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On the Benefits and Pitfalls of Analogies for Innovative Design: Ideation Performance Based on Analogical Distance, Commonness, and Modality of Examples

Drawing inspiration from examples by analogy can be a powerful tool for innovative design during conceptual ideation but also carries the risk of negative design outcomes (e.g., design fixation), depending on key properties of examples. Understanding these properties is critical for effectively harnessing the power of analogy. The current research explores how variations in analogical distance, commonness, and representation modality influence the effects of examples on conceptual ideation. Senior-level engineering students generated solution concepts for an engineering design problem with or without provided examples drawn from the U.S. Patent database. Examples were crossed by analogical distance (near-field vs. far-field), commonness (more vs. less-common), and modality (picture vs. text). A control group that received no examples was included for comparison. Effects were examined on a mixture of ideation process and product variables. Our results show positive effects of far-field and less-common examples on novelty and variability in quality of solution concepts. These effects are not modulated by modality. However, detailed analyses of process variables suggest divergent inspiration pathways for far-field vs. less-common examples. Additionally, the combination of far-field, less-common examples resulted in more novel concepts than in the control group. These findings suggest guidelines for the effective design and implementation of design-by-analogy methods, particularly a focus on far-field, less-common examples during the ideation process. [DOI: 10.1115/1.4004396]

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1 Introduction

Innovation, defined as the capacity to generate ideas or products that are both novel and useful, is a critical component of successful design in today's economy [1,2]. A number of investigators have argued that innovation can be best managed in the "fuzzy front end" of the design process [3,4], notably in the ideation phase, where concepts are created either intuitively or through systematic processes. While many approaches exist to create ideas and concepts as part of ideation, the search for and use of analogies have been shown to be quite powerful [5–8]. Analogy is a mapping of knowledge from one domain to another enabled by a supporting system of relations or representations between situations [9]. This process of comparison between situations fosters new inferences and promotes construing problems in new insightful ways. This process likewise is dependent on how the problem is represented, encouraging multiple representations to more fully enable analogical reasoning [10,11]. As an illustrative example, the design concept for the bipolar plate of a fuel cell could be usefully informed by analogy to a plant leaf due to its similarity in functionality. The most significant functions affecting the current generation capability of a bipolar plate are "distribute fluid," "guide fluid," and "disperse fluid." The plant leaf possesses a similar function chain, where the veins and lamina perform the functions. As a result of this analogy, the bipolar plate flow field can be designed to mimic the structure of a leaf [10,11].

Design-by-analogy is clearly a powerful tool in the conceptual design process, and a number of methods have been developed to harness its power, such as Synectics [12]—group design through analogy types; French's work on inspiration from nature [13]; Biomimetic concept generation [14]—a systematic tool to index biological phenomena that links to textbook information; and analogous design using the Function and Flow Basis [15,16]—analogous and nonobvious product exploration using the functional and flow basis. However, fundamental questions surround the proper use of design-by-analogy methods. Most critical, and the problems that are the focus in our work, are what should one analogize over, and what reasoning modalities and associated representations make innovative design-by-analogy more likely?

While these questions have remained largely unanswered in specific knowledge domains such as engineering design, there is related research literature in the domain of psychological studies of creativity, reasoning, and problem solving. In what follows, we review the relevant literature that motivate our present hypotheses, describe the methods and findings of our cognitive study, and then discuss the insights and implications of our work.

2 Background

2.1 Analogical Distance of Example Designs. One key variable of interest with respect to the question of what one should analogize over is analogical distance. This variable can be

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conceptualized as ranging over a continuum from far-field (from a different problem domain) to near-field (from the same or very similar problem domain), where analogies closer to the far-field end point share little or no surface features with the target domain, while analogies closer to the near-field end point share a significant number of surface features. The potential for creative insights seems clearest when the two domains being compared are very different on the surface [17]. Classic accounts of creative discoveries and inventions often highlight the potential of far-field analogies for creative insights, including George Mestral's invention of Velcro via analogy to burdock root seeds, and Niels Bohr's discovery of the structure of atoms via analogy to the solar system. Empirical work has also supported a link between far-field analogies and innovative outcomes. For instance, it has been shown 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]. Further, exposure to surface dissimilar design examples increases idea novelty relative to using no examples, and exposure to surface similar examples decreases the variety of ideas generated relative to surface dissimilar examples [19].

On the other hand, far-field analogies can be difficult to retrieve from memory [20] or notice as relevant to one's target problem [5]. In addition, some investigators have disputed the privileged role of far-field analogies in prominent inventions and discoveries [21,22]. As such, it is an open question whether far-field analogies are always beneficial to the design process. One way to tease apart possible ways in which far-field and near-field analogies might help or hinder designers is to use multiple measures of ideation processes, including novelty and variety of ideas, as well as average quality and variance in idea quality. An initial testable hypothesis is that providing far-field examples would allow one to generate more novel ideas relative to near-field or no examples.

2.2 Commonness of Example Designs. Another potential variable of interest is the commonness of example designs (i.e., how common the designs are found in designers' worlds). The commonness of the example design in its respective design space increases the probability that a designer would have had prior exposure and/or experience with the design. Psychologically, the commonness of an example design is related to the degree to which it activates relevant prior knowledge of a designer. This knowledge can come from exposure to instances (since designed objects exist in the world), or from deliberately structured experiences, such as in engineering coursework or in the course of professional design [23]. The psychological literature on creativity and problem solving suggests that prior experience with an artifact might influence one's ability to flexibly re-represent and use it and combine it with other concepts in a novel fashion. Take for instance, Duncker's [24] classic candle problem, where the task is to fix a lighted candle on a wall in such a way that the candle wax will not drip onto a table below, and the given materials are a candle, a book of matches, and a box of thumb-tacks. A correct solution involves emptying the box of tacks and using it as a platform for the candle; however, this solution eludes most solvers because it requires recognizing an unconventional use of the box as a platform. In fact, when the box is presented to solvers empty, with the tacks beside it, solvers are much more likely to find the unconventional solution [25]. Similarly, in Maier's [26] two string problem, where the task is to tie two strings together that are hanging from the ceiling just out of arm's reach from each other using various objects available (e.g., a chair, a pair of pliers, etc.), people often fail to recognize the solution of tying the pair of pliers to one string and swinging it like a pendulum and catching it while standing on a chair between the strings. These findings demonstrate the phenomenon of "functional fixedness," where individuals have difficulty seeing unusual alternative uses for an artifact.

Another potentially relevant finding in the psychological literature is that individuals who acquire experience with classes of information and procedures tend to represent them in relatively large, holistic "chunks" in memory, organized by deep functional and relational principles [27–29]. Many researchers have argued that this ability to "chunk" underlies expertise and skill acquisition [27,30,31]. However, if the task at hand requires the individual to perceive or represent information in novel ways, e.g., to stimulate creative ideation in design, representation of that information in chunks might become a barrier to success, particularly if processing of component parts of the information chunks helps with re-representation [32–34].

These findings lead to a hypothesis that less-common example designs, which designers are less likely to have been exposed to, might present a unique advantage over more-common example designs in terms of the potential for stimulating creative ideation. Specifically, it could be that less-common examples are more likely to support multiple interpretations, and thus facilitate broader search through the space of possible solutions. Additionally, given that the commonness of example designs in the world (e.g., in practice, curriculum, etc.) is related to its representation in designers' long-term memory, e.g., ease/probability of recall, one could hypothesize that less-common examples might confer an advantage in terms of the novelty of solution paths they inspire. However, the literature gives no a priori reason to expect effects of commonness on mean quality of solution concepts.

2.3 Modality of Example Designs. With respect to the question of optimal reasoning modalities, a potential variable of interest is the contrast between pictorial and text-based representations of examples. One possible reason to investigate this contrast is that pictorial representations, e.g., sketches, photographs, and engineering drawings, often contain a higher degree of superficial features than text-based representations of the same information. This might be detrimental to conceptual design, as the presence of representations with a high degree of superficial detail, such as in detailed prototypes, in the physical design environment tend to restrict the retrieval of far-field analogies from memory [7]. On the other hand, some investigators argue that pictorial-based representations are better for conceptual design; for example, it has been shown that novice designers who are presented with sketches of example designs produce more novel and higher quality solution concepts on average relative to being presented with text-based example designs [35]. At a pragmatic level, too, in creating design-by-analogy tools, one ultimately has to decide on a representation format for potential analogies; thus, it is important to investigate if it matters whether they are represented in pictorial or text-based formats [10,11]. Additionally, it is important to know if the effects of example analogical distance or commonness are modulated by their representation modality.

2.4 Summary. In summary, a review of the relevant psychological literature suggests that investigating variations in example analogical distance, commonness, and modality might shed some important light on the questions regarding what to analogize over and whether there are optimal reasoning modalities. Prior work tentatively supports a hypothesis favoring far-field over near-field examples. With respect to commonness, to our knowledge, no studies have directly tested the effects of example commonness on conceptual ideation; however, the literature does suggest a hypothesis favoring less-common over more-common examples. Importantly, the theoretical and empirical literature suggest that there might be different effects of example analogical distance and commonness along different dimensions of the ideation process, thus motivating a fine-grained analytic approach to ensure that the effects of these variables can be clearly understood. Finally, the literature appears to be relatively equivocal about the contrast between pictorial and text-based representations; thus, our investigation of this variable in the present study is more exploratory than hypothesis-driven.

Table 1 Distribution of participants across conditions

	Near-field		Far-field	
	More-common	Less-common	More-common	Less-common
Picture	13	17	15	16
Text	17	16	16	17
Control		24		

3 Experimental Methods

3.1 Design. To investigate the effects of example analogical distance and commonness on conceptual design processes and possible interactions with modality, we conducted a 2 (distance: far-field vs. near-field) ×2 (commonness: more-common vs. less-common) ×2 (modality: pictures vs. text) factorial experiment, where participants, i.e., senior-level engineering students, were given a real-world design problem and were asked to generate solution concepts first briefly without examples, such that they understood the problem, and then with examples, to evaluate the effects of examples on problem solving. To establish whether examples of different types enabled or hindered problem solving, a control group of students executed a similar procedure but received no examples.

3.2 Participants. Participants were 153 students (predominantly mechanical engineering undergraduates) enrolled at two research universities in the United States. Participants were recruited from classes and were given either extra credit or compensation of $15 for their participation. Participants ranged from 20 to 38 years in age (M = 22, SD = 1.89). 70% were male. 87% were undergraduate engineering students (95% mechanical engineering, 5% electrical engineering and others) and 13% masters students in disciplines related to product design (e.g., mechanical engineering, product development, business administration). 66% of the participants had at least 1–6 months of engineering internship experience, and all but 2 out of the 153 students had experience with at least one prior design project in their engineering curriculum. Approximately 82% of the students had taken at least one course where a structured approach to design was taught. Thus, most of the participants had relevant mechanical engineering domain knowledge and design experience.

Participants were randomly assigned to one of the nine possible conditions in each class by distributing folders of paper materials prior to students arriving in class. The obtained distribution of participants across the nine conditions is shown in Table 1—the sample populations, *N*s, are unequal not because of dropout but rather from stochasticity in where students chose to sit down. With these sample populations, statistical power for detecting three-way interactions (not our theoretical goal) is modest, but power for detecting two-way interactions and main effects is good.

3.3 Design Problem. The design problem 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, many African countries. This design problem was selected to be meaningful and challenging to our participants. The problem was meaningful in the sense that real-world engineering firms are seeking solutions to this problem and the problem involves social value; thus, students would be appropriately engaged during the task [36–38]. The problem was challenging in the sense that a dominant or accepted set of solutions to the problem has yet to be developed (so students would not simply retrieve past solutions), but it was not so complex as to be a hopeless task requiring a large design team and very detailed task analysis.

3.4 Selection of Examples. Examples were patents selected from the U.S. Patent Database. Candidate patents were retrieved using keyword search on the U.S. Patent and Trade Office website. The keywords used were basic physical principles, such as *induction*, *heat transfer*, *potential energy*, as well as larger categorical terms like *mechanical energy*. The final set of eight patents was selected by two PhD-level mechanical engineering faculty based on two sets of criteria: (1) balanced crossing of the analogical distance and commonness factors, such that there would be two patents in each of the four possible combinations, and (2) overall applicability to the design problem, over and above analogical distance and commonness. Each participant in the analogy conditions received two examples of a particular type, roughly balanced across conditions for applicability. The patents for each of the conditions are shown in Table 2.

With respect to the first set of criteria, the specific guidelines for selection were as follows:

1. *Distance*: Far-field patents were devices judged to be not directly for the purpose of generating electricity, while near-field patents were those judged to be directly for the purpose of generating electricity.
2. *Commonness*: More-common patents were devices judged likely to be encountered by our target population in their standard engineering curriculum and/or everyday life, while less-common patents were those judged unlikely to be seen previously by the participants under typical circumstances.

With respect to the modality factor, in the picture conditions, participants received a representative first figure from the patent, which typically provides a good overview of the device, while in the text conditions, participants received the patent abstract. In some cases, abstracts differed substantially in length; to equate for quantity of text across conditions, overly brief abstracts were augmented with additional text from the body of the patent, which elaborated on the details of the design and technology. To provide some foundational context, all text-and-picture-condition participants also received the patent title.

3.5 Experimental Procedure. The experiments were conducted during class. Participants generated solution concepts in three phases and subsequently completed a background survey. Participants proceeded through the phases using a sequence of envelopes to carefully control timing of the task and exposure to examples across conditions. In particular, we wanted to ensure that design examples were received only after participants had made some substantial progress in ideation, since prior work has shown that examples and potential analogies are most helpful when received after ideation has already begun [39,40]. The overall time allowed for this task was sufficient to allow for broad exploration of the concept space, but not enough to develop

Table 2 Patents for each condition

	Near-field	Far-field
More-common	-Waterwheel-driven generating assembly (6208037) -Recovery of geothermal energy (4030549)	-Escapement mechanism for pendulum clocks (4139981) -Induction loop vehicle detector (4568937)
Less-common	-Apparatus for producing electrical energy from ocean waves (4266143) -Freeway power generator (4247785)	-Accelerometer (4335611) -Earthquake isolation floor (4402483)

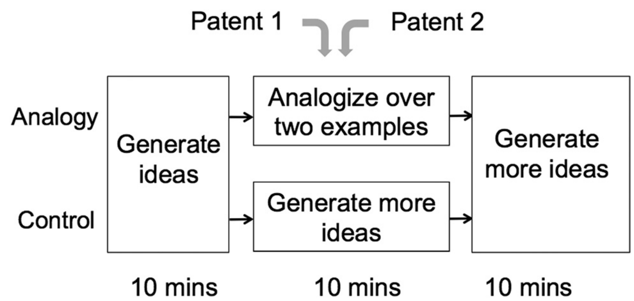

Fig. 1 Comparison of experimental procedures for analogy vs. control groups

particular ideas in depth, matching our focus on the ideation process.

Analogy and control groups executed the same overall sequence, but differed in the particular activities in the second phase of ideation (see Fig. 1 for a comparison of the procedures). In general, the sequence of phases was to: (1) read design problem and generate solution concepts, (2) either (a) review two patents and write/draw solutions/ideas that come to mind when looking at the patents or (b) continue generating concepts, and (3) generate more solution concepts. Each phase lasted 10 min.

With respect to idea generation, participants were instructed to generate and record as many solution concepts to the design problem as they could, including novel and experimental ones, using words and/or sketches to describe their solution concepts.

4 Ideation Metrics

The experiment generated 1321 total ideas. To thoroughly explore the range of effects of varying the analogical distance, commonness, and modality of design examples on conceptual design processes, we applied a range of ideation metrics to these ideas: (1) the extent to which solution features were transferred from examples, (2) quantity of ideation, (3) breadth of search through the space of possible solutions, (4) quality of solution concepts, and (5) novelty of solution concepts. The first three metrics provided measures of the ideation process of participants and how they processed the examples: examining *solution transfer* provides insight into the mechanisms by which participants might be stimulated by the examples, e.g., did they actually use solution elements; measuring *quantity* of ideation gave a sense of how participants were exploring the design space, i.e., whether they were generating and refining a small number of ideas, or exploring multiple concepts and variations of concepts, which is associated with higher likelihood of generating high-quality concepts [4]; finally, *breadth of search* was taken to be a measure of the ability to generate a wide variety of ideas, which is associated with the ability to restructure problems, an important component of creative ability [41–43]. The final two metrics focused on the ideation products of participants. We investigated quality because in design, a baseline requirement is that concepts must meet customer specifications; design concepts that are novel but do not meet customer specifications cannot be considered acceptable designs, let alone creative ones [41]. We investigated novelty because there is a high degree of consensus in the literature that creative products are at least novel [41,42].

4.1 Data Preprocessing.

The raw output of each participant was in the form of sketches and/or verbal descriptions of concepts. Examples of participant-generated solution concepts are shown in Fig. 2. A number of preprocessing steps were necessary to prepare the data for coding and analysis.

First, each participant's raw output was segmented by a trained coder into solution concepts. A sketch and/or verbal description was segmented as one solution concept if it was judged to describe one distinct solution to the design problem. Variations of solutions (e.g., with minor modifications) were counted as distinct solution concepts. Segmentation was independently checked by a second coder. Inter-rater agreement was high (96%), and all disagreements were resolved by discussion. Next, sets of two senior mechanical engineering students rated each solution concept as meeting or not meeting the minimum constraints of the design problem, as described above, to remove off-topic inspirations generated by the patent examples, especially in the second phase. Inter-rater agreement was acceptable, with an average Cohen's kappa of 0.72. All disagreements were resolved through discussion. The 1066 solution concepts remaining after preprocessing constituted the final data set for analysis.

4.2 Solution Transfer.

Solution transfer was defined as the degree to which a given participant's idea set contained solution features from the examples she/he received. The process of producing a solution transfer score for each participant was as follows. First, key features were generated by one of the co-authors for each of the eight patent examples, and the list was cross-checked for relevance by the other co-authors. Recall that each participant received two examples; however, since picture and text examples were essentially the same examples (only in different representations), the $2 \times 2 \times 2$ design reduced to a 2×2 design, leaving a total of eight examples. A total of 39 key features were identified. Because some features overlapped across examples (e.g., "built into ground, stationary, or permanent" was

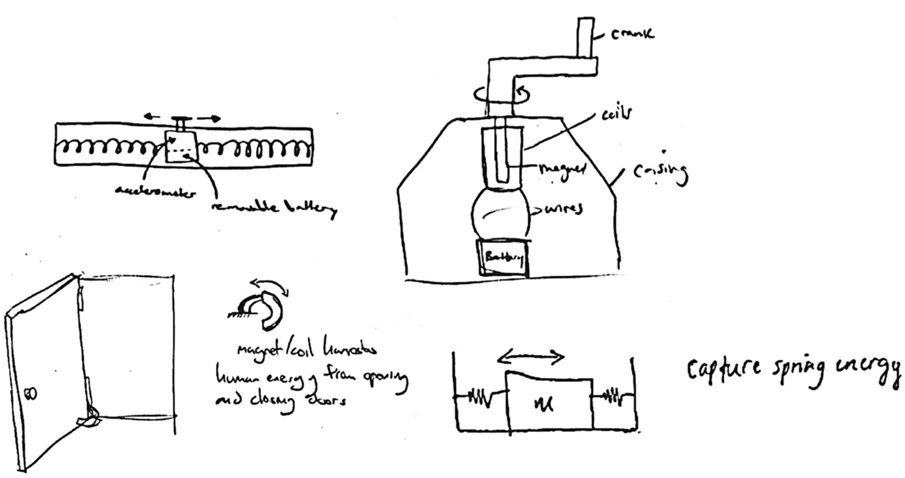

Fig. 2 Example participant solution concepts

associated with four patent examples), there was not a simple one-to-one mapping of features to examples. The number of features associated with each of the eight examples ranged from 4 to 7 ($M = 4.9$, $SD = 1.0$). Second, each participant solution concept was coded for the presence or absence of a set of the features found in the full set of patent examples presented to participants. The first 50% of solution concepts was double-coded by two senior mechanical engineering students to establish reliability. Later, all coding was completed by one student only. Test-retest measures of reliability were obtained in lieu of inter-rater reliabilities. Cohen's kappa averaged across features was 0.57. Because some features had low coding reliability or high overlap of features across many of the patents or simply were common elements of most proposed solutions across all conditions, the initial set of 39 features was filtered down to 23 features according to three criteria:

1. Acceptable inter-rater agreement, i.e., Cohen's kappa greater than 0.4.
2. Not shared by more than three examples.
3. Not too common, i.e., base rate (collapsed across conditions) less than 0.5.

After filtering, the number of features ranged from 1 to 5 ($M = 2.9$, $SD = 1.4$) per example and from 4 to 8 ($M = 5.8$, $SD = 1.7$) per each of the four conditions in the distance by commonness 2×2 design. Cohen's kappa averaged across the filtered set of features was 0.66.

To produce solution transfer scores for each participant, the following procedure was used. First, for each cell in the 2×2 (distance $\times$ commonness), we computed for each participant the proportion of his/her ideas that had at least one solution feature from the examples she/he received. Next, this proportion was converted into a standardized z-score by subtracting the mean and dividing by the standard deviation of proportion scores for all participants who were *not* in that 2×2 cell. The reason for using this transformation was that solution features from examples could occur in participants' ideas even if they never saw the relevant examples; this transformation allows us to separate the probability of participants using solution features from examples they have seen from the probability of using those solution features even if they had never seen the examples. For each participant, the transfer score was the z-score of each feature relevant to the examples they actually received.

The solution transfer score thus gave a measure of the degree to which a given participant's idea set differed from "normal" in terms of the proportion of ideas with at least one feature from the examples she/he received. To illustrate, suppose participant 1001 had a z-score of 1.34 for far-field, more-common examples. This number would say that the proportion of 1001's ideas with at least one solution feature from the examples s/he received was 1.34 standard deviations higher than the mean proportion of ideas with at least one solution from those examples under "normal" circumstances (i.e., without having seen either of the two far-field, more-common examples).

4.3 Quantity of Ideation. Quantity of ideation was defined as the number of solution concepts generated post analogy, i.e., from the second phase of ideation onwards, that met the minimum constraints of the design problem, viz. (1) the device generates electricity, and (2) it uses human motion as the primary input. As noted in the introduction, quantity is often taken to be a key component of creativity. Quantity was defined at the level of the participant, i.e., each participant received a single quantity score. Because we were primarily interested in the effects of examples on quantity, analyses concentrated on the number of solution concepts generated after receiving examples (i.e., after the first phase) adjusting 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).

4.4 Breadth of Search. Breadth of search was conceptualized in our study as the proportion of the space of possible solutions searched by a given participant. To determine the space of possible solutions, the design problem was first functionally decomposed into potential subfunctions by one of the authors, drawing from the reconciled function and flow basis of Hirtz and colleagues [16].

Due to the open-ended nature of the design problem, a relatively large number of subfunctions were initially generated, as follows:

1. Import/accept human interaction
2. Transform human energy to mechanical energy
3. Transform human energy to alternative energy
4. Import other material
5. Contain/store other material
6. Transfer other material
7. Import alternative energy source
8. Transform alternative energy source into mechanical energy
9. Transform alternative energy source to alternative energy
10. Transform collected energy to mechanical energy
11. Transmit mechanical energy
12. Transform mechanical energy
13. Store mechanical energy
14. Transform mechanical to alternative energy
15. Transform alternative energy to electrical energy
16. Actuate/deactuate energy
17. Transform mechanical energy to electrical energy
18. Condition electrical energy
19. Store electrical energy
20. Supply electrical energy
21. Transmit electrical energy
22. Convert electrical to light or EM

Each subfunction solution consisted of a *how* and *what* component, where the former specifies the component of the solution concept that implements the subfunction, and the latter specifies either the input or the output of the subfunction (whichever is the less specified). For example, a solution for the subfunction "import human" might be "*foot* with *pedals*."

Two senior mechanical engineering students independently coded the solutions to the subfunctions for each solution concept. The solution types for the *how* and *what* components of each subfunction were generated bottom-up by the students as they coded, with each new solution type being added to a running list of solution types; the running list of solution types for each subfunction constituted the coding scheme. Inter-rater reliability was high, with an average Cohen's kappa across subfunctions of 0.84. All disagreements were resolved by discussion.

While the nature of the design problem was open-ended, a core set of subfunctions emerged from the dataset: only a small subset of the initial set of subfunctions occurred often enough for stable estimates of breadth and novelty (i.e., base rate greater than 0.1, collapsed across conditions):

1. Import human
2. Transform human energy to mechanical energy
3. Import alternative energy
4. Transform alternative energy to mechanical energy
5. Transform mechanical energy to electrical energy
6. Store electrical energy

Upon more detailed analysis, it turned out that there were only two solution types for the subfunction "store electrical energy," namely "battery" or "capacitor," and the frequency of occurrence for each solution type was relatively equivalent; thus, novelty scores for this subfunction would be unlikely to differentiate between participants. Furthermore, since the design problem was focused on the problem of harvesting (vs. storing) energy, data for this subfunction were not included in computations of breadth.

We defined the space of possible solutions for each of the *what* and *how* components of each subfunction by enumerating the number of distinct solution types generated by participants across all phases of ideation. A breadth score b_j for each participant on subfunction j was then computed with

$$b_j = \sum_{k=1}^{n} w_{jk} \times \frac{C_{jk}}{\mathrm{T}_{jk}} \tag{1}$$

where C_{jk} is the total number of solution *types* generated by the participant for level k of subfunction j, T_{jk} is the total number of solution *types* produced by *all* participants for level k of subfunction j, and w_k is the weight assigned level k. To give priority to breadth of search in the *what* space (types of energy/material manipulated), we gave a weight of 0.66 to the *what* level (which was assigned to $k=1$), and a weight of .33 to the *how* level (which was assigned to $k=2$). An overall breadth score for each participant was given by the average of breadth scores for each of the three subfunctions j.

4.5 Quality. Quality of solution concepts was measured using holistic ratings on a set of subdimensions of quality. Two other senior mechanical engineering students independently coded solution concepts on 5-point scales ranging from 0 to 4 (0 is unacceptable and 4 is excellent) for six subdimensions of quality, corresponding to a set of possible customer specifications:

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

These subdimensions were generated by the second author, who is a Ph.D. candidate in mechanical engineering focusing on design methods and cognition, and checked for validity by two other authors, who are mechanical engineering faculty specializing in engineering design. For each subdimension, each point on the 5-point scale was anchored with a unique descriptor. For example, for the "feasibility of energy input/output ratio" subdimension, 0 was "unfeasible design or input energy completely dwarfs output," 1 was "input less than output", 2 was "I/O about even," 3 was "sustainable/little surplus output; human input easy," and 4 was "output significantly higher than input." Inter-rater agreement was computed using a Pearson correlation between the ratings of the two coders for each subdimension. The average of correlations across subdimensions was 0.65, and the range was from 0.49 to 0.77. An overall quality score was computed for each solution concept, as given by

$$Q = \frac{\sum_{j=1}^{n} q_j \times r_j}{Q_{\max}} \tag{2}$$

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 setting q_j to 4 for each subdimension. The contributions of subdimension scores to the overall quality score were weighted by reliability to minimize the influence of measurement error. Since the overall quality score was a proportion of the maximum possible quality score, the score ranged from 0 to 1. Agreement between coders at the level of this composite score was acceptable ($r = 0.68$).

4.6 Novelty. Novelty was defined as the degree to which a particular solution type was unusual within a space of possible solutions. This approach allowed us to avoid the difficulties of judging the novelty of thousands of solution concepts via holistic rating methods. Recall that for the breadth metric, the space of possible solutions was defined in terms of a set of five core subfunctions for the design problem; recall further that each subfunction was decomposed further into *what* and *how* components, where the former specifies the component of the solution concept that implements the subfunction, and the latter specifies either the input or the output of the subfunction (whichever is the less specified). Rather than computing novelty scores for solutions to each level of each subfunction (the *what* and *how* levels), we chose to compute novelty scores for the *conjunction* of *what* and *how* solution components for each subfunction. For example, rather than computing the relative unusualness of the solution components "foot" and "pedals" separately for the solution "foot with pedals" for the subfunction "import human interaction," the relative unusualness of the solution "foot with pedals" relative to other solutions would be computed. The rationale for this choice was that these words in conjunction as a solution have a specific meaning that needed to be considered. Novelty scores were computed for each subfunction solution using Eq. (3), which is a formula adapted from Ref. [39]

$$N_i = \frac{T_i - C_i}{T_i} \tag{3}$$

where T_i is the total number of solution *tokens* generated for subfunction i in the first phase of ideation (collapsed across all participants), and C_i is the total number of solution tokens of the current solution *type* in the first phase of ideation. Because this measure was essentially a measure of proportion, the novelty score for each idea ranged from 0 to 1, with 0 representing solution types found in every solution (this extreme was never observed) and 1 representing solution types that never occurred in the first phase. The initial set of solution concepts (generated in the first phase of ideation) was taken to be the original design space of the participants since it corresponded to concepts generated prior to receiving examples. The final novelty score for each solution concept was the average of its subfunction novelty scores.

5 Results

5.1 Relationships Between Metrics. Analysis of the interrelationships between the ideation metrics suggested a preliminary process model that could account for these correlations and help to conceptually organize the results (see Fig. 3). Of course, correlations per se do not guarantee causation and other causal models are possible.

The preliminary process model is as follows:

- Increased solution transfer results in decreased quantity, possibly because many participants had trouble thinking of solutions beyond the ones presented.
- A high quantity of ideation allows for greater breadth of search, even if only on a statistical sampling basis.

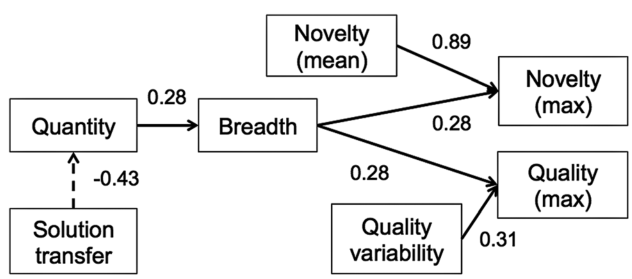

Fig. 3 Summary of intermetric correlations. Numbers shown are Pearson's *r*. All correlations are significant at $p<0.01$.

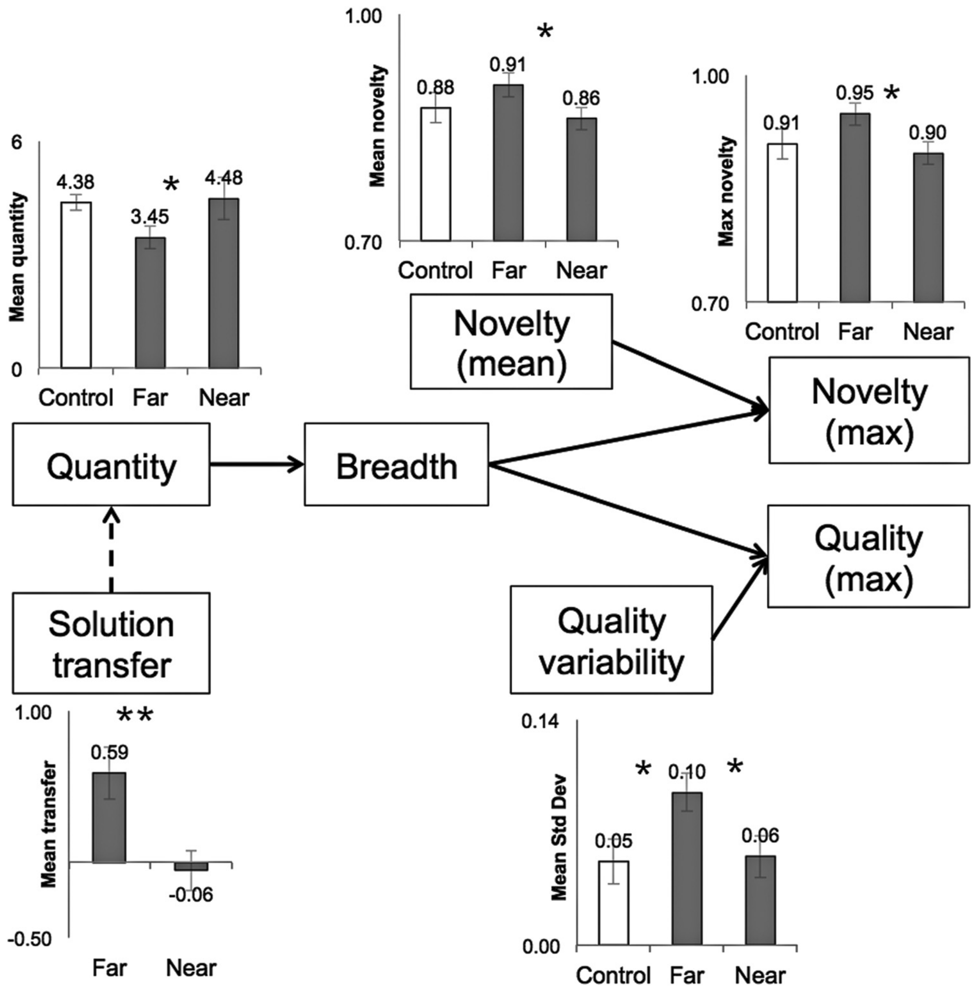

Fig. 4 Summary of effects of example distance. $^*p<0.05$ and $^{**}p<0.01$. Control group data are shown in white bars. Error bars are ±1 standard error.

- Greater breadth of search, perhaps also only on a statistical sampling basis, in turn allows for the generation of higher novelty and higher quality solution concepts.
- Repeatedly searching on the fringes of the design space (as measured by high average novelty) further increases the probability of finding a highly novel concept.
- Finally, increasing the variability of the quality of solution concepts increases the probability of generating a high-quality solution concept. This last relationship is in accord with the work of Ulrich and colleagues in the field of innovation management, who have argued and showed empirically that one way to increase the likelihood of finding high market potential product concepts is to increase the variance of the quality of the concepts that are generated [4,44].

5.2 Effects of Analogy Manipulations on Ideation Metrics. We now present our findings by manipulation (distance, commonness, and modality), using the preliminary process model as an organizational framework. Effects of manipulations on the ideation metrics will be described following the flow of the process model, first considering solution transfer, quantity, and breadth, followed by consideration of effects on quality and novelty of ideation. Separate 3-way (distance × commonness × modality) analysis of variance (ANOVA) models were computed for each process variable in the model. In some cases (indicated in each case), the level of that variable during the pre-analogy phase was used as a covariate in the analysis because the baseline measure was a significant predictor of postanalogy performance.

5.2.1 Analogical Distance of Examples. There was a main effect of example distance ($p<0.01$, $\eta^2=0.08$) on solution transfer, where participants who received far-field examples were much more likely than participants who received near-field examples to use solution elements from the examples they received ($d=0.60$);[1] in fact, solution features from near-field examples were no more likely to be present in participant solutions after processing examples relative to the pre-example phase (see Fig. 4, bottom left).

There was also a main effect on quantity ($p<0.01$, $\eta=0.05$), where participants who received far-field examples generated significantly fewer solution concepts relative to participants who received near-field examples ($p<0.05$, $d=-0.30$; see Fig. 4, upper left). There were no significant differences in terms of quantity between receiving no examples (control) and receiving either far- or near-field examples. However, the small effect of distance on quantity did not translate into an effect on breadth: there were no reliable effects of distance on breadth of search ($p=0.78$, $\eta^2=0.00$).

With respect to quality of solution concepts, there were no effects of distance on either mean or maximum quality. However, there was a main effect of distance of the variability in quality of participants' solution concepts ($p<0.05$, $\eta^2=0.06$; see Fig. 4, lower right), where participants who received far-field examples had a larger standard deviation in quality of solution concepts

[1] d statistics estimate the size of the difference in group means in terms of the average standard deviation of the two groups in the contrast; in this case, $d=0.60$ estimates that the mean probability of transfer is greater with far-field vs nearfield examples by 0.60 of a standard deviation (a moderate to large difference).

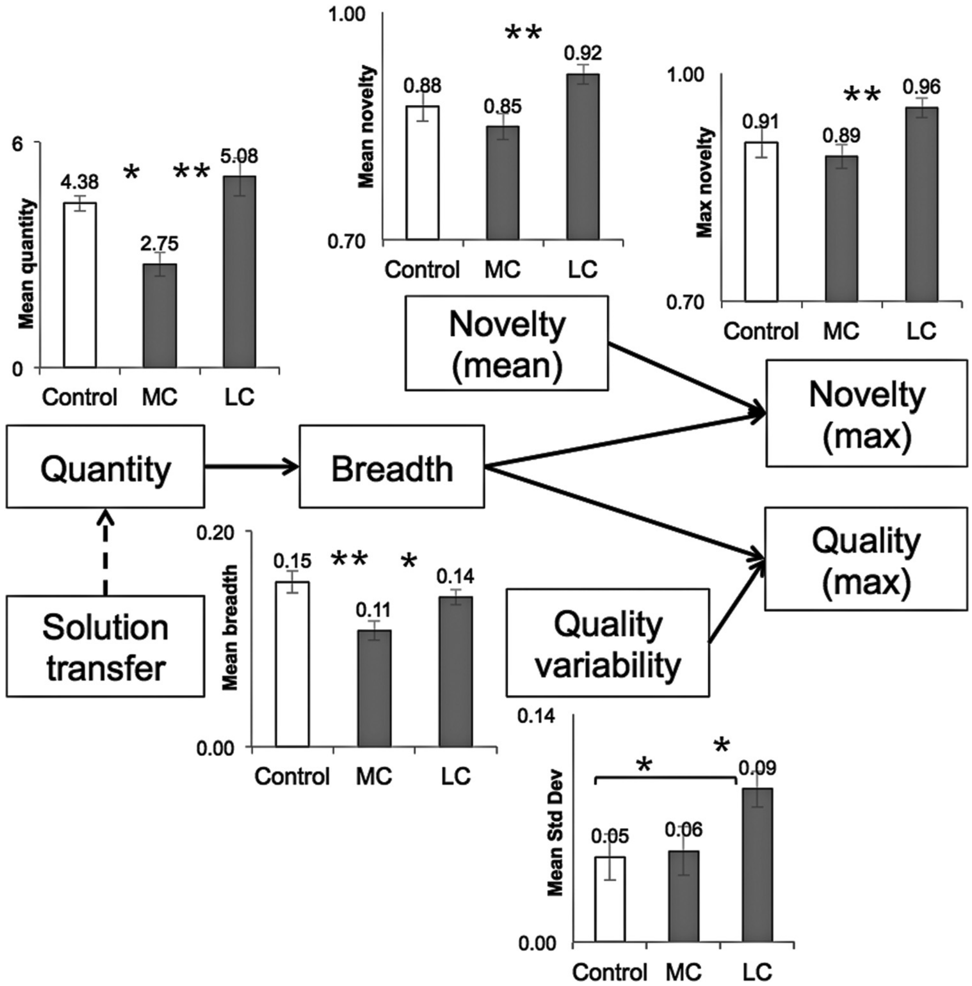

Fig. 5 Summary of effects of example commonness. *$p<0.05$and **$p<0.01$. Control group data are shown in white bars. Error bars are ±1 standard error.

than participants who received either near-field examples ($p<0.05$, $d=0.64$) or no examples ($p<0.05$, $d=0.78$). There were no significant differences between receiving near-field examples vs. no examples.

Finally, there was a main effect of distance on mean novelty ($p<0.05$, $\eta^2=0.04$), where participants who received far-field examples generated solution concepts that were more novel on average relative to participants who received near-field examples ($p<0.05$, $d=0.56$; see Fig. 4, upper right). Similar patterns of effects were found with maximum novelty of solution concepts ($p<0.05$, $\eta^2=0.04$), where the most novel solution concept of participants who received far-field examples was more novel on average relative to the most novel solution concept of participants who received near-field examples ($p < 0.05$, $d=0.56$). There were no significant differences between participants who received no examples (control) vs. near- or far-field examples on either mean or maximum novelty.

In summary (see Fig. 4), example distance appeared to have significant effects on multiple aspects of ideation. Specifically, novelty and variability in quality of concepts increased as a function of receiving far-field examples, although only in the latter case was the contrast with control statistically significant. The solution transfer metric suggests that these increases might be associated with incorporating solution elements from the far-field examples. However, the benefits of far-field examples came with a slight cost, viz. a reduction in quantity: in meaningful terms, the cost of processing far-field examples given a standard time for ideation appeared to be, on average, about one solution concept.

5.2.2 Commonness of Examples. Turning now to the main effects of commonness in the same ANOVAs, there were no reliable effects on *solution transfer* (p = 0.30, $\eta^2=0.01$). However, there was a main effect on *quantity* ($p<0.01$, $\eta^2=0.12$), where participants who received more-common examples generated significantly fewer solution concepts relative to participants who received either more-common examples ($p < 0.01$, $d=-0.67$) or no examples ($p < 0.01$, $d=-0.76$; Fig. 5, upper left). There were no significant differences in quantity between participants who received less-common vs. no examples (control). There was also a main effect of on *breadth of search* ($p<0.01$, $\eta^2=0.07$), where participants who received more-common examples searched less of the design space than participants who received either less-common examples ($p<0.05$, $d=-0.61$; Fig. 5, lower middle) or no examples ($p<0.01$, $d=-1.03$). There were no significant differences in breadth of search between participants who received less-common vs. no examples (control).

With respect to *quality* of solution concepts, there were no reliable effects of commonness on either mean or max quality. However, there was a main effect on variability in quality of participants' solution concepts ($p<0.05$, $\eta^2=0.06$; see Fig. 5, lower right), where participants who received less-common examples had a larger standard deviation in quality of solution concepts than participants who received either more-common examples ($p<0.05$, $d=0.62$) or no examples ($p<0.05$, $d=0.68$). There were no significant differences between receiving more-common examples vs. no examples.

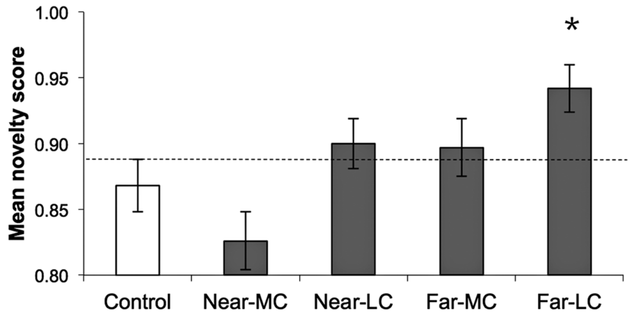

Fig. 6 Mean novelty of solution concepts by example distance and commonness. *$p<0.05$. Error bars are ±1 standard error.

Finally, there were main effects on mean *novelty* ($p<0.01$, $\eta^2=0.10$), where participants who received less-common examples generated solution concepts that were more novel on average relative to participants who received more-common examples ($p<0.01$, $d=0.61$; see Fig. 5 upper right) and maximum novelty ($p<0.01$, $\eta^2=0.96$), where the most novel solution concept of participants who received less-common examples was more novel on average relative to the most novel solution concept of participants who received more-common examples ($p<0.01$, $d=0.61$). There were no significant differences between participants who received no examples (control) vs. more- or less-common examples on either mean or maximum novelty.

In summary (see Fig. 5), example commonness also appeared to have significant effects on ideation. Less-common examples were associated with more positive ideation processes and products relative to more-common examples, with benefits for quantity and breadth of ideation, variability in solution quality, and novelty of solution concepts, although only in the case of variability in solution quality was the contrast with control statistically significant.

5.2.3 Joint Effects of Example Distance and Commonness on Novelty. While far-field and less-common examples separately increased novelty of ideas, neither far-field examples as a whole nor less-common examples as a whole were significantly different from control, which sat in the middle. To examine whether the *combination* of far-field and less-common properties increased novelty over control, we used a Dunnett's multiple comparison post hoc test. Since there were no effects of modality on novelty (described below), we collapsed across the picture and text factors and conducted the post hoc test comparing each of the combinations in the 2×2 matrix (distance x commonness) with the control condition as a reference group. The post hoc test showed that the combination of far-field, less-common examples did in fact increase novelty vs. control, for both mean ($d=1.14$; see Fig. 6) and max ($d=1.29$).

5.3 Effects of Example Modality. Turning to the effects of modality in the overall ANOVAs, there was a main effect of example modality ($p<0.01$, $\eta^2=0.09$) on solution transfer, where participants who received their examples in text form were more likely to use solution elements from the examples they received, regardless of distance or commonness of the example ($d=0.60$; Fig. 7, lower left).

There was also a main effect of on quantity ($p<0.01$, $\eta=0.12$; Fig. 7, upper left), where participants who received text examples generated significantly fewer solution concepts relative to participants who received either picture examples ($p<0.01$, $d=-0.67$) or no examples (control; $p<0.05$, $d=-0.56$). There were no significant differences between participants who received picture examples vs. no examples (control). Thus, receiving examples in text form increased the likelihood of being able to use solution

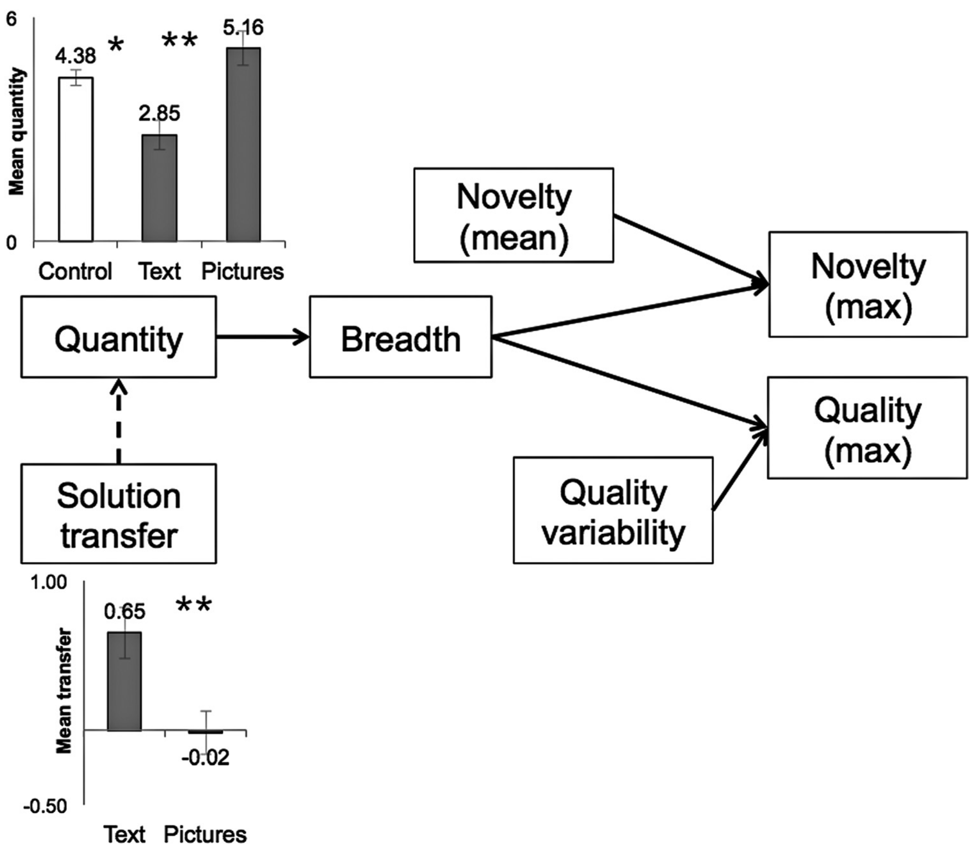

Fig. 7 Summary of effects of example modality. *$p<0.05$ and **$p<0.01$. Control group data are shown in white bars. Error bars are ±1 standard error.

elements from those examples relative to picture form, but also decreased quantity by an average of about two concepts relative to receiving either picture or text examples.

There were no additional effects of modality on the other dependent measures (breadth, $p = 0.11$, $\eta^2 = 0.03$; mean novelty, $p = 0.20$, $\eta^2 = 0.02$; max novelty, $p = 0.49$, $\eta^2 = 0.00$; quality variability, $p = 0.44$, $\eta^2 = 0.01$). Thus, modality had little impact on the key end-state outputs of the ideation process, unlike the effects of example commonness or example analogical distance.

6 Discussion

6.1 Optimal Example Types. Our findings demonstrate that the analogical distance and commonness of examples significantly influences their impact on designers' ideation. With respect to analogical distance, augmenting ideation with far-field examples brings significant benefits vis-à-vis the kinds of concepts that can be generated; specifically, ideation with far-field examples enhances the ability to generate highly novel solution concepts and also allows for more variability in the quality of concepts, which may increase the likelihood of generating high quality concepts. It is interesting to note that, even though the far-field examples we gave participants were not energy-generating devices, they were still able to benefit from the concepts and solution elements in the devices. This sort of transfer is greater in distance than typically seen in the analogy literature, where far-field analogies in problem solving are usually from cases in other domains that are surface dissimilar but still solve the same basic problem [20,45].

However, the use of far-field examples was not without some cost. Far-field examples reduced overall quantity of ideation relative to near-field or no examples. This finding can be interpreted in terms of processing difficulty. When we computed an additional 3-way ANOVA model on quantity for only the final phase of ideation, removing from consideration quantity of ideation while processing examples, the effects of distance were no longer present ($p = 0.47$). This suggests that the reduction in quantity can be attributed to the time taken to map the far-field example to the design problem. Thus, it appears that far-field examples not only carry with them the potential to increase novelty and quality of design concepts generated but also carry an initial processing cost in terms of time taken to map them to the target problem.

With respect to commonness of examples, we found that the use of less-common examples positively impacts ideation. Less-common examples resulted in increased quantity of ideation, breadth of search, and higher novelty of ideas relative to more-common examples. In a follow-up analysis analyzing quantity for only the final phase of ideation, the positive effects of less-common examples relative to more-common examples were still present ($p < 0.05$, $d = 0.56$), suggesting that the effects cannot be explained simply in terms of initial processing costs, as in the case of distance effects on quantity. Thus, it seems that less-common examples might be more beneficial for stimulating ideation, particularly in terms of novelty of concepts generated. This finding is in accord with some work in the domain of artistic creativity, where it has been shown that copying novel artworks has a positive effect on the ability of art students to flexibly re-interpret artwork and increases the novelty of the artworks produced [46].

While distance and commonness had some similar effects on ideation processes and products, our fine-grained analytic approach suggests some potentially important distinctions. The critical contrast seems to be with respect to effects on quantity and breadth of ideation. Far-field examples increased novelty of solutions and variability in solution quality, but appeared to do so via solution transfer, and resulted in decreased quantity; in contrast, less-common examples also increased novelty and quality variability, but appeared to do so via broadening the search space and increasing quantity. One way to interpret this contrast is that example distance and commonness have different mechanisms of inspiration. Based on the results, one could hypothesize that far-field examples inspire designers by moving them into one or two novel regions of the design space (high solution transfer, high novelty), which they then explore in more depth (low quantity, no benefits on breadth); in contrast, one could hypothesize that less-common examples inspire designers by moving them into multiple different regions of the design space via re-interpretation of design functions and features (low solution transfer, high breadth, and quantity).

6.2 Optimal Representation Modality of Examples. With regard to the outcome measures of novelty and quality of solution concepts, we found that the representation modality of examples did not change the effects of the distance and commonness factors on ideation. However, we did find evidence for a negative effect of text representations on overall quantity of ideation relative to picture or no examples. Similar to the effects of distance on quantity, this suppression effect of text representations can be interpreted in terms of initial processing costs: when we analyzed only the last phase of ideation, the effect of modality was weaker (pictures vs. text, $d = 0.32$; pictures vs. control, $d = 0.45$) and no longer statistically significant ($p = 0.07$). As an ancient proverb puts it, one picture may be worth 10,000 words with respect to conveying design concepts.

6.3 Caveats. The current work comes with a number of caveats. First, we have examined only one design problem. Although a real design problem of some complexity, examples may have different effects on more complex design problems. Second, we examined the effects of particular examples rather than a range of examples sampled multiple times from a class of examples. This experimental design choice made it more feasible to analyze solution transfer but raises possibilities of effects being caused by odd examples or example descriptions. To reduce this threat, we had two examples per condition, and the factorial design of the study permits for multiple replications of main effects. Third, our participants were senior-level engineering students, for the most part, rather than expert designers, and there is some research to suggest that novices have more difficulty with analogical mappings [5,47]. However, design teams sometimes include less experienced designers. Finally, our study focused only on the earliest ideation phase, and future work will have to examine the effects of examples on downstream, and in particular finished, solutions. This restriction was most salient in the analyses of quality in that many of the ideas were not feasible or not fleshed out sufficiently to determine feasibility. However, a number of studies point to early ideation as a key moment for intervention to generate innovative designs [3,4].

6.4 Practical Implications and Future Work. The overall focus of this study was on whether particular kinds of examples are more helpful than others for stimulating ideation. However, with the inclusion of a control group, which received no examples, we were able to answer a separate but related question: all things considered, does analogizing over examples confer benefits over and above ideating without examples? In other words, is design-by-analogy worth the extra time and effort? Our findings suggest that if the goal of conceptual ideation is to ultimately generate and develop a concept that is high quality *and* novel, then the answer is yes.

There are also implications for the design of tools and methods to support design-by-analogy. As noted in the introduction, a range of previous design-by-analogy methods have been developed; of particular interest is the development of computational tools that automate the search for analogies [48]. It is well known in the psychological literature that retrieving far-field analogies is cognitively difficult; remindings tend to be significantly constrained by surface similarity [49], reducing the probability of retrieving potentially relevant surface dissimilar analogies. Thus, computational tools that are able to define and compute functional and surface similarity between items in a design space in a principled manner relative to the current design problem would hold excellent potential as aids for inspiration. These tools might be able to maximize the potential benefits of analogies by retrieving and delivering to the designer in a timely manner surface dissimilar analogies and potentially (as our findings suggest) even analogies that do not necessarily provide direct solutions to the target problem. Additionally, if these systems are able to give priority to analogies that are relatively unusual or infrequently encountered, the potential for inspiration might be even higher.

Currently, the state of the art for computational design-by-analogy tools has not reached the point of being able to provide flexible and real-time support in this manner. The present work provides an impetus for investment into this important research area, as the potential benefits to engineering practice and to society via increased innovation is high

Acknowledgment

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