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IDEATION METRICS: INTERDEPENDENCY BETWEEN AVERAGE NOVELTY AND VARIETY

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1. Introduction

The engineering design process covers a range of stages from the identification of a need to a stage, where a solution is completely described such that the solution can be produced and implemented to fulfill the need. The conceptual design phase at the front end of this process, is one of the most important phases. In this phase, requirements are identified, principles of solutions are developed and the best candidate solution is selected for its further development [Pahl and Beitz 1996]. The cost incurred in this phase is relatively small compared to that in later phases [Berliner and Brimson 1988], and this phase provides maximum scope for most striking improvements [French 1999].

The importance of ideation in the conceptual design phase has been widely accepted. A greater number of alternative solutions helps to produce a higher quality design [Fricke 1996], [Dylla 1991] has shown a positive correlation between the amount of design space considered during idea generation and the quality of final design. Design space is a hypothetical space that includes all possible solutions to a given problem [Ullman 2010]. Several studies have been carried out in the area of ideation. These studies are aimed at: (1) understanding the cognitive processes during the idea generation [Finke et al. 1996], [Nijstad et al. 2002] and (2) evaluating different idea generation methods [Goldschmidt et al. 2011], [Hernandez et al. 2010], [Shah et al. 2003]. The idea generation methods can be evaluated through process-based and/or outcome-based approaches. The process-based approaches are difficult due to the inherent complexity of examining cognitive processes responsible for creative thought. Due to this, outcome-based evaluation approaches are frequently used [Shah et al. 2003]. In the outcome-based approaches, the designs/outcomes produced by designers during ideation are evaluated. An idea generation method is considered effective if the method helps to improve the outcomes based on predefined metrics.

[Shah et al. 2003] developed four key metrics for evaluating a designer's exploration and expansion of design space. The four metrics are: novelty, variety, quality, and quantity of designs. Several design ideation studies have used all or some of these four metrics (e.g. [Wilson et al. 2010], [Hernandez et al. 2010], [Chan et al. 2011], [Viswanathan et al. 2011]). According to [Shah et al. 2003], novelty is a measure of how unusual or unexpected an idea is as compared to other ideas including those from other individuals. Variety is defined as the degree to which the ideas from a single designer are dissimilar from other ideas from that designer [Shah et al. 2003]. Variety is a measure of the explored solution space during an idea generation process. The variety of a set of similar ideas is low. Quantity refers to the number of different ideas generated by a designer. Quality is a subjective measure of the degree to which a concept is considered to be feasible and meets design requirements. While the work of [Shah et al. 2003] in the area of design ideation metrics is foundational, they have not examined the interdependencies between these metrics.

The mean of novelty scores of ideas in a set (i.e. average novelty) has also been used in some ideation studies [Wilson et al. 2010], [Hernandez et al. 2010], [Chan et al. 2011], [Srinivasan et al. 2010]. As explained further in this paper, there appears to be a correlation between the average novelty (AN) of a given set of ideas and the variety of that set. However, many of the studies that have computed AN and variety, have not examined the interdependency between them (e.g. [Wilson et al. 2010], [Hernandez et al. 2010], [Chan et al. 2011], [Srinivasan et al. 2011]). In this paper, we define the interdependency between AN and variety as a correlation or association between them. The interpretation of the findings of an ideation study regarding the metrics AN and variety, without considering the interdependency between them, may be inaccurate. The tools and methods, based on such an inaccurate interpretation and aimed at improving ideation effectiveness, may not achieve desired effect or they may result into an undesired effect on ideation effectiveness. An example of an undesired effect of a tool or method on ideation effectiveness can be decrease in the novelty scores of ideas or variety score of the set of ideas when the tool or method is developed to enhance these scores. See Blessing and Chakrabarti's [Blessing and Chakrabarti 2009] work on Design Research Methodology (DRM) for discussion on desired and undesired effects of a tool or method that is developed to improve some aspects of a design process. The above discussion shows that it is important to examine the interdependency between the AN and variety. This research aims at examining:

- the interdependency between Average Novelty (AN) and variety; and
- the interdependency between Individual Average Novelty (IAN) and variety.

The difference between AN and IAN is as follows. *AN* of a set of ideas generated by an individual is computed by using the novelty scores of ideas in that set and these novelty scores are estimated *by comparing each of those ideas with other ideas including those from other individuals.* On the other hand, *IAN* of a given set is computed by using novelty scores of ideas in that set and these novelty scores are estimated *by comparing each of those ideas with other ideas in that given set.*

2. Background literature

2.1 Novelty

According to [Shah et al. 2003], novelty is a measure of how unusual or unexpected an idea is as compared to other ideas including those from other individuals. This suggests that uncommon ideas are likely to be seen as novel. In terms of a design space, novelty is a measure of whether the exploration of ideas occurred in areas of the design space that are well-travelled or little-travelled [Nelson et al. 2009]. In a design space, novel ideas occupy points that are initially not perceived to be within the design space [Shah et al. 2003]. An agent generates a novel outcome when it is not replicated from any existing outcome(s) [Sarkar 2007]. [Lopez-Mesa and Vidal 2006] employ 'infrequency' as a measure of novelty. [Shah et al. 2003] classified novelty into three different types, namely personal novelty (the outcomes of an individual are new according to that individual), societal novelty (a product or idea is new to all people in a particular society), and historical novelty (a product or idea is the first of its kind in the history of all societies and civilizations).

There are several methods of novelty assessment. To assess novelty of a product, [Sarkar 2007] suggests the use of experienced designers having knowledge of the domain(s) of the product whose novelty is to be assessed. [Amabile 1996] also suggests the use of experts to assess novelty. [Chakrabarti and Khadilkar 2003] developed a method to assess novelty of a product by assessing its similarity or difference with existing products as reference. [Sarkar and Chakrabarti 2011] developed a method to assess novelty of a product at various degrees: very high, high, medium, or low. The method uses function–behavior–structure (FBS) and SAPPhIRE (state change, action, parts, phenomenon, input, organs, and effect) models together. The FBS model is used first for determining novelty followed by the use of SAPPhIRE model to assess the relative degree of novelty.

In their foundational work on design ideation metrics, [Shah et al. 2003] proposed the following two approaches to measure novelty. (1) The first approach uses the 'priory' perspective. In this approach, the universe of ideas for comparison is obtained by defining what is usual or expected, preferably before analysing any data. This helps to avoid bias. (2) The second approach uses the 'posteriori' perspective. In this approach, ideas generated by all participants from all methods are collected. Then, the key attributes of these ideas (e.g. motion type, propulsion, etc.) are identified. This is followed by

the identification of different ways in which each of those attributes is satisfied (e.g. the attribute 'motion type' can be satisfied by using different ways such as rotation, oscillation, sliding, etc.). Then one can count how many instances of each solution method occur in the entire collection of ideas. If the count is lower (i.e. the less a characteristic is found), the novelty is higher.
[Shah et al. 2003] have explained in detail the procedure to measure novelty of an idea. The problem is first decomposed into its key functions or characteristics. Each generated idea is analysed by first identifying which functions it satisfies and also by describing how it fulfils these functions at levels/stages such as conceptual level and/or embodiment level. Each description is then graded for novelty according to one of the two above approaches (i.e. a priori or posteriori). The overall novelty of each idea can be computed from (1).

$$N = \sum_{j=1}^{m} f_j \sum_{k=1}^{q} S_{1jk} p_k \tag{1}$$

N is the overall novelty score for the idea having m functions or attributes and q levels. Weights (f_j) are assigned depending on the importance of each function. Each function can be addressed at the conceptual and/or embodiment level and weights (p_k) are assigned according to the level's importance. The calculation of S_{1jk} depends on the approach chosen. For the first approach (a priori knowledge) a universe of ideas for comparison is subjectively defined for each function or attribute, and at each level. A novelty score S_{1jk} is assigned to each idea in this universe. In order to evaluate the function and level of an idea, a closest match is found. For the second approach, S_{1jk} is calculated from (2).

$$S_{1jk} = \frac{T_{jk} - C_{jk}}{T_{jk}} \times 10 \tag{2}$$

Where T_{jk} is the total number of ideas produced for function (or key attribute) j and level k, and C_{jk} is the count of the current solution for that function (or key attribute) and level. Multiplying by 10 normalizes the expression.

2.2 Variety

Variety is defined as the degree to which the ideas from a single designer are dissimilar from other ideas from that designer [Shah et al. 2003]. Variety is a measure of the explored solution space during an idea generation process. The variety of a set of similar ideas is low. The metric variety indicates how well one has explored the design space. Generating a large number of ideas that are very similar to each other does not guarantee an effective idea generation. In an idea generation process, variety indicates the number of categories of ideas that one can imagine.
Shah et al. [Shah et al. 2003] have also proposed a procedure to estimate variety of a set of ideas. For measuring variety, one examines how each function is satisfied. Ideas are gathered based on how different two ideas are from each other. The use of a different physical principle to satisfy the same function implies that two ideas very different. In contrast, if two ideas differ only in some secondary construction level detail (e.g. a dimension value), the ideas are slightly different. The variety is calculated from equation (3).

$$M_3 = \sum_{j=1}^{m} f_j \sum_{k=1}^{4} S_k b_k / T \tag{3}$$

Where M_3 is the variety score, b_k is the number of branches at level k, m is the total number of functions, T is total number of ideas, and S_k is the score for level k (four scores 10, 6, 3, and 1 are assigned for physical principle, working principle, embodiment, and detail levels, respectively). For greater variety, branches at upper levels (physical principle differences) should get higher rating than the number of branches at lower levels.

The metric novelty measures the quality or usefulness of the design space exploration that the variety quantifies [Nelson et al. 2009]. The metric novelty applies to a single idea, and the metric variety applies to a set of ideas. The novelty of an idea generated by an individual is estimated by comparing that idea to his/her other ideas and also to ideas from other individuals. On the other hand, the metric variety considers the degree to which the ideas from a single designer are dissimilar from other ideas from that designer.

3. Research method

In this paper, we have used Shah et al.'s [Shah et al. 2003] widely accepted metrics of novelty and variety. As mentioned in Section 1, we have distinguished between IAN and AN. By using equations (1) and (2), we developed an equation to compute the IAN of a set of ideas for a single function and one level (i.e. level of physical principles). The collection of empirical data was not required to investigate the interdependency between IAN and variety for a single function and one level. In order to investigate the interdependency between AN and variety, we used the data from the empirical study of Shah et al. [Shah et al. 2003]. This is secondary data. However, this does not matter as our aim is only to check if there is a correlation between AN and variety. Use of this data was suitable for our research, and helped us to save time and effort by avoiding the collection of primary data.

4. Average novelty (AN) and individual average novelty (IAN)

Novelty of an idea is a measure of how unusual or unexpected an idea is as compared to other ideas including those from other individuals. The metric novelty applies to a single idea. Average novelty (AN) is computed for a set of ideas. Consider for example a design ideation experiment involving three designers (Da, Db, and Dc). Suppose that they have generated some ideas individually to satisfy a given function. Figure illustrates the sets of ideas generated by the three designers to satisfy the given function. For example, the set 'a' consists of three ideas (a1, a2, and a3) generated by the designer Da. The set 'e' consists of five ideas (x1, x2, x3, x4, and x5) that existed even before the experiment to satisfy that given function. The set 'u' includes all the ideas generated by the three designers plus the ideas in set 'e'. We call the set 'u' as the universe of ideas for the ideation experiment that is exemplified.

As shown in Figure, the novelty score of idea 'a1' as computed by comparing it with other ideas from the universe of ideas is denoted as $Na1_u$ (novelty of idea 'a1' computed from set 'u'). Similarly, $Nb2_u$ is the novelty score of idea 'b2' computed by comparing it with other ideas from the universe of ideas, and $Nc5_u$ is the novelty score of the idea 'c5' computed by comparing it with other ideas from the universe of ideas. Average novelty (ANa) of the set 'a' is $(Na1_u+Na2_u+Na3_u)/3$. Similarly, the average novelty (ANb) of the set 'b' is $(Nb1_u+Nb2_u+Nb3_u+Nb4_u)/4$, and the average novelty (ANc) of set 'c' is $(Nc1_u+Nc2_u+Nc3_u+Nc4_u+Nc5_u)/5$.

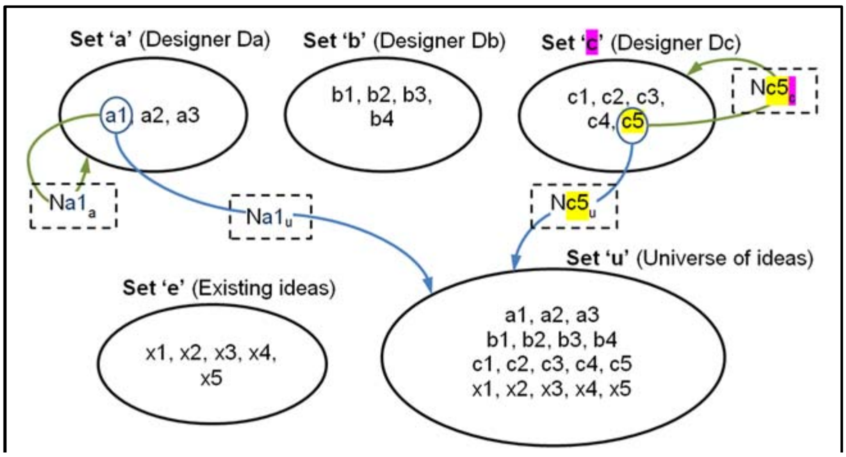

Figure 1. Illustration of different types of sets and novelty score of an idea

The novelty of the idea 'a1' can also be computed by comparing it with other ideas from the set 'a'. We denote this novelty as $Na1_a$ (novelty of idea a1 computed from set 'a'). Similarly, the novelty score of the idea 'c5' as computed by comparing it with other ideas from the set 'c' is $Nc5_c$ (see Figure). We call the average novelty of set 'a', computed by using novelty scores $Na1_a$, $Na2_a$, and $Na3_a$, as Individual Average Novelty of set 'a' and denote it by (IAN)a. Therefore, IANa is $(Na1_a + Na2_a + Na3_a)/3$. Similarly, (IAN)b is $(Nb1_b + Nb2_b + Nb3_b + Nb4_b)/4$.
The difference between the AN and IAN is as follows. AN of a given set is computed by using the novelty scores of ideas in that set and these novelty scores are estimated by comparing each of those ideas with other ideas in the universe of ideas. On the other hand, IAN of a given set is computed by using novelty scores of ideas in that set and these novelty scores are estimated by comparing each of those ideas with other ideas in that given set.

5. IAN and variety

We explain the interdependency between IAN and variety for a single function and one level (i.e. the level of physical principles). Consider for example a set 'b' of ideas (b1, b2, b3…bt) generated by a designer to satisfy one function. The IAN of this set 'b' is calculated from equation (4).

$$(IAN)b = \frac{Nb1_b + Nb2_b + Nb3_b + \cdots + Nbt_b}{T} \tag{4}$$

Where $Nb1_b$ is the novelty score of idea b1 computed by comparing this idea with other ideas from the set 'b', and T is the total number of ideas in this set. Suppose that the total number of physical principles used in the set of T ideas is n (see Table). One physical principle is used to satisfy the single function. There can be differences in ideas at the embodiment and detail level; however for simplification we will not consider these levels. As shown in Table , the number of ideas that have used the third physical principle (i.e. PP3) is C3. In this table, the values of Cj are organized in descending order (i.e. C1≥C2≥C3…≥Cn). This is illustrated by using the coloured horizontal bars in this table.
From equation (1), for a single function and for one level (i.e. level of physical principles), the novelty score of the idea b1 (computed by comparing this idea with other ideas in the set 'b') is found as follows: $Nb1_b = f_1 S_1 = S_1$, because $f_1 = 1$ for a single function. Where $S_1 = [10*(T-C_j)]/T$. Suppose that the idea b1 uses the physical principle PP3. The number of idea using the PP3 is C3. Therefore, for the idea b1, the S1 score is [10*(T-C3)]/T, which is its novelty score as well. In Table , we have organized the values of Cj in descending order. Therefore, the novelty scores of ideas using physical principles in the lower rows of this table will be relatively higher.

Table 1. Calculation of S_1

Physical Principle (PP)	C_j	S_1
PP1	C_1	$[10*(T-C_1)]/T$
PP2	C_2	$[10*(T-C_2)]/T$
PP3	C_3	$[10*(T-C_3)]/T$
…	…	…
PPn	C_n	$[10*(T-C_n)]/T$

From equation (4), the (IAN)b can be computed as follows.

$$(IAN)b = \frac{(S_1 \text{ score for the idea b1})+(S_1 \text{ score for the idea b2})+\ldots+(S_1 \text{ score for the idea bt})}{T} \tag{5}$$

The numerator on the right hand side of the above equation (5) is the addition of S_1 scores of T ideas. The number of ideas using the PP1 is C_1, using the PP2 is C_2, and so on. Therefore, in this numerator, S_1 score for PP1 will be counted C_1 times, S_1 score for PP2 will be counted C_2 times, and so on. Using this information, equation (5) reduces to:

$$(IAN)b = \frac{C_1(S_1 \text{ score for PP1})+C_2(S_1 \text{ score for PP2})+\ldots+C_n(S_1 \text{ score for PPn})}{T}.$$

Considering the fact that $C_1+C_2+C_3+\ldots+C_n = T$, and substituting S_1 scores for different physical principles, the above equation reduces to:

$$(IAN)b = \frac{10\,[T^2 - (C_1{}^2 + C_2{}^2 + \cdots + C_n{}^2)]}{T^2}.$$

Taking into account the standard deviation (s) of the data set (C_1, C_2, $C_3\ldots C_n$) of the values of C_j, the above equation reduces to:

$$(IAN)b = 10(n-1)\left(\frac{1}{n} - \frac{s^2}{T^2}\right). \tag{6}$$

For a single function and one level (i.e. the level of physical principles), the IAN of a set of ideas thus depends on the number of physical principles used (n), the standard deviation (s) of the data set of the values of C_j, and the total number of ideas generated.

In order to illustrate the variation of the IAN with the values of n and s for a given T, we now compute the values of IAN for a set of 10 ideas (i.e. T = 10). In this case, for nine physical principles (i.e. n = 9), there is one data set of the values of C_j - that is - (2, 1, 1, 1, 1, 1, 1, 1, 1). The standard deviation of this data set is 0.33. Therefore, from equation (6), for n = 9 and s = 0.33, the IAN score is 8.8. For eight physical principles (n = 8), there are two data sets of the values of C_j: (3, 1, 1, 1, 1, 1, 1, 1) and (2, 2, 1, 1, 1, 1, 1, 1). For the first data set of C_j, the standard deviation is 0.71 and for second set it is 0.46. The IAN scores for n = 8 and s = 0.71 is 8.41, and for n = 8 and s = 0.46 it is 8.60. Similarly, we computed IAN scores for the set of 10 ideas for different values of n and the possible data sets of the values of C_j. The result is presented in Figure .

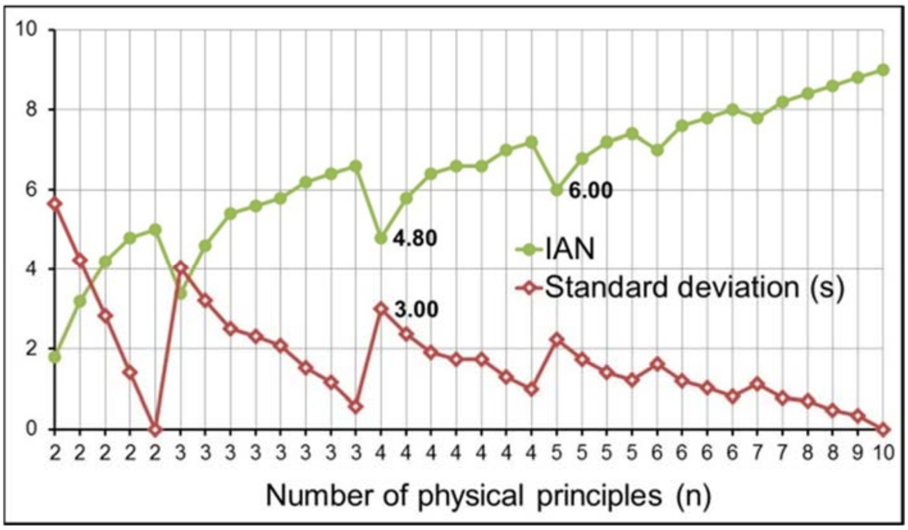

Figure 2. IAN and standard deviation for T = 10 and n = 2 to 10 (one function and one level)

From Figure , we can note that for given T and n, the IAN score increases with the decrease in s. The lowest possible score of IAN for given T and n is obtained when the value of s for that n is highest. For example, in the case of n = 4, the standard deviation for the lowest IAN score is 3, and the corresponding IAN score is 4.8 (see Figure). We compared the lowest possible score of IAN for n+1 and that for n. The value of s is highest for a given n and T when one of the physical principles has [T – (n – 1)] number of ideas and each of the remaining physical principles has one idea. Using this information we found that when T > n, the lowest possible IAN score for (n+1) is higher than that for n because [(lowest possible IAN score for n+1) – (lowest possible IAN score for n)] > 0 as per the following equation:

$$\text{(lowest possible IAN score for n+1)} - \text{(lowest possible IAN score for n)} = \frac{20 \times (T - n)}{T^2}.$$

For example, (lowest possible IAN score for 5 physical principles) – (lowest possible IAN score for 4 physical principles) = $20*(10-4)/10^2$ which is 1.2 (see Figure). The above discussion shows that for a given T, increasing the number of physical principles and decreasing the standard deviation of the data set of the values of C_j prove effective idea generation in terms of the IAN score for a single function and one level.

From equation (3), variety of a set of T ideas for one function and one level (i.e. level of physical principles) can be computed from the equation: $M_3 = (fj*S1*b_1)/T = (1*10*n)/T$. Where $f_j = 1$ for one function, S1 = 10 for the level of physical principles, and b1 = n (number of physical principles).

For the above example of a set of 10 ideas (T = 10) generated by a designer, variety is computed from the equation M3 = (10*n)/10 = n. This means that for a given T, variety of a set of ideas for one level (i.e. level of physical principles) and a single function is proportional to the number of physical principles. Figure shows the scatterplot of IAN and variety for the above example (T = 10). We also conducted a correlation study. The Pearson's correlation coefficient between the IAN and variety is strong (0.84).

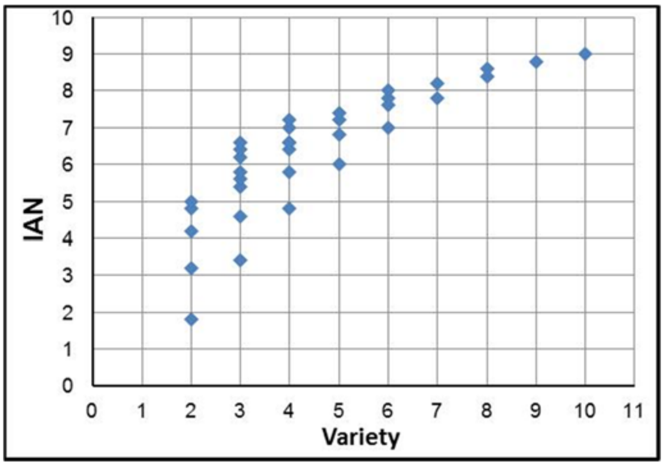

Figure 3. Scatterplot of IAN vs. variety for one function and one level (correlation coefficient = 0.84)

6. AN and variety

The AN of a given set is computed by using the novelty scores of ideas in that set and these novelty scores are estimated by comparing each of those ideas with other ideas in the universe of ideas. Consider for example a universe of ideas for a given single function. This universe of ideas consists of ideas generated by different designers (for example in an ideation experiment) plus existing ideas that satisfy the given function. In order to compute the AN of a set of ideas generated by a designer, each of those ideas is compared with other ideas in the universe of ideas.

While we cannot control the ideas in the universe of ideas, it is probable that designers will generate several ideas to satisfy a given function by using physical principles which are frequently seen in the universe of ideas. A reason for this can be that the designers are probably aware of the use of physical principles that are employed in commercially available products for satisfying the given function, and are therefore likely to generate several ideas using these physical principles. Therefore, these physical principles are likely to be frequently seen in the universe of ideas. For example consider that the given function is to boil 1 liter of water. There are several commercially available products (e.g. an electric kettle, a pot containing water placed on a heat-source, etc.) that satisfy this given function. The main physical principle used in these products is to transfer heat to water. It is therefore probable that the designers will generate several ideas using this physical principle, and therefore this physical principle is likely to be frequently seen in the universe of ideas. The designers can generate ideas to boil water by employing an increased number of physical principles (e.g. an idea to boil water by reducing pressure). If a designer generates ideas using greater number of physical principles, he/she is likely to use the physical principles which are not frequently seen in the universe if ideas. This can enhance the AN score of a set of ideas generated by using greater number of physical principles. From equation (3), for a given function, greater number of physical principles used helps to increase the variety of the set of ideas. We therefore hypothesise that an increase in the AN of a set of ideas should enhance the variety of that set. We used data from the empirical study of [Shah et al. 2003] to check if there is a correlation between AN and variety of a set of ideas.

[Shah et al. 2003] have illustrated the procedure to compute the novelty score of an idea with the help of a design problem used in a student design competition. The design aimed at building a device using fixed set of materials and powered by a given volume of pressurized air. The device that travelled the longest distance from the starting position was considered as a winner. In total, there were 46 ideas. Figure shows some ideas.

From equation (1), [Shah et al. 2003] computed the novelty score of each idea by comparing the idea with other ideas in the set of 46 ideas. They computed the novelty scores only at the conceptual level and for the following four functions or characteristics: (1) propulsion/thrust method (jet, sail, etc.); (2) medium of travel (air, land, water). (3) motion of device (rolling, sliding, tumbling, etc.), and (4) number of pieces into which the device separated in operation.

Using 46 ideas, we created 14 sets of ideas (set-1 to set-14). For example, set-1 included 23 ideas, and the set-2 included the remaining 23 ideas. A few ideas were common in some of the 14 sets. However, this is irrelevant because these sets have different AN scores and variety scores as explained further in this section. Therefore, the 14 sets can be considered as sets of ideas generated by 14 designers.

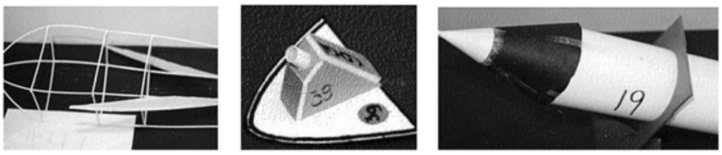

Figure 4. Three design ideas from the 46 ideas (adopted from [Shah et al. 2003])

From equation (3), we computed the variety score of each of the 14 sets at conceptual level and for four functions or characteristics. For example, the set-7 employed four ways for the propulsion/thrust method. Therefore, number of branches for this function is four. Similarly, we identified the number of branches for the remaining functions or characteristics (‘medium of travel’ - 2 branches, ‘motion of device’ - 2 branches, and ‘number of pieces’ - 2 branches). Figure shows the genealogy trees for four functions or characteristics in the case of the set-7.

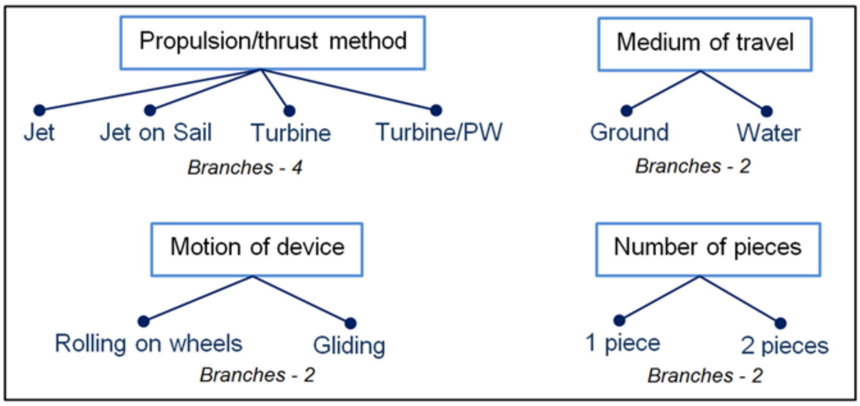

Figure 5. Genealogy trees for four functions or characteristics in the case of the set-7 (at conceptual level)

We used the following values for f_j: $f_1 = 0.35$, $f_2 = 0.35$, $f_3 = 0.2$, and $f_4 = 0.1$ (these values have been used by Shah et al. [Shah et al. 2003] in computing the novelty scores of 46 ideas). Then, the variety score of the set-7, consisting of 12 ideas, is calculated from equation (3) as follows: variety score (set-7) = $(f_1S_1b_1 + f2S_1b_1 + f3S_1b_1 + f_4S_1b_1)/12 = (0.35*10*4 + 0.35*10*2 + 0.2*10*2 + 0.1*10*2)/12 = 2.25$. Similarly, we calculated variety scores of all the 14 sets. In order to compute the AN scores of each of these sets we used the novelty scores (posteriori) of 46 ideas as computed by Shah et al. [Shah et al. 2003]. Note that the authors have not used the set of existing ideas (e.g. Set 'e' in Figure) in computing these novelty scores. Figure shows the scatterplot of AN vs. variety for the 14 sets. The Pearson's correlation coefficient between the AN and variety is fairly strong (0.79). This value supports our hypothesis that an increase in the AN of a set of ideas should enhance the variety of that set.

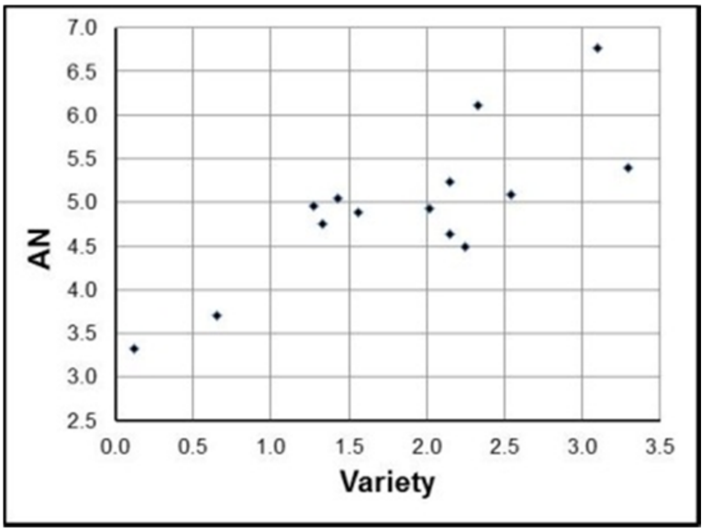

Figure 6. Scatterplot of AN vs. variety - correlation coefficient = 0.79

7. Discussion, conclusions and limitations

In this research, we examined the interdependency between AN/IAN and variety. In this section, we compare the findings of our research with the relevant studies in the reviewed literature. We identified two studies that have checked the correlation between AN and variety. The study of [Kurtoglu et al. 2009] aimed at testing the effects of a computational design tool on concept generation. They carried out laboratory experiments with designers and employed experts to evaluate novelty of each idea and the variety of sets of ideas. In their study, the correlation coefficient between the AN and variety was 0.77. Srinivasan et al.'s [Srinivasan et al. 2010] study mainly aimed at understanding the relationship between the constructs of the SAPPhIRE model of causality (state change, action, parts, phenomenon, input, organs, and effect) and novelty. These seven constructs of the SAPPhIRE model constitute the causal connection between the various levels of abstraction at which a design can be described. The authors used this model to compute variety and novelty. They collected the empirical data through laboratory experiments with designers. In their study, the correlation coefficient between AN and variety was 0.95. The definitions of novelty and variety, used by [Srinivasan et al. 2010], are different from those used by [Shah et al. 2003]. Note that the ideation metrics of [Shah et al. 2003] have been relatively widely used. In our study, the correlation coefficient between AN and variety is 0.79. In addition, we computed the correlation coefficient between IAN and variety (0.84). For a single function and one level, we developed equation (6) to compute IAN of a set of ideas. This equation can be used to compute IAN for a given T and n (number of physical principles) without the need to collect empirical data as we have illustrated through an example (T = 10 and standard deviations of different data sets of the values of C_j). For the correlation between AN and variety, we used the empirical data available in the study of [Shah et al. 2003].

The above discussion shows that the correlation coefficient between AN and variety in our study and the two studies found in the reviewed literature is fairly strong. Note that these studies have used different methods to compute novelty and variety scores (see Table). Furthermore, these studies have computed novelty and variety scores for different functions and levels. This increases our confidence in the interdependency between AN and variety.

Table 2. Studies that have checked the interdependency between AN and variety

	Our research	**[Kurtoglu et al. 2009]**	**[Srinivasan et al. 2010]**
Main aim of the study	To investigate the interdependency between IAN/AN and variety.	To test the effects of a computational design tool on concept generation.	To understand the relationship between the SAPPhIRE model's constructs and novelty.
Method to compute novelty and variety	Method developed by [Shah et al. 2003].	Three experts evaluated novelty and variety.	SAPPhIRE model was used.
Number of levels	One level for IAN, AN, and variety.	The experts holistically evaluated the ideas.	Multiple levels by using the SAPPhIRE model's constructs.
Number of functions	For IAN - one function. For AN - four functions. For variety with IAN - one function. For variety with AN - four functions.	The experts holistically evaluated the ideas.	Multiple functions.
Data collection	Empirical data was not required for IAN and variety as we developed Eq. (6). For AN and variety we used Shah et al.'s [Shah et al. 2003] data.	Laboratory experiments with designers.	Laboratory experiments with designers.
Correlation	Between IAN and AN: **0.84**. Between AN and variety: **0.79**.	Between AN and variety: **0.77**.	Between AN and variety: **0.95**.

The following conclusions are drawn from the research reported in this paper. (1) For a set of ideas (given T and n), the IAN score increases with the decrease in standard deviation of the data set of the values of C_j. (2) For a set of given number of ideas, variety of the set for one level (i.e. level of physical principles) and a single function is proportional to the number of physical principles used. (3) There is interdependency between IAN/AN and variety. (4) Ideation studies that use the metrics AN and variety, need to check the interdependency between these metrics, and accordingly interpret and discuss their findings. Considering the interdependency between AN and variety can help to improve the understanding of ideation in design, and thereby can help to develop tools and methods to enhance ideation effectiveness.

The limitations of this research are as follows. We developed equation (6) to compute IAN of a set of ideas only for one function and one level. This means that we investigated the correlation between IAN and variety only for one function and one level. While we examined the interdependency between AN and variety for four functions, the number of levels was one. Further work involves developing a way to measure IAN of a set of ideas for multiple functions and levels. In addition, we will carry out an ideation study to collect primary empirical data for investigating the interdependency between AN and variety for multiple functions and levels. Furthermore, it would be interesting and worthwhile to examine the interdependency between AN and variety based on the data collected through an empirical research in an industry.

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