

The Meaning of “Near” and “Far”: The Impact of Structuring Design Databases and the Effect of Distance of Analogy on Design Output

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This work lends insight into the meaning and impact of “near” and “far” analogies. A cognitive engineering design study is presented that examines the effect of the distance of analogical design stimuli on design solution generation, and places those findings in context of results from the literature. The work ultimately sheds new light on the impact of analogies in the design process and the significance of their distance from a design problem. In this work, the design repository from which analogical stimuli are chosen is the U.S. patent database, a natural choice, as it is one of the largest and easily accessed catalogued databases of inventions. The “near” and “far” analogical stimuli for this study were chosen based on a structure of patents, created using a combination of latent semantic analysis and a Bayesian based algorithm for discovering structural form, resulting in clusters of patents connected by their relative similarity. The findings of this engineering design study are juxtaposed with the findings of a previous study by the authors in design by analogy, which appear to be contradictory when viewed independently. However, by mapping the analogical stimuli used in the earlier work into similar structures along with the patents used in the current study, a relationship between all of the stimuli and their relative distance from the design problem is discovered. The results confirm that “near” and “far” are relative terms, and depend on the characteristics of the potential stimuli. Further, although the literature has shown that “far” analogical stimuli are more likely to lead to the generation of innovative solutions with novel characteristics, there is such a thing as too far. That is, if the stimuli are too distant, they then can become harmful to the design process. Importantly, as well, the data mapping approach to identify analogies works, and is able to impact the effectiveness of the design process. This work has implications not only in the area of finding inspirational designs to use for design by analogy processes in practice, but also for synthesis, or perhaps even unification, of future studies in the field of design by analogy. [DOI: 10.1115/1.4023158]

1 Introduction

Design-by-analogy is a practice in which designers use solutions from other domains in order to gain inspiration or insight for the design problem at hand, and has been shown to be an effective method for inspiring innovative design solutions [1–4]. However, more work is needed to build an understanding of which analogies presented to designers achieve the best design outcomes, as well to develop methods for finding these analogies in an efficient way. Here, design-by-analogy is studied from a cognitive perspective, and a patent structuring methodology [5–7] is used to both find analogical stimuli for designers, as well as to analyze the results. The results are compared with previous work to gain a more complete understanding of the discovered effects. The results of both studies are then synthesized with an analysis of the relationship and relative distance of the analogical stimuli used in each study to each other and to the design problem at hand. Outcomes are in the form of recommendations on analogical distance of stimuli for effective design outcomes, methods that form the basis for automatically selecting these stimuli, and a method to support and structure a more rigorous method of defining, and thus exploring

analogical distance in design research. First, we review the current understanding of the use of analogy in design, and competing theories regarding the benefits of near versus far-field analogy in design. Then, we discuss the computational design tools that have been created to facilitate design-by-analogy, and the technical foundation of the computational method we use for aiding in the location of these analogies.

1.1 Design-by-Analogy. In this section, we review the salient current perspectives and work to date in design research on design-by-analogy, the central topic of this work. The use of analogy in design has been studied to gain an understanding of how it affects the ideation process and outcomes [4,8–12], with some studies specifically examining how the introduction of analogies with different levels of applicability to the design problem affects individual designers [3,8]. Other work has examined the timing of the introduction of external analogical stimuli within the ideation process, for example by studying the effects of “open goals” [8–10]. Additionally, work has been done to examine the effects of biologically inspired design-by-analogy on design tasks of solution generation, evaluation, and explanation and analogical methods such as direct transfer, relational abstraction, and problem transformation [13]. The work presented here examines design solution generation based on analogical stimuli, and does not explore the particular methods by which designers might generate or use analogies.

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A large area of exploration in the study of design-by-analogy [14–16], and the focus of this work, is analogical distance. In the literature, analogical distance is typically operationalized and studied as a dichotomous variable, with analogies being either near-field or far-field. Near generally means that the analogy is found in the same or similar domain, while far generally means that it is found from a different domain. Further, near-field analogies tend to share a significant number of surface features with the design problem, while far-field tend to share little or none. Far-field analogies, however, can have functional similarities to the design problem that make them apt for analogical transfer. Some literature points to far analogies as being the most promising for creative insights, in which the two domains being compared are very different [17]. Work by Dahl and Moreau showed that the number of far-field analogies used by designers during ideation is positively related to the originality of proposed solutions, as rated by a sample of potential customers [18]. Wilson et al. found that idea novelty increased with exposure to surface dissimilar design examples relative to using no examples, and variety of ideas decreased with exposure to surface similar examples relative to surface dissimilar examples [19]. Often, it is even recommended to use random analogical stimuli, which can perhaps be thought of as “extremely far-field,” to make free or wild associations when ideating, as it can encourage wider search of the design space and potentially higher quality ideas as a result [20].

Other literature questions the benefit of far-field analogies [21,22]. Far-field analogies can be hard to conceive as relevant to a design problem [1], and they can be cognitively challenging to retrieve from memory [23,24]. It is evident that a cohesive theory on the effect of analogical distance on design outcomes does not currently exist. One possible reason for this is that there is a lack of consistency and standardization of meaning of the terms “near” and “far,” making results difficult to compare. Analogical distance is a continuum rather than a simple dichotomy with categories applied in somewhat arbitrary regions of the continuum; thus, existing studies in the literature may be examining and contrasting different points on the continuum from near to far. It is possible that more than two meaningful levels of distance exist along the continuum, with potentially different patterns of effects at these different points on the continuum. For instance, the potential usefulness of analogical stimuli for supporting creative ideation could vary in a curvilinear fashion from near to far, with very near and very far stimuli being less helpful (e.g., due to low novelty at the near end and low relevance at the far end).

Aside from what kinds of analogies are most beneficial and stimulating for designers, it remains unclear how to find these analogies in an efficient or automatic way. There have been methodologies developed to employ design-by-analogy, however, including Synectics [25]—group design through analogy types; French’s work on inspiration from nature [26]; a semantic active verb mapping of design problems known as the WordTree method [27–29]; Biomimetic concept generation [30]—a systematic tool to index biological phenomena that links to textbook information; and analogous design using the function and flow basis [31,32]—analogous and nonobvious product exploration using the functional and flow basis. Though these “pen-and-paper” and semi-automated methods can be beneficial, they can also be cumbersome or inefficient, highlighting one of the major benefits of computational design tools, reviewed next.

1.2 Computational Design Tools. In this section, we review some of the computational design tools that have been created to facilitate design by analogy, an area that is one of the main thrusts of this research. Computational design tools provide a promising way of efficiently and automatically finding analogical stimuli with which to inspire designers. A natural source for analogical stimuli is the U.S. patent database, which is the source of analogies for the work presented here, as well as a great deal of other research, including TRIZ [33] using heuristic rules to help

engineers overcome impasses in functional reasoning by searching through patents; an axiomatic conceptual design tool [34] combining TRIZ and functional basis; patent mining [35–37] characterizing them by citations, claims, average number of words per claim, number of classes that the patent spans, etc.; design repository work incorporating function-based search using Chi Matrix and morphological matrix techniques [38]; PatViz [39], allowing for visual exploration of iterative and complex patent searches and queries using all types of patent data, including full text, which relies on structures that are either predefined or user-defined classification schemes; patent database search using a mapped functional basis [40]; a BioMedical Patent Semantic Web [41] finding semantic associations between biological terms within biomedical patent abstracts and returning a ranked list of patent resources and a fully connected Semantic Web that displays the relationships between the important terms and between resources; and a topic model based taxonomy or hierarchical structure only used to categorize the remaining documents into “topics” [42]. Our work is differentiated from these efforts in that it focuses on using the full textual content of the patents, which it is hoped will allow for richer outcomes, on structuring design repositories and more open ended analogical transfer, and on multiple structure types generated using a hierarchical Bayesian algorithm. The retrieved data are limited to the full text of the patents and does not include any relational or classification data, with the goal of limiting the influence of the pre-existing structure devised by human minds on the structuring algorithm. Looking at unexpected or new representations of the space might present new insights into relationships previously unconsidered.

The size and complexity of the U.S. patent database presents considerable challenges to making it useful to designers. The methodology for structuring patents, first presented by Fu et al. [5–7], and briefly reviewed here, enables the extraction of their interrelatedness and interconnectedness. Ultimately, designers might be able to use these structures to strategically choose analogical stimuli to expose themselves to, or even traverse and explore the space in a more intentional and meaningful way. Designers have the potential to create more innovative designs with more efficient and insightful access to analogical stimuli. We delve into the first steps of using these structures in this manner by testing their output with a cognitive engineering design study, to be described in Sec. 2.3. The method and algorithm for creating these structures is presented next.

1.3 Discovering Structural Form. This section and Sec. 1.4 describe the computational foundation of the automated method we propose for finding useful analogical stimuli. There is a history of describing human cognition using Bayesian models [43], and this link between the Bayesian algorithm and human cognition is a main motivation for choosing this algorithm. The closer the output is to human conceptualization of the data or information, the more easily understood and useful it will be to humans in design practice.

Kemp and Tenenbaum [44] use Bayes Rule to calculate the probability that the data have structure S and form F given data D . A form is defined by the graph grammar that is used to create it. These forms, including a partition, chain, order, ring, tree, hierarchy, grid, and cylinder, and their associated graph grammars, are described in more detail in the source literature [44]. These structures originate from psychology literature [45] and appear in formal models in many different research efforts [46–57]. Kemp and Tenenbaum argue that the structural forms included in the algorithm are often and commonly found, are “useful for describing the world, and that they spring to mind naturally when scientists seek formal descriptions of a domain” [44]. Structures have been used successfully to uncover previously unconsidered or unknown relationships in biology and chemistry—i.e., Linnaeus’ discovery of the tree structure that best describes the relationships between living organisms, or Mendeleev’s periodic structure of

elements [44]. The Bayesian algorithm for discovery of structure in the patent database can facilitate a meaningful exploration of potentially analogous solutions, and potentially stimulate the discovery of useful, perhaps previously unconsidered, relationships and functional solutions by designers.

A structure S is a particular instantiation of a form F . To be clear, a graph of data D with a certain form can be represented by a number of different configurations, or structures. The three terms that go into calculating this posterior probability, which serves as the score of a particular structural form within the algorithm, were chosen and calculated as follows [43]:

$$P(S, F|D) \propto P(D|S)P(S|F)P(F) \quad (1)$$

Where

- (1) $P(F)$, the prior on the space of forms, is a uniform distribution over the forms under consideration.
- (2) $P(S|F)$, the prior on the structures, favors graphs where k , the number of clusters, is small: $P(S|F) \propto \theta^k$ if S is compatible with F , and $P(S|F) = 0$ otherwise; here, $\theta = 10^{-3}$, which favors simpler structures with fewer nodes [58].
- (3) $P(D|S)$, the likelihood, measures how well the structure S accounts for the data D . $P(D|S)$ will be high if the features in D vary smoothly over the graph S , that is, if entities nearby in S tend to have similar feature values.
- (4) The normalizing constant, the marginal probability, is calculated using set theory, as a sum of the products of the number of F-structures with k occupied cluster nodes and the number of ways to partition n elements into k nonempty sets.

1.4 Latent Semantic Analysis. Latent semantic analysis (LSA) is used to preprocess design document texts (here, patent texts) in order to extract the contextual similarity of documents [59]. LSA is a powerful method for context similarity, but has mixed results in matching some types of observed data, for example predicting human word associations. This is due to the nature of the compressed numerical representation that is intrinsic to LSA, forcing symmetry in similarity of words (i.e., the word “meow” is more often associated with the word “cat” than “cat” is associated with “meow”), imposition of the triangle inequality (x is similar to y , y is similar to z , but z is not necessarily similar to x), among others. However, LSA has been successfully used in studies of communication among designers [60,61] and functional content in engineers’ descriptions of devices [62], and hence the authors have chosen it as an apt tool for this application. The output is a similarity matrix [63–65], which serves as the input to Kemp and Tenenbaum’s algorithm. LSA has four main steps:

1. Creating a word-by-document matrix, in which the columns represent the documents, the rows represent the words within the documents, and the cells are populated by the number of times each word appears in each document.
2. Performing an “entropy weighting,” which is a two part transformation on the word-by-document matrix that gives a more accurate weighting of the word-type occurrences based on their inferred importance in the passages.
3. Performing singular value decomposition on the transformed word-by-document matrix, with an output of the U , S , and V matrices.
4. Calculating the cosine similarity between documents by multiplying S and the transpose of V and calculating the dot product between all pairs of resulting vectors, yielding a similarity matrix for the documents [63–65].

2 Methodology

This study serves (1) as an examination of the structuring of patents generated using LSA and the Kemp and Tenenbaum

algorithm for discovering structural form and (2) as an exploration of the effect of “near” and “far” external analogical stimuli on design output quality. The first part of the methodology section describes the steps taken to generate the structure of patents, while the second part details the set up and process by which the cognitive engineering design study was performed. Further details of the structuring procedure and the design metrics used can be found in Refs. [66] and [7].

2.1 Generating Structures

2.1.1 Choosing Initial Patent Set. A random number generator was used to create a list of random patent numbers, from which a subset of 45 patents was chosen that were classified within the U.S. Patent classification system as “Body Treatment and Care, Heating and Cooling, Material Handling and Treatment, Mechanical Manufacturing, Mechanical Power, Static, and Related Arts.” The full text of these 45 random “mechanical” patents were used in the next steps in Sec. 2.1 to generate the structure used to choose the analogical stimuli for the cognitive experiment.

2.1.2 LSA Preprocessing. In order to extract the relationships between the patents in the set, the contextual similarity of the patents was evaluated through the use of LSA. This contextual similarity took the form of a symmetric similarity matrix populated by pairwise cosine similarity values describing the level of semantic similarity between any two patent documents. The full text, including the abstract and description of each of the 45 patents was run through a part-of-speech tagger, in which the verbs, adverbs, adjectives, and nouns are tagged separately, including repeated words. In this application, the part-of-speech tagger served to remove any nonwords from the documents. LSA as described in Sec. 1.4 was then run on the set of 45 full text part-of-speech tagged patents. Due to the small size of the corpus, full dimensionality was maintained. The resulting cosine similarity matrix served as the input data to the algorithm for discovering structural form. It is important to recognize that this data is not unlike the similarity data used in Kemp and Tenenbaum’s work [44]. This LSA preprocessing step does not change the functionality of the algorithm devised by Kemp and Tenenbaum, though it does serve as a novel way of generating similarity data for input to the algorithm.

2.1.3 Structural Form Discovery. Kemp and Tenenbaum’s algorithm for discovering structural form as it was applied to the output data described in Sec. 2.1.2 involves the following steps [44,58]: Preprocessing the similarity data D by shifting the mean of the matrix to zero; finding the form F and the structure S of that form that best capture the relationships between the set of 45 patents by maximizing the posterior probability—the probability that the data has structure S and form F given data D ; running a separate greedy search for each of the eight candidate forms, in order to identify the structure and form that maximize the posterior probability.

The eight forms explored with the algorithm were the partition, chain, order, ring, tree, hierarchy, grid, and cylinder. More detail on these forms and their generative grammars can be found in the source literature of Kemp and Tenenbaum [44,58]. The output of this step of the methodology is the best structure (instantiation) of each candidate form, and the associated posterior probability. The best structure of the set of eight can be judged by which has the highest posterior probability value.

2.2 Choosing Varying Stimulus Set. The main thrusts of the experiment were to (1) validate the use of structuring patents as an automatic analogical inspiration generator and (2) explore, using the structure of patents, how analogical stimuli of different levels of distance from the design problem would affect the design output quality. In order to achieve these two goals, the winning

structure generated in the previous step was a hierarchy, and was used to choose five patents that were “near” and five patents that were “far” from the design problem description in the structure. The location of the design problem description, or perhaps “starting point,” was determined by calculating its semantic similarity to each cluster in the structure and choosing the node with the highest similarity. Near patents were chosen from nodes that were 0 to 1 node away from the design problem description location. Far patents were chosen from nodes 3 away from the design problem description. The five near and five far patents served as the varying stimulus set for the cognitive engineering design study described in Sec. 2.3. The structure is presented as Fig. 6 in Sec. 4.

2.3 Experimental Procedure

2.3.1 Participants. This study was performed at the University of Texas at Austin, United States of America with students enrolled at the university. There were 72 participants total, two of which were not included in the analysis and results due to lack of complete participation. There were 10 graduate level participants, and 62 undergraduate level participants. Seventeen participants were female, 52 participants were male, and 3 participants did not indicate their gender. All participants had adequate domain knowledge of engineering and all but 2 had at least some design experience, consisting of some combination of course-related design projects, industry experience, structured design courses and training in design tools. Detailed in the next step, there were 24 participants in the “near” condition, 24 participants in the “far” condition, and 24 participants in the Control condition.

2.3.2 Conditions. The independent variable was the patent distance in structure, measured from design problem description position. There were three conditions:

1. “Near” Patents—These patents were zero or one node away from where the design problem laid in structure. The varying stimulus set included 5 near patents, with each participant exposed to some combination of 3 of the 5.
2. “Far” Patents—These patents were three nodes away from where the design problem laid in structure. The varying stimulus set included 5 near patents, with each participant exposed to some combination of 3 of the 5.
3. Control—This condition of participants received no external stimulus during the experiment.

2.3.3 Design Problem. The design problem given to the participants to test the effect of the external analogical stimuli on the design quality output was to design a low cost, easy to manufacture, and portable device to collect energy from human motion for use in developing and impoverished rural communities, e.g., India and many African countries. The design problem description as supplied to the participants is as follows:

Design a device to collect energy from human motion for use in developing and impoverished rural communities in places like India and many African countries. Our goal is to build a low-cost, easy to manufacture device targeted at individuals and small households to provide energy to be stored in a rechargeable battery with approximately 80% efficiency. The energy is intended to be used by small, low power draw electrical devices, such as a radio or lighting device, hopefully leading to an increase in the quality of life of the communities by increasing productivity, connection to the outside world, etc. The target energy production is 1 kW-h per day, roughly enough to power eight 25 W compact florescent light bulbs for 5 h each per day, or enough to power a CB radio for the entire day.

For reference, an average adult human can output about 200 W with full body physical activity for short periods of time, with a significant reduction for sustained power output.

This design problem has been used in previous work to examine design-by-analogy [67]. As in the previous work, the problem was

chosen to be challenging and meaningful to the participants. The lack of known or successfully implemented solutions make this design problem appropriately challenging, yet it is sufficiently simple such that meaningful design ideation could begin immediately. The problem is judged as meaningful due to its social impact and relevancy to current efforts in the engineering and product design fields, encouraging an appropriate level of engagement from the students during ideation [68–70].

2.3.4 Materials. Each participant received an envelope at the outset of the study, which included: Consent form; design problem description; three patents, one to a page, including the abstract and one key diagram from each (these were not included in Control condition envelopes); one stapled packet including: instructions for Phases A, B, and C, ideation box sheets for Phases A and C, post experiment survey, demographics survey.

2.3.5 Cognitive Study Procedure. The study was run in three separate sections, one 10-student graduate class, and two undergraduate classes with 39 and 23 students. There were three phases in the study. Phase A was a pre-stimuli ideation phase, in which participants in all conditions worked for 10 min on the design problem described in Sec. 2.3.3. In Phase B, participants in the “near” and “far” conditions had 5 minutes to read and understand three patents from their respective varying stimulus sets. The Control condition participants continued to ideate during Phase B. In Phase C, all participants returned to ideating on the given design problem.

Envelopes containing the materials listed in Sec. 2.3.4 were distributed in a random manner by condition and geographic location in the room for all three sections of the study. Participants signed consent forms, and were told the overall timeline of the study. They then completed the three phases described above, and were given one minute warnings before each phase was over. The experimenter announced that Phase C had concluded after 15 min had elapsed. The participants were then asked to complete the debriefing survey and the demographics survey. After they completed the two surveys, they were asked to place all materials back into the envelope in which they came and return the envelope to the experimenter.

3 Design Metrics

The design output from the participant was expressed on paper provided to the participants. The paper had two boxes per page, in which participants were instructed to include one idea per box. Each idea included either textual description of the concept, a sketch of the concept, or the majority of the time, both a textual description and sketch. To fully understand the effects of the inspirational stimuli on the participants’ ideation, participant-generated ideas were coded for a range of design metrics. Section 3.1 briefly describes the metrics used to understand the design output and performance of the participants. Further details of the design metrics used can be found in Refs. [66] and [7].

3.1 Design Evaluation Metrics. To explore the effect of the external inspirational stimuli of different analogical distances on design output quality of individuals, several design evaluation metrics were used. For consistency and comparability, these metrics are the same as those used in our previous work with design by analogy with minor modifications noted below [67]. The metrics used were: (1) quantity of ideas, (2) breadth of search through the design solution space, (3) novelty of ideas, and (4) quality of ideas. Quantity and breadth were used to examine how the participants were ideating; quantity of ideas was meant to give a sense of whether participants were generating and/or refining a small number of ideas or exploring larger numbers of concepts and variations on these concepts, the latter of which is correlated with a greater likelihood of higher quality ideas [63]; breadth of search was intended to gauge participants’ ability to come up with

a wide variety of ideas, a skill found to correlate with the ability to restructure problems – arguably a vital skill in design problem solving [71–73]. No significant effects were seen across conditions in quantity ($F(2, 67) = 0.05, p = 0.94$) or breadth of ideas ($F(2, 61) = 0.47, p = 0.62$, so for the sake of brevity, we refer interested readers to Ref. [67] for description of these metrics. The novelty and quality metrics focused on the design output of the participants. Quality of design output was measured because it is most important that design solutions meet customer requirements. A design might be novel, but if it does not meet customer needs or specifications, it is not an acceptable solution to the problem [71]. Novelty was examined due to the general consensus in the literature that creative products are at least novel [71,72].

3.2 Quantity. Quantity of ideation was defined as the number of solution concepts generated after receiving examples, i.e., from the Phase C of the experiment, that met the minimum constraints of the design problem, namely (1) the device generates electricity and (2) it uses human motion as the primary input. To account for effects of individual differences in quantity of ideation and focus on the effects of examples, analyses adjusted for the number of solution concepts generated in the first phase, which acted as a covariate to adjust for baseline variation in quantity across participants.

3.3 Novelty. Novelty was conceptualized as an idea’s rarity in the space of possible ideas for the design problem. The space was defined by using functional decomposition to create a set of possible sub-functions of solutions to the design problem, based on the methodology and consistent with those used in our previous design-by-analogy study [67] informed by the function and flow basis of Hirtz et al. [32]. The original set of sub-functions was the same as that used in the previous study [67]. The sub-functions were divided into two parts—*how* and *what*; *how* signifies the component that implements the sub-function, and *what* signifies either the input or output flow of the sub-function, whichever is less specified. For example, for the sub-function “import human”, the *how* might be “crank” and the *flow* might be “hand.” The initial set of solutions, or possible instantiations of each sub-function, was re-used from the previous design-by-analogy work [67], and a few were added if they were not already in the pre-existing solution space. A doctoral candidate in mechanical engineering coded the solutions to the sub-functions for each idea, and a second mechanical engineering doctoral candidate independently coded 25% of the data for inter-rater agreement. Agreement was assessed at two levels: the first level assessed the degree to which the two coders agreed whether or not an idea provided a solution to a given sub-function; the second level assessed the agreement between coders on the type of solution to the sub-function, given that they had agreed a solution was provided. Agreement on the first level was excellent (Cohen’s $\kappa = 0.94$), and agreement on the second level was acceptable ($\kappa = 0.74$ averaged across sub-functions).

As in the previous work [67], only a small subset of the sub-functions that were coded were common enough for stable estimates of novelty (i.e., base rate greater than 0.1, collapsed across conditions). The subset of sub-functions used were the same as in Ref. [67]:

- (1) Import human energy (*how*)
Import/accept (*what*) human interaction
- (2) Transform human energy to mechanical energy (*how*)
Transform human energy to (*what*) mechanical energy
- (3) Import other energy source (*how*)
Import (*what*) other energy source
- (4) Transform other energy source to mechanical energy (*how*)
Transform other energy source to (*what*) mech. energy
- (5) Transform mechanical energy to electrical energy (*how*)
Transform (*what*) mechanical energy to electrical energy

Each idea’s novelty score was given by:

$$\frac{1}{i} \times \sum_j \frac{w_j \times R}{1} \quad (2)$$

where R is the rarity score for the idea’s solution for the j th component of the i th sub-function. The overall rarity score for the i th sub-function is given by the weighted average of the rarity scores for the j components of the sub-function, with w_j as the weight for each component. All j weights summed to 1. The unweighted average of rarity scores for all i sub-functions constituted the aggregate novelty score for each idea.

R for each solution was computed using a formula adapted from [72]

$$\frac{T - C}{T} \quad (3)$$

where T is the total number of solution *tokens* for a given component of a given sub-function in a *baseline* solution space, and C is the number of solutions tokens of the same *type* as the current solution. This baseline space included only solution types from a universe of 583 ideas generated by participants who either had or had not received patent examples, including ideas from participants in a previous ideation study using the same design problem [67]. Solution types that did not occur in this space were automatically set to $R = 1$. This metric design allowed for example-inspired novel solutions shared by participants who saw the same example to still be counted as novel, assuming that these solution types were unlikely to be generated in the absence of the example, and therefore unlikely to be represented in the baseline solution space.

Recall that each idea was coded for functionality in terms of its *how* and *what* for a set of given sub-functions. For purposes of computing R , each sub-function had three components: a description of (1) the type of flow, or the *what* (e.g., energy and human body part) being acted upon, (2) the type of instantiated device function, or the *how* (e.g., pedals and piezoelectric plate) acting upon the flow, and (3) a description combining the function (*how*) and flow (*what*) into a *compound* function statement. For example, one common idea was transforming human pedaling action into rotational energy, which is then transformed into electrical energy via a dynamo-type generator. This idea would provide a solution to the sub-function “import human energy/interaction,” the *what* for this solution would be “foot”, the *how* would be “pedals”, and the *compound* statement would be “foot with pedals”.

The flow (*what*), function (*how*), and *compound* components for each sub-function were given weights of 0.5, 0.3, and 0.2, respectively. These weights were chosen to reflect the order of “difficulty” in achieving rarity. The variety of flows (*whats*) tends to be more limited (e.g., most ideas transform human energy into *rotational* mechanical energy); thus, rarity should count for more in this space. However, in the *compound* space, the likelihood of finding two ideas with the exact same combination of flow (*what*) and function (*how*) is much lower, thereby lowering the threshold for rarity; thus, rarity should count for less in this space.

Figure 1 shows an example of concepts that were given high and low novelty metric scores using our method. The concept in the top half of the figure is a relatively rare idea of transforming translational motion from a hanging pendulum like mechanism that swings while walking into electrical energy via induction. The concept in the lower half is a very common and thus low novelty idea of creating rotational motion through some kind of pedal-based mechanism and transforming that rotational motion into electrical energy via induction or some similar mechanism.

3.4 Quality. The quality of solution concepts was determined by first selecting the best concept from each phase for each

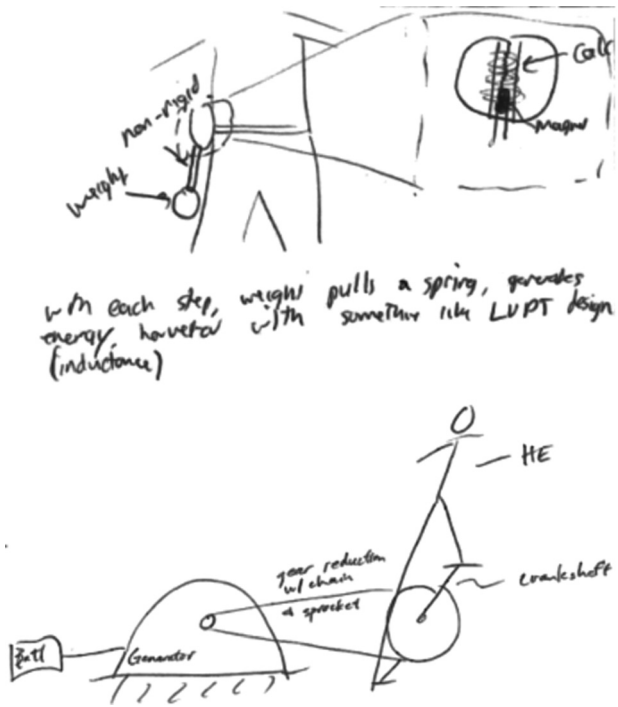


Fig. 1 Example high novelty (top) and low novelty (bottom) concepts

participant across all phases. This coding was done by a doctoral candidate in mechanical engineering. Twenty-five percent of the data was independently coded by a second doctoral candidate in mechanical engineering for inter-rater reliability, which was found to be at an acceptable level of 74% agreement. These “best” concepts were then evaluated using a detailed quality analysis, similar to that which was used in our previous design-by-analogy work [67]. This analysis involved measuring quality on a set of 7 subdimensions, in a Pugh chart type of format, from [67]. The subdimensions, corresponding to a set of projected customer requirements, were as follows:

- (1) Cost
- (2) Feasibility of materials/cost/manufacturing
- (3) Feasibility of energy input/output ratio
- (4) Number of people required to operate device at a given moment
- (5) Estimated energy output
- (6) Portability
- (7) Time to set up and build, assuming all parts already available at hand

The solution concepts were scored on each of the subdimensions on a 5-point scale ranging from 0 to 4, where 0 is unacceptable and 4 is excellent. Inter-rater reliability for the first and last sub-dimensions (cost and time to set up and build) was unacceptable ($r < 0.2$), so these dimensions were dropped. Reliability averaged across the remaining sub-dimensions was acceptable at $r = 0.52$.

The overall quality score for each solution for the detailed quality analysis was computed using the following formula:

$$Q = \frac{\sum_{j=1}^n q_j \times r_j}{Q_{\max}} \quad (4)$$

where q_j is the quality score for quality subdimension j , r_j is the reliability of the coding for that subdimension, and Q_{\max} is the maximum possible overall quality score, which would be given by

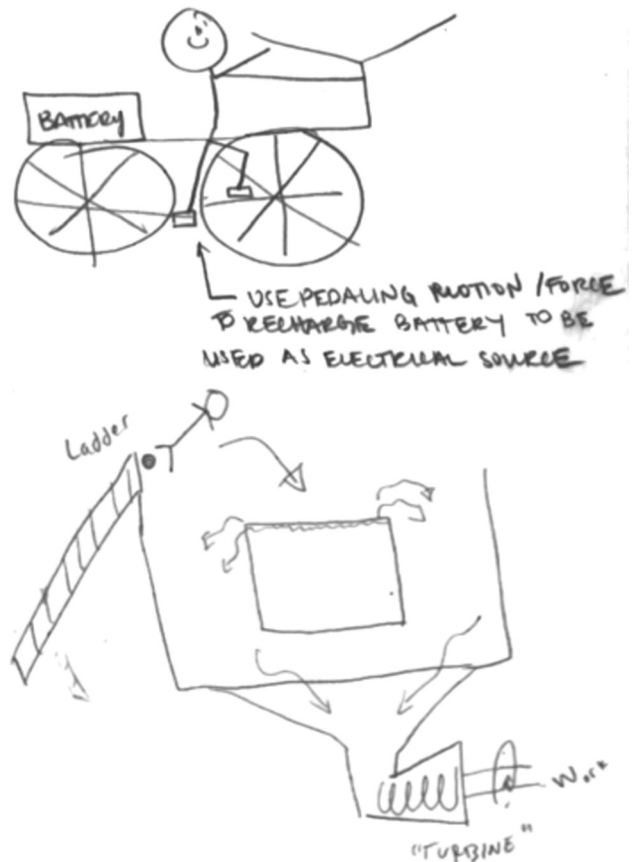


Fig. 2 Example high quality (top) and low quality (bottom) concepts

setting q_j to 4 for each subdimension. The subdimensions were weighted by reliability as judged by the raters to minimize the influence of measurement error. The overall quality score for the detailed analysis was a proportion of the maximum possible quality score, yielding values between 0 and 1.

Figure 2 shows an example of concepts that were given high and low quality metric scores using our method. The concept in the top half of the figure is given a high quality score due to its favorable energy input/output ratio, because bicycles are a common mode of transportation, size/portability, and feasibility of manufacturing. The concept in the bottom half of the figure is given a low quality score due to its low feasibility of manufacturing and unfavorable energy input/output ratio and size/portability.

4 Results

Separate analyses of variance were performed for each of the metrics described in Sec. 3. Bonferroni corrections were applied to all post hoc contrasts to correct for Type I error inflation (false alarms) due to multiple comparisons.

In novelty for the current study, we examined both mean novelty and maximum novelty. The independent variable of distance of analogical stimuli had a significant effect on maximum novelty of ideas, ($F(2,59) = 4.139, p = 0.02$). Post hoc pairwise comparisons showed that the most novel concepts generated by participants in the far condition were, on average, significantly less novel compared to concepts generated by participants in either the near (Cohen's $d = -0.82, p = 0.02$) or control conditions ($d = -0.91, p = 0.008$; see Fig. 3, right). There was no significant effect on mean novelty ($F(2, 61) = 1.626, p = 0.20$), but the mean trends were similar to those in maximum novelty, where the far condition achieved less novelty than the near and control conditions. These results are contradictory to those found in our

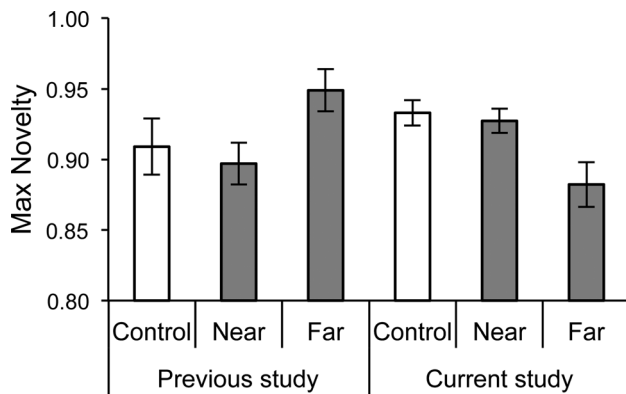


Fig. 3 Effect of distance of analogical stimuli on novelty, previous study, and current study results

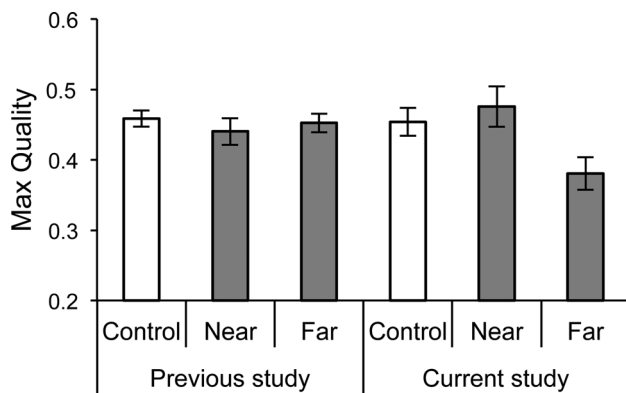


Fig. 4 Effect of distance of analogical stimuli on quality, previous study, and current study results

previous work, which stated that “far” analogical stimuli are correlated with higher maximum novelty. This discrepancy will be discussed in detail in Sec. 5. Novelty results from the previous study and the current study are depicted in on the left in Fig. 3.

A significant effect of distance of analogical stimuli on mean quality was found ($F(2, 65) = 4.07, p = 0.02$). In post hoc pairwise contrasts, it was found that the near condition had significantly higher quality design output than the far condition ($d = 0.76, p = 0.02$), and was trending (though not significantly) toward higher quality design output than the control condition ($d = 0.54, p = 0.23$).

In addition, in the current study, a significant effect of distance of analogical stimuli on maximum quality was found ($F(2, 65) = 4.13, p = 0.02$; see Fig. 4 right). Post hoc contrasts showed that the highest quality concepts generated by participants in the far condition were, on average, of significantly lower quality compared to concepts generated in the near condition ($d = -0.76, p = 0.02$), and trending (though not significantly) toward worse quality than the control condition ($d = -0.72, p = 0.11$). As with novelty, these results are contrary to those found in our previous work, which states that far analogical stimuli have a positive, albeit indirect, effect on quality: the far stimuli resulted in higher variability in quality of ideas [69], which was positively associated with maximum quality (in accord with other findings in the literature [67,74]). Variability of quality was not calculated in the current study because we only coded the best concepts from each participant. The discrepancy between the quality results in the current study and the previous study will be discussed in depth in Sec. 5.

One final result concerned the debriefing survey administered to the participants after the ideation phases of the experiment:

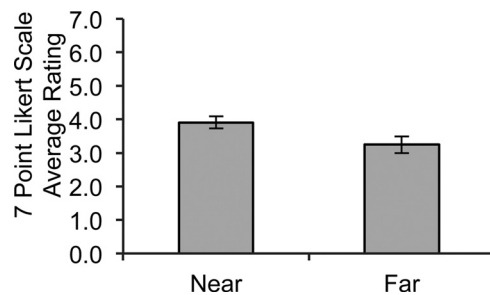


Fig. 5 Participant judgment of relevance of analogical stimuli to design problem

participants rated the far analogical stimuli as significantly less relevant to the design problem than the near analogical stimuli ($F(1, 44) = 4.72, p = 0.035, d = -0.64$; see Fig. 5). This was a composite measure, calculated by averaging ratings across two Likert scale questions from the survey: “This device is similar to devices that generate energy from human motion,” and “The mechanisms in this device are relevant to designing devices that generate energy from human motion.”

The results found in the study presented here are compared with the results found in a previous recent study by the authors [67], which examined the effect of analogical distance, commonness, and modality of external analogical stimuli on ideation performance. In that study, the experimental procedure, design problem, and metrics used to measure ideation performance were nearly identical to those used in the current study. The only discrepancies were that feature transfer and variability in design metrics were not coded for the current study due to a lower total number of ideas generated. The “near” stimuli were defined as “within domain” technologies, being patents describing energy generation technologies that could be used for analogical transfer to the human motion energy generation design problem. The “far” stimuli were defined as “cross domain technologies, or rather patents that described technologies that were not pertaining to energy/electricity generation, but could still potentially be used for analogical transfer to the design problem. These patents were chosen by mechanical engineering design faculty and a mechanical engineering design Ph.D. candidate. This previous work indicated that far-field analogical stimuli were correlated with significantly *better* ideation performance over the near-field analogies in terms of novelty and quality. An exploration of the reconciliation of this previous study and the current study stimulates interesting, validating, and thought provoking discussion.

5 Discussion

As indicated by the results presented in Sec. 4, it is encouraging to recognize that, in the current study, participants exposed to “near” patents were not significantly worse than the control condition participants in terms of novelty and quality of their design output—meaning that the external stimuli, though causing a greater cognitive load on the participants, was not detrimental to their performance on the design task. Further, the results in Sec. 4 indicate that the patents designated as “near” patents in this study were significantly less harmful to designers during their ideation than the patents designated as “far” in terms of their effect on design output, and in their perceived relevance to the design problem.

Figures 3 and 4, displaying the novelty and quality results from the previous and current studies, suggest what appear to be opposing conclusions regarding whether “near” or “far” patents are more beneficial to the design output. These seemingly opposing results raised the question: how consistently are the labels “near” and “far” used, not only in these two studies but also in the literature as a whole? Unfortunately, “near” and “far” when talking about the distance of analogies often mean something different to

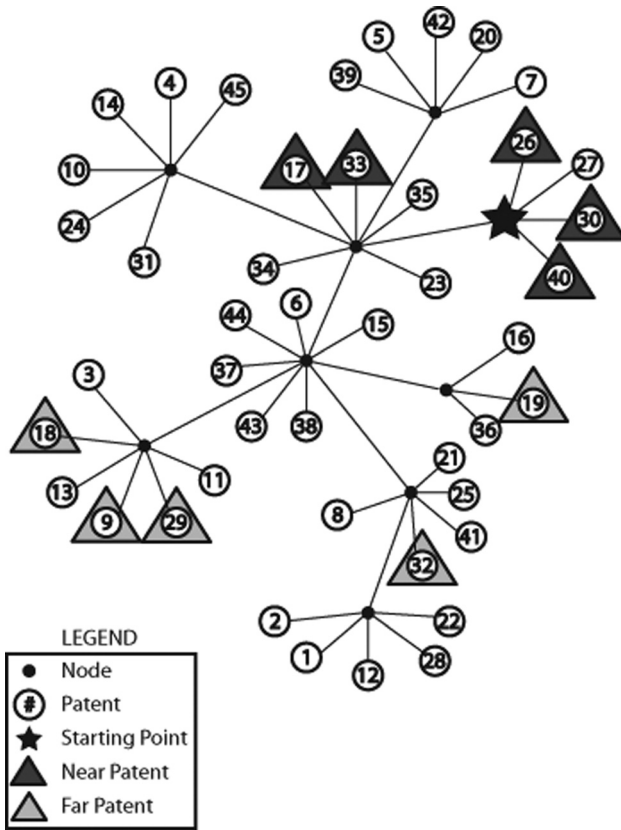


Fig. 6 Original structure of 45 random patents used to choose stimuli sets in the current study

each researcher, and to each individual study or discussion. This makes generalization about the effects of distance of analogy on design and ideation a difficult task. To reconcile the findings of our two studies, we took advantage of the same process and tool used to choose the stimuli in the most recent work in this paper to understand how our definitions of “near” and “far” compared to one another.

Figure 6 displays the hierarchy structure created and used to choose the near and far patents for this study. All patent index numbers and corresponding U.S. patent database numbers can be found in Appendix. The text of the design problem was used within LSA to find the effective “starting point” within the structure, chosen by calculating which node was most semantically similar to the design problem text. As stated in Sec. 2, the near patents were chosen from the set of 45 if they were zero or one node away from the starting point. The far patents were chosen to be 3 nodes away from the starting point.

The 8 patents, 4 “near” and 4 “far” from the previous study were added to the structure of 45 random patents used to choose stimuli for this study. The resulting hierarchy structure is shown in Fig. 7. Patents numbered 46–49 were “far” patents and those numbered 50–53 were “near” patents from the previous study.

It is interesting to find that all 8 patents from the previous study clustered closely, within zero or one node, around the design problem “starting point”, with the “near” patents from the previous study being an average of 0 nodes away from the starting point and the “far” patents from the previous study being an average of 0.5 nodes away from the starting point; the patents designated as “near” in the current study were placed one or two nodes away from the starting point, an average of 1.4 nodes away (and thus farther away than the near patents from the first study); and the patents designated as “far” in this work were now placed, in all but one case, three or four nodes away from the starting point, with an average of 2.8 nodes away. This structure quantifies the

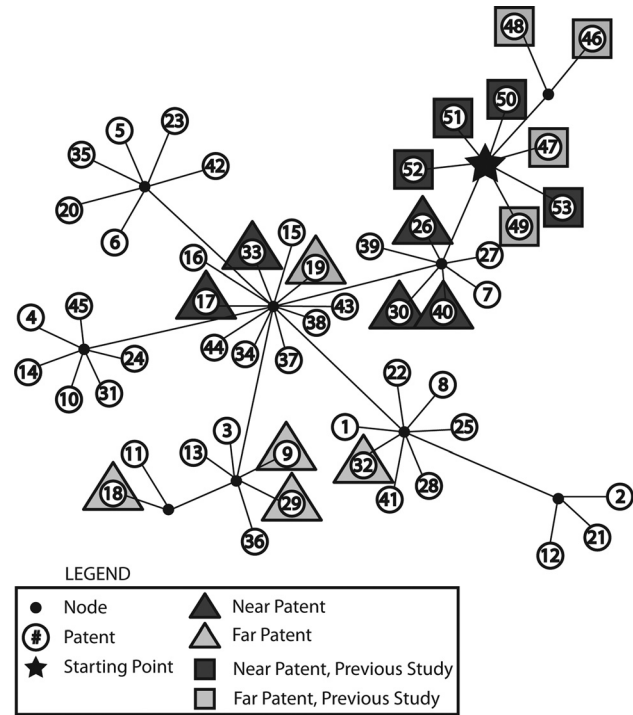


Fig. 7 Original structure of 45 random patents with 8 patents from previous work

relative distance of the external analogical stimuli to the design problem starting point, for two different studies. The hand-picked near patents from the previous study are the closest set of patents to the design problem in the structure. The hand picked far patents from the previous study are still closer than the near patents chosen by the algorithm from the current study. This relative distance relationship makes sense in that the likelihood of having truly useful patents from only a random selection of 45 is small. As the better analogies are added to the mix, the set of randomly selected patents spreads out from the design problem. The relative distances in number of nodes in each distinct structure should be viewed not as an absolute measure but as a means for qualitative comparison—as the space and meaning of distance in the structures will change as the particular patents and number of patents within them change.

These results support our argument that near and far can have distinctly different meanings across the literature. In addition, it is a validation of the structuring methodology and its ability to portray relative analogical distance. This analysis method can be taken one step further, by adding yet another 100 random “mechanical” patents (as described in Sec. 2.1.1) to the space to see how the relationships might change in an even larger context pool, better mimicking how these patents might be situated in the entire patent database. The resulting structure is shown in Fig. 8.

The hierarchy structure in Fig. 8 shows similarities to that in Fig. 7, but with some interesting differences. The 8 patents from the previous work remain closely clustered around the design problem starting point, with the “near” patents being an average of 0.5 nodes away and the “far” patents being an average of 1.5 nodes away. However, the patents from the study presented in this paper are scattered in the structure in a more unexpected way. The “near” patents are now an average of 4.4 nodes away from the design problem starting point, and the “far” patents are further out at an average of 6 nodes away; but in many cases, the patents from this work called “near” are found in the same cluster as those called “far”, or are found the same distance away from the starting point. In a few cases, “far” patents are even found closer to the starting point than “near” patents.

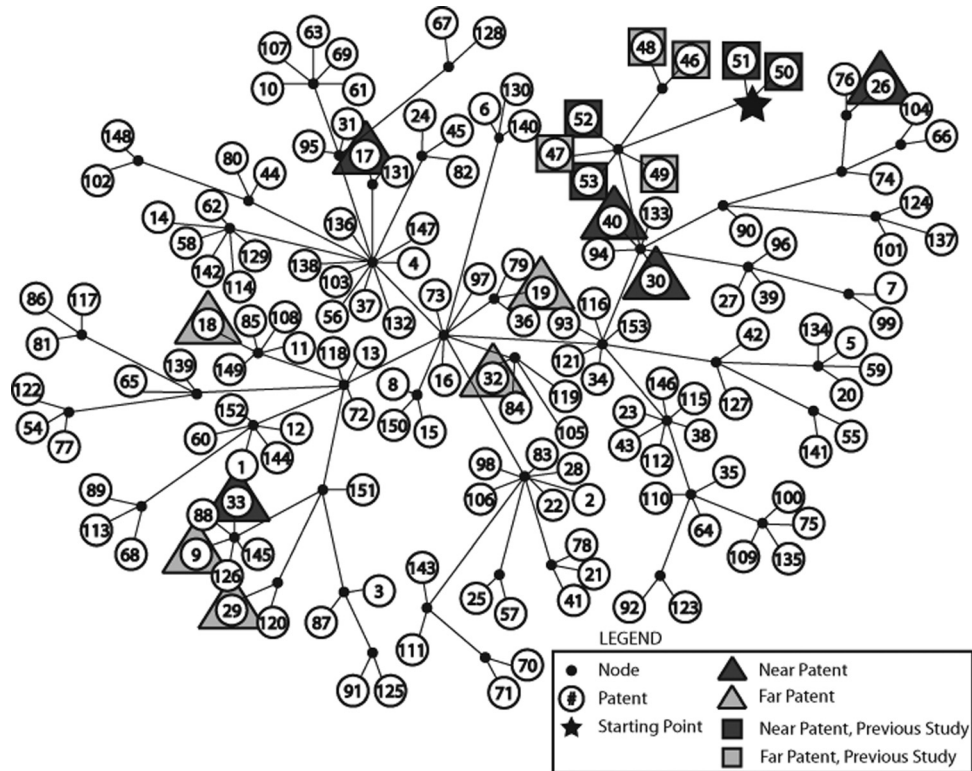


Fig. 8 Original structure of 45 random patents with 8 patents from previous study and 100 additional random patents

It is hypothesized that the larger the structures become, the more well-tuned the structure will be, much the same to the logic behind using large sample sizes. As the number of patents that are included in the representative space and subsequent structure increases, the clustering, connections, and associations represented within the structure will become more meaningful, as there are more likely to be useful patents for analogical stimulation. With this hypothesis in mind, we focus discussion on the structure in Fig. 8. The results in the previous study imply that “far” patents as analogical stimuli are more beneficial than “near” patents to design output quality. The structure in Fig. 8 shows that the “near” patents from the previous study are closer to the design problem in semantic similarity than the “far” patents. The results from the current study imply that “far” patents are less beneficial than “near” patents to design output quality. The “near” patents from the current study are closer to the design problem starting point than the “far” patents from the current study, but not as near as the “far” patents from the previous study.

These results taken all together suggest that there is a “sweet spot” for distance from the design problem when choosing analogical stimuli—in other words, there may be such a thing as “too near” and “too far” when searching for analogies to employ in design-by-analogy ideation practice. The “near” patents from the previous study were too “near” to be beneficial to designers as analogical stimuli. The “far” patents from the current study were too “far” to be useful to the designers, as well. This conclusion is reinforced by the finding presented in Fig. 5, showing that the participants found the “far” patents to be significantly less relevant to the design problem. Our findings directly challenge the random inspiration methods that some suggest can be helpful to design inspiration [20], in that random analogical stimuli may be too distant from the design problem to allow for mapping or transfer to occur. The current study explored the impact of example solutions on novice designers, arguing for a sweet spot for analogical distance to the given design problem. Based on previous work showing that experts do use analogies but can be fixated by those that

include very near or close examples [75], we expect that a similar “sweet spot” exists, possibly with different parameters that should be explored in future work. It is important to note that this suggested “sweet spot” is dependent upon and specific to the patents and design problem, and number of patents used in this study, and would change as these variables change. The stabilization of this “sweet spot” is an area for future work.

The results presented here are impactful for a few reasons. First, there is promise for the use of this structuring technique as the basis of a design inspiration tool for automatically finding design analogies. Designers often employ design-by-analogy through coming up with the analogies themselves, through a stroke of luck, low hanging fruit, or genius. The current most widely used method for searching for analogical inspiration in the patent database is through keyword search. The results of key word searches can be an overwhelming undertaking to explore for design inspiration. There are also computational “innovation support tools” for sale to businesses and innovators [76]. All of these methods and tools place the onus largely on designers to generate the terms or analogies of their own accord and comb through search results. It is known in the psychology literature that the retrieval of far-field analogies is cognitively difficult [23]. In addition, reminders tend to be constrained by surface similarity [24], meaning the probability of retrieving surface dissimilar analogies is low. Thus, a computational design tool that could find analogies in the “sweet spot” that is indicated from the work presented here, which would not easily be located by a designer due to surface dissimilarity or rarity of occurrence, could be exceedingly helpful to facilitating the practical use of the design-by-analogy method. With a large population of patents to build the structures, designers could have fast and relatively easy access to relevant analogies that could be useful or inspirational to them, that they may not have otherwise thought of or been able to find.

Future work includes extending this methodology to create very large, descriptive structures of the patent database to use as a tool in cognitive studies to explore the design space in a methodical,

quantified way. One particular avenue of extension would take advantage of the potential information contained in the structuring and clustering of the patents that goes beyond simply delineating potential relevance to the design problem. For example, the grouping of patents into clusters based on functional similarity could highlight features and functional principles that would otherwise potentially be overlooked (e.g., via analogical comparison; [77,78]) yielding fresh insights for creative ideation. In the cognitive psychology literature, it has been shown that enabling changes in representation of objects and/or ideas, for example by leading problem solvers to attend to previously ignored features, is an effective way of dealing with “functional fixedness,” where problem solvers have difficulty seeing a potential creative use of an object with which they are familiar [79,80]. Labeling of nodes or entities in these structures could also facilitate multiple representations of potentially relevant functional principles for design-by-analogy.

The broader goal of this work is to reach a robust cohesive theory of the ways in which analogical stimuli could be most optimally structured and prepared for exploration to support creative design ideation.

6 Conclusions

The cognitive engineering design experiment presented in this paper, combined with the previous study performed by the authors, suggest that the terms “near” and “far” when referring to distance of analogies are contextual and relative terms. The nature of the use of these terms in the literature makes it difficult to formulate a cohesive theory of analogical distance and its effect on design output quality. The analysis presented in this paper takes a step toward reconciling diverse findings. The use of a structuring method combining latent semantic analysis and a hierarchical Bayesian algorithm for choosing and analyzing the analogical stimuli in both studies suggests that there is a “sweet spot” for distance of analogies, and that there is such a thing as *too* “near” and *too* “far” in design analogies. The structuring method presented shows promise as a facilitator for a unified methodology and eventual development of a cohesive and robust theory on the effect of distance of analogy on design output, as well as providing a basis for an automated design analogy finding tool for supporting creative design ideation.

Acknowledgment

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Appendix: Patent Index

Patent index	U.S. patent number
1	5,626,594
2	3,945,652
3	6,264,019
4	6,298,842
5	5,343,936
6	6,300,699
7	4,400,154
8	4,078,716
9	5,234,096
10	4,780,075
11	5,988,780
12	5,542,526
13	5,107,608
14	6,543,101
15	6,398,066
16	4,026,453
17	6,685,268

Patent index	U.S. patent number
18	4,508,361
19	5,085,240
20	5,171,128
21	6,551,037
22	4,343,498
23	5,165,473
24	4,232,428
25	3,963,052
28	5,018,908
29	5,277,276
30	6,109,307
31	6,666,211
32	6,082,923
33	6,453,834
34	4,440,105
35	4,389,922
36	5,378,106
37	4,950,250
38	4,050,047
39	5,452,860
40	5,160,091
41	5,377,379
42	4,162,046
43	4,380,216
44	6,669,716
45	3,977,562
46	4,335,611
47	4,402,483
48	4,568,937
49	4,139,981
50	4,266,143
51	4,247,785
52	6,208,037
55	4,506,651
56	5,239,707
57	4,535,756
58	4,304,332
59	6,612,806
60	5,762,169
61	6,716,115
62	4,678,083
63	4,813,672
64	4,649,970
65	6,481,735
66	4,380,233
67	6,991,656
68	7,059,508
69	4,488,547
70	5,228,241
71	4,379,706
72	4,233,773
73	5,416,955
74	7,215,986
75	4,705,065
76	4,432,481
77	4,203,505
78	3,970,149
79	5,590,608
82	5,768,928
83	6,044,919
84	5,921,843
85	4,483,066
86	6,776,447
87	4,913,681
88	5,964,159
89	6,505,991
90	6,616,409
91	6,769,593
92	6,782,855
93	4,251,075
94	5,528,878
95	5,819,391
96	5,842,652
97	4,407,173

Patent index	U.S. patent number
98	4,230,228
99	5,305,697
100	4,241,749
101	4,876,854
102	6,143,013
103	6,186,701
104	5,931,180
105	7,083,469
106	5,437,133
109	5,265,643
110	5,984,148
111	5,375,948
112	6,367,521
113	6,497,607
114	4,853,977
115	5,993,410
116	4,223,996
117	4,589,668
118	3,962,735
119	4,124,051
120	7,175,212
121	4,984,583
122	4,259,034
123	6,634,325
124	4,123,000
125	5,909,815
126	3,975,130
127	4,103,708
128	3,964,473
129	4,705,064
130	6,142,689
131	5,273,173
132	5,438,724
133	6,974,456
135	3,941,514
136	6,109,282
137	4,303,397
138	5,899,571
139	6,234,452
140	4,841,621
141	4,142,679
142	6,634,044
143	4,270,310
144	5,423,097
145	5,572,898
146	3,938,909
147	5,647,066
148	6,119,041
149	4,484,762
150	4,762,262
151	6,164,698
152	6,062,856
153	4,739,727

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