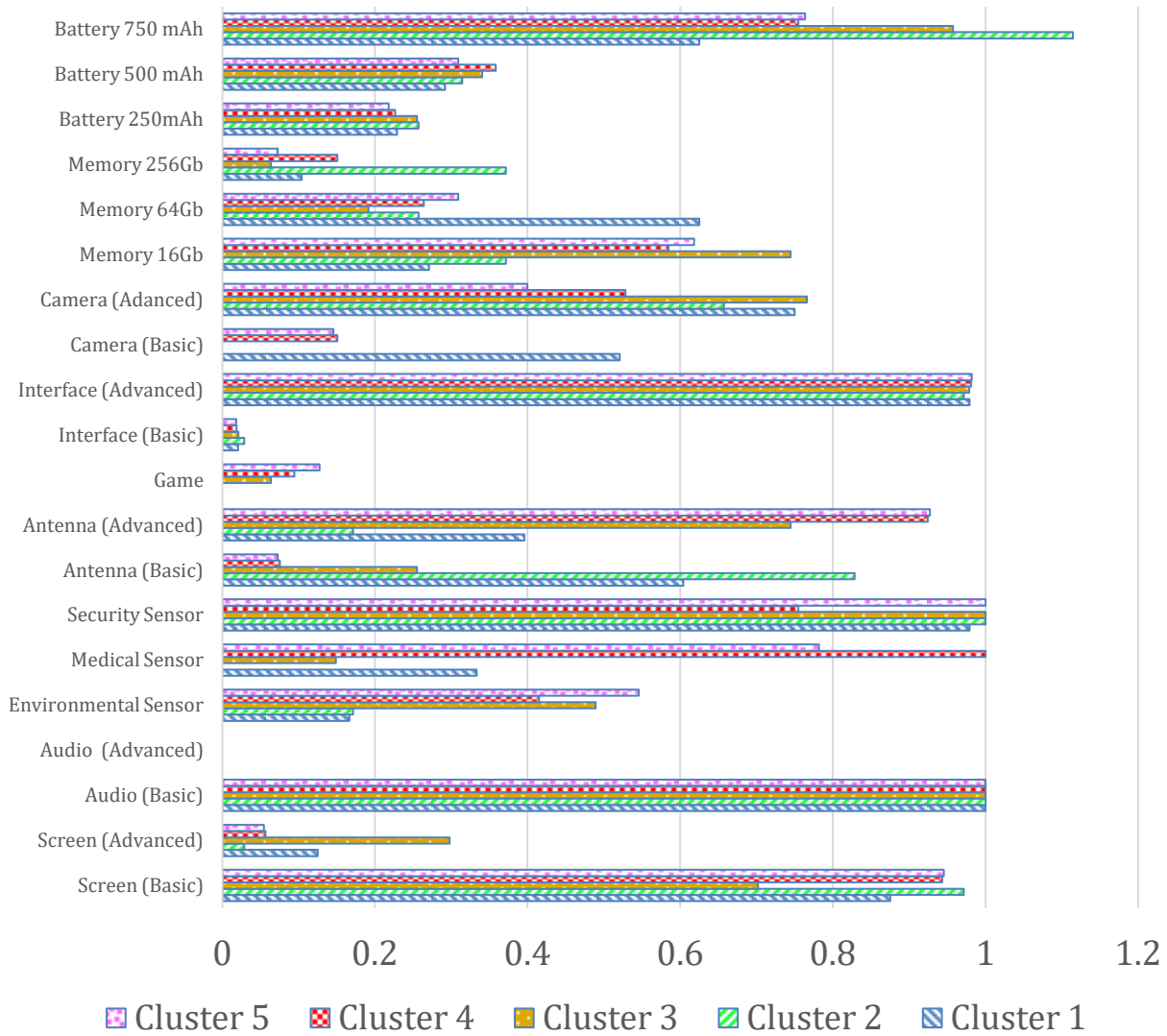

Figure 6: Fraction of Pareto-front architectures containing certain module types for each cluster of respondents. A number greater than one indicates that more than one module exists in each Pareto-front architecture of that type on average.

5.5 Results presentation and implementation

The results of the analysis were presented to the Google ARA development team and positive comments were received. In particular, the stakeholders were interested in preferentially supporting

the most valuable modules and focusing the testing activity on the Pareto architectures identified in Figure 5. The Value analysis demonstrated here supports the development of the customizable modular platform in a number of ways: Table 3 provides the most valuable device architectures for each cluster, while Figure 5 shows the best trade-off between price and benefits for each cluster. This allows a strategic comparison among clusters. Finally, the frequency of module types contained in Pareto-front architectures (Figure 6) indicates which module types will likely be in higher demand.

Presented with this information, the stakeholders in the ecosystem were interested in preferentially supporting the most valuable modules and focusing the testing activity on the Pareto architectures identified in Figure 5. The platform development team can prioritize the module development planning and the platform verification and validation process by focusing their testing on the most valuable modular platform combinations. Furthermore, the marketing team can utilize this information to plan the go-to-market strategy and the modules bundling.

The results of the analysis were presented to the Google ARA development team for subsequent planning and implementation.

6 Conclusions and future developments

This paper proposes a methodology to compare modular product platform variants by tailoring the well-known Value Engineering approach to product platform design. In order to rank the large number of platform architectures that can be configured from available modules, a novel definition of Value is presented, called Logit Value. Logit Value (see Equation 6) ranks products according to the part-worth utilities inferred from conjoint analysis questionnaires. Its numerator combines the benefits that a certain platform can bring to the customer in terms of functional Value and other intangible benefits such as customizability and uniqueness, while the denominator contains the price sensitivity function computed for a particular platform-derived variant. After detailing the five steps of the Platform Value analysis, this paper applies them to prioritize the most valuable modules in a

customizable modular smartphone, based on the Google ARA spiral-2 configuration. A self-explicative conjoint analysis was carried out, and the answers from 200 respondents were clustered into five main groups; technical data about modules and modules prices were derived from publicly available data and expert knowledge. The feasibility of different module combinations was assessed thanks to an automated architecture synthesis algorithm, and a numerical model that allowed simulation of battery life. The most valuable modular platform architectures were then extracted from the analysis and examined.

The proposed methodology improves the traditional Value engineering approach in several ways. First, it is based on a definition of Value that is able to rank different alternatives in a consistent way, thus reducing the subjectivity in the evaluation process. Furthermore, this methodology is able to deal with the complexities that arise in platform design, because it addresses a large variety of possible platform-derived module combinations and focuses the attention on the most valuable module bundles and module types. In particular, the use of design automation tools to generate feasible architectures and the representation of alternatives through tradespaces permits to manage complexity more easily. Finally, it provides a holistic view of Value, which takes into consideration several technical and psychological factors. As noted in the case study, the selection likelihood of module types depends not only on their specific Value, but also on other modules, the platform and feasibility constraints. These aspects are present in several works in different fields, but they have never be considered together for the design of evolving modular systems completely managed by end-users.

As shown in the case study, using the methodology is highly beneficial during the early development phases of customizable platforms. Applying this methodology, it was possible to highlight: (1) how appealing is customizability of features/modules for different customer segments, (2) what are the combinations of modules with the highest benefits-to-price ratio and (3) how attractive are modules categories. These notions can affect the decisions taken both at operational level (e.g. which modules

have to be prioritized, which configurations have to be tested more carefully) and at strategic marketing level (e.g. what are the most suitable module bundles to target a certain segment, what is the most appropriate pricing strategy). It is important to underline that this information could not be obtained through analyses measuring the value of single modules, as the value of a configuration (and the modules inside it) emerges holistically from the interactions between all modules.

This work opens up further developments and research directions. In order to compare customizable products against standard monolithic ones, the benefits of uniqueness (i.e. the utility of having modules that few other people have) and customization (i.e. the utility of being able to personalize the device) should be assessed; however, the utility of these features is difficult to quantify through a conjoint analysis: in-depth descriptive studies are needed to characterize these aspects and compare them with other part-worth utilities. If scope of the analysis is expanded to consider truly novel modules, it is important to take into account that, according to (Kano et al. 1984), there are features which are taken for granted, features that are linearly correlated to quality and features that generate excitement; integrating this model inside the Value analysis may allow more consistent comparisons among platform architectures. Further developments can be achieved by removing some assumptions on the customer preferences. For example, (Ma and Kim 2016) proposes a product family design methodology where market segments are not rigid and customer preferences are not static, while (Ghosh et al. 2016) proposed a framework to measure both manifest and latent customer preferences.

Section 4.1 suggests how to make use of Logit Value in more advanced product life-cycle phases, like the product launch (which configurations have to be advertised more?) or product selection (how to avoid the choice paradox and make module selection an enjoyable activity?) usage and upgrade (which new modules increase Value the most, starting from a given configuration?). The usefulness of the methodology during different life-cycle phases could be evaluated by further applying it on popular customizable platforms, like for example smartphone operating systems, fashion order-to-make clothes, modular smartwatches or (re-)configurable furniture. Given the increasing popularity

of product configurators on e-commerce websites, an interesting testing methodology could leverage A/B testing over real buyers, by comparing the attachment rate and the user satisfaction in traditional recommendation systems and Value analysis-empowered ones. These activities can be framed inside the Descriptive Study II phase of DRM, and can be supported by the suggestions from (Blessing and Chakrabarti 2009).

The methodology highlights some weaknesses in the case study that could be addressed by future research. For example, the limited number of Pareto-front architectures suggests that the current pricing strategy does not encourage customization; moreover, some modules are not present in the optimal architectures at all. These findings may inspire a method to increase platform architecture differentiation by changing both module technical features and pricing in a concurrent fashion.

The shape of the Pareto-frontiers and the architectures inside them can be influenced by available module types, system-level functions and module pricing. In the Google ARA case study, how these factors can influence the Value of the Pareto set has not been investigated. Future research will include a pricing optimization algorithm to maximize the number of architectures inside the Pareto-frontiers or a core topological optimization to find the best combinations of modules in the combinatorial space of customizable platform-derived products. Finally, it will be important to compare the performance of the modular platform under different market and supply chain strategies, ranging from a completely open two-sided market to a more traditional supply chain where modules are only provided by captive suppliers.

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