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MEASURING AND COMPARING THE EFFECTS OF DESIGN INTERVENTIONS ON IDEATION FLEXIBILITY

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ABSTRACT

This thesis is divided into two studies on ideation in design. The first study measures and compares the effects of design interventions on ideation, and the second compares and contrasts methods for assessing the variety within a group of design ideas. Examining the effects of design interventions is important because design interventions are intended to impact the way engineers and designers ideate. While there have been several studies done to examine the effects of design interventions with small samples and one or two specific metrics, they have been relatively narrow in focus and there has not yet been an overarching comparison to get a wider perspective. This study looks across samples and metrics to see what large-scale effects design interventions have, especially in comparison to one other.

Additionally, variety is an important attribute of design ideas, because it indicates the extent to which the solution space has been explored. There is a greater likelihood of successfully solving a design problem when a more diverse set of ideas is generated in the early stages of design. While there are three popular existing metrics for variety, it has not been established how well they correlate with each other, so it is unknown whether they provide similar assessments of variety. This uncertainty inspired the investigation of the three existing metrics and, eventually, the development of a new variety metric—all of which were compared statistically and qualitatively.

In particular, 966 design ideas collected from 155 engineering students and 104 design ideas collected from 29 engineering students were analyzed for the interventions study and the variety study, respectively. Paired t-tests and correlation analyses were used to investigate relationships between the values of interest. The qualitative differences were also considered

among the variety metrics, along with where they might be used most effectively. In the interventions study, there were paired relationships and correlations found primarily for the teaming intervention that provide insights into how teaming affects ideation flexibility. In the variety study, there were varying levels of statistically significant correlations among the four metrics, indicating that they are dependent. Even so, each metric offers a unique perspective on variety and may be useful in different situations. The interventions study has implications for design education in terms of gathering insights about how design interventions affect students, which can lead to improvements in future design interventions. The variety study has implications for design theory and methodology in terms of having a better understanding how existing variety metrics relate to one another as well as developing a new variety metric with which ideas can be evaluated.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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Chapter 1

Introduction

There are two motivations for the work presented in this thesis. First, to obtain a better idea of the relative effects of three specific design interventions (problem framing, ideation tools, and teaming) on students' performance in terms of the ideation metrics of acceptability, applicability, clarity, effectiveness, implementability, and implicational explicitness. Second, to further the development of metrics by testing and comparing the existing variety metrics alongside a new metric. This research exists at the intersection of engineering design, psychology, and engineering education. Design interventions like those described later in this chapter have the capability of improving the concept generation performance of engineering students and professional engineers alike. Also, the quality of ideation analysis is only as strong as the metrics that provide the numerical data, so it is important for the improvement of ideation research that there are explorations into preexisting and new methods of evaluating ideas. With this in mind, the potential impacts of the research are as wide-reaching as the projects that these individuals or teams undertake. Improving the ideation methods of engineers will lead to better design outcomes, which could include more affordable, ecological, and/or more contextually appropriate solutions to contemporary problems.

This thesis is organized into chapters that explain the various tasks undertaken in this research project. Chapter 1 lays the foundation for the topic of ideation specifically with respect to creativity and cognitive style; the Ideation Flexibility team and their work; and ideation metrics. Chapter 2 covers existing variety metrics and a proposed new metric for measuring variety, setting the groundwork for the variety study. Chapter 3 consists of the research questions for the interventions and variety studies, and Chapters 4 and 5 explain the methods of the two studies, respectively. The results of the interventions and variety studies are presented in Chapters 6 and 7, respectively, and Chapter 8 discusses the implications, limitations, and future work derived from both studies.

1.1 Ideation, Creativity, and Cognitive Style

Ideation is an important part of the engineering design process. The design process always involves the need to define a problem and generate ways in which to solve the problem. A popular perception of this relationship was developed by Maher and Poon [1], who described the co-evolution of a problem space and a solution space. The problem space consists of the formulation and refinement of the problem, and the solution space consists of the set of design ideas generated to address the problem. These spaces are dynamic and evolve together over time. Information is exchanged between the spaces as the design process progresses, leading to both a better understanding of the problem and more appropriate solutions to that problem [2] [3]. As an engineer's solution space expands, he or she has a greater potential of finding a solution that satisfies the current design problem's constraints. If he or she does not fully explore the design space and remains localized near his or her initial set of ideas, the pool of possible solutions to explore later in the design process is limited [4]. In addition to that, having fewer ideas in the early stages of the design process is related to design fixation [5].

To generate ideas is to express creativity. A person's "cognitive style" is his or her preferred way to use his or her creativity in solving problems [6]. People think differently from one another in all aspects of life. However, similarities in patterns of thought allow for classification of different styles of thinking. A popular model of cognitive style is the Kirton Adaption–Innovation (A–I) Theory [7]. In the context of design and A–I Theory, cognitive style relates to the amount of structure the designer prefers to have in ideation [6]. Those who prefer more structure in their ideation are considered to be more “adaptive”, whereas those who tend to eschew structure in ideation are considered to be more “innovative.” [7]. More adaptive thinkers tend to offer incremental design ideas, which typically adhere to existing paradigms and problem definitions through “tried and true” methods of improving or modifying preexisting solutions. As they generate ideas, they remain connected to the given constraints of a design problem and work within those boundaries. More innovative thinkers, on the other hand, prefer to generate more radical ideas that may challenge problem definitions and break paradigms [7] [8] [9] [10]. Neither adaptive nor innovative thinkers are inherently better than the other, but certain types of thinking can be considered beneficial for given circumstances [11].

It is important to note that cognitive style is independent of a person’s knowledge, experience, or skills—i.e., in this context, it is their *ability* to generate solutions to a design problem, which is referred to as “cognitive level” or “cognitive ability” [6]. Cognitive level relates to various measures like intelligence (e.g., IQ score), capability (e.g., relevant experience), and performance (e.g., GPA). Whereas cognitive style indicates how one approaches design, cognitive level indicates how well-equipped one is to successfully face design problems [6]. In this thesis, cognitive level appears in the form of academic standing. Those of higher academic standing (e.g., upperclassmen) in engineering have more experience in design than those of lower academic standing (e.g., underclassmen), so there is a difference in cognitive level between these two groups. Other demographic factors may influence outcomes on ideation as well, and this thesis specifically explores gender, which has been a topic of interest in other design and education studies [12] [13].

It is important to note that cognitive style is a preference, so given sufficient reason, people can be motivated to ideate in ways counter to their cognitive style; this can be referred to as “ideation flexibility” [14]. More generally, this is an example of “coping behavior” [7], which enables an individual to behave in ways that do not align with their cognitive style when the need arises and sufficient motivation is present. The immediate value for an adaptive thinker to generate ideas in an innovative way or vice versa is to broaden their solution space [4]. As mentioned before, it is agreed that a broader solution space at the beginning of a project allows for more opportunity to narrow down to a better final solution than a limited initial solution space [3].

A–I Theory has a corresponding psychometric instrument, the KAI Inventory, which is a research-backed and widely regarded instrument to measure cognitive style [7] [9] [15] [16] [17]. The KAI assesses one’s preference for structure in ideation along a bipolar spectrum from highly adaptive to highly innovative. KAI scores follow a normal distribution in large general populations, with more adaptive individuals having lower scores and more innovative individuals having higher scores [7]. These scores are useful for analyses that aim to find relationships between one’s cognitive style and his or her ideation outcomes. Further details regarding KAI scores will be provided in Chapter 4.

1.2 The Ideation Flexibility Project

The Ideation Flexibility Project involves an NSF-funded multi-university research team that works to develop methods and products that encourage and enhance the ideation flexibility of engineers, students, and designers, which is defined as the ability to ideate in both adaptive and innovative ways depending on the needs of the problem, as opposed to ideating only in accordance with their cognitive style [14]. To meet these goals, the Ideation Flexibility team developed three interventions to use in design contexts: Ideation Teaming, Problem Framing, and Ideation Tools. Figure 1 shows a visual summary of the Ideation Flexibility Project. Using this framework, the team has collected several thousand design ideas from students in sessions in which the participants ideate in their preferred way with no external influences (called "neutral" ideation) and in sessions in which they ideate under the influence of one of the three design interventions.

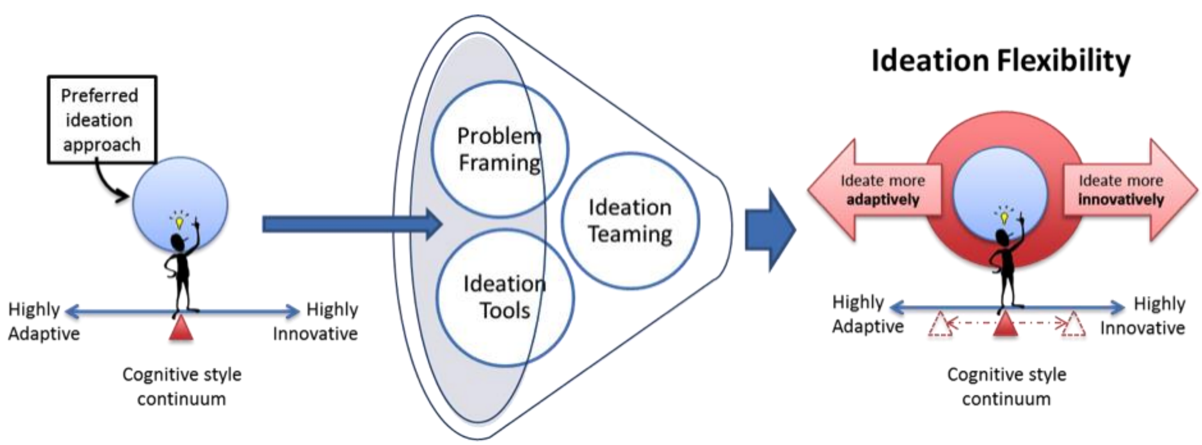

Figure 1: Preferred ideation approach, interventions, and ideation flexibility **[14]**

1.3 Ideation Teaming

The Ideation Teaming intervention involves students working with partners in dyads to generate ideas for a given design problem [14]. Each dyad consists of two students with distinct cognitive styles and preferred ideation approaches. Depending on the degree of difference between the partners' cognitive styles, dyads may experience teamwork very differently [7]. Understanding how teamwork influences the idea generation process is important, because much of professional engineering work is done in teams, so knowing how teams behave and work together is crucial for employers and engineers alike [14] [18]. Perhaps the team members have very similar KAI scores, so they approach ideation in very similar ways and cooperate well, but they do not generate ideas that lie beyond their preferred ideation approach. On the other hand, a team may consist of two people with very different KAI scores, so they approach ideation differently from one another and generate diverse ideas, but they must resolve their interpersonal differences as they work together. Some research suggests that heterogeneous teams with less expertise can outperform homogeneous teams of greater expertise because of the lack of creative diversity [19]. However, if a team that is homogeneous in cognitive style is able to generate diverse ideas despite their preference towards one type of ideation—and thus achieve ideation flexibility—they can perform more strongly as a team. The challenge for teams that are heterogeneous in cognitive style is overcoming their differences in cognitive style as they attempt to generate diverse ideas.

1.4 Problem Framing

In addition to teaming, the way in which problems are presented, or framed, can be integral in the ideation experience. If a problem statement includes biased phrases that correlate to either adaptive or innovative thinking, the designers may be swayed to ideate in different ways than their preferred ideation approach [7]. Thus, the Ideation Flexibility team generated the Problem Framing Profile, which takes a given design problem and restates it in an adaptive and innovative way in order to provoke those types of design ideas [20]. A neutrally framed problem statement provides only the context, need, and goal for the design problem without providing specific criteria or constraints that may bias a designer towards incremental or radical ideas [20]. As one reads the prompt, he or she should not feel encouraged to ideate in any particular way; consequently, he or she is likely to generate solutions consistent with his or her preferred ideation approach [7]. Neutrally framed design problems are useful in analyses because ideas generated from these problems provide the benchmark results for the designer.

However, as noted previously, design prompts can be modified to have inherent biases towards a specific type of ideation. These modifications concentrate on A–I theory and the understanding that adaptive thinkers prefer more structure whereas innovative thinkers prefer less structure [7]. Adaptively framing a design problem encourages incremental design ideas by introducing constraints and criteria that further define structure in the design problem statement. An innovative framing, on the other hand, encourages radical idea generation by introducing criteria and constraints (or freedoms) that lessen the structure of the design problem statement. An example of a design prompt framed in both an adaptive way and an innovative way is shown in Figure 2. The text in the blue background of Figure 2 is consistent with the neutral version of the design problem, and the text highlighted in orange is added to frame the problem. Phrases like "focus on improving existing designs" and "cost-effective and immediately workable" are examples of criteria and constraints, respectively, that encourage designers to generate ideas in an adaptive manner [20]. In contrast, phrases like "focus on creating totally new designs" and "without concern for cost or immediate workability" are examples of the criteria and constraints, respectively, that encourage innovative thinking [20]. In this intervention, flexibility is achieved when adaptive thinkers could successfully generate ideas in more radical manners when given an innovative framing, and when innovative thinkers could successfully generate ideas in more incremental ways when given an adaptive framing.

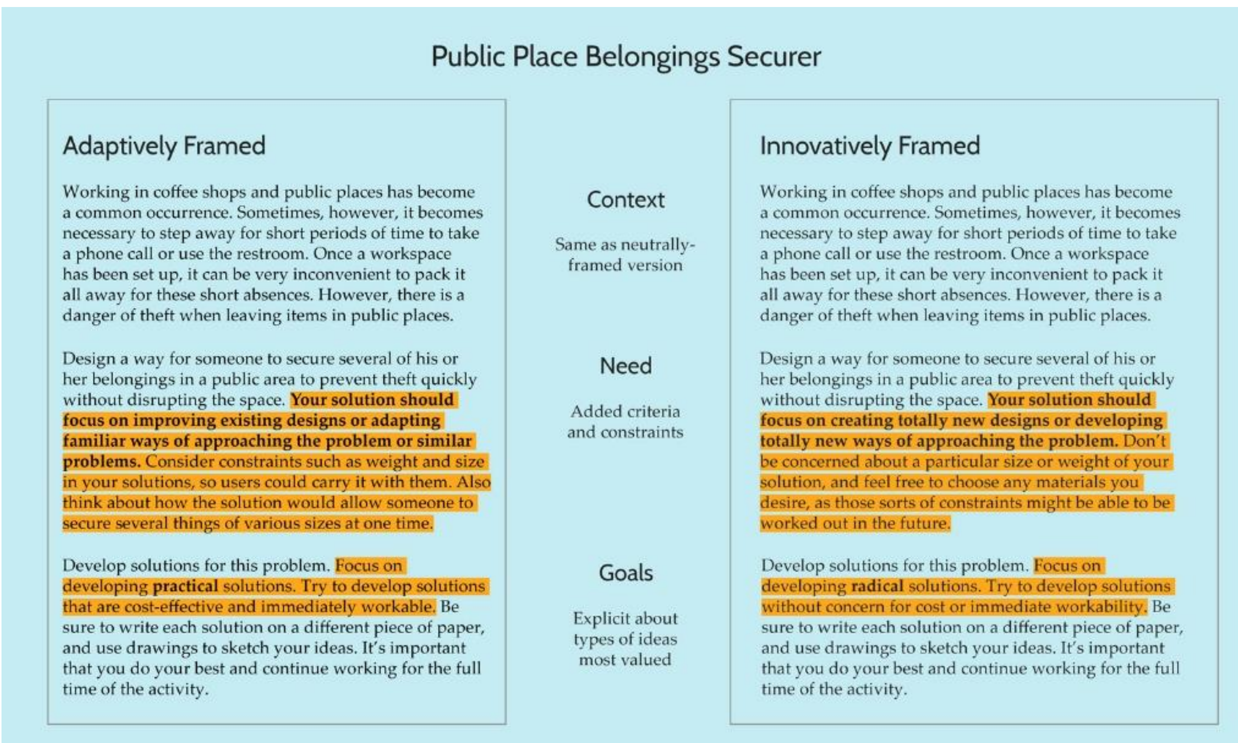

Figure 2: Comparison of adaptively and innovatively framed versions of a design problem **[20]**

1.5 Ideation Tools

In addition to teaming and framing, other tools can be provided to help encourage flexibility in ideation. One such tool is the *77 Cards, Design Heuristics for Inspiring Ideas*, or the "DH cards" for short [21] [22]. The DH cards are the final intervention explored by the Ideation Flexibility team. Each card has a short design heuristic, an explanation of that heuristic, and an abstract example on the front side. The reverse side has two concrete examples of the design heuristic as applied to products. Across all of the DH cards, one of these two concrete examples is implemented in a seating structure, which provides some consistency between cards. The 76th card, "Utilize Opposite Surface", is shown in Figure 3 as an example.

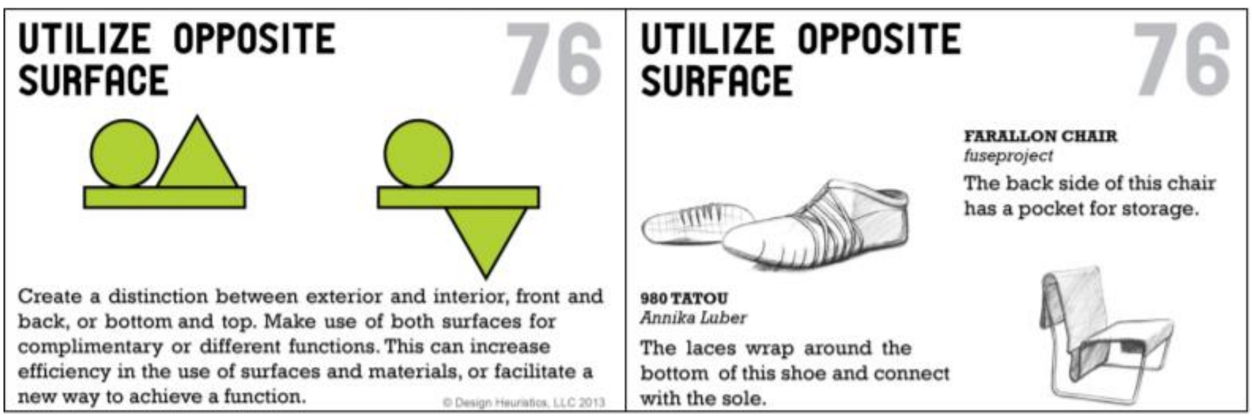

Figure 3: Example of the *77 Cards* ideation tool (front and back of card #76) **[23].**

The DH cards were developed by examining thousands of design concepts and extracting strategies/heuristics often used by product designers [21] [24]. The intention of the DH cards is to affect ideation by providing short design heuristics that may spark new thoughts during ideation. Perhaps a designer applies the heuristic from the DH card to their existing idea, or a DH card might inspire an entirely new idea. The cards can be used in multiple ways, but using a card in any way has the capability of pushing someone's ideation toward a non-preferred approach [21].

1.6 Ideation Metrics

There are many different metrics used to assess various aspects of design concepts in ideation research. Most were proposed by ideation researchers, such as Dean et al. [25], Shah et al. [26], and Besemer et al. [27], who used comprehensive literature reviews to suggest that quality, variety, novelty, and elaboration are important aspects of design solutions. These metrics are needed to provide quantitative assessment of design ideas; subsequently, these quantitative data can be used for statistical and other analyses.

The quality metrics utilized in this study were generated by Dean et al. [25], who, after a comprehensive literature review of existing ideation metrics, created a framework that organizes quality dimensions into categories. This thesis explores three of his categories: relevance, specificity, and workability as shown in Table 1. Dean et al. subdivided the dimensions to create seven independent quality metrics [25]. Each metric measures design ideas on a three- or four-point scale and includes clear anchors for each level of the scale. Six of the seven metrics below were used in this study. The metric for completeness was excluded because of low inter-rater reliability (described further in Chapter 4).

Table 1: Dean et al. quality metrics **[25]**

Dimension	**Sub-dimension**	**Definition**
Relevance	Applicability	The degree to which the idea clearly applies to the stated problem
	Effectiveness	The degree to which the idea will solve the problem
Specificity	Implicational Explicitness	The degree to which there is a clear relationship between the recommended action and the expected outcome
	Completeness	The number of independent subcomponents into which the idea can be decomposed, and the breadth of coverage with regard to who, what, where, when, why, and how
	Clarity	The degree to which the idea is clearly communicated with regard to grammar and word usage
Workability	Acceptability	The degree to which the idea is socially, legally, or politically acceptable
	Implementability	The degree to which the idea can be easily implemented

Tables 2-8 are scoring guides for each of the seven metrics from Dean et al. [25]. These scoring guides are used by raters who evaluate ideas and assign a score to each idea based on the description of each level. The metrics in Table 2 and Table 3, applicability and effectiveness, fall under Dean et al.'s category of "Relevance", which requires an idea to both specifically apply to the design problem and be reasonably expected to solve the design problem [25]. Therefore, an idea that either fails to apply to a problem (applicability) or cannot reasonably be expected to succeed (effectiveness) is not considered to be relevant [25]. A score of 4 in either metric indicates the highest levels of applicability or effectiveness, whereas a score of 1 indicates the lowest level of applicability or effectiveness.

Table 2: Applicability scoring guide **[25]**

Applicability

Score	Level Description
4	Solves an identified problem that is directly related to the stated problem (do X to get Y, and Y is part of the stated problem)
3	Solves an implied problem that is related to the stated problem (do X to get an implied Y, which applies to the stated problem)
2	May have some benefit within a special situation and somehow relates to the stated problem (do X, which somehow relates to the stated problem)
1	Intervention is not stated or does not produce a useful outcome (no X) or (do X for useless Y)

Table 3: Effectiveness scoring guide **[25]**

Effectiveness

Score	Level Description
4	Reasonable and will solve the stated problem without regard for workability (if you could do it, it would solve the main problem)
3	Reasonable and will contribute to the solution of the problem (it helps, but is only a partial solution)
2	Unreasonable or unlikely to solve the problem (it probably will not work)
1	Solves an unrelated problem (it would not work, even if you could do it)

Table 4, Table 5, and Table 6 show the scoring guides for the implicational explicitness, completeness, and clarity metrics. These three metrics compose the dimension of “Specificity”, which requires an idea to be well-developed in both design and description.

Table 4: Implicational explicitness scoring guide **[25]**

Implicational Explicitness

Score	Level Description
3	Implication is clearly stated and makes sense (X → Y)
2	Implication is not generally accepted or vaguely stated (X might → Y, X → Y (vague))
1	Implication is not stated, even though it might be relevant (X w/o Y)

Table 5: Completeness scoring guide **[25]**

Completeness	
Score	**Level Description**
3	Comprehensive, with three or more parts from at least two of the 5 Ws + H (who, what, why, when, where, + how), e.g., (what + when + where) or (what + what + why)
2	Contains two parts from different dimensions (5 Ws + H), such as, but not limited to, (what + where), (what + why), (what + how), or three or more parts of only one of the 5 Ws + H (e.g., what + what + what)
1	Contains one or two parts from the same dimension and usually the "what" (e.g., (what) or (what + what))

Table 6: Clarity scoring guide **[25]**

Clarity	
Score	**Level Description**
3	Well-developed written description or visual representation. The components are clear and commonly understood
2	Understandable but some of the descriptions or drawings might not be commonly understood. Contains fragments or obviously missing components to make the concept clear
1	Written description and drawing are vague/ambiguous. Difficult to understand.

The acceptability and implementability metrics, shown Table 7 and Table 8, respectively, comprise the dimension of "Workability" [25]. Ideas are workable if they are able to be executed easily and do not disregard known constraints or criteria.

Table 7: Acceptability scoring guide **[25]**

Acceptability	
Score	**Level Description**
4	Common strategies that do not violate norms or sensibilities
3	Somewhat uncommon or unusual strategies that do not offend sensibilities
2	Offends sensibilities or totally unaccepted by society
1	Radically violates laws or sensibilities. Totally unacceptable business practice or totally unethical.

Table 8: Implementability scoring guide **[25]**

Implementability	
Score	**Level Description**
4	Low cost. No change to accommodate product
3	Reasonable cost. Some change necessary for product
2	Very expensive. Significant change necessary for product
1	Financially unviable. Unachievable changes need to be made.

1.7 Measuring Ideation Flexibility

All of the metrics in Section 1.6 relate to A–I theory. Since adaptive thinkers and innovative thinkers approach ideation differently, characteristics of their ideas also differ [7]. The quality metrics evaluate the characteristics of ideas, so by extension, innovative thinkers' radical ideas and adaptive thinkers' incremental ideas are assessed differently by the metrics. Therefore, the metric scores reflect the different ways in which people ideate. By examining how and if these metric scores change for each intervention, some amount of ideation flexibility can be measured. If someone's metric scores do not differ between ideating neutrally and ideating with an intervention, it is less likely that they are applying ideation flexibility. However, if someone's metric scores differ between ideating neutrally and ideating with an intervention, it is likely that they are applying ideation flexibility. Different metrics may be more or less effective at showing where there is flexibility in ideation, so while certain metrics may indicate no change from ideating neutrally to ideating with an intervention, there could be other metrics not considered in this study that would show how the ideation shifts.

Chapter 2

Variety Metric Background[1]

With the knowledge gained from the assessment of design ideas, the effectiveness of ideation can be assessed. The research relating to this aspect of the thesis builds on studies of metrics [27] [25] [26] [28] and other previous investigations by Jablokow et al. [29] that explore the effects of cognitive style and design heuristics on ideation variety. In that prior work, the Ideation Flexibility team investigated one cognitive factor (cognitive style) and one cognitive intervention (Design Heuristics cards) and their relationships with students' ideation variety, both actual and perceived. The results showed statistically significant correlations between the students' perceived variety and their variety performance, and between cognitive style and both variety performance and student perceptions [29]. The variety of the students' ideation outcomes was assessed using two metrics developed by Shah et al. [26] and Nelson et al. [28], respectively. Although both of these variety metrics were applied successfully, they were also time-consuming and challenging to use, leading to a consideration of the viability and value of other options.

2.1 Existing Variety Metrics

In the context of design assessment, ideation variety is defined as the extent to which the design ideas in a group differ from each other; it can also be thought of as the "diversity" of one's design solution space. A solution space that is "very diverse" contains ideas that vary greatly from one another [25] [28] [26]. An individual may generate many ideas, but if each idea

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[1] *Author's note: Chapters/Sections 2, 3.2, 5 and 7 are parts of a conference paper I wrote and are a subset of this thesis. That paper was published by the American Society of Mechanical Engineers (ASME) in the proceedings of the International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2017), which took place on August 6-9 in Cleveland, OH.*

is only a slight modification of the others, then the variety of that solution space is low. However, if someone generates ideas that are less similar to each other (more diverse), they have explored a greater amount of the potential solution space. As a start to the research, three existing metrics from the literature were investigated, i.e., the variety metrics of (1) Shah et al. [26], (2) Nelson et al. [28], and (3) Linsey [30].

The first variety metric in this investigation was introduced by Shah et al. [26] and later modified by Nelson et al. [28]. In order to use this metric (in either form), the researcher must create four-level trees that describe the possible physical principles, working principles, embodiments, and details that could arise in a design solution space for a particular design context. Because a researcher might see differences in variety with regard to multiple technical functions occurring simultaneously in a problem context, the design space may be separated into multiple functions that each require their own separate tree [31].

As noted above, Shah et al.'s four levels, ordered from the highest to the lowest levels of abstraction, are: (1) physical principle, (2) working principle, (3) embodiment, and (4) detail [26]. With both Shah's and Nelson's approaches for assessing variety, ideas that differ at the physical principle level are considered to be the "most different" from each other, while ideas that differ at the detail level are considered to be the "most similar". To represent these distinctions, Shah et al. proposed the use of a genealogical tree to calculate variety [26]. Each branch in the tree represents some distinction between ideas. Based on the premise that the different levels should be valued differently, Shah et al. gave branches at the physical principle level a weight of 10, branches at the working principle level a weight of 6, branches at the embodiment level a weight of 3, and branches at the detail level a weight of 1. Nelson et al. proposed a slight modification to this weighting scheme, using the values of 10, 5, 2, and 1, respectively. According to Nelson et al., these weights ensure that “at least two ideas at a lower hierarchical level must be added to equalize the variety gain by adding a single idea at the next higher hierarchical level” [28].

Using Shah et al.’s approach, the overall variety metric for a set of ideas is calculated using the following equation:

$$V = \sum_{j=1}^{m} f_j \sum_{k=1}^{4} \frac{S_k b_k}{N}, \tag{1}$$

where V is the variety score; m is the total number of required functions addressed by the design; f_j is the weight assigned to function j; S_k is the weight for hierarchical level k (weights of 10, 6, 3, and 1 according to Shah et al.) [26]; N is the number of ideas in the set; and b_k is the number of branches at hierarchical level k. An exception for b_k occurs for any hierarchical level with only one branch; in such a case, because having one branch is not adding to variety, b_k is set to 0.

As an example of this variety metric calculation, consider a theoretical genealogical tree for a set of six design ideas, as shown in Figure 4. Using Shah et al.’s method of calculation, the variety score for this set of ideas is computed as follows:

$$V = \frac{(10 \times 3) + (6 \times 3) + (3 \times 3) + (1 \times 2)}{6} = 9.83. \tag{2}$$

To avoid counting the same ideas more than once, Nelson et al. suggested that it is better to assign points based on the number of *differentiations* at each level rather than the number of branches or nodes. He also suggested changing the weightings at each level to 10, 5, 2, and 1, respectively, believing that two differentiations at the working principles level does not represent greater variety than one differentiation at the physical principles level [28]. In this case, the variety metric equation becomes:

$$V = \sum_{j=1}^{m} f_j \left(S_1 (b_1 - 1) + \sum_{k=2}^{4} \frac{S_k \sum_{l=1}^{b_{k-1}} d_l}{N - 1} \right), \tag{3}$$

where the first term inside the parenthesis is the score for differentiation at the physical principle level; d_l is the number of differentiations at node l (one less than the number of branches emanating from node l); and 1 is subtracted from N to preserve the normalization from 0 to 10, since the maximum number of differentiations is one less than the number of ideas. Finally, Nelson et al. also suggested removing the normalization constant ($N - 1$) from the equation, since variety is measured across an entire ideation set, not per idea [28]. Adopting these revisions and revisiting the genealogical tree from Figure 4, the variety metric can be recalculated as follows using Nelson et al.'s approach:

$$V = (10 \times 2) + (5 \times 1) + (2 \times 1) + (1 \times 1) = 28\,. \tag{4}$$

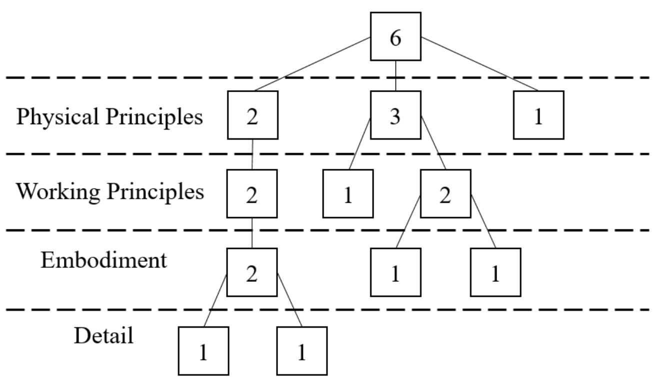


Figure 4: A genealogical tree for a set of six design ideas **[32]**

The second approach (and third metric) was introduced by Linsey et al. [30]; it assesses variety holistically without dividing a design context into functions to create variety trees. Instead, a rater intuitively categorizes ideas based on their general overall differences (assessed "by eye") and sorts ideas with similar features into different "bins". At the completion of this sorting process, an individual's idea variety score is determined by counting the number of bins into which their ideas were sorted and dividing that number by the total number of bins. As an example, for a particular set of ideas, say that a rater divides the set into ten different bins. A designer may have generated four ideas, and two were placed into unique bins, while the other two were placed in the same third bin. Thus, this designer "explored" three out of the ten bins, and their Linsey variety score would be 3/10 or 0.30.

2.2 Brief Comparison of Existing Variety Metrics

The three existing metrics described previously provide different perspectives for assessing variety, and each has its own benefits and challenges. Shah et al. [26] and Nelson et al. [28] approach every design context hierarchically, essentially breaking down a particular problem into all the ideas designers have generated, resulting in a variety tree built from data. In that sense, theirs is a top-down, deductive approach. On the other hand, Linsey et al. [30] takes a bottom-up, inductive approach; raters look for patterns and similarities in a set of design ideas and organize them into bins based on their observable features.

These three metrics also differ in the amount of time and effort they take to apply, and in the general amount of rigor they employ, with tradeoffs between the two. Shah's and Nelson's variety metrics, for example, are very rigorous, but they require considerable time and effort to construct the variety trees. In contrast, Linsey's variety metric requires much less time and effort to use, but it is also very subjective and relies more on intuition than quantitative reasoning. Considering these trade-offs, there is an opportunity to develop a new metric for assessing variety that retains some of the rigor that makes Shah et al. and Nelson et al. so appealing, while benefiting from a more direct quantitative approach, similar to Linsey.

Conceptually, these metrics differ as well. Shah and Nelson break down a design with respect to aspects of its functionality. Specifically, a variety tree breaks one function into the physical principles, working principles, embodiments, and details of the designs. Appendix A displays the variety trees constructed from the data in this experiment. This approach to interpreting variety is tied directly to the function of designs, i.e., a designer's variety score reflects how functionally different their ideas are from each other. The variety metric described by Linsey is not directly tied to functionality, but is based more holistically on overall differences between design ideas (which may or may not include functionality). In essence, Linsey's approach could capture a broader set of features than Shah or Nelson; however, a Linsey variety score may also sacrifice resolution in favor of inclusiveness.

2.3 A Proposed New Metric for Variety

The proposed metric for measuring variety leverages other metrics used to assess design ideas for attributes that contribute to the variety of the solutions, such as quality, elaboration, and paradigm relatedness [25]. This new metric calculates variety by looking at how a collection of ideas covers a potential design space based on the diversity of the other metrics used to assess those ideas. For instance, an idea that has been assessed using *n* metrics can be mapped as a point in an *n*-dimensional design space. The dimensions of this design space are the metrics themselves (e.g., quality, effectiveness, novelty, applicability, etc.). Different sets of ideas can be said to have more or less variety depending on how "far apart" they are (i.e., how diverse they are) within this *n*-dimensional design space. Imagining the situation in three dimensions, if one were to calculate the three-dimensional distances between ideas, idea sets with greater distances between the ideas would have more variety compared to collections with smaller distances among them.

The proposed metric assesses variety systematically based on “distances” within sets of ideas using a centroid approach, as summarized in Table 9. Users first decide which metrics to use (e.g., quality, novelty, etc.) and construct a design space that incorporates those metrics as dimensions. All ideas are assessed using those metrics. Each participant’s set of ideas is then mapped to the appropriate coordinates in the design space, and the coordinates of the centroid of the set of ideas are calculated. The “distances” between each idea and the centroid of the set are computed, and the mean distance and standard deviation among the distances are used to represent variety.

Table 9: Steps for proposed metric **[32]**

Step 1	Decide how many and which metrics to use
Step 2	Create an n-dimensional design space, where n is the number of metrics
Step 3	Select a collection of ideas: $\{W_1, W_2, \dots, W_m\}$ where m is the number of ideas in the collection and where $W_i \subseteq R^n$ is a vector representing the coordinates of the i^{th} idea with regard to the design space
Step 4	Determine the coordinates of W_i for all ideas
Step 5	Calculate the coordinates of the centroid $P \subseteq R^n$ as: $$P = \frac{W_1 + W_2 + \dots + W_{m-1} + W_m}{m}$$
Step 6	Calculate the Euclidean distance, D_i between each idea, W_i, and the centroid, P, as: $$D_i = \left(\sum_{j=1}^{m} \left| W_j - p_j \right|^2 \right)^{1/2}$$ where $W = (W_1, W_2, \dots, W_M)$ and $p = (p_1, p_2, \dots, p_M)$
Step 7	Calculate proposed variety as a mean of distances, V_M, and a standard deviation of the distances, V_{SD}: $$V_M = \frac{D_1 + D_2 + \dots + D_{m-1} + D_m}{m}$$ $$V_{SD} = \left(\frac{1}{m} \sum_{i=1}^{m} \left| D_i - V_M \right|^2 \right)^{1/2}$$

V_M and V_{SD} provide a rough estimation of the variety associated with a collection of ideas. For a collection of ideas to have high variety, the distances among those ideas (on average) should be high. V_M captures this aspect; however, many different distributions of ideas could yield similar results for V_M. For instance, in a two-dimensional space, one collection of ideas might have a single, radially symmetrical cluster, whereas another collection might consist of two or more clusters. Even though these collections appear radically different “by eye”, their variety as measured by V_M might be equivalent. V_{SD} adds a measure of the deviations among the distances between ideas, so these collections can be differentiated in their coverage of the design space.

In this study, the proposed new metric for variety was explored using a set of six existing quality metrics from Dean, et al. [25], which were described previously in Chapter 1. Conceptually, the new variety metric is based on differences in design concept characteristics as derived from the aforementioned quality metrics. This differs from the Shah and Nelson variety metrics (based on functions) and Linsey (based on general differences), and paints a slightly different picture of variety. It is proposed that this new characteristics-based variety score will have greater resolution but a tighter scope than a Linsey variety score, and differ in focus from the function-based Shah and Nelson variety scores. In addition, the new metric generates two scores, V_M and V_{SD}, which capture both the average difference to the centroid and the spread of those average differences, respectively.

With the backgrounds established for both the interventions and variety study, the next step is to determine what questions should guide the remainder of the research. The next chapter establishes the research questions as well as the reasoning behind asking those questions.

Chapter 3

Research Questions

This chapter defines the research questions that guide the remainder of the thesis. The research questions are separated according to the two main studies of this thesis: design interventions and variety metrics.

3.1 Design Interventions Research Questions

To determine the main effects of the ideation teaming, problem framing, and ideation tools interventions on ideation flexibility, the following question is considered:

- How do the characteristics of a student's ideas (as reflected in the ideas' metric scores) differ between a neutral session (i.e., no intervention) and an intervention session (i.e., using ideation teaming, problem framing, or ideation tools?)

Overall, this question tells us if an intervention affects ideation flexibility (reflected in the ideas' metric scores) compared to neutral ideation. The importance of metrics to ideation flexibility was established previously in Sections 1.6 and 1.7. This question focuses on all students in general to see if the interventions impact their ideation flexibility.

To determine if the effects of the three interventions are different depending on the cognitive style of the individual—i.e., if cognitive style moderates the general results—the population is divided based on cognitive style. Specifically, the full sample is divided into three sub-groups: (1) those on the adaptive side of the cognitive style spectrum; (2) those in the middle of the spectrum; and (3) those on the innovative side of the spectrum [7]. The following question guides the analysis for the cognitive style subgroups:

- How do the characteristics of a student's ideas (as reflected in the ideas' metric scores) differ between a neutral session and an intervention session (ideation teaming, problem framing, or ideation tools) for students with a particular cognitive style (adaptive, mid-range, or innovative)?

This question shows whether the specific cognitive style subgroups are affected differently by the three interventions than the population in general.

Similar to the cognitive style research question, it is important to see whether the interventions impact different genders in different ways compared to the general population. To do this, the population is split based on gender, and the goal is to see how the gender groups' ideation flexibility (via their metric scores) is affected by interventions. The following research question guides the analysis:

- How do the characteristics of a student's ideas (as reflected in the ideas' metric scores) differ between a neutral session and an intervention session (ideation teaming, problem framing, or ideation tools) for students of different genders?

This question determines whether the three interventions affected scores for the individuals of the gender. Subsequently, this informs whether or not the interventions differently affect the general population and the genders.

Mirroring the research questions for gender and cognitive style, the academic standing research question splits the population based on the academic standing of the students at the time of participating in the study. Academic standing is a form of cognitive level. While cognitive level is independent of cognitive style, it still may contribute to the characteristics of design ideas, so we frame the question:

- How do the characteristics of a student's ideas (as reflected in the ideas' metric scores) differ between a neutral session and an intervention session (ideation teaming, problem framing, or ideation tools) for students of different academic standing?

The question determines if the interventions impact the ideation flexibility of people of different academic standings differently than the general population.

3.2 Variety Metrics Study Research Questions

The primary focus of the variety study is to analyze existing metrics for assessing the variety of design ideas (Shah et al. [26], Nelson et al. [28], and Linsey et al. [30]) in comparison with each other and a new metric (uses the geometric centroid method). Each metric is investigated by assessing a small sample of ideas generated by engineering students. The variety study is guided by the following research questions:

1. How are existing metrics for assessing variety correlated?
2. How does the new metric correlate with existing metrics?
3. How do the different methods for assessing variety compare qualitatively in terms of benefits and ease of use?

With the research questions established for both studies, the next step is to determine the means of testing those questions. Chapters 4 and 5 describe the methods of the interventions and variety studies, respectively.

Chapter 4

Methods of the Interventions Study

The design concepts used in the interventions study were collected from 155 undergraduate students in engineering from the Pennsylvania State University and Iowa State University. Of these students, 16 were female and 139 were male. Most (122) of the students were sophomores, 26 were first-year students, and 4 were juniors at their respective institutions. All of the sophomore and junior students were from Iowa State University in either a sophomore-level mechanical engineering class or a junior-level industrial design studio class, respectively. The first-year students were from Penn State in a first-year introduction to engineering design course.

4.1 Ideation Sessions

The timeline of a typical session in the intervention study is shown in Figure 5. After being introduced to the study, students completed the KAI inventory to determine their cognitive style. Then, they generated ideas for 20 minutes in a neutral session. Students were asked to generate as many design ideas as possible and to record each idea on a separate sheet of paper using sketches and written descriptions. Following a short break, they received a new design problem and generated ideas for 20 more minutes with one of the three interventions.

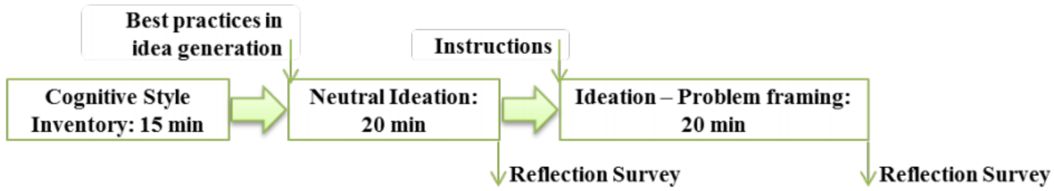


Figure 5: Example flow of an Ideation Flexibility study **[14]**

The teaming intervention involved students working together in dyads to generate ideas. Of the 155 students, 87 of them completed the teaming intervention. In the framing intervention, students were randomly assigned either the adaptive or innovative problem framing [14]. Another 44 students completed the framing intervention. For the ideation tools interventions, students were given the same ten DH Cards to use as they ideate [14]. The final 21 students used the design tools intervention. The neutral sessions can be treated as a benchmark, in which each person's natural preferred ideation approach is used, and the intervention sessions can be treated as experimental groups, in which an intervention's influence can be evaluated.

4.2 Evaluation of Design Ideas and Analysis Methods

Six out of the seven ideation metrics from Dean et al. that were introduced in Section 1.6 were used in this study. The completeness metric was excluded from the study due to poor inter-rater reliability in its assessment. In total, the 155 students generated 966 ideas in both neutral and intervention sessions. The metric raters were undergraduate and graduate engineering students who had taken project-based engineering design courses prior to this study; they were paired to establish reliability. Raters first familiarized themselves with the problem contexts and the quality metrics. In order to demonstrate strong inter-rater reliability for a given variety metric, raters evaluated a preliminary set of 50 design ideas independently. These ideas were not used as data in this study. After raters completed this initial assessment, they compared their results for inter-rater reliability using Cronbach alpha scores. If the Cronbach alpha score was greater than 0.7, then reliability was considered sufficient; otherwise, raters determined discrepancies and tried again with a new set of 50 design ideas. This method for demonstrating reliability was first implemented by Teerlink [33]. The evaluated ideas were combined so that each student had an average score for each metric in both their neutral session and their intervention session. These values were used in Minitab to run t-tests and Pearson correlation analyses.

4.3 KAI Statistics and Generating Samples

The average (mean) KAI score for the general population (across cultures) is 95 (± 0.5) with a standard deviation of approximately 17 points. Even though the theoretical range is broader (32 to 160), the observed range is 45 points to 145 points. Two thirds of all people fall between the scores of 78 and 112, and the vast majority (95%) fall between 61 and 129 [7].

For this study, the more adaptive, mid-range, and more innovative samples were determined by considering the only the students with a reliable KAI (95 out of 155 total students) score and then finding the mean and standard deviation of KAI scores. The mean was found to be 91.5 and the standard deviation was 14.4. In order to get subgroups that captured those who are more adaptive, more innovative, and mid-range while avoiding small ($N < 20$) sample sizes, the groups were separated based on the mean plus or minus one half of the standard deviation. Therefore, those with a KAI score of 98.7 or above were considered to be more innovative ($N = 28$). Those with a KAI score of 84.4 or below were considered to be more adaptive

(*N* = 28). Those that fall between those values are considered to be mid-range (*N* = 39). Both paired t-tests and Pearson correlations were conducted to answer the cognitive style research questions.

In terms of the gender-oriented research question, the original sample was simply split into two samples: those who are male and those who are female, and only paired t-tests were conducted, as Pearson correlations would require gender to be a quantitative value. The same applies for the academic standing research question. The samples were formed by combining the sophomore undergraduate students into one group and the first-year undergraduate students into another group.

Chapter 5

Methods of the Variety Metric Study

The design concepts used in the variety metric study were collected from 29 sophomore undergraduate students in mechanical engineering from Iowa State University. Compared to the sample used in the interventions study, this sample contains ideas generated only in neutral sessions with the same design problem statement. Controlling the sample in this way ensures that the different variety metrics can be fairly compared to one another. Students were given 20 minutes to generate solutions for the design prompt shown in Figure 6. In total, the 29 participants generated 104 concepts for the given prompt, with a range of 2 to 6 concepts and an average of 3.59 concepts per participant.

Today, skis and snowboards are widely used as personal transportation tools on snow. To be able to use them, however, a lot of skill and experience are required that a user cannot normally learn within one day. Moreover, skis and snowboards cannot run uphill easily. It would be better if there were other options of personal tools for transportation on snow, which still allowed the user to control direction and braking, but did not require much time to learn how to use. Design a way for individuals without lots of skill and experience skiing or snowboarding to transport themselves on snow. Develop solutions for this problem. Be sure to write each solution on a different piece of paper, and use drawings to sketch your ideas. It is important that you do your best and continue working for the full time of the activity.

Figure 6: Prompt for design ideation activity **[32]**

After the participants' names were removed from the data, raters were trained to use all four variety metrics (Shah, Nelson, Linsey, and new metric). The raters then assessed the 104 ideas generated by the students. To apply the variety metrics of Nelson et al. and Shah et al., three functions were defined, as shown in Table 10; the functions were weighted equally. Each function's corresponding variety tree is shown in Appendix A.

Table 10: Shah/Nelson function descriptions and weighting **[32]**

Function Name	Function Description	Function Weighting
1. Contain User	How does the user fit into the device? How does the device fit onto the user?	0.33
2. Operate Control	How does the user control the device?	0.33
3. Transport User	How do the user and the device move?	0.33

To apply the Linsey metric, two raters independently separated the full set of 104 design concepts into 17 and 22 bins, respectively. Participants' Linsey variety scores were determined by dividing the number of unique bins in which an individual's design concepts appeared by the total number of bins. To apply the proposed new metric, ideas were evaluated with 6 quality metrics (Table 1, excluding completeness) and used in the algorithm outlined in Table 9 to find the centroid of all the ideas, the average distance from the centroid (V_M), and the standard deviation of the distances (V_{SD}).

5.1 A Sample Set of Ideas and Variety Scores

Variety results for an example set of three ideas are shown in Table 11 and Table 12. Idea 1 introduces retractable spikes to traditional skis; the position of the boot controls whether or not the spikes are protruding. Idea 2 adds a motorized track to the back of a traditional ski, and Idea 3 is a snowmobile modified to be lighter, more stable, and easier to operate. In Table 11, the function values or addresses used in applying the variety trees for Shah and Nelson are provided for each idea, as well as values for the 6 quality metrics. In Table 12, short-hand summaries of the variety calculations are shown for all the metrics explored in this study (Nelson et al., Shah et al., Linsey et al., and the proposed new metric).

Table 11: Example idea set with functions and quality metrics **[32]**

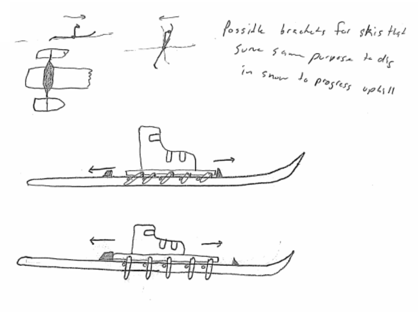
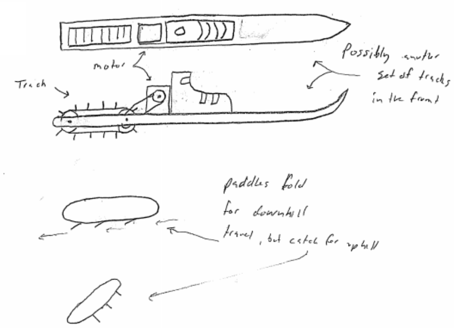
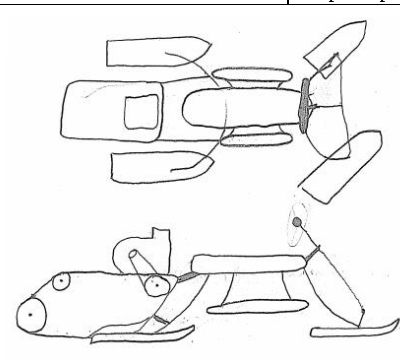
Idea 1  	
Function Values: Contain User = 10 (feet) Operate Control = 8 (legs) Transport User = 1 (skis)	Effectiveness = 2 Applicability = 4 Implementability = 4 Acceptability= 4 Clarity = 2 Imp. Explicitness = 2
Idea 2  	
Function Values: Contain User = 10 (feet) Operate Control = 8 (legs) Transport User = 9 (treads)	Effectiveness = 3 Applicability = 4 Implementability = 3 Acceptability= 4 Clarity = 2 Imp. Explicitness = 3
Idea 3 	
Function Values: Contain User = 3 (relaxed seat) Operate Control = 5 (steering wheel) Transport User = 9 (treads)	Effectiveness = 4 Applicability = 4 Implementability = 3 Acceptability= 1 Clarity = 2 Imp. Explicitness = 2

Table 12: Variety metric comparison for example idea set **[32]**

Shah Variety and Nelson Variety Calculations	Shah Function 1 = 7.3 Shah Function 2 = 7.3 Shah Function 3 = 7.3 *Shah Overall = 5* Nelson Function 1 = 5.5 Nelson Function 2 = 5.5 Nelson Function 3 = 5.5 *Nelson Overall = 5*
Linsey Variety Calculations	Rater 1 # of Bins Used = 3 Rater 2 # of Bins Used= 3 Rater 1 # of Total Bins = 17 Rater 2 # of Total Bins = 22 Linsey Rater 1 = 3/17 = 17.6% Linsey Rater 2 = 3/22 = 13.6% *Linsey Overall = 15.6%*
Proposed Metric Calculations	# of Dimensions = 6 Idea Coordinates (quality metrics): {2,4,4,4,2,2} {3,4,3,4,2,3} {4,4,3,1,2,2} Centroid Coordinates: {3,4,3.33, 3, 2, 2.33} V_M *(Mean Distance): 0.91* V_{SD} *(Std. Dev.): 0.20*

In Table 12, the Shah and Nelson variety metrics are computed using the function values shown in Table 11 and Equations (1) and (3); the intermediate values for each of the three functions are shown for both metrics for illustration, in addition to each overall variety score. For the Linsey approach, Table 12 shows the number of bins into which each rater placed the three example ideas, as well as the total number of bins each rater identified for the full idea set (104 ideas). The overall Linsey variety metric is the average of the metric values for the two raters. Finally, for the proposed new metric, the idea coordinates are composed of the quality metrics shown in Table 1; these values were used in the equations shown in Table 9 to find the centroid of the example idea set, the average distance from each idea to the centroid, and the standard deviation among those distances.

5.2 Analysis Methods

The four variety metrics were compared quantitatively using descriptive statistics and Pearson's correlations. The variety metrics and idea count (quantity) were compared at the participant level, in which the focus was on each participant's *set of ideas*. For the Shah and Nelson metrics, two forms were explored: *Form 1*: the original versions of the metrics as shown in Equations (1) and (3), respectively, in which the values are scaled through division by N for Shah and ($N - 1$) for Nelson; and *Form 2*: non-normalized versions, in which this scaling is omitted. These two forms will be called F1 and F2 in the following sections. In addition to these quantitative comparisons, all four metrics were also compared qualitatively with respect to their complexity, ease of use, and suitability for different situations.

Statistical analyses were carried out using Minitab. Only statistically significant correlations ($p < 0.05$) are reported here. When comparing descriptive statistics, the values were scaled to a range of 0 to 1 using unity/feature scaling, as described here: if X is a set of variety scores, and Y is a set mapped from X using feature scaling, then when $X \rightarrow Y$, $\forall\, x \in X\ \exists\, y \in Y$, such that:

$$y = \frac{x - \min(Y)}{\max(Y) - \min(Y)} \tag{4}$$

Because of each metric having a different scale for its score, using unity scaling allows for the descriptive statistics to be easily compared. The methods described in this and the previous chapter generated the results reported in Chapters 6 and 7 for the interventions study and the variety study, respectively.

Chapter 6

Interventions Study Findings

The research questions regarding the three interventions (ideation teaming, problem framing, and ideation tools) study were tested using paired t-tests and Pearson correlations. This chapter is organized into four sections, each relating to one of the research questions from Section 3.1: first is the main effects of the interventions on the characteristics of student ideas; second, the effects of the interventions on the characteristics of student ideas for students of different cognitive styles; third, the effects of the interventions on the characteristics of student ideas for students of different genders; and fourth, the effects of the three interventions on ideation flexibility for students of different academic standings.

6.1 Main Effect Findings

There was only one statistically significant difference found as a main effect of an intervention on the characteristics of a student's ideas. As shown in Table 13, the t-test *p*-value of 0.006 and the mean score for each sample indicate that the average implicational explicitness score in the neutral session is higher than the average implicational explicitness score in the teaming intervention session. As a reminder, implicational explicitness is "the degree to which there is a clear relationship between the recommended action and the expected outcome" [25]. This result indicates that an individual's design ideas generated in a teaming session lose some of the connection between what the ideas entail and how they satisfy the given task. In other words, a logical flow is lacking between the features of an idea and how it solves the problem. Implicational explicitness is measured on a scale from 1 to 3 (Table 4 in Section 1.6), and the mean values from Table 13 for the neutral session and teaming session are 2.042 and 1.835, respectively. This decrease, while significant, is not such a large difference to cause alarm, nor is it an indication of the teaming intervention making ideas "worse" by decreasing their implicational explicitness. Rather, as described in Section 1.7, the characteristics of ideas (as measured by metrics like implicational explicitness) relate to A–I theory and the way people approach design problems. This result is a sign of ideation flexibility being prominent throughout the general sample.

Table 13: Paired t-test for teaming's main effect on implicational explicitness

Implicational Explicitness		
Sample	***N***	**Mean**
Neutral	87	2.042
Teaming	87	1.835
$^*\mu$_difference: mean of (Neutral − Teaming)		
T-Value		*P*-Value
2.83		0.006

Neither the ideation tools nor the problem framing interventions were found to create a significant difference in the characteristics of the ideas. This suggests that, on the scale of a general sample, the variations in the characteristics of design ideas do not follow a particular pattern, and the students do not apply ideation flexibility in a significant way during the ideation tools or problem framing sessions with respect to the metrics considered in this study.

6.2 Cognitive Style Findings

For the teaming intervention, additional statistically significant differences appeared in the data when the general sample was divided by cognitive style into smaller samples. Table 14 shows that, for more adaptive students, both clarity and implicational explicitness scores decreased with the teaming intervention. Clarity and implicational explicitness are both sub-dimensions of specificity, as defined by Dean et al. [25]. Compared to the main effect of teaming on idea characteristics, this result for the more adaptive thinkers shows some similarities and differences. First, implicational explicitness is again higher in the neutral session than in the teaming session. However, the size of the difference is larger when only the more adaptive thinkers are considered. Unlike the general sample, the more adaptive thinkers also lose some clarity in their design ideas from the teaming intervention.

Table 14: Paired t-test for teaming's effect on adaptive students' implicational explicitness and clarity

Implicational Explicitness				**Clarity**	
Sample	***N***	**Mean**		**Mean**	
Neutral	20	2.205		2.586	
Teaming	20	1.864		2.333	
**μ_difference: mean of (Neutral − Teaming)*					
T-Value			*P*-Value	T-Value	*P*-Value
2.23			0.038	2.34	0.031

The mid-range cognitive style students displayed a decrease in implicational explicitness scores in Table 15, which again matches the results from the general sample. Intuitively, it makes sense that the effect on the general sample was smaller (from 2.042 to 1.835) than the effects on the more adaptive thinkers (from 2.205 to 1.864) and the mid-range thinkers (from 2.122 to 1.761). The general sample included the more innovative thinkers, and because they showed no statistically significant difference in their implicational explicitness scores, and their results effectually dilute the differences established within the more adaptive and mid-range groups.

Table 15: Paired t-test for teaming's effect on mid-range student's implicational explicitness

Implicational Explicitness		
Sample	***N***	**Mean**
Neutral	22	2.122
Teaming	22	1.761
**μ_difference: mean of (Neutral - Teaming)*		
T-Value		P-Value
2.41		0.025

Another result in the teaming intervention that reinforced the results from the previous tests is a correlation between KAI and metric scores. Table 16 shows that there was a weak negative correlation between KAI and the clarity and implicational explicitness scores for ideas generated during a teaming session. While not a strong correlation, this has consistency with the results in Table 14. More adaptive thinkers—i.e. those with a lower KAI score—tend to have ideas with higher scores for clarity and implicational explicitness, even when their ideas' scores for those metrics decrease from a neutral session to the teaming session.

Table 16: Correlations for metrics and KAI in teaming

Metric	Pearson correlation and P-value
Clarity	−0.343 0.001
Implicational Explicitness	−0.286 0.005

With these results, it can be concluded that the teaming intervention affects the ideas generated by the more adaptive and mid-range thinkers in similar (though not identical) ways and yet does not affect the ideas generated by the more innovative thinkers in any significant way. Perhaps, when paired with a partner and ideation in a dyad, adaptive and mid-range thinkers were more willing to ideate like a more innovative partner than a more innovative thinker was willing to ideate like an adaptive partner.

The only significant relationship in terms of cognitive style arising from the framing intervention was a weak positive correlation between KAI and the scores of the implementability and implicational explicitness metrics. Table 17 shows this relationship. More innovative thinkers—i.e. those with a higher KAI score—tend to have their ideas scored higher in implementability and implicational explicitness than their more adaptive counterparts.

Table 17: Correlations for metrics and KAI in framing

Metric	Pearson correlation and P-value
Implementability	0.386 0.047
Implicational Explicitness	0.404 0.037

The Ideation Tools Intervention did not show any significant relationships to the characteristics of the ideas, but it is important to note the small sample sizes (All $N < 10$ for more adaptive, mid-range, and more innovative cognitive styles).

6.3 Gender Findings

For the teaming intervention, males were found to have a statistically significant difference in their ideas' implicational explicitness scores. This result, shown in Table 18, mirrors the main effect from Section 6.1. Since males composed such a large percentage of the general sample (approximately 90%), it is not unanticipated to see this result mirroring the main effect. Only around 10% of participants in the sample (16 out of 155) were female; with so few students, the lack of statistically significant differences for females is also to be expected.

Table 18: Implicational explicitness for males in teaming

Implicational Explicitness		
Sample	***N***	**Mean**
Neutral	76	2.006
Teaming	76	1.819
**μ_difference: mean of (Neutral - Teaming)*		
T-Value		P-Value
3.08		0.003

6.4 Academic Standing Findings

Finally, for the samples separated by academic standing, the teaming intervention once again provided statistically significant differences. For first-year students, Table 19 displays how their ideas' implicational explicitness scores decreased from their neutral session to their teaming session in accordance with the main effect from Section 6.1.

Table 19: Implicational explicitness for first-year students in teaming

Implicational Explicitness		
Sample	***N***	**Mean**
Neutral	26	2.233
Teaming	26	1.920
**μ_difference: mean of (Neutral - Teaming)*		
T-Value		P-Value
2.13		0.043

However, a new difference appeared for sophomore students. Table 20 displays how the ideas' effectiveness scores increased from the neutral session to the teaming session. As a reminder, effectiveness, as defined by Dean et al. [25] is "the degree to which the idea will solve the problem." This result was unexpected in two ways: (1) it did not follow the main effect, which only showed an indication that ideas' implicational explicitness scores changed from the neutral to the teaming session, and (2) it suggested that a higher cognitive level (as represented by an higher academic standing) leads to ideation that produces more effective design ideas.

Sophomore engineering student dyads led to characteristics in the design ideas that differed from their first-year counterparts. First-year students' relative lack of engineering experience might have precluded them from producing ideas in dyads that were more effective than their individual ideas. On the other hand, when sophomore students worked in dyads, the pairs generated ideas that were significantly more effective than their individual ideas.

Table 20: Effectiveness for sophomores in teaming

Effectiveness		
Sample	***N***	**Mean**
Neutral	60	2.949
Teaming	60	3.200
**μ_difference: mean of (Neutral - Teaming)*		
T-Value		P-Value
−2.63		0.011

With the results presented in this chapter, several implications can be drawn from the intervention study. Those appear in Chapter 8 alongside the implications of the variety study, whose results are discussed in Chapter 7.

Chapter 7

Variety Metric Study Findings

The research questions for the variety study were tested using Pearson correlations, descriptive statistics, and qualitative analysis. The goals in this study were to compare the existing variety metrics with each other and with the new proposed metric, both quantitatively and qualitatively—as framed through three research questions. This chapter is organized around those research questions.

Table 21 shows descriptive statistics for the four variety metrics in their original and unity-scaled forms, respectively, as well as quantity of ideas. From these results, it is seen that all four metrics exhibit wide ranges of values based on the relevant scale. In comparing descriptive statistics for the unity-scaled metrics, it is noteworthy that the means of the non-normalized (F2) forms of Shah and Nelson are almost identical, with greater differences exhibited between the normalized (F1) forms. Across the unity-scaled metrics, the standard deviations appear to be quite similar, while the medians differ more significantly. In general, however, all of the variety metrics explored in this study appear to have good discriminatory value.

Table 21: Descriptive statistics – variety and quantity **[32]**

Metric	Mean	SD	Unity Mean	Unity SD
Nelson (F1)	5.26	1.91	0.414	0.236
Shah (F1)	7.34	2.03	0.787	0.294
Nelson (F2)	18.0	7.26	0.418	0.240
Shah (F2)	27.0	13.8	0.417	0.285
V_M	1.04	0.389	0.650	0.243
V_{SD}	0.265	0.214	0.339	0.275
Linsey	15.4	5.77	0.490	0.277
Quantity	3.59	1.40	0.397	0.350

Table 22 shows the Pearson correlations computed among all of the variety metrics (including both the F1 and F2 forms of Shah and Nelson). These correlation results show strong relationships among several of the variety metrics examined in this study, which will be discussed further below. In addition, Linsey and the non-normalized (F2) forms of Shah and Nelson were all moderately to strongly correlated with quantity, as was the new proposed metric (both V_M and V_{SD}). Intuitively, it makes sense for a variety metric to be correlated with quantity, since the more ideas one generates, the greater the chances are that a greater portion of the solution space will be "covered" by those ideas—i.e., the greater the variety of one's idea set can be. Note that the normalized (F1) forms of Shah and Nelson's variety metrics were not correlated with quantity, as would be expected.

Table 22: Correlations between variety metrics and quantity **[32]**

Metric	Correlated Metrics	*R* Coefficient
Quantity	Nelson (F2)	0.676
	Shah (F2)	0.881
	V_M	0.592
	V_{SD}	0.692
	Linsey	0.781

All correlations: $p < .001$

As noted earlier in this thesis, the existing variety metrics of Shah, Nelson, and Linsey differ in the amount of time and effort they take to apply, the general amount of quantitative rigor they employ, and the degree of subjectivity involved. Shah's and Nelson's variety metrics (both F1 and F2) are detailed and dig deeply into the functional nature of design solutions, but they require a substantial investment of time and effort to apply in the construction of the associated variety trees. In contrast, Linsey's variety metric is more intuitively obvious and can be less time-consuming (if the data set is not too large), but it is also more subjective and open to variations in interpretation when raters define idea bins and place design solutions in those bins.

Such trade-offs in ease of use and general conceptual approach inspired us to consider the new metric for assessing variety based on a geometric interpretation of the design solution space that would be both quantitatively rigorous and intuitively appealing.

7.1 Correlations between Existing Metrics

Based on the correlations and descriptive statistics, the results indicate moderate to strong relationships among the existing variety measures examined in this study. As shown in Table 23, the Shah and Nelson variety metrics correlate strongly with each other (R>0.7), particularly between their non-normalized (F2) forms. In addition, Linsey's variety metric correlates moderately to strongly with all but one of the other methods (Nelson F1); the strongest of these correlations is between Linsey and Shah (F2). The results suggest that the three existing metrics may not be as different in their actual assessments of variety as the substantive differences in their conceptual approaches might lead us to expect. This is a positive outcome in its implications for researchers, who may wish to compare the variety of their experimental subjects' design concepts while employing their preferred (different) metrics for its assessment.

Table 23: Correlations among existing variety metrics **[32]**

Metric	Correlated Metrics	*R* Coefficient
Nelson (F1)	Shah (F1)	0.745
	Nelson (F2)	0.400
Shah (F1)	Nelson (F2)	0.781
	Shah (F2)	0.632
Nelson (F2)	Shah (F2)	0.900
Linsey	Shah (F1)	0.441
	Shah (F2)	0.855
	Nelson (F2)	0.785
All correlations: $p < 0.05$		

7.2 Correlations with the New Metric

The analyses also indicate moderate relationships between the new proposed metric and the existing variety metrics of Shah, Nelson, and Linsey. As shown in Table 24, the strongest correlation involving the proposed metric exists between V_{SD} and Shah (F2); although this correlation is moderate ($R > 0.6$), it is weaker than the correlations between Shah (F2) and other existing metrics, as shown in Table 23. This raises interesting questions about the definition and construction of the new metric. In the current study, the prototype metric was tested using a specific set of quality metrics (see Table 1). Many other metrics might have been used in the *n*-dimensional geometric approach (e.g., novelty, feasibility, paradigm relatedness), or a smaller subset of the quality metrics might have been chosen. Based on the correlations between the proposed metric and the existing approaches, future studies will focus on exploring how the choice of these "building block" metrics for use in the proposed geometric approach influences these relationships.

Table 24: Correlations between new and existing metrics **[32]**

Metric	Correlated Metrics	*R* Coefficient
$\boldsymbol{V}_{M}$	V_{SD}	0.658
	Nelson (F2)	0.428
	Shah (F2)	0.561
	Linsey	0.546
$\boldsymbol{V}_{SD}$	Nelson (F2)	0.395
	Shah (F2)	0.614
	Linsey	0.562
All correlations: $\boldsymbol{p} < 0.05$		

7.3 Qualitative Comparison of Variety Metrics

In addition to the quantitative differences among the variety metrics investigated in this study, their qualitative characteristics may be even more distinctive. Shah and Nelson's general approach is both specific and thorough. Ideas are mapped onto multi-level variety trees that represent the design space from a functional perspective and use detailed descriptions and requirements to characterize design solutions. This functional approach also benefits designers by helping them focus on one aspect of a technical problem context at a time. Other variety metrics (e.g., Linsey) may analyze ideas from a more holistic perspective, providing less specific information about what makes one concept different from another. Finally, for a large data set and/or one that continues to grow (associated with the same design problem), the re-usability of the variety trees can increase efficiency. That being said, there are some significant challenges associated with the Shah/Nelson approach as well. The front-end work required to create the variety trees that map the space of design solutions is very time consuming; if the trees are used only once, then that time comes at an even greater cost. Once the trees have been created, the calculations involved are also slightly more complex than the other variety metrics under consideration.

Moving to Linsey's variety metric, its benefits include quicker and simpler coding than the Shah/Nelson approach. The "bin" system is straightforward and requires little preparation, and the required calculations are simple as well. For small data sets, Linsey's method is both quick and easy, and the intuitive nature of the binning process gives the evaluator a very tangible view of the idea pool: the user essentially constructs the design space in real time. On the other hand, Linsey's method is more subjective and includes few specific guidelines, in contrast to Shah/Nelson, which spells out the assessment process in detail. By asking raters to assess ideas holistically, rather than by function, Linsey's method is also more general, providing fewer quantitative results to work with statistically, and limiting the design space to the ideas you have in the current set. If those ideas happen to be clustered, the number of separate bins will be low, making the variety scores larger than they should be on a more general scale. Finally, Linsey's approach is challenging to use for large data sets; the greater the number of ideas, the more difficult the metric becomes due to the sheer volume of design solutions that must be evaluated at the same time.

Finally, the proposed metric shares some of the benefits and the challenges of the foregoing metrics for variety. It is highly flexible, as it relies on the number and selection of other metrics chosen to use in constructing the *n*-dimensional space (i.e., the "building block" metrics). The required computations are deterministic (similar to Shah/Nelson) but simple (like Linsey), and the method is equally feasible for small and large data sets. The physical link with geometry (the *n*-dimensional space) provides an appealing way to visualize a complex design space, and the resulting components of the metric (mean distance and variation) provide a physically relatable "average value" of design space exploration and a sense of the spread of that exploration as well. On the other hand, the new metric's reliance on other metrics may reduce its reliability: its results will only be as reliable as the other metrics themselves. Likewise, one must spend the time to evaluate those "other metrics", which may be an arduous task in and of itself, depending on how many and which metrics have been selected for use. Finally, the geometric interpretation of the results may become challenging if a large number of metrics (dimensions) is used. Even the mean and variation components do not fully explain all potential differences among idea distributions in an *n*-dimensional space.

In summary, each of the variety metrics investigated in this study has benefits and challenges: there is no clear overall "winner" among them. Nevertheless, the results of this simple study may provide insights for design educators and practitioners in their use of variety metrics. One of these metrics may be more or less meaningful and convenient to use, for example, depending on what the user wants to gain from the analysis and how much data they need to evaluate. Conceptually, these metrics provide separate but similar perspectives on variety, so if a functional, holistic, or characteristic approach to variety is specifically desired in a given setting, the choice of which metric to use may be clearer. In an educational environment, this comparison of variety methods may be helpful when deciding which method best applies for student projects. In a professional setting, design teams may find different variety metrics more appropriate to use under different time or resource constraints. While future research is clearly needed, especially with regard to the proposed new metric, these analyses have revealed interesting findings related to the assessment of variety that may contribute to the understanding of design assessment overall.

Chapter 8

Discussion and Future Work

8.1 Implications

Developing design interventions opens many opportunities to alter and improve the ideation of engineers. The results of the interventions study indicate that, of the three interventions (ideation teaming, problem framing, and ideation tools), ideation teaming generated the most noticeable effects on the characteristics of design ideas. The results show that working in dyads decreased ideas' implicational explicitness scores as a main effect, but other relationships also grew out of the teaming intervention, including an increase of ideas' effectiveness scores for sophomore students working in dyads. The problem framing and ideation tools interventions show fewer relationships in this particular study, but other studies done by the Ideation Flexibility team [20] [24] [29] have shown significant outcomes from the interventions. A clearer understanding of these interventions and their effects on ideation flexibility as measured by the characteristics of the ideas (this study) or by other methods, can inform how and when interventions should be implemented with engineers (both students and practitioners), what improvements can be made to design interventions, and why one intervention may be more useful for a certain type of participants than another intervention.

Generating a variety of solutions in the ideation phase of design is critical, as it leads to greater exploration of the solution space [4]. Knowing how to assess the variety of one's ideas in this phase will help a designer evaluate the quality of his or her solutions, the best time to move to the concept selection phase, as well as how to predict performance. The results of the variety study suggest that although the existing metrics all assess variety, they also vary in conceptual approach, ease of use, amount of training needed for reliability, and rigor. A clearer understanding of these metrics and their trade-offs may allow practitioners, students, and educators to better comprehend what variety means in concept generation, how to assess it reliably, and how to advance performance in generating design solutions that vary from each other.

8.2 Limitations

The first limitation of both studies was small sample sizes. In the interventions study, the initial sample size of 155 students was relatively large. However, the sample sizes rapidly decreased when each intervention was isolated. When the samples were separated based on cognitive style, gender, or academic standing, the sizes shrunk even further. Due to a current lack of reliably paired raters in the research group, there are many ideas that have not yet been reliably evaluated for all the metrics considered in this study, so in the future, adding in these students to the analysis could prove to be useful to increase sample sizes and conduct further tests. In the variety metrics study, the small sample size was primarily due to isolating one design problem with neutral session ideas, which was done to have as many extraneous variables controlled as possible. While useful to ensure control, further analysis of the variety metric would need to utilize larger samples. Further research is needed to determine how each of the variety metrics explored here (old and new) can be implemented most efficiently and reliably in practical settings. Another limitation was the selection of the specific quality metrics used in the proposed variety metric. If other “building block” metrics were used, the outcomes may have differed.

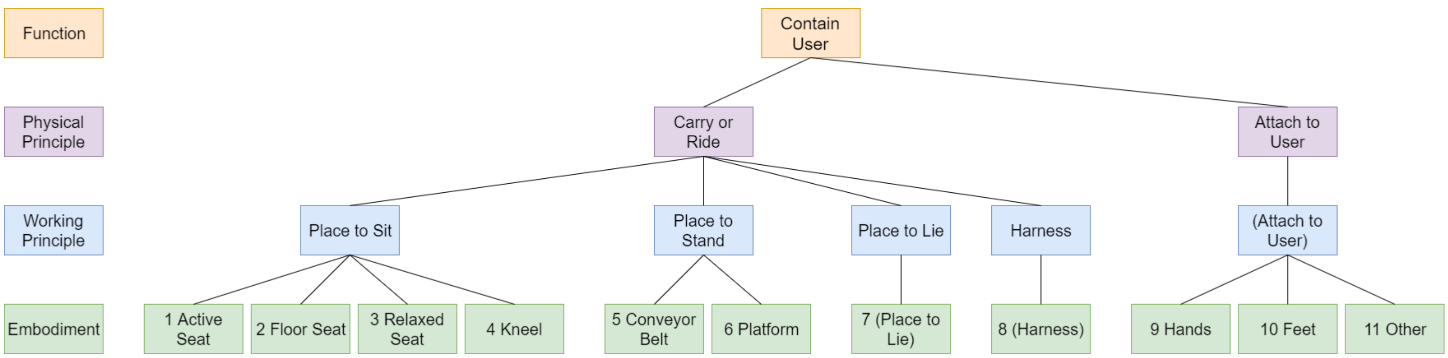
8.3 Future Work

The Ideation Flexibility team has been developing a second generation of design interventions to improve upon and address the weaknesses of the original interventions. The next interventions include new DH cards that include radical and incremental examples, a new framing tool that is more interactive for the designer, and a new teaming intervention with an interactive tool called the idea mapping board. Additional effort should be dedicated to finding a more resolute way of measuring ideation flexibility than comparing metric scores during neutral and intervention sessions. While this method captures some parts of ideation flexibility, there are likely other approaches that could either fill in the gaps or completely replace the use of quality metrics.

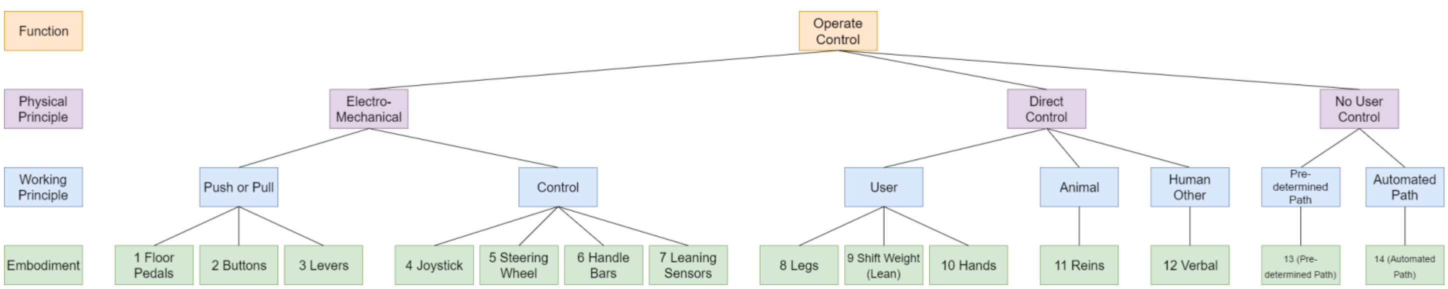
Further work on the new variety metric would be to refine the geometric approach and test it on more ideas. At the IDETC conference where the variety study was initially published and presented, the use of convex hulls was suggested as an alternative approach to the centroid and Euclidean distances. Exploring the potential sensitivity to the choice of underlying metrics will also require further investigation. If the “building block” nature of the metric can be utilized with greater pragmatism, the new variety metric may be found to be a useful tool for determining variety in terms of specific characteristics of interest.

Appendix A

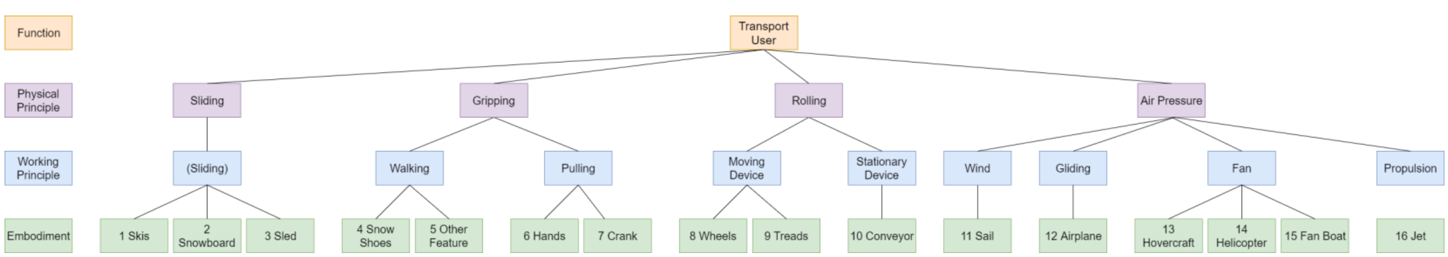
Variety Trees Used for the Shah and Nelson Metrics



A1: Function 1 (Contain User)



A2: Function 2 (Operate Control)



A3: Function 3 (Transport User)

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