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A decision support framework for identifying novel ideas in New Product Development from cross-domain analysis

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Abstract: In current competitive times, product manufacturers are in fierce competition not only to retain their existing customer base but also to increase their market share by taking new customers from their competitors. One way by which they can achieve this is by generating new ideas and developing novel products with new features. While generating new ideas to make novel products, the importance of product designers not just to satisfy the current customer needs with minor innovations but also to generate ideas that assist them to capture new customers have been highlighted in the literature. However, despite the large number of existing studies that identify novel features in the ideation phase, product designers do not have a systematic framework that utilises an extra slice of information relating to products from either far-field or related domains; to generate such new ideas in the ideation phase. This paper presents our proposed framework FEATURE that provides such a systemic framework to the product designers in the ideation phase of new product development. FEATURE has three phases, the first of which identifies and recommends to the product designers with the novel features that can be added to the next version of a reference product. In order to incorporate the customer's voice into the ideation phase, the second phase ascertains the popularity of the proposed features by using social media. The third phase ranks the proposed features based on the designer's decision criteria to select those that should be the considered further in the next phases of new product development. We explain the importance of each phase of FEATURE and show the working of its first module in detail.

Keywords: New product development, Ideation, Sentiment analysis, Feature-drift[1]

1- Introduction

A *new* product as defined in the glossary of statistical terms is one *that differs significantly in their characteristics or intended uses from products previously produced by the firm* [1]. A more specialised definition of a new product as mentioned by Goulding [2] is that which satisfies new needs, desires, produces outstanding performance and is a result of imaginative combinations of ideas and needs etc. Thus, it can mean either a completely new product or an existing product enhanced with new features. New Product Development (NPD) is one of the old fields of research in the literature that focusses on bringing a new product to the market. It is a combination of many different inherent and interdependent steps, which starts from identifying the product need and ending with the product launch. However, as shown in Figure 1 between these two steps are various interdependent steps to be completed in order to successfully launch a new product in the market. These steps span across various departments of an organisation and will

[1] This paper is the extended version of the paper submitted in ICEBE 2016

involve many stakeholders. Hence, they require the efficient and effective collaboration among all of them to reach the end goal of product launch.

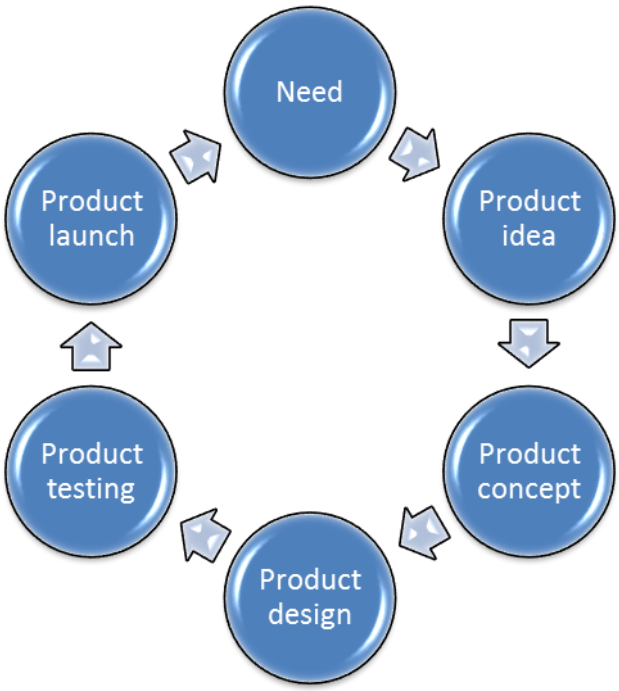


Figure 1- General overview of steps of NPD

Our focus in this paper is on the NPD phase of *ideation* also known as product idea generation. As the name states, product designers in this phase form idea that will eventually lead to the launch of a new product. Ideation is one of the initial phases of the NPD cycle but also one of the most important ones as it focusses on identifying new ideas that can be introduced in the new product when it is launched. This is also supported by existing researches who state that innovation can be best managed and developed in the idea generation phase of NPD [3]. Nowadays, organisations need to ensure that they not only retain their existing customer base but also increase it by taking new customers from their competitors, which can be achieved by developing novel products with the different level/s of newness in them. However, in the current product proliferation and competitive times, introducing a new product is not an easy job to do. But it is required as it will satisfy customers' ever-growing needs and capture their attention in the short time period, which they have especially for products of short shelf life. Goulding [2] classifies newness of products as either *evolutionary* or *revolutionary*. Evolutionary newness is used to define those products that have changed or evolved from their predecessors, however; the level of newness in them is minor. On the other hand, revolutionary newness is used to define a completely new product or a new line of product as a result of using new technological innovation and concepts. Other researchers have classified newness arising from ideation phase either as *routine*, *innovative* or *creative* [4]. Routine refers to keeping the product variables

and their values same in the new product. This is particularly applicable to commodity products that do not undergo a change in their design often. Innovative newness refers to scenarios where the product variables do not change but their values do. In the creative type of newness, both the product variables and their values change.

Product designers in order to generate new ideas for achieving any type of newness need a systematic framework that helps them in the identification process [5]. Furthermore, the new ideas generated should not just be demand-driven based; i.e. just to satisfy the present customer needs as they limit the exploration capability of the designers and introduce poor-valued products with minor innovations [6]. In other words, product designers apart from generating ideas to satisfy the current needs should also generate ideas by which they will constantly get new customers apart from retaining their market share. Hence, they need novel approaches of ideation that assists them to generate such new ideas. The process of ideation has changed over the years from being a close-discussion activity mostly among product designers (ranging from brainstorming to a lateral, scenario-based thinking) to a knowledge extraction from data activity with the advent of Web 2.0. While these methods have been widely diffused in the industry, they suffer from providing low systematic level and generating smaller quantity of ideas [7,8] as they were mainly focused on the product designers and/or focus groups to come up with new ideas. However, with the data deluge that we currently have, product designers can exploit that by using a data-centric approach to expanding the horizon from which they can generate new ideas. In other words, they can now consider data from far-field products or from products of different domains and use analytics to identify what new ideas from those products can be incorporated. This thereby enhances the novelty, variability and also quality of ideas generated from the ideation phase.

While existing approaches in the literature have started to use such data analytics- based approaches, they do not address all the required steps needed to have a systemised framework. Our objective in this paper is to highlight this gap and propose a systematic data analytics based approach named FEATURE that will assist product designers to generate such new ideas in the ideation phase. By considering products from related domains in Section 2, we present the motivation for doing this work and the need to address the problem. Section 3, reviews the literature relevant to this study. The proposed model, FEATURE, is introduced in Section 4. Section 5 details on the first module of FEATURE. The performance of first module of the proposed model is tested and evaluated during Section 6 & 7. We conclude the paper in Section 8 by reviewing the model, its contribution and the future work.

2- Motivation

Before discussing the motivation of doing this work, we first define some key terms.

Reference Product (RP): A reference product is that product in which designers are looking for new ideas in the ideation phase to improve it in its next iteration. An example of reference product is a mobile phone.

Feature (F): A feature is a product's part by which it provides functionality to the users. For example, if we consider mobile phone as our reference product it provides functionalities such as photo-taking ability, playing music & video clips or connecting to the internet. These functionalities are delivered through features such as *camera*, *display* and *Wi-Fi* built-in modem as shown in Table 1.

Attribute (A): Each feature of a product has its own specifications, which describes its functionalities in more detail. These specifications are termed as the feature's attributes. For example, as shown in Table 1, the specifications of a mobile phone's (RP) camera (F) are described by its resolution, flash and special effects etc., which are its attributes.

Value (V): Value shows the quantified representation of a product's attributes in either numbers or text. For example, the resolution (A) of a mobile phone's (RP) camera (F) is 8MP (value).

Table 1- Example of features, attributes, and their values for a reference product

Reference Product	Feature	Attribute	Value
Mobile Phone	***Display***	Type	LED-backlit
		Size	4.0 inches
		Resolution	640 x 1136 pixels
		Multi-touch	Yes
	Camera	Resolution	8MP
		Video	720p@30fps
		Flash	Yes

Every product will have its own features, attributes, and their values. When new ideas are generated during the ideation phase, we categorise them into one of three types depending on the newness is there. They are as follows:

(a) ***Concept Drift:*** In this type of ideation, the features and/or attributes in the new product are the same as that of the previous or old product but their values change. For example, Table 1 shows a mobile phone (reference product) with the camera resolution of 8MP. In the newer version of the product, this value may change (mostly upwards) as shown in Table 2 thereby giving the customers with the new option of taking photos in higher quality. We term such level of newness as *concept drift* [9].

Table 2- Example of concept drift

Feature	Attribute	Value
Camera	Resolution	12MP
	Video	1080p@30fps
	Flash	Yes

In the literature, such type of newness is defined as changes in outputs with or without changes in inputs [10,11]. In other words, concept drift is just the evolution of product features values over a period of time and hence the newness in them is evolutionary. For example in concept drift, two monitors have the same specifications except for their display size, which has been evolved from 15 to 17 inches as shown in Figure 2. In other words, comparing the old and new version of a product may reveal that both have the same set of features with slightly different values (changes in input) and consequently have different levels of performance but no changes can be noticed in product's function (stable output) [9].

Figure 2 - Evolutionary product (Concept Drift)

(b) ***<u>Feature Drift:</u>*** In this type of ideation, the values of features and/or attributes in the next product's version may change as it happens in concept drift but apart from that, either new features and/or attributes will be added too. An example of feature drift when the reference product is a digital camera can be introducing the photo-printing capability to it as a new feature in its next iteration as shown in Figure 3. This will result in having the next generation of the digital camera that contains a novel feature of printing photos apart from just taking them, as was the case in the digital camera's previous version (Table 3). In other words, this type of ideation leads to the addition of a new feature to the product apart from the existing ones. The addition need not necessarily be at the product's feature level but can also be at its attributes. For instance, if we consider a mobile phone represented in Table 1 as our reference product, then the addition of a new attribute such as panorama technology to the existing attributes of its camera (F) as shown in Table

4, will lead to a new version of the product where professional photography capabilities are added to the product's old version.

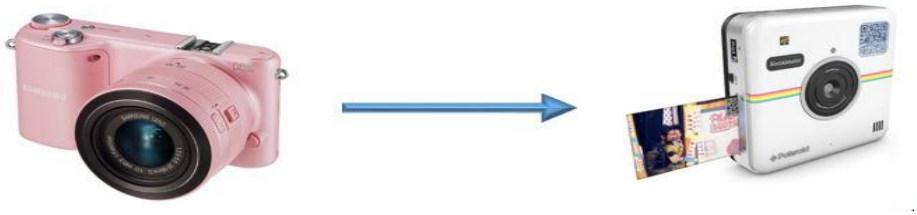


Figure 3- Revolutionary product (Feature Drift)

Table 3- New features being added by feature drift to a digital camera

Old Version of Digital Camera			***New Version of Digital Camera***		
Features	**Attribute**	**Value**	**Features**	**Attribute**	**Value**
Sensor	Resolution	36.3MP	*Sensor*	Resolution	36.3MP
Display	Size	3.2 inches	*Display*	Size	3.2 inches
Flash	Red eye reduction	Yes	*Flash*	Red eye reduction	Yes
			Photo Printing	-	Yes

Table 4- New attributes being added by feature drift to a mobile phone

Feature	**Attribute**	**Value**
Display	Type	LED-backlit
	Size	4.0 inches
	Resolution	640 x 1136 pixels
	Multi-touch	Yes
Camera	Resolution	8MP
	Video	720p@30fps
	Flash	Yes
	Panorama Technology	Yes

In other words, feature drift incorporates the addition of unique features and/or attributes to the reference product that can lead us to use that reference product in a new way. Since a feature and/or attribute has drifted into the reference product, we termed type of ideation as Feature Drift [9]. Bringing such types of

newness in reference products will move it from being evolutionary type of newness to revolutionary type. The newness introduced from this type may result in having a new product of similar shape and/or size as compared to its predecessors, but which is equipped with new competencies. At the same time, it may also result in cases which require changing the shape or size of the new product from the old one. This leads us to define the third type of newness.

(c) ***<u>Conceiving Design:</u>*** In this type of ideation, adding new features and/or attributes both from concept and feature drift to the next generation of a reference product may result in conceiving a new product that may have a different shape, behavior and/or functions from that of the earlier ones. In other words, this type of ideation will lead product designers to introduce a new line of product in the industry. An example of this type of newness as shown in Figure 4 is the development and introduction of a laptop in the 1970s from a desktop. The new product provided the capability of a desktop computer in a smaller and portable chassis thus had a different shape, design. It also rendered new capabilities and functionalities as the result of the mutation of customer's need and preferences.

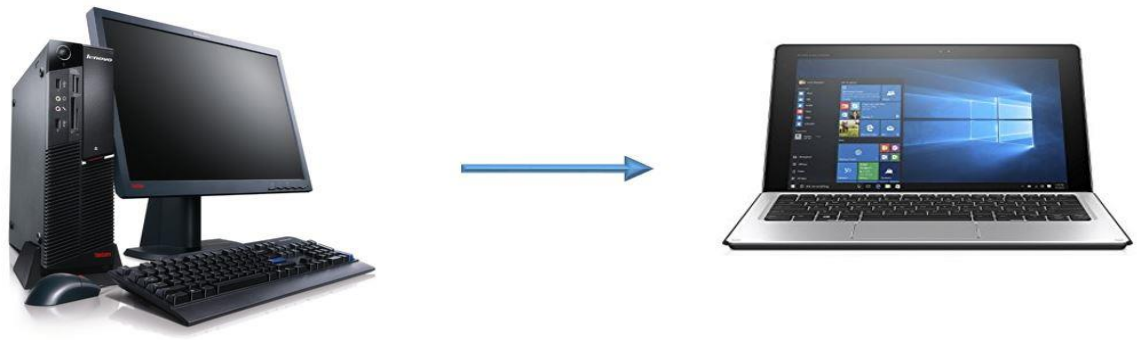


Figure 4 – Conceiving design

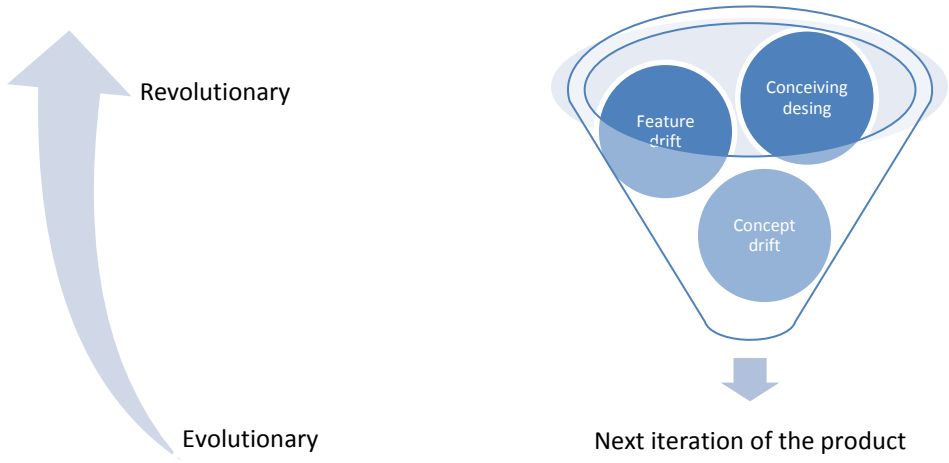


Figure 5- Arranging the three different types of ideation according to their newness

Figure 5 shows the three different types of newness that can come out of the ideation phase arranged according to the level of newness they bring. It is important to note that each type of newness is not mutually exclusive to each other but are complementary. However, each of them needs a source from where such new ideas of newness are generated which can then be drifted into the reference product. We discuss that further in the next sub-section.

2.1- Sources of *drift* in the different types of ideation

In each of the three types of ideation above, new features and/or attributes and/or their values are being *drifted* to the reference product. Our interpretation of *drift* in the context of ideation phase is one of the two types as follows:

Type 1: When the value of an attribute in the next iteration of the product changes from that of its predecessor, we term it as drifting to its new value. In other words, the product's features and attributes remain same but the value of some drifts in the product's next iteration as compared to its previous version as shown in Table 2.

Type 2: When new features and/or attributes are added in the next iteration of a reference product, we term them to be drifting to the reference product. In other words, new features and/or attributes drift to the reference product and become a part of it in the product's next iteration as shown in Table 3 & 4.

As mentioned earlier, type 1 drift is more evolutionary in nature whereas type 2 drift moves toward revolutionary. To achieve such type of drift, product designers in the ideation phase need sophisticated methods and techniques by which they are able to source the ideas from different avenues and identify the features and/or attributes that they can drift into the reference product's next iteration. While previous approaches have focused on customer opinions and/or product designers themselves to source such ideas from, it did not lead product designers to develop the revolutionary type of products that they were after.

However, recent works have started to source such new ideas to be drifted in the product's next iteration by considering the far-field products from different domains in contrast to near-field or very similar problem domain given by customer reviews [3].

Far-field products are those products that may be from different domains as that of the reference products but have some similarity in terms of the functionality and/or capability that they provide. Analysing such far field products, product designers in the ideation phase can source ideas in terms of the features, attributes, and their values that they can add in the product's next iteration. For example, as shown in Figure 6 (a), if a wrist watch is taken as the reference product and mobile phone is considered as a far-field product from a related domain to it, then the next iteration of the reference product may result in a smart watch. In

such case, features from a mobile phone such as message sending capability, web-browsing capability etc. are drifted from the mobile phone to the wrist watch to make it a smart watch. In another example, as shown in Figure 6(b), if we take digital camera as our reference product, mobile phone and color printer as the far-field products, then the resultant Polaroid camera is a combination of features such as photo-printing, Wi-Fi communication capability which are drifted from printer and mobile respectively to the reference product (digital camera).

Figure 6– Drifting of new features and/or attributes from far-field products

Such phenomenon of applying learnings from a different area to a new area has been studied in the literature although in a different perspective, namely human behavior. It is known as *learning transfer* where broadly the skills, knowledge, and/or attitudes that were learned in one situation were applied to another situation to improve the results [12]. Recent works in new product development have looked at the analogical design that involves transferring of knowledge about a product's design in one area to another in order to generate novel products in NPD [13,14]. However, what they lack is having a systemized framework that assists product designers in doing the complete facets of this process. We discuss them further in the next sub-section.

2.2- Steps required in having a systemised framework to assist in the ideation phase

A systemised framework, which assists product designers in the ideation phase, should help them:

(a) To determine which products are considered as a near/far field with respect to the reference product. As the source of ideation, these days is more data centric rather than expert opinion based, the

framework should determine which features/attributes can be drifted from the far-field products to the reference product in its next iteration.

(b) To ascertain the popularity of features and/or attributes to be drifted from the customers' viewpoint. Consistent with the well-known saying of all that glitters is not gold, not all the identified features and/or attributes to be drifted come with the guarantee of being liked by customers. So the framework should allow product designers to ascertain their popularity in order to gauge either customer's interest and/or find what improvements to be made to those features/attributes before drifting them.

(c) Even after discarding those features and/or attributes that are unpopular with the customers in step (b) the product designers needs to decide which features and/or attributes to pursue with further in the next stages of NPD. From the remaining features and/or attributes a decision-making framework that assists product designers to a trade-off between the different decision criteria is needed to come up with the final set of features and/or attributes to pursue further. An example of decision criteria may be the *level of newness that the product designers intends to bring in the product's next version*, *the design constraints of the existing product*, *financial resources available etc.* that will change the features and/or attributes to be pursued further.

In other words, the systemised framework needs to be comprehensive so that assists product designers in deciding which features and/or attributes should be carried out to the next phases of NPD. In the next section, we present a survey of the existing literature on data-centric based approaches of ideation. We then critically evaluate them from the perspective of providing systemized framework for ideation.

3- Literature Review

We categorise the existing literature on data-centric methods that assists product designers in the ideation phase into two broad groups. The first group discusses those studies that identify features and/or attributes that can be drifted to the reference product from the previous iterations of the same product type and/or its competitors. In other words, these products are from the same domain as that of the reference product. We term such approaches as *ideation from same-domain products* and discuss them in sub-section 3.1. The second group discusses those studies that identify features and/or attributes to be drifted into the reference product by analysing products of other domains. We term such approaches as *ideation from cross-domain products* and discuss them in sub-section 3.2. In Section 3.3, we evaluate the approaches from the different aspects that are required in having a systemised framework for idea generation in NPD.

3.1-Ideation from same-domain product

Ideation from same-domain products focusses on collecting information from customers on either the same product type's features or that from the competitors' one. Customer opinion in this case is captured either by using surveys or by crawling information from social media. Product designers can then exploit this knowledge for different purposes such as categorising customer requirements, ranking existing features based on their importance in customers' minds and finding a product's weak/strong features to discovering latent features proposed by customers [9].

Recognising critical features in a product is one the key steps in product development. Several studies are available on finding important features of a product using customer reviews. Li et al. [15] propose a rule-based linear regression approach is proposed to find the important features in a product. They consider frequent nouns as the candidates for product features. A Double Propagation (DP) algorithm is employed to extract more features and the sentiment words, which modify those using pre-defined rules. Next, a linear regression method is conducted using overall rating of reviews to rank product features. They compare their model with existing approaches and describe two applications of product feature ranking in real cases. Shamim et al. [16] propose an approach for detecting critical features based on opinion intensity. The algorithm first extracts frequent nouns from reviews as product features. Next, the opinion words that are within *K* words of the selected features are considered as associated sentiment words. Opinion intensity is then manually calculated. In their study, they present an equation for classifying user's reviews based on their quality using review's rating, helpfulness score, the number of opinion words and features within it. Finally, the negative/positive rank for each feature is computed aggregating the number of weakly, mildly and strongly negative/positive occurrences of opinion words modifying that feature. Stone and Choi [17] propose a visualisation tool that helps designers to gain insights on customers' preferences for different features of a product, based on social media data. The algorithm first requires the designers to define some keywords as product features that are extended further by analysing customer reviews. Next, starred reviews from Amazon.com are used to train SVM for sentiment classification of the collected data. Their 2D visualisation tool helps designers to find the most important features of a product and their values, as perceived by customers. Jin et al [18] propose an approach that ascertains the relative importance of a product's different engineering characteristics (ECs). Their proposed algorithm uses a pairwise-based ordinary classification method to learn the weights of ECs from the reviews. Next, an integer linear programming model is developed to derive the original customer satisfaction levels from pairwise results. Designers can use the model's results to determine the most important engineering characteristics, which should be the focus when developing the next generation of a product.

Lin et al. [19] propose UNISON framework which identifies the reasons of users satisfactory or unsatisfactory experiences from a product. They apply their framework to analyse users' experiences in wearable devices. They survey the attitudes of users by questionnaire and by using a decision tree extract user experience rules, which can help the designers in identifying appropriate product factors and forms to be considered in product development. Chien et al [20] propose an approach for capturing consumer preferences for design concepts and visual aesthetics of a product. In order to evaluate the perception of different users and their satisfaction level for product visual factors, they first conduct a scenario journey. After that, considering the background and demographic information of the users, they develop Rough Set Theory (RST), which detects the hidden relationships between product visual features and data of decision makers and finally proposes rules to assist product designers in selecting proper aesthetics factors. Bae et al. [21] propose a framework which looks for the functional attributes of a digital camera that influence the purchasing decision of the customers. They first gather the users' preferences about the product by distributing questionnaires among them. Next, using association rules and developing a decision tree, they analyse the customers' responses and extract rules, which can help the product designers in finding the most important features in customers' opinions. Bacciotti et al. [6] propose a method which helps product designers in idea generation by fostering the design space. In other words, the authors proposed approach provides a large number of stimuli for the designers and provoke their creativity capabilities through introducing a structured roadmap to them. They categorise the sources of benefits in producing a new product into four dimensions, such as general demands, stakeholders, lifecycle phases and hierarchies of systems. The combination of these elements presents to the product designer the opportunities for introducing new product attributes.

Product weakness and strength assessment are known as another key step to developing a new product. Tuarob et al. [22] propose an approach to detect the features which should be added /omitted in the next version of the product using social media data. They first define three metrics (polarity, subjectivity, and popularity) to determine customers' favorability toward existing products. Then, top *K* favorable products are selected for further analysis. In order to find the feature-opinion pairs, a bootstrapping learning algorithm is employed which extract the features, opinions along with templates surrounding seed words. In doing so, the weak and strong features of top *K* favorable products will be discovered which can be treated as insight for designers to omitted or integrated specific features into the next generation of a product. In another work, Jin et al. [23] find comparative sentences discussed in social media in order to find the strong features of the competitors' products. Utilising POS tagging tool, product features are extracted from reviews and the polarity of the sentences are found using a Naïve Bayes classifier. They then determine those sentences that discuss a common feature of two competing products. Tucker and Kim

[24] propose a framework which identifies popular and obsolete features of a product from the preference trends of customers. Frequent nouns from product reviews are extracted as product features and the sentences that relate to those features are identified. Those sentences that are mentioned in pros are assigned a positive polarity and the cons reviews are considered as negative ones. Wang and Wang [25] propose an approach to determine the product's weakness by examining both comparative and non-comparative online reviews. After collecting and cleaning the reviews, product features and related opinions are extracted using a semi-supervised self-tagging machine learning approach. SentiStrength software is used to calculate the sentiment score of non-comparative reviews. Next, a network is built in which its edges represent the existence of a comparative sentence for two products (nodes) and its weights reveal the sentiment strength of that sentence. Finally, to compute the level of popularity of each feature, a composite score is proposed which aggregates both comparative and non-comparative results. Those features that gain the composite score less than a pre-defined threshold are considered as the product weakness.

Discovering and then employing latent customer needs is another key step to the success of new product development process. Zhou et al. [26] proposed a model to elicit customers' latent needs from social media data while examining them for extraordinary use cases. First, Association Rule Mining (ARM) is used to extract product features. In order to classify the sentiments of product reviews, a fuzzy support vector machine (FSVM) is utilised. Once the ordinary usage of the product is defined, through customising them, extraordinary use cases and also latent needs are discovered using case-based analogical reasoning. In another study, Tuarob and Tucker [27] propose an approach for extracting latent features leads to identify innovative consumers (lead users). To do so, product ground-truth features are obtained through analysing product reviews and also product specification document. Next, using mathematical model latent features are discovered. Finally, they exploit these latent features to identify innovative consumers. Guo et al. [28] propose an approach to excavating potential needs of customers and using them to diversify existing products. They argue that the evolution of social and cultural factors influence product innovation. Hence, in their framework, after selecting the main research object, the super-system resources for the product are analysed and defined. Next, the feature set for both direct-relevance and indirect-relevance environmental factors are defined (like age, gender, behavior habits, etc.). Finally, potential needs are excavating through changing the cover range of the features.

Since the goal of most businesses is to make a profit, several researchers have proposed models to find product features that maximise customer satisfaction and consequently profit. Wang et al. [29] propose an approach which uses User-Generated Content (UGC) in designing products. The algorithm first elicits product features from customer reviews based on word frequency rates. To remove false feature candidates, redundancy and independency pruning rules are employed in next step. Next, the polarity of each feature

is defined by the presence of the feature in the pros/cons reviews. The algorithm exploits the finite mixture regression in order to model unobserved customer heterogeneity in customer data. Finally, the proposed customer preference model will help in selecting the product design, which maximises the profit. In other work, Tucker and Kim [30] propose an approach that predicts what customers want and then designing the most profitable products based on these predictions. First, customer preferences are captured by doing a survey along with analysing the existing available data. Next, a decision tree is created to determine the maximum price that customers would be willing to pay for a different combination of product features. Doing so, the algorithm is able to generate candidate product concepts and also estimate the demand. Considering the cost of each product concept, the product feasibility is checked at the engineering level. Finally, the profit of each product variant is computed based on demand, maximum price and production cost.

Table 5 - Categorising the approaches of ideation from same-domain products

Broad objectives of same-domain studies to determine new ideas in the ideation phase	**References**
Recognising critical features in a product by analysing customer reviews, determining their opinion intensity, capturing their preference etc.	[6,15–21]
Determining a product's weakness and strength by using customers' social media information	[22–25]
Discovering customers' latent needs	[26–28]
Discovering most profitable features of a product from the customers' reviews	[29,30]

Table 5 summarises the discussed approaches for ideation from same-domain products. While the above-mentioned approaches assist product designers to acquire new ideas for ideation, we argue that the source from which they generate that is limited. In other words, their source for ideation is limited and they consider either the previous version of the reference product or similar products or product from competitors. While this provides product designers with new ideas, it does not provide any room for them to think out-of-the-box and identify features that can be considered as novel to be added to the reference product. Although data-driven methodologies play a significant role in designing products, they concentrate only on data relating to a specific domain, which means they are unable to give designers insights beyond that domain. They suffer from the drawback of only providing ideas which are of low systematic level and generating a low level of novelty in the reference product's next iteration [7,8]. To address this, researchers have attempted to link product from one domain to those from other domains in an attempt to generate innovative ideas for designers in the ideation phase. To the best of our knowledge, very few research studies have addressed this issue. We discuss such approaches in the next section.

3.2 Ideation from cross-domain products

Design-by-analogy recently has attracted many researchers due to its ability to broaden the novelty of ideas proposed in concept generation phase using similarity relationships from solutions to analogous problems [31]. Analogical reasoning can play a critical role in proposing a creative design. It includes recalling and transferring elements of one design problem to another design problem, which can take place in different contexts such as components, relations between them, or configurations of components and relations [4]. Two main groups of methods are discussed in the literature as sources of inspiration for the design analogy; first are those, which are inspired by nature, and the other group that does not use nature as a source of inspiration [32]. A variety of computational tools is developed which uses physics principles and functional similarities to find analogies for the design problem within nature.

The biomimetic design is an established area of study which helps designers in finding the solution for their design problems through inspiring from biological phenomena. Chie et al. [33] introduce a search approach which bridges the cross-domain terminology in biomimetic design. In another word, since the functional keywords in engineering are different from those used in biological papers, they proposed a method which extends the scope of the search for required functions through finding the troponyms of them in WordNet dictionary. They also have used the high-frequency words, which have been collocated with or occurred in the vicinity of search words, as alternatives to improve the quantity and quality of matches found in biological databases. Nagel and Stone [34] develop a computational approach for doing analogical reasoning in the early stages of product design. The algorithm first wants the designer to select the required functions. It then generates a list of verbs and words which occurs in the vicinity of the keywords. Selecting the found verbs as functions and nouns as flow, it starts searching the Design Repository and also a chosen biological corpus for each of the function/flow pair. The solution from both existing products and also the biological phenomena inspires the designers in suggesting innovative design ideas. Deldin et al. [35] develop a web-based tool, which translates biological information in a way that it can be used as a source of inspiration for biomimetic design accessible to non-biologists. Once a designer identifies the required function, AskNature searches its database for the examples of functions and physics principles, which have been used by nature to fulfill this function. A knowledge-based design environment is developed in Vattam et al [36] which finds the analogical mapping by means of the structure-function-behavior schema for representing biological systems. Their main goal is to assist the interdisciplinary design team in identifying solution and transferring functions from biological systems to their design problem.

In the second group of approaches that does not use nature as the source of inspiration, they mostly focus on building a function-behaviour-structure model of design prototype in the form of graphs. Then by comparing the graphs' similarity, they will suggest the solutions [4]. A hybrid list-based and web-based

design tool have been proposed in [37] which produces design solutions for a product design problem. It first asks the designer to input a file containing a full functional model of the product. Using the repository of existing design solutions, it forms the function-component relationships and presents a feasible alternative for each sub-function in as a morphological matrix. This tool allows the user to pick options that solve each function in the product functional model. Tucker and Kang [13] propose an approach that discovers new design knowledge across unrelated product domains. Their proposed algorithm first decomposes the artifact into its function, form/structure and behavior. Next, it discovers the similarities between the main artifact and products of other domains in each of these three metrics. They use a mathematical 3D model for representing the form of a product. The structure and behavior of the artifact are then described using the vector of words, which will be used as metrics to compare other products' structure and behavior with those of the main artifact. Kang et al. [38] propose an alternative name as resynthesising, for end-of-life (EOL) products which introduce assemblies/subassemblies of existing out-of-date products from different domains to develop a new product. They determine the best candidate for resynthesising by determining the possibilities between subassemblies by using 3D graph analysis and a cosine similarity measure. The costs, price and environmental feasibility for each option is determined and the best option is selected using a mixed integer linear optimisation model. Kang and Tucker [14] propose a methodology that helps designers in finding suitable forms and functions from products of other domains for their functional requirements in developing new products. The algorithm first extracts different functions of proposed products using topic modeling. Once the similarity between the required functions and the functions of different products is calculated, the most similar products are chosen to combine with each other for their dissimilar form characters and functions. Finally, form candidates are proposed using a morphing technique. They finally compare their proposed new features and form for a hybrid marine vehicle with an existing hybrid model.

Fu et al. [31] evaluate the effect of presenting existing analogous patents to the designers in the concept generation phase on the quantity and novelty of proposed ideas. They first collect patents in the form of text and after processing them, each document is presented in the form of a vector of terms. Next, the patent database is indexed against the functions that it covers. Finally, the most similar patents to the designer's problem are retrieved using cosine similarity function. Their experimental results confirm the positive effect of employing functionally analogous patents during the concept generation on the novelty of proposed solutions. While in another study proposed by Verhaegen et al. [39], patents are employed to first extracting the product aspects and then using them again to transfer knowledge between analogous products. According to their framework, the patents are filtered for the words which do not exist in the WorldNet. Through next filtering process, they manually remove those words which do not contribute valuable

information about a product's attributes, functions or structure. After stemming the remaining terms, Principle Component Analysis (PCA) is employed to expressing the terms in smaller uncorrelated variables (PCs). The PCs are then turned into product aspects using Varimax rotation. Using the radar plot for visualising a product with its aspects and through computing the cosine similarity between two products, they propose cross-domain and within-domain similar products to the target product or product aspect. Vandevenne et al [40] bridges the gap between the engineering and biological domain in order to help the designers gain insights from both patents and nature in the ideation phase. They first create corpus consisting of both patents and biological articles. Next, the corpus is transformed into a vector of space model. Product Aspects (PA) and Organism Aspects (OA) are extracted from the corpus using the word co-occurrence analysis. In order to link the technical and biological systems, the similarity value is measured between the PAs and OAs through multiplication of their matrices. In next step, the algorithm will link the products and organism to their corresponding patents and biological papers, respectively, through calculating the similarity between the product-patent matrix and the patent-PA one, along with organism-paper matrix and paper-OA matrix similarity computation. Finally, it proposes the abstracts and title of relevant academic papers.

While the above-mentioned approaches determine new ideas from cross-domain products, they still require some decision criteria that helps product designers to decide which of the identified features to consider further in the NPD phases. In this regard, Kobayashi proposes a methodology in [41] which integrates quality, cost, environmental aspects and design risk in the idea generation phase of product development. According to the proposed framework, target specifications of the product are first collected from the customer and the environmental perspective. If the target specifications are too far from the existing product features, TRIZ contradiction matrix is employed to find innovative solutions. Next, the proposed ideas are evaluated from the quality, cost and environmental aspects. Finally, the design risk, which has been defined as uncertainty of the effectiveness of a solution, is estimated using Monte Carlo simulation. In another study, Chin et al. [42] propose a Bayesian Network to assess risk involved in the NPD process. They first investigate the risk factors. Next, rather than relying on experts' knowledge, their proposed approach computes the prior probabilities of different nodes by doing pair-wise comparison between the states of the nodes. They validate their model by assessing two alternative product design concept. Park et al. [43] identify risk factors in different stages of a product development project. Using AHP and fuzzy models, they develop a framework to analyse risk degree of the identified factors. Finally, the optimal responding activity is selected for each of the risk factors utilising the evolution strategy.

3.3 Research gaps in existing approaches of ideation from cross-domain products in having a systemised framework for idea generation in NPD.

While the aforementioned studies offer novel features or designs for producing new products because they do not limit the scope of the search for finding commonalities between products, they may need having access to a big database containing different product features, otherwise, they will be so time-consuming. Additionally, asking for pre-defined functional requirements probably limits the applicability of these methods where the designers have no idea about what features that can be integrated into the next version of a product. However, since the proposed approaches don't check the customers' opinions for determining their level of satisfaction with current products and their feature, they may result in introducing new products which are not successful enough in the market. Table 6 summarises the related works based on their objectives and decision criteria, and compares them with the criteria that are required to have a systemised framework for idea generation in NPD.

Examining this table and considering the issues that have been discussed earlier under both single and cross-domain product design models, the need to have an approach that proposes new features to be integrated into the next iteration of a product by examining related products from other domains for novel features is shown. However, the favorability of the proposed features needs to be checked on social media with regard to the significant role of public acceptance in a product success. Furthermore, in developing a new product, apart from considering the customers' opinions in relation to their preferred features of a product, company managers also need to consider the level of innovativeness and also the viability of each proposed feature while simultaneously taking into account the degree of risk that the company can bear in introducing a new product. According to the Table 6, none of the existing works consider the risk factor in idea generation phase of new product development. Therefore, an approach is required to rank the newly proposed features based on the customers' preferences as well as taking into consideration the company managers' criteria, such as their attitude to risk. This recommendation system will be able to rank features with regard to not only their level of innovativeness but also the amount of profit (viability) they will generate for the company. In the next section, we propose our approach to address these short comings in the ideation phase of NPD from cross-domain products.

Table 6 – Summary of related works

	Article	Proposing new		Decision-making approaches		
		Feature/ Attribute	Design	Risk attitudes	Popularity	Feasibility
Single-Domain Product Design	Tucker et al. [30]				√	√
	Tucker et al. [24]				√	
	Bae et al. [21]				√	
	Wang et al. [29]				√	√
	Li et al. [15]				√	
	Tuarob et al. [27]	√			√	
	Wang et al. [25]				√	
	Shamim et al. [16]				√	
	Stone et al. [17]				√	
	Jin et al. [18]				√	
	Tuarob et al. [22]	√			√	
	Zhou et al. [26]	√			√	
	Guo et al. [28]	√	√			
	Jin et al. [23]				√	
	Lin et al. [19]				√	
	Chien et al. [20]		√		√	
	Bacciotti et al. [6]	√	√			
Cross-Domain Product Design	Chiu et al. [33]	√	√			
	Bryant et al. [37]	√	√			√
	Verhaegen et al [39]	√	√			
	Tucker et al. [13]		√			
	Nagel et al. [34]	√	√			
	Kang et al. [38]	√	√			√
	Fu et al. [31]	√	√			
	Deldin et al. [35]	√	√			
	Vattam et al. [36]	√	√			
	Kang et al. (2015)	√	√			
	Vandevenne et al. [40]	√	√			
Risk in	Kobayashi [41]		√	√	√	√

	Chin et al. [42]			√		
	Park et al. [43]			√		

4- Proposed Framework: FEATURE

In this section, we present FEATURE (FEAture drifT-based framework for Unique aspect REcommendation) that provides product designers with a systemised framework to assist them in the product ideation phase by using a data-centric approach. FEATURE, as shown in Figure 7, has three modules in it. The analysis of FEATURE starts by the product designers' first setting up a reference product. Module 1 named as the *New Feature Finder (NFA)* then ascertains the new features and/or attributes that can be drifted into the reference product in its next iteration. Module 2 named as the *Feature Sentiment Analyzer (FSA)* determines the popularity of the ascertained features and/or attributes from the customers. This analysis is then passed to Module 3 termed as the *Feature Recommender (FR)* that assists the product designers in selecting the features and/or attributes to be considered further in the next stages of NPD according to their decision criteria. The details of the working of each module are explained below.

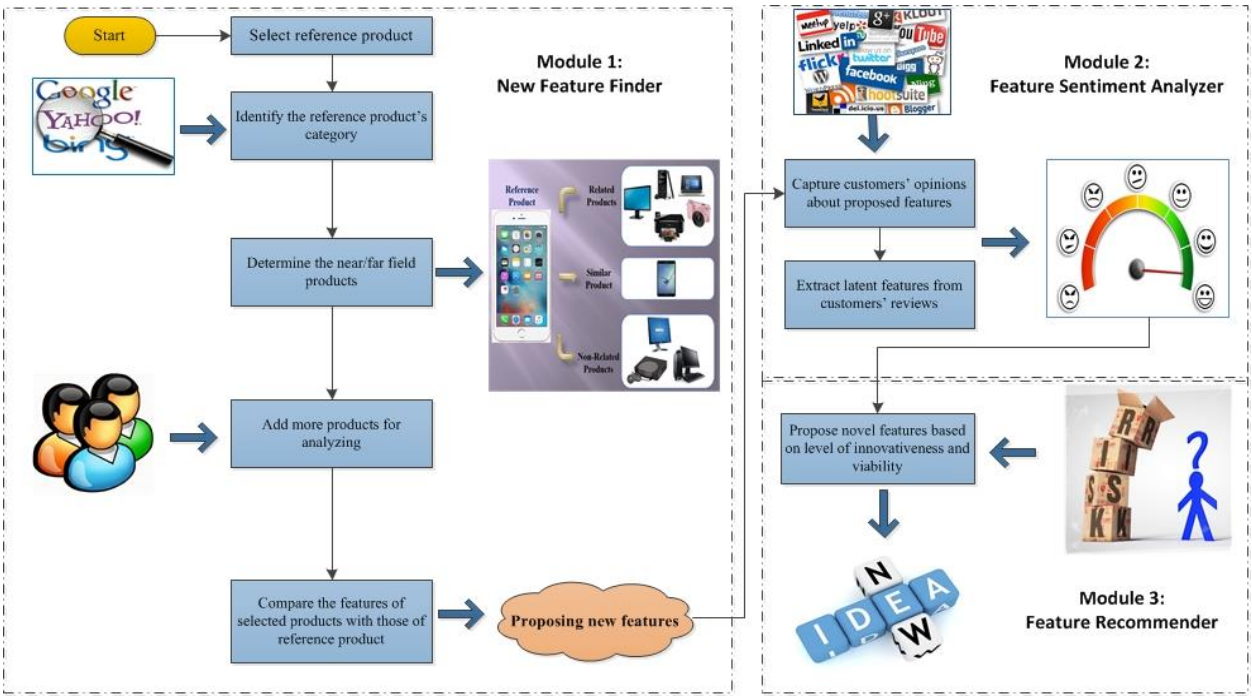


Figure 7 - Overview of FEATURE

Module 1: New Feature Finder (NFF)

The objective of this module is to identify the features and/or attributes that can be introduced in the next iteration of the reference product, for example, mobile phone. These features and/or attributes are identified from *source products* that can be categorised either as *related* and/or *interested* products to that of the reference product. The module's objective is achieved in three steps.

- In Step one, the product designers define the category of the reference product. For example, if we consider mobile phone as the reference product then its category is set as an *electronic product* by the product designers. Once this is done, products from the category of *electronic product* are identified.
- This leads to step two of NFF that has two sub-parts in it.
    - In the first part of step two, identified products from the category of *electronic product* are classified automatically as *related*, *non-related* or *similar* products based on their similarity with the reference product. This is done by comparing the features of the reference product with that of products that come under the category of electronic products and computing a similarity score. If the similarity score is between the two defined thresholds by the product designers, it is classified as a *related* product. Those products, which their similarity score exceed the defined upper bound are categorised as *similar* products. The rest of them are known as *non-related* product.
    - However, apart from just considering related products from the same category of the reference product, there may be cases where product designers may prefer to expand their search horizon. In other words, based on their intuitiveness they may want to examine a product from a different category as that of the reference product and see what features and/or attributes from that product can be introduced in the next iteration of the reference product. As an example, a fitness series of watches may come under the product category of *Apparel & Accessories*, which is different from electronic products under which a mobile phone comes in. However, features from fitness watches can be drifted into the next iteration of the mobile phone for improving its capability and hence product designers may be interested in analysing it further. We term such products as *interested products*. In part two of step two, NFF provides product designers with the option to add interested products for further analysis that were not added automatically in part one.
- This leads to step three of NFF in which the new features and/or attributes that do not exist in the reference product as compared to related and interested products are determined and presented to

the product designers. Product designers based on their decision criteria select the features to analyse further in Module 2. Such presented new features and/or attributes are termed as *proposed features* from now on in the paper.

Module 2: Feature Sentiment Analyzer (FSA)

Feature Sentiment Analyser (FSA) finds the popularity of the *proposed features* by analysing the customers' reviews of the products they come from. The customers' reviews are extracted from various social media platforms and are then analysed to ascertain to the sentiment of the proposed features. The premise behind this step is to omit those features, which are not so popular among the customers from further analysis of FEATURE. The module's objective is achieved in three steps.

- In step one, FSA's algorithm crawls and collect a corpus of reviews related to the products from where the proposed features come. The collected reviews are analysed by using a rule-based approach and the product's features to which a part of the review relate to along with their sentiment value is determined.
- In step two, the product features for which the sentiment value is determined are matched to the proposed feature that comes from phase 1. At this stage, it is possible that the term used to describe the proposed feature is not consistent with what the customers' use to describe it in their reviews. So the issue of bridging the gap between the proposed features and the features mentioned in the customer reviews will be addressed in this step. When matched, the sentiment value associated with each feature from customers' reviews is transferred to the proposed feature.
- In step three, customers' latent needs which are mentioned in their reviews are identified and appended to the list of proposed features. The latent needs mention the customers' preference and/or desire to have those features in a product. So, the FSA algorithm assigns the highest positive polarity value to them and adds them to the list of proposed features for further analysis in Module 3.

Module 3: Feature Recommender (FR)

The purpose of Feature Recommender (FR) is to take the list of proposed features along with their determined sentiment value and according to the product designer's decision criteria recommend what features to pursue further in the stages of NPD. It achieves this by ranking the proposed features according to the following two criteria:

- *Innovativeness:* This criterion ranks the proposed features according to their high level of popularity among customers irrespective of their launch costs and potential profit. In other words,

this decision criterion ranks the proposed features that have the highest positive polarity strength on the top of the list.

- *Viability:* This criterion ranks the proposed features according to the profit that each of them generates. The profit is ascertained by determining the demand for the reference product with the added feature and the margin of profit on each of them.

Using these three modules, FEATURE recommends the product designers in the ideation phase with features and/or attributes that can be considered further in the next stages of NPD. In the next section, we discuss further the working of NFF in more details. Figure 8 presents the FEATURE algorithm.

Figure 8 - FEATURE algorithm

Input: Reference Product (RP), Category of Reference Product, α, β

Output: Proposed Features/Attributes based on level of Innovativeness (PFI), Proposed Features/Attributes based on Viability (PFV)

1. FEATURE (RP, Category, α, β)
2. Begin
    a. SPF :NFF(RP, Category, α, β)
    b. ProFeature_DB :FSA(SPF)
    c. (PFI,PFV):FR(ProFeature_DB)
3. End

1. NFF(RP,Category, α, β)
2. Begin
    a. POD: Other products in Category
    b. For each PODi in POD
        1. SCi: Calculate Similarity Score (ss) between RP and POD based on their product specifications.
        2. If(SCi> α and SCi< β)
        3. Add PODi to Related Product
        4. endIf
    c. EndFor
    d. Get Interested Products
        i. Add Interested Products to Source
    e. Add Related Products to Source
    f. For each Si in Source
        1. RC: Relative Compliment of features between RP and Si
        2. Add RC to PF
    g. EndFor
    h. SPF: selected proposed features by designers based on PF
3. End
4. FSA(SPF)
5. Begin
    a. FOR each product in Related Product & IP
        i. Collect product reviews (PRv)
        ii. FOR each sentence in PRv
            1. Extract Feature and Opinion word using the syntactic rules
            2. Compute Sentiment Score (SS) for each pair using dictionary
        iii. ENDFOR
        iv. Compute sentiment score (SS) considering all collected reviews
        v. Find corresponding feature in SPF (CF)
        vi. Aggregate the corresponding Sentiment Score using Feature_DB
        vii. Store (SPFi,SS) in ProFeature_DB
    b. EndFor
    c. Collect product reviews about RF(Ref_PRv)
    d. Extract Latent Features using syntactic rules.
    e. For each Latent Feature
        i. Store(Latent Feature, highest positive Sentiment Score) in ProFeature_DB
    f. EndFor
6. End
7. FR(ProFeature_DB)
8. Begin
    a. For each Fi in ProFeature_DB
        1. CPi: Cost Production of Fi
        2. Add CPi to PRoFeature_DB
    b. EndFor
    c. PFI: Sort features ProFeature_DB based on Sentiment Score in descending order
    d. PFV: Sort features ProFeature_DB based on Cost Production in in descending order
9. End

5- Module 1: New Feature Finder

As previously mentioned, the objective of this module is to identify the unique features that can be incorporated into a reference product by analysing different source products. An overview of the different steps in this module is presented in Figure 9.

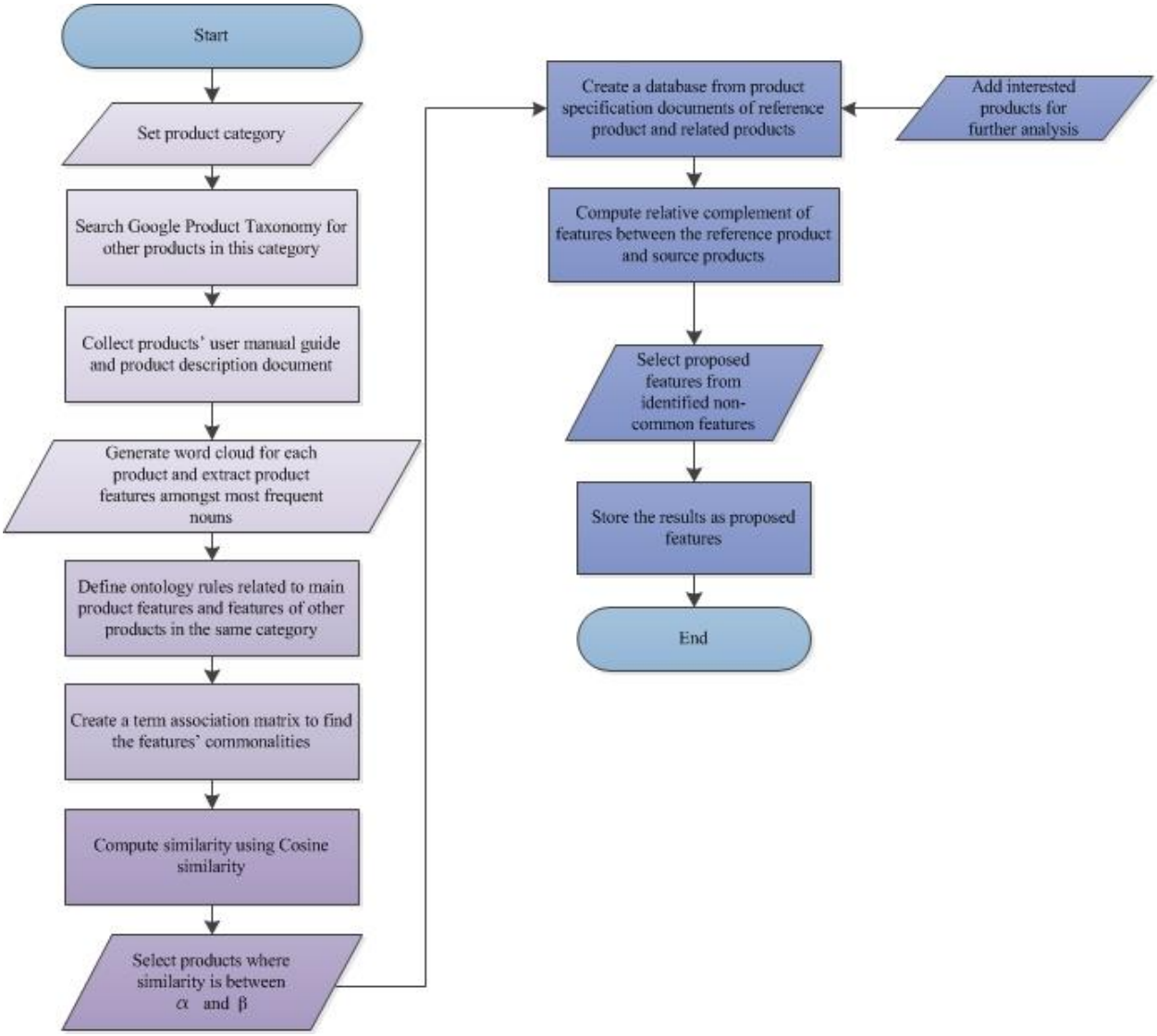


Figure 9 - Overview of the working steps of NFF

Step 1: Setting reference product category

In this step, the product category of the reference product is set. It can be done either by the product designer setting the category of the reference product or by NFF using Google Product Taxonomy [44] as the search engine to find the parent nodes of the selected reference product. As shown in Figure 10, Google Product

Taxonomy is a tree of different product categories that describe product families. NFF uses it to identify the category of the selected reference product. However as the last version of Google Product Taxonomy was released in 2015, there is a possibility of NFF not able to determine the category of new products. Therefore, in such cases, NFF asks the product designers to define the category of the reference product.

```
Electronics > Communications > Telephony > Mobile Phone Accessories > SIM Card Ejection Tools
Electronics > Communications > Telephony > Mobile Phones
Electronics > Communications > Telephony > Satellite Phones
Electronics > Communications > Telephony > Telephone Accessories
Electronics > Communications > Telephony > Telephone Accessories > Phone Cards
Electronics > Communications > Video Conferencing
```

Figure 10- A snapshot of Google Product Taxonomy

To explain with an example, if the product designers consider a mobile phone as the reference product then NFF sets its category as an *Electronic product.* Once this is done NFF identifies other products from that same category by using Google Product Taxonomy for further analysis. As an example, the following products are shortlisted by NFF from the category of electronic products for further analysis:

{Mobile phones, Camera, Laptop, Tablet, Monitor, TV, Music Player, Printer, Video Game Console}

Step 2: Determining the related products from the same product category

The objective of this step is to find related products to the reference product from the same product category. This is done by computing the similarity between the features of the reference product with those products identified in the same category as the reference product. However, various challenges arise when such task has to be fulfilled. They are:

(a) There should be a database, which describes all feature of the products coming under the same category.
(b) Tagging features, attributes, and values for each product that has been stored in the database for further analysis.

Since most of the product categories consist of a large number of products and the specifications of the products may vary constantly, achieving points (a) & (b) is labor intensive and time-consuming task. To overcome these issues, NFF uses an alternative approach that is less computationally expensive and uses product specification documents and user manuals to identify related products to the reference product.

Step 2.1: Using Word Cloud to identify features of reference product and products from the same category.

To determine related products to a reference product, NFF generates a *Word Cloud* of the products under analysis. Word cloud is a graphical representation of text data, which typically is used to depict the keywords in a text so that the size of each word indicates its frequency or importance [45]. According to previous researches [46–48], features of a product are described amongst the most frequent nouns mentioned in its description articles or its product reviews. Therefore, to find such nouns and in turn the products' features, NFF generates word clouds for the reference product and for those products that come in the same category. An example of word cloud generated for a mobile phone (reference product) and camera (similar category product) is shown in Figure 11.

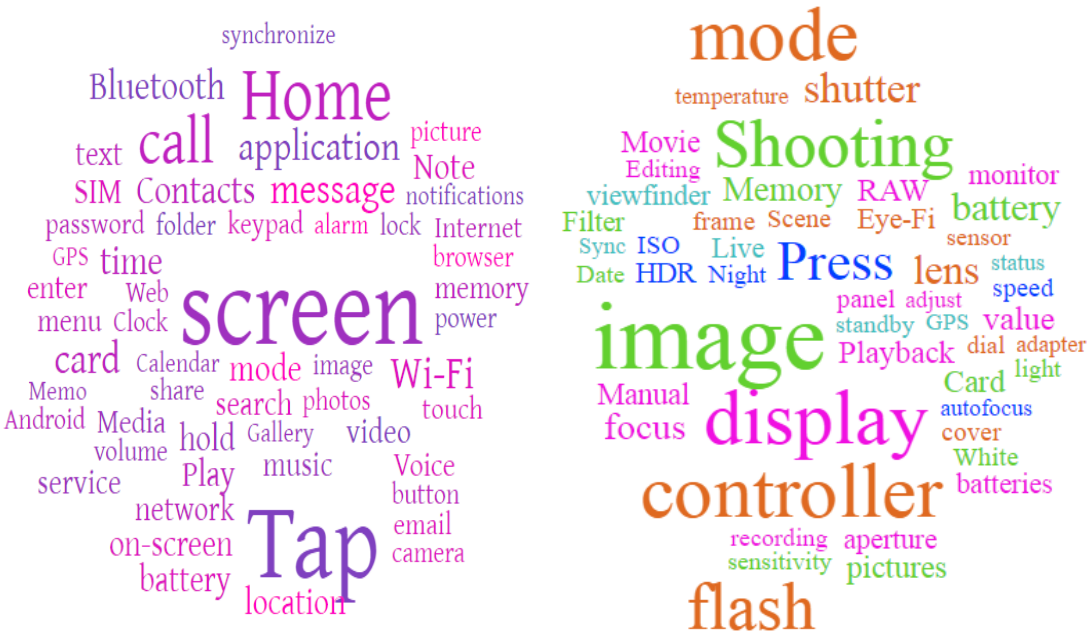


Figure 11- Word cloud of mobile phone (left shape) and camera (right shape)

While the generated word cloud the most common occurring terms in its user manual guide, apart from the product's features, it may also represent terms which are irrelevant for us in our further analysis such as "allows", "keep", etc. Therefore, the next step after generation of the word cloud is to prune the extracted terms. The pruning process involves asking an expert to omit those terms which do not either represent a function, capability or a feature of the mobile phone. Once the pruning is done, the product designers have a list of product's features as shown in Table 6. They can either consider all the features or select only the most frequently occurring terms for further analysis in the next stages. This is done by computing the frequency of occurrence of a feature in the total occurrence of all features as shown in Table 7. This table represents features of a mobile phone, which has been extracted from its word cloud along with their

frequency in the mobile phone's user manual guide. The document contains 31735 words, which we have selected the 50 most frequent nouns as mobile phone's features after doing the pruning process.

Table 7- Features of mobile phone extracted from word cloud

Feature	***Frequency***	***Feature***	***Frequency***	***Feature***	***Frequency***	***Feature***	***Frequency***
screen	591	Play	90	GPS	56	volume	34
Tap	566	hold	89	menu	56	photos	34
Home	348	on-screen	87	memory	53	button	31
call	279	battery	87	touch	51	Search	31
Wi-Fi	142	location	84	Internet	50	picture	30
message	140	SIM	81	keypad	48	Android	30
card	134	network	76	email	47	browser	28
application	127	text	76	password	45	folder	28
Bluetooth	109	service	71	search	45	Clock	28
Contacts	104	music	68	camera	38	lock	28
time	104	video	68	power	37	Web	28
Note	103	Voice	58	image	37		
mode	102	Media	56	share	36		

Step 2.2: Mapping similar terms from the generated Word Clouds of the reference product and products from the same category.

Once the features of the reference and similar category products have been extracted in step 2.1, there may exist features that have the same meaning but are represented by different abbreviations, synonyms or different terminologies. For example "screen" in reference product from Table 6 and "display" in camera as shown in the right shape of Figure 11 has the same meaning. Another example is "image" which has the same meaning as "picture". NFF handles these cases by defining ontology rules for the most frequently occurring terms and grouping the terms with similar meaning in one cluster.

Step 2.3: Computing similarity between a reference product and products that come in the same category.

The next step is to generate a term association matrix to quantify the feature commonalities between the reference product and products identified to be in the same product category as presented in Table 8.

Table 8- Term association matrix

		Feature of the reference product					
		t_1	t_2	.	.	.	t_m
Related Products	s_1	$c_{1,1}$	$c_{1,2}$	.	.	.	$c_{1,m}$
	s_2	$c_{2,1}$	$c_{2,2}$	.	.	.	$c_{2,m}$
	.			.	.	.	.
	s_i	$c_{i,1}$	$c_{i,2}$	.	.	.	$c_{i,m}$

Where,

t_m: represents the extracted features from reference product's word cloud

s_i: represents the product identified to be in the similar category of the reference product

$$c_{i,m}: \begin{cases} 0; & \text{if feature } \mathrm{t_m} \text{ doesn't exist in word cloud of product } \mathrm{s}_i \\ 1; & \text{if feature } \mathrm{t_m} \text{ exists in word cloud of product } \mathrm{s}_i \end{cases}$$

Once such a matrix has been formed, a similarity value between the reference product and each of the considered products is computed by determining their cosine similarity. Cosine similarity is one of the popular metrics in text mining, that measures the similarity between two non-zero vectors [13,38,39,49]. It is computed as:

$$SIM(X,Y) = \cos(\theta) = \frac{\vec{X}.\vec{Y}}{\|X\|\|Y\|} \qquad \textbf{Eq.1}$$

Where X and Y represent the term vector of reference product and those of other products in its category, respectively from the term association matrix. The results of cosine similarity range from 0 to 1 in positive spaces. Each value in this range represents a different level of similarity between the reference product and those come in the same category. As our objective is to find related/non-related/similar products to the reference product, we define two threshold values α & β. These two values range from 0 to 1. The products that their similarity with the reference product exceeds β are called as similar products. Those products, which their cosine similarity with the reference product is between α and β, are considered as related products. A product is labeled as the non-related product if its similarity value is less than α. However, these thresholds are not fixed and can be defined differently by product designers. At the end of this step, the following products are identified as related products by NFF:

Related products = {Camera, Laptop, TV, Music Player, Printer}

Step 3: Setting Interested products

Since FEATURE is a semi-automated approach and interacts with designers at different stages, we have considered an option for designers to add those products that they are interested in analysing them but have not been suggested as related products by the algorithm. We call these products as *Interested products* which can be either from a different category or from the same category but being recognised as non-related or similar clusters. For instance, considering mobile phone as the reference product which is from the category of electronic products, it is probable that the designers are interested in Fitness watch features and want to check its novel features of health monitoring and their popularity within the market. Since the fitness watch is from a different category, namely apparel & accessories, we have proposed the option of "interested product" to the framework to add this kind of product to the list of products that we want to analyse further. Therefore, our source product will be updated as followings:

Source product = {Camera, Laptop, TV, Music Player, Printer, Fitness watch}

Step 4: Identifying unique features from source products

The last objective of this phase is to identify the unique features, which can be integrated into the reference product from the source products. In order to accomplish this goal, a database is created from product specification documents of reference product and also the ones of its source products which reveal those features that are not in common within the two models being compared. In other words, through analysing product specification database, we are able to find novel features of source products by computing the relative complement of features between the reference product and those of source products. These features will satisfy Eq.2.

$$F = \sum_{r=1}^{R} F_r \cap (F_m)^c \qquad \textbf{Eq.2}$$

here,

F: represents the set of features which are not in common with the reference product compared to all its related products

F_r: represents features of related products

F_m: represents features of reference product

Table 9 presents a snap shot of comparison between some features of mobile phone as reference product with those of digital camera and printer as the related products. Those cells, which are highlighted in pink, describe novel features in the source products that do not exist in the reference product. For example, fitness watch is equipped with a laser sensor, which enables you to track your heartbeat. However, this feature can

be transferred to the mobile phone. Another example is scanning technology, which can be drifted from printer to the reference product.

Table 9- Comparing features of reference products with those of source products

	Reference Product	**Related Product**		**Interested Product**
	Mobile phone	*Digital Camera*	*Printer*	*Fitness watch*
Features	Display	Display	Display	Display
	Battery	Battery	Battery	Battery
	Memory	2 slots Memory	-	Memory
	-	-	Scanner	-
	-	-	Photo-printing technology	-
	-	Optical lens	-	-
	-	-	-	Heart rate sensor

Note that examining the database, there might be some common features but with a different value in related products feature set. For instance, in Table 9 all mentioned products have a display but the size and resolution of it are various amongst different products. Since we are not focusing on concept drift in this study, we only consider those features that are completely new comparing to feature set of our reference product and keep the rest for future research. Next step is asking designers to select proposed features from available novel feature set. Figure 12 presents the algorithm for the NFF module of FEATURE.

Figure 12- NFF module of FEATURE algorithm

Input: Reference Product (RP), Category of Reference Product, α, β

Output: Proposed Features from source products (PF), Selected proposed features by designers (SPF)

1. NFF(RP,Category, α, β)
2. **Begin Procedure**
3. POD: Find the products from other domains in the Category
4. FOR each POD_i in POD
    a. Collect product's user manual guide
    b. Generate Word cloud for it using the product's user manual guide (WCi)
    c. for each Ti in WCi
        i. If (Ti does not either represent a function, capability or a feature of the product)
            1. Delete it from WCi
        ii. EndIf
    d. EndFor
    e. POD_features[i]: the most 50 frequent nouns from WCi as product's features
5. ENDFOR
6. Repeat the steps 4.a to 4.e for extracting features of RP (RP_features)
7. For each Ti in POD_features
    a. For each RTi in RP_features
        i. If Ti has similar meaning with RTi
            1. Group Ti and RTi in one cluster based on Ontology Rules
        ii. Else
            1. Consider Ti as a Cluster
        iii. EndIF
    b. EndFor
8. EndFor
9. For each POD_features[i] in POD_features
    a. For each C in POD_features[i]
        1. For each RC in RF_features
            a. If RCj is similar with C
                i. TAmatrix[i][j]:1
            b. Else
                i. TAmatrix[i][j]:0
            c. EndIf
        2. EndFor
    b. EndFor
10. EndFor
11. $\vec{X}$: $[1,1,1,\ldots.1]_{1*50}$
12. FOR each POD_i in POD
    a. $\vec{Y}$: TAmatrix[i]
    b. SCi= $SIM[(RP\_features),(POD_i\_features)] = \frac{\vec{X}.\vec{Y}}{\|X\|\|Y\|}$
    c. IF(SC_i >= β)
        i. Set the POD_i as Similar product
    d. ELSEIF (α < SC_i< β)
        i. the POD_i as Related product
    e. ELSE
        i. Set the POD_i as Non-Related product
    f. ENDIF
13. ENDFOR
14. Get Interested Products
15. Add Interested Products to Source
16. Add Related Products to Source
17. For each Si in Source
    a. RC: Relative Compliment of features between RP and Si
    b. Add RC to PF
18. EndFor
19. SPF: selected proposed features by designers based on PF
20. **End Procedure**

6- Experimental Results

Experiments are conducted to evaluate the efficacy of NFF module of FEATURE to complement the idea generation phase of new product development. Using these experiments, we want to show how product

designers by using FEATURE are able to identify new features that can be integrated into the reference product from the source products. For the experiments, we have selected a mobile phone as our reference product. Specifically, we selected the Samsung Galaxy S3 phone, which was launched to the market in 2013. Our reason to choose the case study from some years back is to show how agile is FEATURE in assisting the product designers to find novel ideas for developing the next iteration of the product that was introduced in the later years. Once the reference product is selected, FEATURE defines its category as an *Electronic product*. It then identifies other products from the category of electronic products. They are:

Electronic products = {Camera, Laptop, Tablet, Monitor, TV, Music Player, Printer, Video Game Console}

Selected models = { Pentax K-50, Alienware M14x R2, ASUS Google Nexus 7, Philips 273E3LHSB, Panasonic VIERA ST50A, iPod nano, HP Officejet Pro X576dw, Sony Playstation 3 Slim }

For each identified product, we select a model that was released in 2013 and was available in the market at the time the reference product was introduced to the customers. User manual guides and product description documents for those models along for the reference product were collected. The next step was to find which of the products from the selected list are known as related products to the reference product. For this, word cloud is generated for the selected models in the electronic products category along with the reference product. The extracted terms from word clouds were pruned to represent only the features from those products and the most 50 frequent ones from each product were considered as products' features. To group similar features with different terminologies into one cluster, the following ontology rules were defined for mapping:

Ontology rules: {video, movie}{monitor, screen, display}{image, photo}{key, button}{application, app}

In the next step, NFF quantified feature commonalities between different products and the reference product by forming term association matrix. This is shown in Table 10 where the mobile phone features are in the column headings whereas the rows represent each product. In the case of a common feature existing between the reference product and the product of the same category, a value of 1 is put in the associated cell, otherwise zero. Due to space limitations, Table 10 shows a shortened representation of the term association matrix.

Table 10- Term association matrix for mobile phone

	Battery	**Screen**	**Wi-Fi**	**Image**	**Video**	**Text**
Camera	1	1	0	1	1	0
Printer	0	0	1	1	0	1
Music Player	1	1	0	1	0	0

Video Game	1	0	0	0	1	0
TV	1	1	0	1	0	0
Monitor	0	1	0	1	0	0
Tablet	1	1	1	1	1	1
Laptop	1	1	1	0	0	0

After forming the term association matrix, a similarity value is computed for each related product with the reference product by using Eq.1. An example of similarity value computed for mobile phone and camera is shown below:

$$SIM(Mobile, Camera) = \frac{\sum(1*1)+(1*1)+(1*0)+(1*1)+(1*1)+(1*0)+\cdots}{\sqrt{\sum(1*1)+(1*1)+\cdots}\sqrt{\sum(1*1)+(1*1)+(0*0)+\cdots}} = 0.60$$

Table 11 shows the similarity value for the products in the electronic category with respect to the reference product. We define the threshold values of α & β as 0.5 and 0.7 respectively. For those products with a similarity value of less than α = 0.5, there were considered as *non-related products*. If the similarity values exceeded β = 0.7, the product was labeled as a *similar product*. Those products that had a similarity value between 0.5 and 0.7 were considered as *related products*.

Table 11 - Similarity value for products in electronic category

Product type	Camera	Printer	Music Player	Video Game	TV	Monitor	Tablet	Laptop
Product model	Pentax K-50	HP Officejet Pro X576dw	iPod nano	Sony Playstation 3 Slim	Panasonic VIERA ST50A	Philips 273E3 LHSB	ASUS Google Nexus 7	Alienware M14x R2
Similarity value	0.60	0.55	0.60	0.46	0.52	0.39	0.76	0.52

We now present the experimental results in *three* different scenarios.

- The first scenario shows how NFF identifies the novel features/attributes that can be drifted in the next iteration of the reference product from the *related products*.
- The second scenario shows how NFF assists in the ideation phase when the product of analysis is a *similar product.*

- The third scenario shows how NFF identifies the novel features that can be drifted in the next iteration of the reference product from an *interested product*.

Scenario 1 – Identifying novel features/attributes to be drifted to the reference product from related products

As mentioned earlier, related products are those that have a similarity value between 0.5 and 0.7. From Table 11, these are the products highlighted in red. Next, product specification documents of the reference and related products are used to group features under the commonly defined heading of *Body, Display, Platform, Memory, Camera, Sound, Connections, Additional features, Battery*. In order to find the unique features from related products that do not exist in the reference product, NFF computes the relative complement of the features of the reference product and those of related products using Eq.2. Figure 13 outlines this process in a smaller scale for a mobile phone (reference product) and a camera (related product). The blue circle represents features of a mobile phone while the orange circle describes features of a camera. The intersection of these two circles involves the common features in these products. Those features highlighted in red are considered as unique features in the camera that can be drifted into the mobile phone.

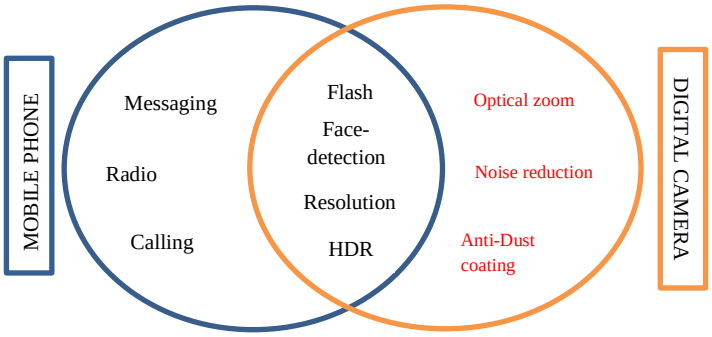


Figure 13 - Relative complement of features between a mobile phone and a digital camera

Table 12 represents the unique features from related products that can be drifted to the reference product. The extracted features are grouped based on their association to the features in a mobile phone. The table includes proposed features, their attributes along with their possible values and the product from where they come. The product designers can use such analysis to select those features that they find novel and suitable for them to be introduced in the next version of the product. Drifting unique features/attributes from related products to reference product can result in introducing *revolutionary type of newness or feature drift* in the next version of the product that can beat their competitors in the market.

Table 12 - Unique features extracted from related products

FEATURE	ATTRIBUTE	VALUE	SOURCE PRODUCT
Display	3D capable	-	TV (Panasonic VIERA ST50A)
	Viewing angle	178 (H), 178(V)	TV (Panasonic VIERA ST50A)
Connections	Component	-	TV (Panasonic VIERA ST50A)
	Composite	-	TV (Panasonic VIERA ST50A)
	Digital audio	-	TV (Panasonic VIERA ST50A)
	Ethernet	-	TV (Panasonic VIERA ST50A)
	HDMI	-	TV (Panasonic VIERA ST50A) Camera (Nikon D800), Laptop (Alienware M14x R2)
	Line in	-	TV (Panasonic VIERA ST50A)
Camera	Optical sensor	-	Camera (Nikon D800)
	Sensor dust reduction	-	Camera (Nikon D800)
	Anti-dust coating	-	Camera (Nikon D800)
	Self- cleaning sensor unit	-	Camera (Nikon D800)
	AE/AF Control	3D-tracking AF, Auto-area AF, Dynamic-area AF, Face-priority AF, Subject-tracking AF	Camera (Nikon D800)
	Exposure Metering	3D color matrix III, Center-weighted, Spot	Camera (Nikon D800)
	Exposure Modes	Aperture-priority, Automatic, Bulb, Manual, Shutter-priority	Camera (Nikon D800)
	Special Effects	Black & White, Blue, Miniature, Monochrome, Neutral, Portrait, Red, Selective Colour, Sepia, Skylight Filter, Soft, Vivid, Colour outline, Warm	Camera (Nikon D800)

		Filter, Colour sketch, Cross Screen, Cyanotype, Fisheye, Green, Image Overlay, Landscape, Autumn Leaves, Night Scene, Pop Colour, Pasteurization, Retro, Sunset, Clear, Toy camera, partial colour, Deep, HDR Painting, Light	
	White Balance Preset	2500K - 10000K, Cloudy, Flash, Fluorescent, Incandescent, Shade, Sunlight	Camera (Nikon D800)
	24p Cinema Mode	-	Camera (Nikon D800)
	NR Slow Shutter	-	Camera (Nikon D800)
	Quick AF Full HD movie recording	-	Camera (Nikon D800)
	Quick AF Live View	-	Camera (Nikon D800)
	RGB primary color filter	-	Camera (Nikon D800)
	Shade Correction	-	Camera (Nikon D800)
	Smart Teleconverter	-	Camera (Nikon D800)
	Smile Detection Auto Shutter	-	Camera (Nikon D800)
	Smile Detection technology	-	Camera (Nikon D800)
	Translucent Mirror technology	-	Camera (Nikon D800)
	Automatic display brightness adjustment	-	Camera (Nikon D800)
	Date/time stamp	-	Camera (Nikon D800)
	Depth-of-field preview button	-	Camera (Nikon D800)
	Digital noise reduction	-	Camera (Nikon D800)
	Active D-Lighting technology	-	Camera (Nikon D800)
	Advanced Scene Recognition System	-	Camera (Nikon D800)

	In-camera movie editing	-	Camera (Nikon D800)
	In-camera red-eye removal	-	Camera (Nikon D800)
	Takes photos while movie recording	-	Camera (Nikon D800)
	Time-Lapse recording	-	Camera (Nikon D800)
Memory	Slots Quantity	2	Camera (Nikon D800), Laptop (Alienware M14x R2)
Additional Features	Radio	-	Music Player (SanDisk Sansa Clip Zip)
	Printing Technology	-	Printer (HP Officejet Pro X576dw Multifunction)
	Fax Technology	-	Printer (HP Officejet Pro X576dw Multifunction)
	Copying Technology	-	Printer (HP Officejet Pro X576dw Multifunction)

Scenario 2 – Identifying novel features/attributes to be drifted to the reference product from similar products

As the similarity value for *tablet* exceeds our pre-defined threshold of 0.7, NFF considers it as a similar product to the reference product. Being similar products mean the products have the same features/attributes and hence the possibility of finding new features/attributes that can be drifting from tablet to the mobile phone is less. Therefore, the search for uniqueness has been done further down at the level of values rather than at features and/or attributes. In other words, NFF ascertains the non-common values for the feature/attributes by computing the relative complement between values of reference product and similar products. Table 13 represents the values of features/attributes of the reference and similar products. Based on these, the designer can decide on which values to drift for the current features/attribute in the reference product. This will result in having an *evolutionary type of newness or concept drift*.

Table 13 – Non-common specifications of similar products comparing to the reference product

Feature	***Attribute***	***Reference product values***	***Value in the source product***		
		Samsung Galaxy S III	ASUS Google Nexus 7	Samsung Google Nexus 10	iPad (4th generation)
Display	Type	Super AMOLED capacitive touchscreen	LED-backlit IPS LCD capacitive touchscreen	Super PLS TFT capacitive touchscreen	LED-backlit Multi-Touch display with IPS technology
	Size	4.8 inches	7.0 inches	10.1 inches	9.7 inches
	Resolution	720 x 1280 pixels	800 x 1280 pixels	2560 x 1600 pixels	2048 x 1536 pixels
Platform	CPU	Quad-core 1.4 GHz Cortex-A9	Quad-core 1.2 GHz Cortex-A9	Dual-core 1.7 GHz Cortex-A15	Dual-core A6X with quad-core graphics
Camera	Resolution	8 MP	1.2 MP	5 MP	5 MP

Scenario 3 – Identifying novel features/attributes to be drifted to the reference product from interested products

In this scenario, we consider that the product designer wants to analyse features to be added to the reference product from an interested product. Fitness watch is selected as an interested product that is under the category of apparel and accessories. Polar RCX5 and Garmin Forerunner 610 are selected as the interested models, which were released in 2013 from the interested product category. Product specifications documents for these two types of fitness watches are collected and by computing relative complement between features of reference product and fitness watch; non-common features, which can be drifted to the reference product, are identified as shown in Table 14. In other words, the ability for the mobile phone to *monitor heart rate* and also being *water resistant* are identified as features that are unique to the reference product and can be drifted into its next version. Drifting such features from products of other categories can result in introducing a *revolutionary type of newness or feature drift* that brings creativity to the reference products.

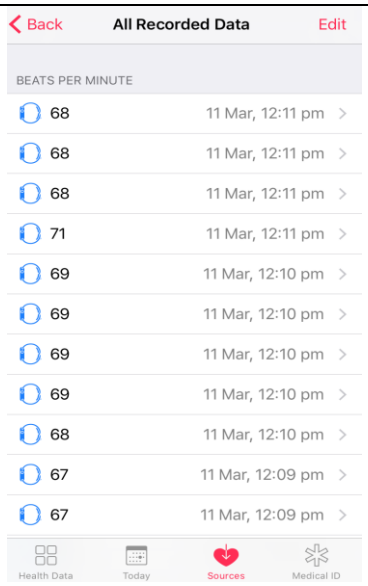
Table 14 – Comparing features of reference products and interested products

	Reference product	Interested product	
Features	Samsung Galaxy S III	Polar RCX5	Garmin Forerunner 610
Display	√	√	√
Battery	√	√	√
Memory	√	√	√
GPS	√	√	√
Heart rate monitoring	-	√	√
Water resistance	-	√	-

How can the product designers use the features/attributes and their values proposed from NFF?

Once the NFF module of FEATURE proposes the novel features/attributes and values that can be given drifted in the reference product's next iteration then they can investigate it further in the next stages of NPD. To drift such proposed features may require product designers to either change the design or the shape of the current product or make improvements to it internally keeping the product design intact. For example, *Apple watch series 1* provides functionality to users in measuring their heart rate as shown in Figure 14(a). Users can see this information on their iPhone (example iPhone6s) that is paired with the apple watch through Bluetooth technology as shown in Figure 14(b). However, this functionality to check their heart rate is only available to iPhone users who have an apple watch paired with their iPhone.

(A)



(B)

(C)

Figure 14 – Heart rate monitoring in Apple watch (A), Health app in iphone6s (B), sensors on Apple watch to measure the heart rate (C)

As can be seen from Table 13, *NFF* recommends to the product designers of drifting the feature of adding *Heart rate monitoring* to the next iteration of the reference product, which is the mobile phone. However, to provide such a feature the product designers may have to change the design of the shape of their existing product. This is because, as shown in Figure 14(c) *apple watch* measures a human's heart rate by using sensors that are at the backside of the watch and when those sensors are in touch with the human's skin. So, to drift such a feature to the *iPhone6s*, product designers may have to develop sensors on the phone which can measure a human's heart rate when they are in touch with the human skin which may require the product designers to develop a new product design.

Another example of how product designers can drift new features into the reference product without having the need to change the product design or the shape is enabling mobile phones with the scanning capability. In 2015, the feature of scanning was drifted to mobile phones but this did not require the product designers to change the design and shape of the mobile phone. Rather it was achieved by updating the operating system of the phone and using the existing camera.

Therefore, the product designers can use the novel features/attributes and their values recommended to be drifted and investigate further in the product concept phase of how to drift them in the product's next iteration. This is not in the scope of NFF that just focusses on recommending these novel features/attributes and their values be drifted.

7- Evaluation

Determining the effectiveness of ideation is one of the ultimate goals in almost all studies of design ideation. In the literature, [50] defines four metrics to measure the different aspects of ideation effectiveness. The first metric is Novelty. It stands for the degree to which the new idea is distinct from existing ones. The next metric is Variety, which measures how different two ideas are from each other. The third metric is Quality that evaluates the technical feasibility and performance of the design alternative against given constraints. Quantity is the fourth metric that represents the number of ideas that a designer submits in the idea generation process.

In order to measure these metrics and in turn the effectiveness of ideation, one requires several predetermined functions and taxonomy as the base principles for comparing and grading the generated ideas. In the case where the design process is starting from a blank sheet as is being done in NFF phase of FEATURE without any ideas for the functions that need to be integrated into the next version of a product, such metrics cannot be used as the criteria to assess ideation performance. Additionally, since NFF proposes new features from other products for developing the reference product, it is probable that each generated

idea only represents one function, which is not comparable to the other ideas regarding the variety or novelty of different features/functions that they are covering. Therefore, the effectiveness of the NFF module of FEATURE in suggesting new ideas is measured by comparing the obtained results for a mobile phone, which has been released in 2013, with the features of the mobile phones/apps/add-ons launched in its following years. In the first column of Table 15, some examples of features, which have been identified by NFF phase of FEATURE as the ideas that can be incorporated into the next version of our reference product, are presented. In the second column, the way that product designers were able to deliver these features to the customers namely by modifying the product or developing a new app/add-on are mentioned along with the product they were introduced in. The third column lists the year in which the products with the proposed features were launched.

Finding the features, which have been proposed by FEATURE in this study, amongst the products/applications that have been launched to the market after 2013 (year of releasing the reference product), shows the superiority of FEATURE in proposing realistic and novel ideas.

Table 15- Showing how & when the identified new features by NFF were incorporated in the next version of mobile phones

Proposed feature by NFF module for a mobile phone released in 2013	The way, which the feature was achieved in the product's next iteration	Launched year
Optical lenses for taking clearer photos	Achieved by having "external optical lenses add-on for smart phone"	2016 [51]
Optical lenses for taking clearer photos	Achieved by "built-in optical lenses in iPhone 7 plus"	2016 [52]
Scanning technology to scan documents by using smartphone	Achieved by having "scanning app for Android"	2015 [53]
Printing technology to print documents by using smartphone	Achieved by having "phone gadget with thermal printing technology"	2016 [54]

8- Conclusion

This paper presents our proposed FEATURE framework that helps product designers in idea generation phase of new product development to gain insights from unique features of related products that can be added in the next generation of a product. It differs with existing approaches in introducing the concept of feature drift, which suggests novel and out-of-the-box features from related products, rather than improving the current features from similar products. FEATURE comprises of three modules; first, it proposes unique features from related products. The popularity of the proposed features is detected within the customers' reviews, in the second module. In the third module, the algorithm ranks the proposed features based on their level of innovativeness or according to their profitability considering the risk attitude of the product designers.

In this study, in addition to introducing FEATURE, the applicability of its first module namely New Feature Finder, has been tested by taking a mobile phone as the reference product. NFF starts by defining the reference product's category and determining other products in its category. In order to find the related products to a reference product, NFF generates a Word Cloud of the products under analysis and extracts their features. Once features with the same meaning but different terminologies are categorized in the same clusters, NFF computes the similarity value between the reference product and each of the considered products. After that, those products, which their similarity value is between the two pre-defined thresholds, are considered for further analysis as related products. However, the designers can add more products for analysing at this stage as the interested products. Finally, the unique features are found through computing the relative complement of reference product's features and those of related and interested ones. The designer will then decide on the proposed features for adding them in the next version of the product. We show the superiority of FEATURE in proposing realistic and novel ideas by finding the features, which have been proposed by its first module in this study, amongst the products/applications that have been launched to the market after 2013 (year of releasing the reference product).

The uniqueness of FEATURE is to provide a broader range of ideas in the ideation phase of new product development by considering the features from related products where the design process starts from a blank sheet. It not only takes into account the voice of customers but also different decision criteria of the designers while developing the next version of a product. Hence, it is assisting in the ideation phase of new product development, the feasibility and technical decisions on these features yet to be made in later steps of this process (e.g. introducing them as software features or hardware ones in the next version). In our future work, we will detect the popularity of the proposed features by NFF amongst customer through analysing product reviews in the second phase of FEATURE and propose a decision making approach in

the third phase that assists product developers to take a decisions of which features to consider further in the next phases of NPD.

References

[1] OECD, The Measurement of Scientific and Technological Activities: Guidelines for Collecting and Interpreting Innovation Data: Oslo Manual, Third Edition, (2005) 158. https://stats.oecd.org/glossary/detail.asp?ID=6869.

[2] I. Goulding, New Product Development: A Literature Review, Eur. J. Mark. 17 (1983) 3–30.

[3] J. Chan, K. Fu, C. Schunn, J. Cagan, K. Wood, K. Kotovsky, On the Benefits and Pitfalls of Analogies for Innovative Design: Ideation Performance Based on Analogical Distance, Commonness, and Modality of Examples, J. Mech. Des. 133 (2011) 81004. doi:10.1115/1.4004396.

[4] A.K. Goel, Design, analogy, and creativity, IEEE Expert. Syst. Their Appl. 12 (1997) 62–70. doi:10.1109/64.590078.

[5] A. Soukhoroukova, M. Spann, B. Skiera, Sourcing, filtering, and evaluating new product ideas: An empirical exploration of the performance of idea markets, J. Prod. Innov. Manag. 29 (2012) 100–112. doi:10.1111/j.1540-5885.2011.00881.x.

[6] D. Bacciotti, Y. Borgianni, F. Rotini, An original design approach for stimulating the ideation of new product features, Comput. Ind. 75 (2016) 80–100. doi:10.1016/j.compind.2015.06.004.

[7] Y. Li, J. Wang, X. Li, W. Zhao, Design creativity in product innovation, Int. J. Adv. Manuf. Technol. 33 (2007) 213–222. doi:10.1007/s00170-006-0457-y.

[8] E.F. Rietzschel, B.A. Nijstad, W. Stroebe, Productivity is not enough: A comparison of interactive and nominal brainstorming groups on idea generation and selection, J. Exp. Soc. Psychol. 42 (2006) 244–251. doi:10.1016/j.jesp.2005.04.005.

[9] M.A. Mirtalaie, O.K. Hussain, E. Chang, FEATURE : New product development using feature-drift based framework for unique aspect recommendation, in: IEEE Int. Conf. E-Bus. Eng., Macau, China, 2016. doi:10.1109/ICEBE.2016.43.

[10] J. Gama, I. Žliobaitė, A. Bifet, M. Pechenizkiy, A. Bouchachia, A survey on concept drift adaptation, ACM Comput. Surv. 46 (2014) 1–37. doi:10.1145/2523813.

[11] N. Lu, G. Zhang, J. Lu, Concept drift detection via competence models, Artif. Intell. 209 (2014) 11–28. doi:10.1016/j.artint.2014.01.001.

[12] D.N. Perkins, G. Salomon, Transfer of learning, Int. Encycl. Educ. Second Ed. Oxford. (1992) 11. doi:10.1145/30851.275631.

[13] C.S. Tucker, S.W. Kang, A Bisociative Design Framework for Knowledge Discovery Across, in: ASME 2012 Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf., Chicago, IL, USA, 2012: pp. 1–13.

[14] S. woo Kang, C.S. Tucker, Automated Concept Generation Based On Function-Form Synthesis, in: ASME 2015 Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf., Boston, Massachusetts, USA, 2015: pp. 1–11.

[15] S.K. Li, Z. Guan, L.Y. Tang, Z. Chen, Exploiting consumer reviews for product feature ranking, J. Comput. Sci. Technol. 27 (2012) 635–649. doi:10.1007/s11390-012-1250-z.

[16] A. Shamim, V. Balakrishnan, M. Tahir, M. Shiraz, Critical product features' identification using an opinion analyzer, Sci. World J. 2014 (2014). doi:10.1155/2014/340583.

[17] T. Stone, S.-K. Choi, Visualization tool for interpreting user needs from usergenerated content via text mining and classification, in: ASME 2014 Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf., Buffalo, New York, USA, 2014: pp. 1–11.

[18] J. Jin, P. Ji, Y. Liu, Prioritising engineering characteristics based on customer online reviews for quality function deployment, 4828 (2014) 37–41. doi:10.1080/09544828.2014.984665.

[19] K.Y. Lin, C.F. Chien, R. Kerh, UNISON framework of data-driven innovation for extracting user experience of product design of wearable devices, Comput. Ind. Eng. 99 (2016) 487–502. doi:10.1016/j.cie.2016.05.023.

[20] C.F. Chien, R. Kerh, K.Y. Lin, A.P.I. Yu, Data-driven innovation to capture user-experience product design: An empirical study for notebook visual aesthetics design, Comput. Ind. Eng. 99 (2016) 162–173. doi:10.1016/j.cie.2016.07.006.

[21] J.K. Bae, J. Kim, Product development with data mining techniques: A case on design of digital camera, Expert Syst. Appl. 38 (2011) 9274–9280. doi:10.1016/j.eswa.2011.01.030.

[22] S. Tuarob, C.S. Tucker, Quantifying Product Favorability and Extracting Notable Product Features

Using Large Scale Social Media Data, J. Comput. Inf. Sci. Eng. 15 (2015) 310031–12. doi:10.1115/1.4030049.

[23] J. Jin, P. Ji, R. Gu, Identifying comparative customer requirements from product online reviews for competitor analysis, Eng. Appl. Artif. Intell. 49 (2016) 61–73. doi:10.1016/j.engappai.2015.12.005.

[24] C. Tucker, H. Kim, Predicting Emerging Product Design Trend By Mining Publicly Available Customer Review Data, in: 18th Int. Conf. Eng. Des., Technical University of Denmark, 2011. https://www.designsociety.org/publication/30612/predicting_emerging_product_design_trend_by_mining_publicly_available_customer_review_data.

[25] H. Wang, W. Wang, Product weakness finder: an opinion-aware system through sentiment analysis, Ind. Manag. Data Syst. Vol. 114 (2014) 1301–1320. http://www.emeraldinsight.com/doi/pdfplus/10.1108/IMDS-02-2014-0069.

[26] F. Zhou, R. Jianxin Jiao, J.S. Linsey, Latent Customer Needs Elicitation by Use Case Analogical Reasoning From Sentiment Analysis of Online Product Reviews, J. Mech. Des. 137 (2015) 71401–12. doi:10.1115/1.4030159.

[27] S. Tuarob, C.S. Tucker, Discovering next generation product innovations by identifying lead user preferences expressed through large scale social media data, Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf. IDETC/CIE 2014. (2014) 1–12.

[28] J. Guo, R. Tan, J. Sun, J. Ren, S. Wu, Y. Qiu, A Needs Analysis Approach to Product Innovation Driven by Design, Procedia CIRP. 39 (2016) 39–44. doi:10.1016/j.procir.2016.01.163.

[29] L. Wang, B.D. Youn, S. Azarm, P.K. Kannan, Customer-driven product design selection using web based user-generated content, in: ASME 2011 Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf., Washington, DC, USA, 2011: pp. 1–15.

[30] C.S. Tucker, H.M. Kim, Data-Driven Decision Tree Classification for Product Portfolio Design Optimization, J. Comput. Inf. Sci. Eng. 9 (2009) 410041–13. doi:10.1115/1.3243634.

[31] K. Fu, J. Murphy, M. Yang, K. Otto, D. Jensen, K. Wood, Design-by-analogy: experimental evaluation of a functional analogy search methodology for concept generation improvement, Res. Eng. Des. 26 (2014) 77–95. doi:10.1007/s00163-014-0186-4.

[32] D. Paola, M. Grandas, M. Yang, K. Wood, Supporting Creativity Across Products , Services and

Product-Service Systems Through Design By Analogy, in: Int. Conf. Eng. Des. ICED ’15, BOVISA CAMPUS - POLITECNICO DI MILANO, MILAN, ITALY, 2015.

[33] I. Chiu, L.H. Shu, Biomimetic design through natural language analysis to facilitate cross-domain information retrieval, Artif. Intell. Eng. Des. Anal. Manuf. 21 (2007) 45–59. doi:10.1017/S0890060407070138.

[34] J.K.S. Nagel, R.B. Stone, A computational approach to biologically inspired design, Artif. Intell. Eng. Des. Anal. Manuf. 26 (2012) 161–176. doi:10.1017/S0890060412000054.

[35] J.-M. Deldin, M. Schuknecht, The AskNature Database: Enabling Solutions in Biomimetic Design, in: Biol. Inspired Des., Springer, 2014: pp. 245–267. doi:10.1007/978-1-4471-5248-4.

[36] S. Vattam, B. Wiltgen, M. Helms, A. Goel, J. Yen, DANE: Fostering Creativity in and Through Biologically Inspired Design, in: First Int. Conf. Des. Creat., Kobe, Japan, 2010: pp. 115–122.

[37] C.R. Bryant Arnold, R.B. Stone, D. a McAdams, Memic: An interactive morphological matrix tool for automated concept generation, IIE Annu. Conf. Expo 2008. (2008) 1196–1201. http://www.scopus.com/inward/record.url?eid=2-s2.0-63849173943&partnerID=40&md5=f07684ddaa26422f01818ebe5e38b7fe.

[38] S.W. Kang, C. Sane, N. Vasudevan, C.S. Tucker, Product resynthesis: knowledge discovery of the value of end-of-life assemblies and subassemblies, ASME J. Mech. Des. 136 (2013) 1–14. doi:10.1115/1.4025526.

[39] P.A. Verhaegen, J. D’Hondt, D. Vandevenne, S. Dewulf, J.R. Duflou, Identifying candidates for design-by-analogy, Comput. Ind. 62 (2011) 446–459. doi:10.1016/j.compind.2010.12.007.

[40] D. Vandevenne, P.-A. Verhaegen, S. Dewulf, J.R. Duflou, SEABIRD: Scalable search for systematic biologically inspired design, Artif. Intell. Eng. Des. Anal. Manuf. 30 (2016) 78–95. doi:10.1017/S0890060415000177.

[41] H. Kobayashi, A systematic approach to eco-innovative product design based on life cycle planning, Adv. Eng. Informatics. 20 (2006) 113–125. doi:10.1016/j.aei.2005.11.002.

[42] K. Chin, D. Tang, J. Yang, S.Y. Wong, H. Wang, Assessing new product development project risk by Bayesian network with a systematic probability generation methodology, Expert Syst. Appl. 36 (2009) 9879–9890. doi:10.1016/j.eswa.2009.02.019.

[43] S. Park, J. Kim, A Risk Management System Framework for New Product Development (NPD), in: 2011 Int. Conf. Econ. Financ. Res., 2011: pp. 51–56.

[44] Google Product Taxonomy, (2015). https://www.google.com/basepages/producttype/taxonomy.en-US.txt (accessed March 8, 2017).

[45] Word Cloud, (n.d.). https://en.wikipedia.org/wiki/Tag_cloud (accessed March 8, 2017).

[46] B. Agarwal, N. Mittal, P. Bansal, S. Garg, Sentiment analysis using common-sense and context information, Comput. Intell. Neurosci. 2015 (2015). doi:10.1155/2015/715730.

[47] S. Mukherjee, S. Joshi, Sentiment Aggregation using ConceptNet Ontology, Proc. Sixth Int. Jt. Conf. Nat. Lang. Process. (2013) 570–578. http://www.aclweb.org/anthology/I13-1065.

[48] A. Jeyapriya, C.S.K. Selvi, Extracting aspects and mining opinions in product reviews using supervised learning algorithm, in: 2nd Int. Conf. Electron. Commun. Syst. ICECS 2015, IEEE, Coimbatore, 2015: pp. 548–552. doi:10.1109/ECS.2015.7124967.

[49] Y. Chen, B. Perozzi, S. Skiena, Vector-based similarity measurements for historical figures, Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 9371 (2015) 179–190. doi:10.1007/978-3-319-25087-8_17.

[50] J. Shah, Metrics for measuring ideation effectiveness, Des. Stud. 24 (2003) 111–134. doi:10.1016/S0142-694X(02)00034-0.

[51] C.L. Rousseau, Getting started with add-on camera lenses for your Android phone, (2016). http://www.androidcentral.com/different-types-phone-photography-lenses-buy (accessed March 14, 2017).

[52] Apple iPhone 7 Plus' optical zoom, (2016). http://www.phonearena.com/news/Apple-iPhone-7-Plus-optical-zoom-vs-iPhone-7s-digital-zoom-heres-why-optical-is-usually-superior_id87129 (accessed March 14, 2017).

[53] S. Mitroff, The best scanning apps for Android, (2015). https://www.cnet.com/au/how-to/best-scanning-apps-for-android-and-iphone/ (accessed March 14, 2017).

[54] Phone gadget with thermal printing technology prints instant photos like a Polaroid, (2016). http://vuing.com/phone-gadget-with-thermal-printing-technology-prints-instant-photos-like-a-polaroid/ (accessed March 14, 2017).