Characterizing the Effects of Multiple Analogs and Extraneous Information for Novice Designers in Design-by-Analogy

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This study examines how the quantity of ideas and analog transfer in design-by-analogy (DbA) are affected by multiple analogs and extraneous information, or noise, using a between-subjects, factorial experiment. To evaluate the effects of multiple analogs and noise on ideation, the study uses two metrics in conjunction with one another; namely, number of ideas (most typical in engineering design) and recognition of high-level principle (more common in psychology). The quantity analysis included three components: number of ideas generated, number of ideas that use example products (analogs and noise stimuli), and number of ideas that use analogs. The results indicate two important findings: (1) providing multiple analogs during ideation had a positive impact on ideation quantity and analog transfer. Specifically, the number of analog-based ideas increased with increasing number of analogs but eventually reached a "saturation point"; (2) introducing extraneous information (noise) diminished the successful mapping of analogs to design solutions. The presence of extraneous information did not significantly affect student designers' ability to identify high-level principles in analogs. The study demonstrated that some extraneous information was perceived as surface similar analogs. Any design analog retrieval method or automated tool will produce extraneous information, and more work is needed to understand and minimize its impact.
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1 Introduction

Continued innovation is essential for economic prosperity. In a knowledge-based economy, profits are increasingly influenced by innovation capabilities [1]. One approach to efficiently increase innovation is the use of design analogies [2–7]. Studies have shown that designers frequently use analogs not only to generate ideas, but also to explain design ideas and at times to predict potential problems [6,7]. Idea generation through design-by-analogy (DbA) can enhance the prospect of producing creative and novel ideas [8]. A well-known example of DbA is Velcro®, which was invented by George de Maestral when he noticed the hooks present in burrs and their tendency to grab onto his pet's fur. Maestral transferred the minuscule hook feature to a textile application and created Velcro®.

A key for successful analog transfer is the identification of the relevant principles to be transferred between analogs. Studies show that increasing the number of analogous items improves analog transfer [7,9–15]. This is likely due to a decrease in the number of similarities in common among a set of analogs, making it easier to identify the relevant content, or high-level principles. Increasing the number of analogs is generally agreed to be beneficial to idea generation; however, the effect of irrelevant information or noise has not been studied.

This study examines how the quantity of ideas and analog transfer in DbA are affected by multiple analogs and extraneous information (or noise). Computer-based systems are being developed to support the identification of useful analogs, but these systems will always contain a degree of extraneous information, and it is unclear how many useful analogs should be presented. It is often possible to group analogs based on the same higher level structural information. Prior research indicates that the introduction of two analogs improves identification of the high-level principle, but the effect of a greater number of analogs has not been explored extensively, nor has the introduction of extraneous information. To this end, a between-subjects factorial experiment presents engineering students with a design problem and a varying number of analogs and noise stimuli.

1.1 Cognitive Science Models for Analogical Reasoning. Various analogical reasoning models have been proposed, with the majority agreeing on a four-step process (Fig. 1) [16]:

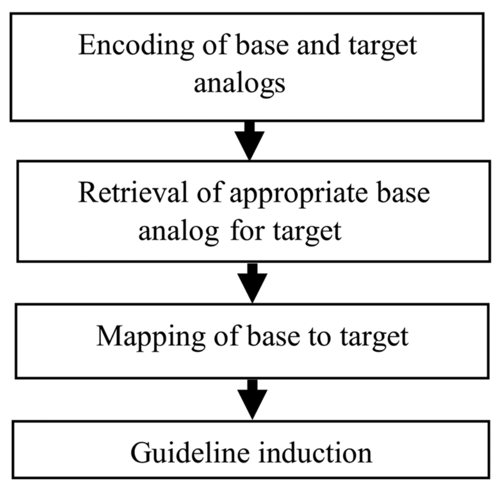

Fig. 1 Schematic of the analogical reasoning process. Adapted from Ref. [16].

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- *Encoding of the base and target analogs:* Identifying abstract principles that characterize the base and target analogs to determine potential similarity.
- *Retrieval of appropriate base analog for target:* Selecting the base analog that is relevant for the given target.
- *Mapping of base to target:* Transferring information from the base analog to the target analog.
- *Guideline induction:* Developing abstract rules or solution principles (*schema*) for application to future problems, without the need for a base analog.

Despite a common process, the various models tend to disagree on the importance of deep structure or *schematic* information, versus the surface feature or *semantic* content, during the analogical reasoning process. For example, structure-mapping [13] and pragmatic-schema [17] theories consider schematic information to be the major factor in the mapping stage, with surface features being used primarily for analog selection. On the other hand, in exemplar-analogy theory [18], semantic information (i.e., surface features) plays a larger role in all stages of analogical reasoning. Exemplar-analogy theory posits that analogs are stored as complete units. In this model, the mapping stage is driven by all aspects of the base analog, and surface features play a role equally as important as deep similarities.

The current study was designed using the generalized analogical reasoning model shown in Fig. 1 [16]. It assumes that content abstraction is critical for the analogical transfer, as Goel [19] and Nersessian [20] have suggested. The study manipulates the encoding and retrieval stages by introducing a predefined set of base analogs, and observes the resulting effects during the mapping and schema induction stages.

1.2 Structural-Mapping. Structure-mapping [13,21] theory considers the structural information to be the major factor in the mapping stage, with surface features being used primarily for analog selection. Surface features are defined as entities (stand-alone individuals or objects) or attributes (generally adjectives or descriptions). Structural elements consist of (a) *first-order predicates*, which form a relationship between two entities and (b) *higher-order relations*, which form connections between entities, attributes, or even first-order predicates. For example, in the higher-order relation “The bicycle moves because crank-a turns wheel-b”; “crank-a turns wheel-b” is a first-order predicate; bicycle, crank-a, and wheel-b are entities or surface features. The transfer of the information in structural elements is what leads to successful analog transfer. Abstraction, discussed in further depth in Sec. 1.3, of structural elements is vital to initiate mapping from base to target analog [16].

1.3 Abstraction. Cognitive science theories argue that abstraction is a key to successful analog transfer [16], and studies in design [22] and artificial intelligence [19] have come to the same conclusion. For example, a biomimicry study found that biomimetic designs are fully realized only when the designers can abstract a strategy from an appropriate biological analog [8]. Abstraction allows designers to ignore the incidental and focus on the essential, allowing the designers to better define the overall functional requirements and constraints [23].

1.4 Embedded Principle Versus Abstract Principle Method. Problem solving methods can be explained by using examples (*embedded principle*) or guidelines (*abstract principle*). For instance, if students are asked to solve a problem after they are given several example problems with principles integrated into the solving of the problems, they learn through embedded principle [24]. If, instead, the students are given a set of explicit general principles and an explanation of how the principle is applied with an example problem, they learn through abstract principle [24]. Studies attempting to determine which is more successful have had inconclusive results [25], and it can be concluded that the appropriate method may be largely case dependent. In the context of learning mathematics, Richland and McDonough [26] found that providing cues, showing alignment between the source and target, to accompany an instructional analog improved students’ abilities to later identify relevant analogs and successfully extend knowledge to new contexts.

1.5 Identifying High-Level Principles. A key step in successful DbA is identifying the relevant high-level principle(s) for a given problem. Research shows that people have inherent difficulty with this task. For one, surface features tend to have a greater influence on base analog selection than do deep similarities [16,27–30], particularly for novices [31]. The primary problem with base analog selection through surface features is that it is often the mapping of deep similarities, or high-level principles, that leads to the functionally effective solutions [32,33].

Despite surface features having greater influence in analog retrieval, studies show that people can more easily make connections when they are presented with two analogs [9,10]. Markman and Gentner have found that by using two analogs instead of one, participants were able to focus more on the high-level relational attributes than on surface features [12]. Lowenstein et al. found a similar effect in the context of extracting abstract schema from negotiation strategy examples [34]. Also, Namy and Gentner’s study of children in comparative learning concluded that children were more likely to form categorization rules that were more abstract when they were given two examples from a given category than when they were given one [15].

In practice, designers, novices and experts alike, have a massive selection of potential analogs from which we choose an appropriate base analog. Computational systems are also beginning to provide analogs. Yet, there is still little knowledge about how idea generation is affected by multiple analogs and extraneous information. Based on the prior studies we reviewed, the researchers propose two hypotheses: that ideation quantity and analog transfer (1) improve with an increasing number of analogs and/or (2) diminish under noise.

2 Methodology

The hypotheses were evaluated with a between-subjects 4X2 factorial experiment (Table 1), where the first factor was the number of analogs (1, 2, 3, and 5), and the second factor was the noise level (none or three noise stimuli per analog). The number of analogs was selected based on the literature reviewed in Sec. 1 [11,12,15], with the goal of exploring whether analog transfer improves when more than two analogs are used and providing an estimate of how many may be highly effective. To this end, a maximum of five analogs were tested, and the 3-analogs condition was selected to be between the 2- and 5-analogs conditions. The 3-analogs condition served as an approximate midpoint data to characterize the continuous ideation result as a function of multiple analogs. A 4-analogs condition was not tested, as it would increase the number of participants beyond that which was feasible to recruit. The noise level was chosen as three times the number of analogs so that there would be 75% noise and 25% analogs in the noise conditions. In DbA practice, a set of examples may contain extraneous information, and often the level of extraneous information outnumbers the useful information. Thus, a consistent 3:1 noise to analog ratio was used to evaluate the effect of noise stimuli in different analog conditions. In addition to the factorial experiment, a condition with 100% noise, or the all-noise condition, was tested. Generally, a control condition (containing no stimulus) is tested as a comparison with other conditions to analyze the net effect of any stimulus; in this study, where the effects of two types of stimuli, namely, analogs and noise, are evaluated, the control condition is limited in evaluating the individual effect of each type of stimulus. Thus, the all-noise condition was tested to serve as a basis for analyzing the ideation results under noise.

Table 1 Summary of 4X2 factorial experiment number of participants in each condition

		Factor 1: number of analogs				
		1 Analog	2 Analogs	3 Analogs	5 Analogs	All-noise
Factor 2: noise level	No-noise	7	14	7	7	7
	Noise	9	7	7	7	

NASA astronauts are on a mission to Mars and the locking mechanism of a latch has broken down.

Your task is to provide a fix to this problem satisfying the following condition.

- **The door locking pin must automatically return to the locked position even when there is no electricity.**

NASA will send supplies to the space station with the astronauts but has not determined what materials and tools will be needed for this problem. It costs them millions of dollars per pound, so they want to send as little material as possible. Since the parts are still being designed, you can add or remove features to the parts.

Constraints:

- **You cannot use a metal coil spring. NASA is aware of this solution and needs others.**

Fig. 2 Design problem statement

2.1 Participants. Seventy-two senior undergraduate mechanical engineering students at a major public U.S. university participated in the experiment. The students were compensated for participating in the study, and they were allowed to choose either extra credit in their design class or $20 compensation. If they did not wish to participate but still wished to receive extra credit in their course, they were given the opportunity to complete an unrelated assignment for extra credit instead. The majority of participants chose the extra credit compensation option. Fifty-seven males and fifteen females enrolled in the study; they were an average of 22.3 years of age and had an average of 4.8 months of full-time engineering work experience.

The participants were randomly distributed across nine conditions, as shown in Table 1. The experiment was run in various sessions with one to four participants at a time. Only one condition was tested per session, and care was taken to limit interaction among participants. Participants were placed at tables separated by cubical walls. At the end of each session, they were asked not to discuss any aspect of the experiment with their peers to prevent bias.

The experiment proctor made an error in the experiment schedule, and as a result, the 2-analogs no-noise and 1-analog with noise conditions were run with more participants than intended, resulting in a total of fourteen and nine participants, respectively. One participant in the 2-analogs no-noise condition informed the experiment proctor that he did not put much effort in the ideation; that participant's ideation result was not used for the data analysis. In total, 71 data sets were used for the analysis.

2.2 Design Problem. The design problem (Fig. 2) asked participants to devise methods to automatically lock a broken door in a Mars habitat. The goal of the design task was to have a pin return to the locked position as shown in a locking mechanism drawing (Fig. 3) without the use of electricity or a metal coil spring. This problem was chosen because it is comprehensible, does not require significant prior experience with the task, and consists of large set of potential solutions. In addition, the problem was chosen for convenience, as there are many commonly available products that have elasticity as functional feature.

2.3 Example Products. Example products were chosen in several different domains (office products, toys, machine components, etc.), so the domain would not be a factor. For the locking mechanism, the chosen functional feature was energy storage and release through elastic deformation. A high-level principle had to be chosen where a large variety of applicable products could be identified that did not share surface features. The researchers acknowledge that there are other principles that could be used to solve this design problem, and there is never only one correct answer to any open-ended design problem.

In the experiment, physical items were given to participants. Each item was explained verbally with a scripted description by an experiment proctor with a video projected on a wall. This was to ensure that the student designers had an adequate understanding of each product. The analogs and noise stimuli are listed in Table 2 and discussed in Secs. 2.3.1 and 2.3.2. The logic used for selecting the specific analog for the 1-analog condition was that it had the fewest surface features. For the 2-analogs condition, the two were chosen that were most different from one another. Beyond these two conditions, the choices of which particular analogs were included in each condition were random.

2.3.1 Analogs. Generally, an analog is a mapping of knowledge from one domain to another, enabled by a supporting system

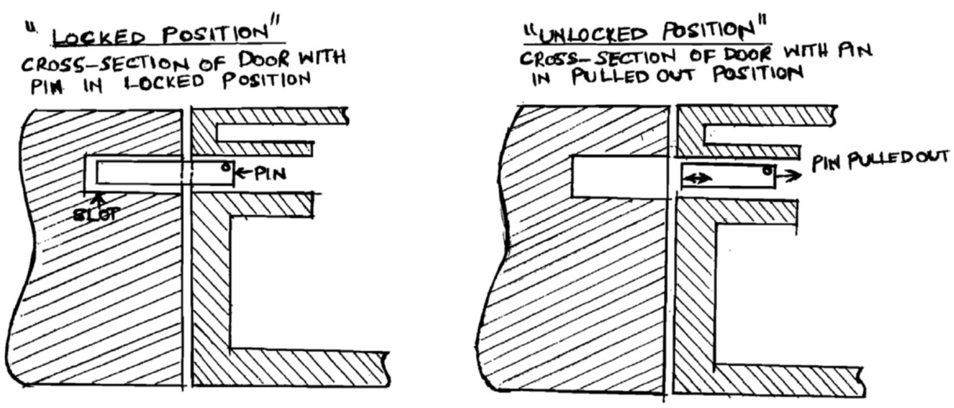

Fig. 3 Drawing of locking mechanism

Table 2 List of example products in each condition

Condition	1-Analog	2-Analogs	3-Analogs	5-Analogs	1-Analog & 3 noise stimuli	2-Analogs & 6 noise stimuli	3-Analogs & 9 noise stimuli	5-Analogs & 15 noise stimuli	15 noise stimuli
Analog	Sticky note holder lid	Constant force spring Bungee blast	Constant force spring Bungee blast Compression spring	Flour duster Constant force spring Sticky note holder lid Bungee blast Compression spring	Sticky note holder lid	Compression spring Bungee blast	Flour duster Bungee Blast Compression spring	Flour duster Constant force spring Sticky note holder lid Bungee Blast Compression spring	None
Noise	None				Sticky note flip book Business card holder Desk organizer	Sticky note flip book Tomato slicer Desk organizer Flour sifter Pool noodle[a] Whisk[a]	Flour sifter Paper airplane Spiral chip holder Tea strainer Tomato slicer Immersion heater Sticky note flip book Egg yolk separator[a] Pool noodle[a]	Flour sifter Paper airplane Spiral chip holder Sticky note flipbook Business card holder Tea strainer Tomato slicer Desk organizer Immersion heater Burner coil Model rocket Egg yolk separator[a] Pen stand[a] Pool noodle[a] Whisk[a]	Flour sifter Paper airplane Spiral chip holder Sticky note flipbook Business card holder Tea strainer Tomato slicer Desk organizer Immersion heater Burner coil Model rocket Egg yolk separator[a] Pen stand[a] Pool noodle[a] Whisk[a]

[a]Noise stimulus with surface feature.

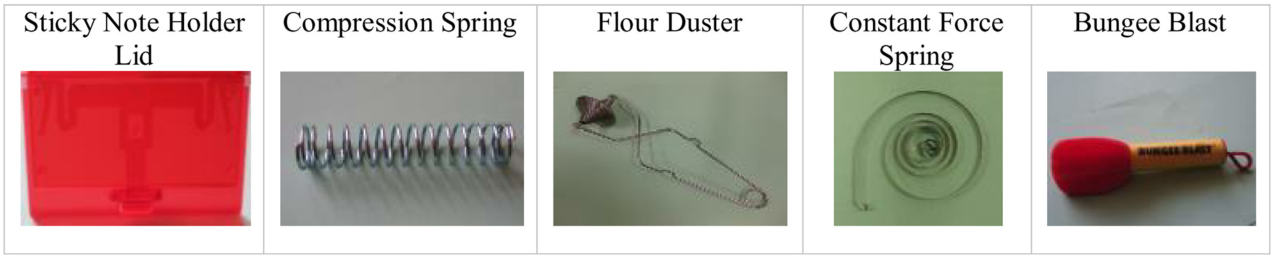

Fig. 4 Analogs used as stimuli in study

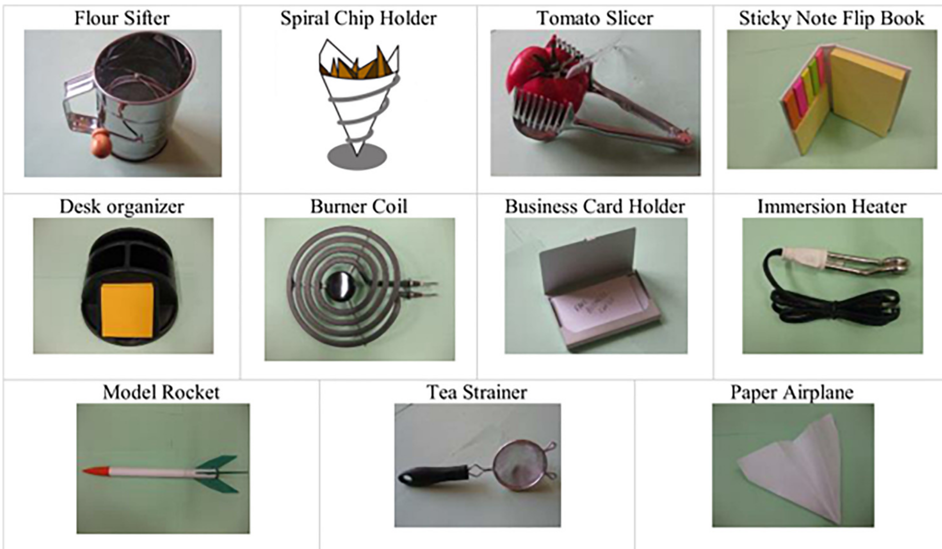

Fig. 5 Pure noise used as stimuli in study

of relations or representations between situations [13]. For the purpose of this study and this particular design problem, the authors had to narrow the definition to be relations connecting the source and the target through energy storage and release through elastic deformation. The experiment used five analogs shown in Fig. 4. All products have a functional feature to store and release energy through elastic deformation. For instance, the bungee blast flies away when a user pulls on the rubber band and releases the grip. Participants were given the physical items to study their features. For the sticky note holder lid, an entire sticky note holder was provided to demonstrate the functional feature to the participants. Although the problem statement explicitly said the metal coil spring cannot be used for the solution, the compression spring and constant force spring were used. The researchers intentionally included these misleading examples to induce potential fixation, and determine if it was a factor in the equation of the effect of noise on DbA. There is precedent for doing this in prior work by the authors in which participants were given an example solution that directly violated the design requirements [35].

2.3.2 Noise. Products without elasticity as the functional feature were considered noise stimuli. For this study, the noise products were further classified into pure noise (Fig. 5) and noise with elasticity as surface feature (Fig. 6). In principle, all products have some level of elasticity or present an elastic deformation. However, it is unlikely to characterize something "elastic" unless it deforms relatively easily by hand and returns to its original shape. Thus, if a product has an ability to return to its original shape after some deformation, it is considered a noise with elasticity as surface feature. On the other hand, if a product is very stiff and would bend permanently (plastically) or fail if a large stress is applied, it is considered a pure noise.

2.4 Experimental Procedure

2.4.1 Conditions. Participants were seated in randomly assigned cubicles on each side to prevent any contact between the participants. Each participant was given a hard copy of the problem statement and physical items of example products as listed in Table 2. In addition, participants were given several sheets of blank paper on which to list and sketch ideas, as well as multiple copies of drawings of the locking mechanism. The drawings of the locking mechanism allowed them to modify the current mechanism and spend less time sketching the repetitive parts for each idea. For

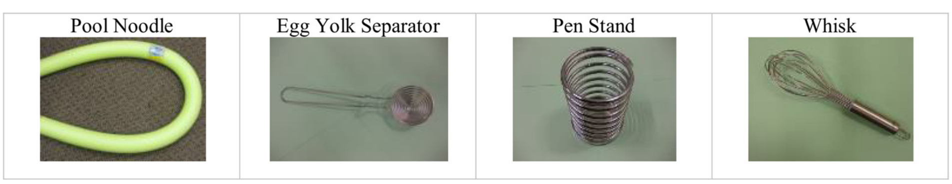

Fig. 6 Noise with elasticity as surface feature used as stimuli in study

ideation, the participants were provided and instructed to use different colors of pens. This allowed the researchers to track the rate of ideation and assure all work was done during the assigned period of task. To avoid an early start, the problem statement and drawings were stacked underneath the sheets of blank paper.

The proctor introduced the example products by stating that they "may or may not be helpful to generate solutions" and described each example product verbally with video projected on a wall. The products were shown in a random order, and there was no indication whether each product was analog or noise stimuli. Once finished, the proctor asked the participants to find the design problem below the blank papers and read along as he read aloud. Before the participants were instructed to begin the idea generation, they were told that their designs were not limited by the example products or the drawing of locking mechanism. At the end of each set of instructions, they were asked whether they understood the directions.

2.4.2 Idea Generation. Participants were then allowed to generate ideas for 40 min. This period allowed them to exhaust their ideas, making the resulting solution set a better representation of each participant's solution space. The rate of ideation was traced by exchanging the color of the participant's pen at the 5, 10, 20, and 30 min points.

2.4.3 Idea Feature Listing. After the ideation phase, the proctor gave participants an example of analogy with Velcro, explaining that its design was based on the spines on a burr. The participants were then asked to number each solution and mark "X" if the solution was not based on an analogy to any given example product. In the next task, the proctor gave examples of two different solutions being based on the same original analog: (1) a water dumbbell and (2) a punching bag, both using inflate/deflate and storage features of an analogy to an air mattress. The participants were then asked to list what example products were used for ideation and what features were mapped for the ideas.

2.4.4 Product Separation and Feature Listing. The experiment proctor asked participants to identify the example products used for idea generation by separating them from the given set of the products. This occurred at approximately the halfway point of the experiment and the participants were allowed to take a 5 min break to avoid fatigue. After the break, they were asked to list, for each of the example products, the features used and features not used, to determine which features were and were not mapped.

2.4.5 Similarity Rating. Participants were asked to rate the similarity between their ideas and example products used. This was intended to capture a more individual, self-reported perspective regarding how the participants viewed each example product and whether they viewed the analogs and noise products differently. The range of the similarity rating was from 1 (low similarity) to 9 (high similarity).

Instructions for the idea-product similarity activity asked the participants to list a similarity rating for only the ideas they generated and "leave unused boxes blank." Unfortunately, thirteen participants across nine conditions did not follow these instructions in the expected way, and left multiple boxes blank that should have been filled. Participants who did not follow instructions completely tended to skip products that had little similarity with their generated concepts. For the analysis, ratings left blank by the participants were not included; they were not entered as 1's.

2.4.6 Listing of High-Level Principle. Participants listed high-level principles in two different stages. In stage I, they were asked to determine if a set of the example products shared a common principle that could be used to solve the design problem. They were asked to list the principle and mark a star next to the ideas that used the principle. Next, in stage II, participants were informed which of the example products were analogs. Again, they were asked to list the principle and put a circle next to the ideas that used the principle. After stage II, the participants were asked to generate ideas using the listed principles for an additional 10 min.

2.4.7 Postexperiment Survey. The final activity was a survey to reinforce the results from the previous metrics and to gather demographic information. A five-level scale questionnaire asked participants about the usefulness and practicality of the example products and about the perceived difficulty of the similarity-rating task (Likert-scale). The experiment concluded by reminding the students not to discuss the experiment with their peers.

3 Metrics for Evaluation

After the data collection, the quantity of ideas and high-level principle recognition rate were used to evaluate ideation quality. Prior studies in design and psychology related to analogy, including external stimuli, have implemented the quantity of ideas and high-level principle recognition as measures of effectiveness [2,5,15,36–39]. In this analysis, they were used in conjunction with one another to fully understand the effects of analogs and extraneous information on ideation.

3.1 Quantity of Ideas. The number of ideas generated was evaluated to determine how participants performed during ideation. Quantity of ideas is often used as an objective measure to assess the effectiveness of ideation, as more ideas can result in a higher chance of producing high quality, novel ideas [40–42]. To investigate how different numbers of example products (analogs) affect analog transfer, three metrics were used to assess the ideation quantity outcomes; these were (1) number of ideas generated, (2) number of ideas that use example products (analogs and noise stimuli), and (3) number of ideas that use analogs. These metrics, ordered such that each metric is a subset of its precedent, were used to assess the participants' reliance on example products during ideation.

3.2 High-Level Principle Recognition Rate. The percentage rate of participants accurately listing "store and release energy through elastic deformation" as the high-level principle was computed to evaluate the analog transfer under different levels of stimuli. Similar to the number of analog-based ideas, this metric was used to objectively measure whether the participants successfully mapped the high-level principle during ideation. The listed principle was assessed by one of the authors and an independent third party using the following criteria: *Does the principle listed show some level of abstraction that can lead to multiple solutions?* For example, if a participant listed "flexible beam," this was not deemed a correct principle since it focuses on a specific solution. On the other hand, listing "the ability to flex and return to the original shape" was considered acceptable. Although the participant did not explicitly list elasticity, this description of the high-level principle can lead the designer to multiple solutions. Additionally, if the participant listed "spring-like," this was accepted as a correct principle since it does not imply a specific solution, but rather a type of behavior. The results from stage II were used to determine whether pointing out which products are analogs increases the high-level principles recognition rate. The two evaluators rated all the data and obtained similar results. Their Pearson's correlation factors were 0.81 and 0.87 for stages I and II, respectively. The results from only one evaluator were used for the analysis.

The objective of the study was to analyze analog transfer and the effects of stimuli types on the overall quantity of ideas generated. Success in analog transfer is the key metric implemented for psychological studies and they generally can measure if a solution was reached or not. In the context of design, there are typically many cognitive paths to reach solutions and multiple solutions can be generated for each solution path. Thus, the researchers choose to have the participants list the high-level principle for each solution, basically the inference between the analog and target problem. In addition to the high-level principle, the number of

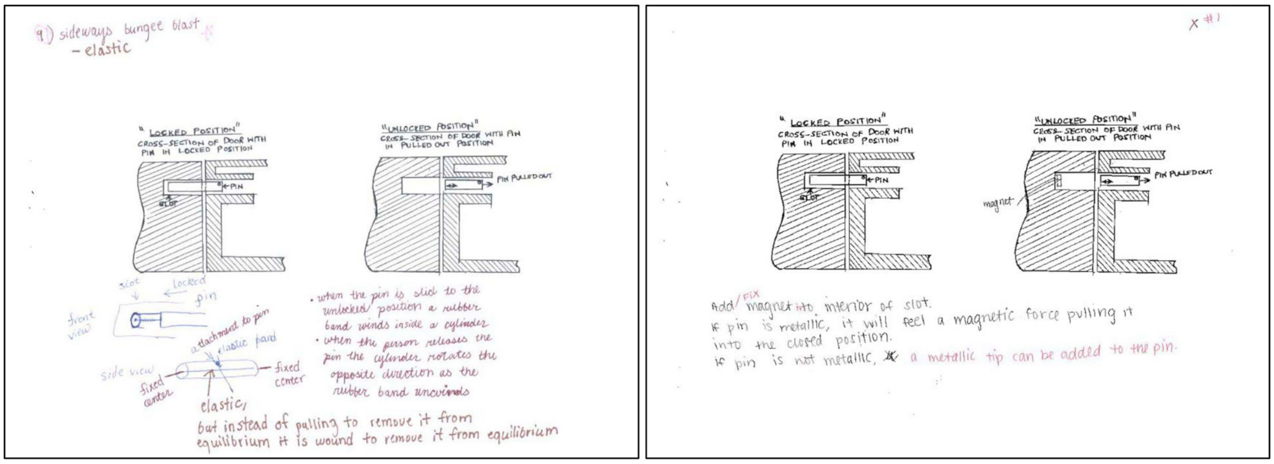

Fig. 7 Sample ideation sketches

analog-based ideas was evaluated, as it represents whether the participants generated functionally an effective solution by mapping the high-level principle, as mentioned in Sec. 1.5, during ideation.

4 Results

This study examines how the quantity of ideas and analog transfer in DbA are affected by multiple analogs and extraneous information, or noise. In Secs. 2.3.1 and 2.3.2, experimental results are presented to address how ideation is affected by varying numbers of analogs and the presence of noise. Figure 7 shows sample ideation sketches from the ideation process. The ideation outcomes are first evaluated by computing the number of ideas generated, followed by an analysis of the high-level principle recognition rate. Finally, postexperiment survey results are presented to provide additional insight into the results. For statistical analysis of the results, IBM SPSS Statistics 24.0 was used.

4.1 Number of Ideas. The number of ideas generated in the different conditions was plotted as a function of number of analogs provided in each condition, for each of the two noise levels (no-noise and noise) (e.g., Fig. 8). The plot provides a graphic overview of how the number of analogs given in each condition and presence of noise affect ideation quantity, and how they interact with each other. Since each provides different insights into the effects of analogs and noise on the process, the experimental results presented in this section are (1) number of ideas generated, (2) number of ideas generated using example products, and (3) number of ideas generated using analogs.

4.1.1 Number of Ideas Generated. Figure 8 shows the number of ideas generated. In general, the trend lines of no-noise and noise conditions are consistent across varying number of analogs. According to Levene's test, the result violated homogeneity ($p = 0.036$). However, ANOVA is robust to violations of the homogeneity assumption and normal distribution is assumed. A 2-way ANOVA validated that the number of ideas generated is not affected by the varying number of analogs, $F(3,56) = 1.0$, $p = 0.38$ and the presence of noise, $F(1,56) = 0.44$, $p = 0.51$. The interaction between the two factors was $F(3,56) = 1.4$, $p = 0.24$. It is also interesting to note that the individuals who received all noise products produced fewer ideas than individuals in other conditions (t-value $= 2.24$, $df = 69$, $p = 0.028$).

4.1.2 Number of Ideas That Use Example Products (Analogs and Noise Stimuli). Figure 9 shows the number of ideas that participants generated using example products. The result generally increases with an increasing number of analogs. However, there is a minor difference between the trend lines of no-noise and noise conditions. The no-noise and noise conditions are unusually different in the 2-analogs condition. This could be due to a random error indicated by a large error bar in 2-analogs with noise condition. The 2-analogs with noise condition is not statistically different from the 3-analogs condition. Also, it is interesting to note that individuals who received 15 noise stimuli (all-noise condition) generated a similar number of example product based ideas as individuals who received one analog. According to Levene's test, the data for this graph violated homogeneity ($p = 0.037$). However, for the same reason stated in Sec. 4.1.1, the normal distribution is assumed for ANOVA. The test validated that the varying number of analogs has statistical significance, $F(3,56) = 7.1$,

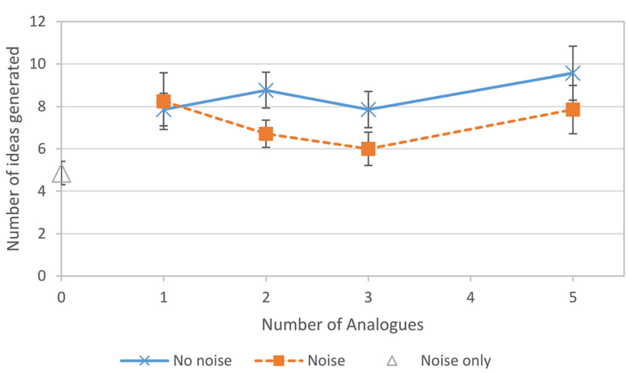

Fig. 8 Number of ideas generated, error bars show ± one standard error

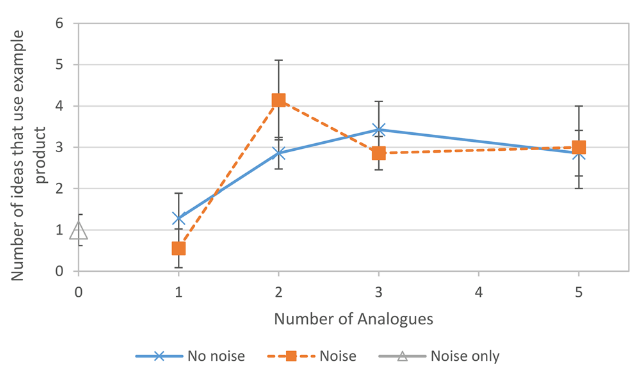

Fig. 9 Number of ideas that use example products, error bars show ± one standard error

Table 3 Post-hoc test result (p-value) for the number of ideas that use example products

	1-Analog	2-Analogs	3-Analogs	5-Analogs
1-Analog		0.001[a]	0.005[a]	0.012[a]
2-Analogs			0.99	0.90
3-Analogs				0.99
5-Analogs				

[a]Significant difference.

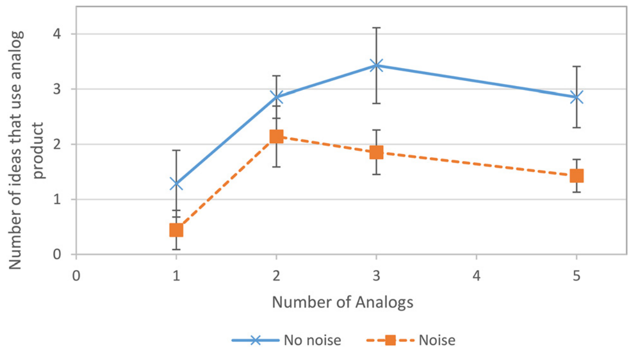

Fig. 10 Number of ideas that analogs, error bars show ± one standard error

Table 4 Post-hoc test result (p-value) for number of ideas that use analogs

	1-Analog	2-Analogs	3-Analogs	5-Analogs
1-Analog		0.001[a]	0.003[a]	0.046[a]
2-Analogs			1	0.71
3-Analogs				0.76
5-Analogs				

[a]Significant difference.

$p < 0.001$, while the presence of noise does not, $F(1,56) = 0.001$, $p = 0.97$. The interaction between the two factors was $F(3,56) = 1.1$, $p = 0.37$. Post-hoc Tukey HSD test result in Table 3, a symmetric table, shows that the one analog condition is significantly different from the rest.

4.1.3 Number of Ideas That Use Analogs. Figure 10 shows the number of ideas that participants generated using analogs. The slopes of the trend lines and a gap between them suggest that the result is affected by the varying number of analogs and presence of noise. According to Levene's test, the result satisfies homogeneity ($p = 0.22$). The test confirmed that the results are significantly affected by the varying number of analogs, $F(3,56) = 5.7$, $p = 0.002$ and the presence of noise, $F(1,56) = 11$, $p = 0.001$. The presence of noise causes participants to be less likely to leverage the effective examples to find solutions. The interaction between the two factors was $F(3,56) = 0.34$, $p = 0.80$. Table 4 shows the post-hoc Tukey HSD test result for the multiple analog conditions.

4.1.4 Alternative ANOVA Result. One participant in 1-analog with noise condition generated twice the number of ideas than the rest of the participants (more than two and a half standard deviations from the mean), suggesting that the data are an outlier. To investigate its effect on the result, ANOVA was performed again after removing the outlier from the dataset.

While the original and refined datasets have similar ANOVA results for the number of ideas that use example products (Table 5) and analogs (Table 6), there is a significant change for noise that

Table 5 ANOVA results of original and refined datasets, number of ideas that use example products

	Original dataset			Refined dataset		
	df	*F*	Sig.	*df*	*F*	Sig.
Number of analogs	3	7.1	<0.001	3	6.5	0.001
Noise	1	0.001	0.97	1	0.005	0.94
Interaction	3	1.1	0.37	3	1.0	0.40
Error	56			55		

Table 6 ANOVA results of original and refined datasets, number of ideas that use analogs

	Original dataset			Refined dataset		
	df	*F*	Sig.	*df*	*F*	Sig.
Number of analogs	3	5.7	0.002	3	5.2	0.003
Noise	1	11	<0.001	1	11	0.002
Interaction	3	0.34	0.80	3	0.36	0.79
Error	56			55		

Table 7 ANOVA results of original and refined datasets, number of ideas generated

	Original dataset			Refined dataset		
	df	*F*	Sig.	*df*	*F*	Sig.
Number of analogs	3	1.0	0.38	3	0.99	0.41
Noise	1	0.44	0.51	1	3.3	0.075
Interaction	3	1.4	0.24	3	0.64	0.60
Error	56			55		

Note: Becomes statistically significant when the outlier is removed.

becomes a statistically significant factor in the number of ideas generated (Table 7), $F(1,55) = 4.8$, $p = 0.075$. The presence of noise significantly reduces the number of ideas generated. The refined dataset satisfies the homogeneity ($p = 0.22$) and normality ($p = 0.57$), according to Levene's test and Shapiro-Wilk's test, respectively. Interestingly, the effect of noise is significant on the number of ideas when the outlier is removed. In removing one outlier, statistical significance is achieved in this case, when it was not in the original data set.

4.1.5 Validation of 2-Way ANOVA Results Using Resampled Dataset. 2-way ANOVA is robust under several assumptions, one being the homogeneity of variance. However, an inconsistency of sample size among different conditions, as seen in Table 1, may violate the assumption and question the quality of ANOVA results. For a two-way treatment structure where every treatment combination is observed at least once, Milliken and Johnson recommend using a general linear model with type II sum of squares, which is the analysis performed by the authors [43]. In order to explore the effect of large sample size difference in 2-analogs no-noise condition, ANOVA was conducted on the dataset after downsampling the condition's participant number from 14 to 9. Since one participant's data were already ignored for the lack of effort, only four participants' data were eliminated. Table 8 shows the original ANOVA results in comparison to that of the sampled dataset. For each metric, four participants who generated the greatest number and four participants who generated the fewest number were removed from the sample. As shown in the table, the removal of the four best or four worst data does not greatly change the significance value, suggesting that the ANOVA results

Table 8 ANOVA results (p-value) of original and resampled datasets

	Number of ideas (p-value)			Number of ideas that use example products (p-value)			Number of ideas that use analogs (p-value)		
	Number of analogs	Noise	Interaction	Number of analogs	Noise	Interaction	Number of analogs	Noise	Interaction
Original dataset	0.38	0.51	0.24	<0.001	0.97	0.37	0.002	0.001	0.80
4 best data removed	0.24	0.78	0.31	0.001	0.72	0.18	0.004	0.005	0.476
4 worst data removed	0.43	0.34	0.16	<0.001	0.70	0.74	<0.001	<0.001	0.843

of the original dataset with one condition having 14 data are still robust.

4.2 High-Level Principle Recognition Rate. Figure 11 shows the percentage of participants correctly identifying the high-level principle in different conditions. For no-noise condition, the recognition rate is consistent across the varying number of analogs, except for the 2-analogs condition where the recognition rate is 100%. For the noise condition, the recognition rate increases with additional analogs, but decreases in the 5-analogs condition. Binary logistic regression with the number of analogs and noise treated as categorical variables was performed. The effect of the number of analogs was statistically significant (Wald = 10.97, $df = 3$, $p = 0.012$), but the effect of noise was not (Wald = 0.43, $df = 1$, $p = 0.50$). The stage II result was compared with the stage I result using Pearson's chi square tests to assess whether the participants could better recognize the high-level principle when they are informed which example products are analogs. However, none of the changes were statistically significant (lowest p-value was 0.15).

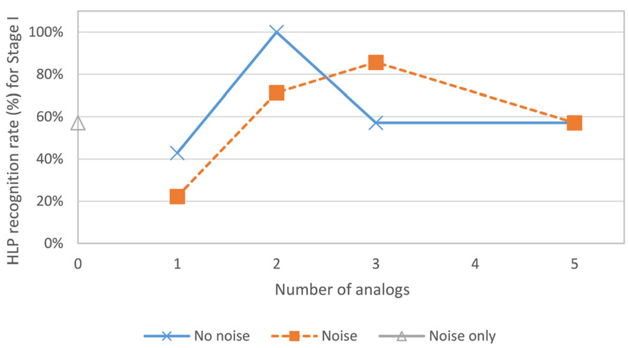

Fig. 11 Percentage of high-level principle recognition rate in stage I

4.3 Similarity Ratings. The similarity ratings were analyzed to determine whether the noise products (pure noise and noise with elasticity as a surface feature) were indeed seen as different from the intended analogs. According to the similarity rating task, the mean similarity ratings were 2.4 for analog, 2.3 for noise with elasticity as a surface feature, and 1.6 for pure noise (Fig. 12). To evaluate the significance of the result, an ANOVA was performed. The result violated normality and homogeneity, but the small sample size is assumed to be normal, and the ANOVA was justified. According to the test, the similarity ratings of all three product types were significantly different, $F(2{,}444) = 26$, $p < 0.001$. The similarity rating of noise with surface feature was more similar to that of analogs than that of pure noise, but still statistically different (t-test unequal variances, $t = 8.7$, $p < 0.001$).

To further validate that the analogs influenced the participants' processes differently, the number of ideas generated using example products was analyzed as a function of time (Fig. 13). The similarity ratings are self-reported data, which can often be inaccurate, and the frequency of usage is another measure of the impact of the analogs. Prior research has also shown that participants may not use distant domain analogs initially in the process, but only later when the problem remains unsolved [44]. Figure 13 shows that participants implemented analogs more frequently than noise products at an early phase of ideation, and generated similar numbers of ideas based on the two noise types throughout the exercise. These findings suggest that the participants use pure noise and noise with a surface feature in a similar fashion to each other, but distinct from analog. The time-series analysis represents the data directly from ideation results, and thus depicts the participant's behavior more clearly than does the similarity-rating task. Thus, researchers decided to group the two noise types together for further data analysis, as originally intended.

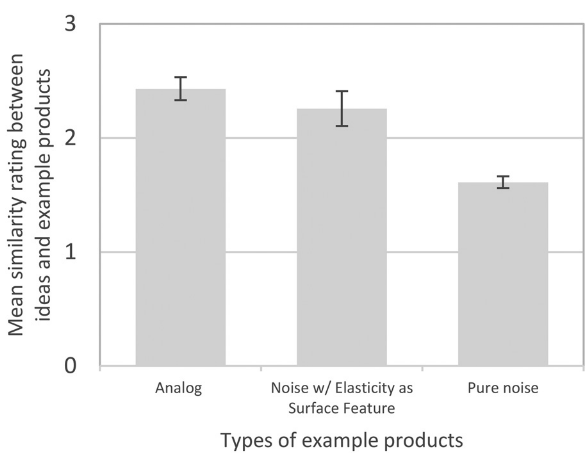

Fig. 12 The mean similarity ratings between ideas and example product, error bars show ± one standard error

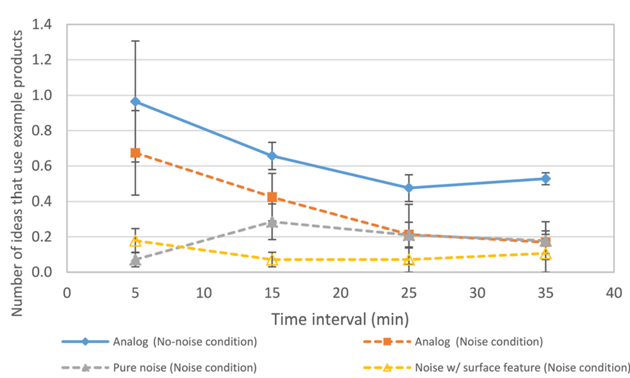

Fig. 13 Number of ideas that use analogs, pure noise, and noise w/surface feature over time, error bars show ± one standard error

Table 9 2-way ANOVA and Levene's homogeneity test results for postexperiment survey

	Question 1			Question 2			Question 3		
	"The given products were useful to create solutions"			"I used the given products to generate solutions"			"I found the similarity rating task hard"		
	df	*F*	Sig	*df*	*F*	Sig	*df*	*F*	Sig
Homogeneity			0.006			0.139			0.168
Number of analogs	3	9.31	<0.001[a]	3	9.92	<0.001[a]	3	0.893	0.451
Noise	1	12.1	0.001[a]	1	6.05	0.017[a]	1	0.216	0.644
Interaction	3	3.88	0.014[a]	3	3.18	0.031[a]	3	0.749	0.528
Error	56			56			56		

[a]Significant difference.

4.4 Postexperiment Survey. The postexperiment survey results characterize the participants' views toward the example products and reinforce the findings presented in Secs. 4.1 and 4.2. Three Likert scale questions were evaluated and the results of no-noise and noise conditions are plotted as a function of the varying number of analogs. The Likert scales were given numerical values from 0 (strongly disagree) to 4 (strongly agree) and the 2-way ANOVA test was performed. To the best of the authors' knowledge, a nonparametric version of an ANOVA with two factors is not widely accepted. Instead, the best option is to implement two one-way K-W ANOVAs to provide statistical insight into the data. A one-way K-W ANOVA with only two levels is equivalent to a Mann-Whitney test, so the Mann-Whitney is reported. The 2-way ANOVA and homogeneity test results are also tabulated in Table 9, and they show the effects of both factors in combination, whereas the K-W one-way ANOVAs collapse the data.

4.4.1 Question 1: "The Given Products Were Useful to Create Solutions". Participants were asked to rate the usefulness of the example products during idea generation process (Fig. 14). For the no-noise condition, the usefulness rating initially increases with additional analogs and decreases in the 5-analogs condition. For the noise condition, the usefulness rating peaks in the 2-analogs condition, while there is a linear increase for the 1-, 3-, and 5-analog(s) conditions. Participants in the noise conditions felt fewer of the products were useful to create solutions (chi-square = 3.95, $p = 0.047$), and the number of analogs also influences this (chi-square = 18.80, $p < 0.001$). Table 10 shows the post-hoc Tukey HSD test result for different analog conditions.

4.4.2 Question 2: "I Used the Given Products to Generate Solutions". Participants were asked to rate whether they used the example product for idea generation (Fig. 15). Participants indicated that they used the products the most in the 3-analogs condition for the no-noise condition and the 2-analogs condition for the noise condition. Participants in the noise conditions also said they used fewer of the products to create solutions (chi-square = 8.6, $p = 0.003$), and the number of analogs influenced this (chi-square = 19.30, $p < 0.001$). Table 11 shows the post-hoc Tukey HSD test result for different analog conditions.

4.4.3 Question 3: "I Found the Similarity Rating Tasks Hard". Participants were asked if they found the similarity-rating tasks hard (Fig. 16). Recall that there were two similarity-rating tasks. The first task asked participants to rate the similarities between features used and features not used for each example product they used for ideation. The second task asked participants to rate the similarities between their solutions and example products they received during ideation. The answer to this question would provide information about whether the participants had

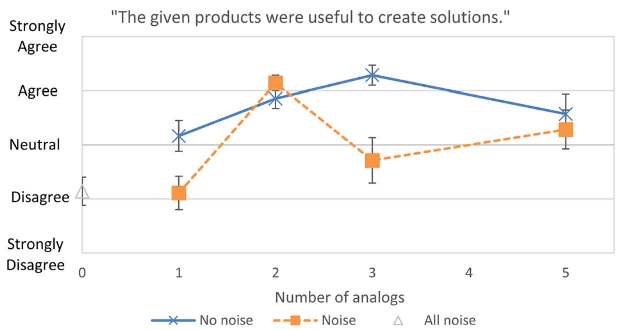

Fig. 14 Rating of example product's usefulness, error bars show ± one standard error

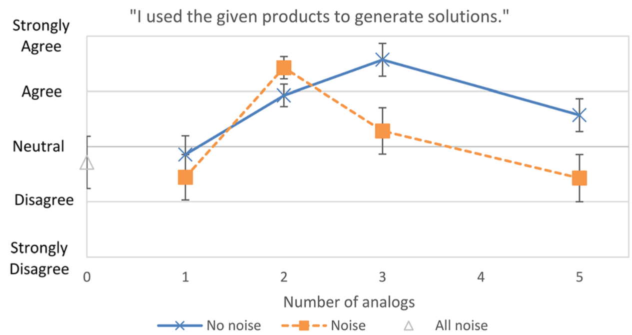

Fig. 15 Rating of use of given example products, error bars show ± one standard error

Table 10 Post-hoc test for example product's usefulness

	1-Analog	2-Analogs	3-Analogs	5-Analogs
1-Analog		<0.001[a]	0.007[a]	0.014[a]
2-Analogs			0.18	0.11
3-Analogs				1.0
5-Analogs				

[a]Significant difference.

Table 11 Post-hoc test for use of given example products

	1-Analog	2-Analogs	3-Analogs	5-Analogs
1-Analog		0.001[a]	0.002[a]	0.69
2-Analogs			0.95	0.007[a]
3-Analogs				0.050
5-Analogs				

[a]Significant difference.

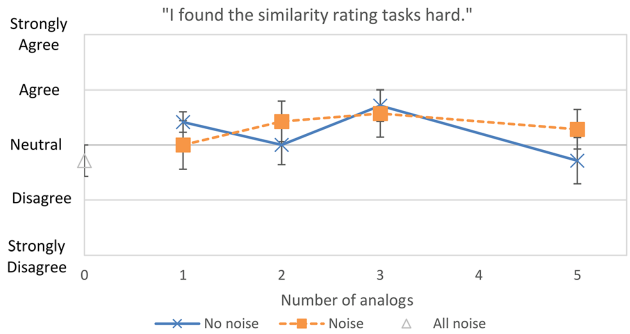

Fig. 16 Rating of difficulty of similarity task, error bars show ± one standard error

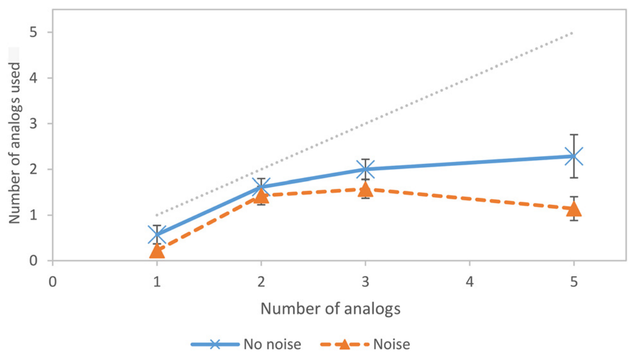

Fig. 17 Number of analogs used in idea generation, error bars show ± one standard error

difficulty judging whether two features are fundamentally similar. The mean responses did not show much variation and were somewhere between "neutral" and "agree." The lack of variation suggests that the participants found comparing elements on a one-to-one basis just as difficult, regardless of how many items were being compared.

5 Discussion and Study Limitations

This section addresses the proposed hypotheses based on the findings in Sec. 4. The proposed hypotheses are as follows: the ideation quantity and analog transfer (1) improve with an increasing number of analogs and (2) diminish under noise.

5.1 Number of Analogs. As presented in Sec. 4, participants generated more analog-based ideas and identified the high-level principle more accurately when they were given multiple analogs (Figs. 10 and 11). The postexperiment survey results also show that the participants found the example products useful and used them during ideation when they were given multiple analogs (Figs. 14 and 15). These results agree with the previous experiments in psychology, which conclude that using two analogs is better than one in analogous mapping process [11,12,15]. Furthermore, the study shows that the ideation results do not increase linearly with increasing number of analogs, but change in a parabolic manner as evidenced by the decrease in the 5-analogs condition (Fig. 10). The same result occurs in the high-level recognition rate shown in Fig. 11. This finding raised a question: Why does the number of analog-based ideas diminish in the 5-analogs condition? It is appealing to hypothesize that more analog-based ideas are generated as the availability of analogs increases. In order to address the question, Fig. 17, displaying the number of analogs used for ideation, was plotted to assess whether the participants used all available analogs represented by a dotted linear line. The figure shows that the quantity does not exceed two, implying that there is an "upper limit" where the student designers did not necessarily use more than two analogs to generate ideas. This is consistent with the post-hoc test results in that the participants in the 2-, 3-, and 5-analogs conditions generated a similar number of analog-based ideas because they used similar number of analogs during ideation. The number of analog-based ideas increases with multiple analogs, but eventually reaches a "saturation point," at which the ideation quantity starts to saturate as the number of analogs increases. Furthermore, it was found that 86% of participants in the 5-analogs conditions with and without noise stimuli used bungee blast, 36% used constant force spring, 29% used flour duster, 14% used compression spring, and none used sticky note holder lid. Analogs were selected by researchers based on their functional feature, but it was apparent in the study that the participants favored the bungee blast over other analogs, and completely overlooked the sticky note holder lid. These findings raise some interesting research questions: How is the "upper limit" or saturation point determined if the design problem has more complex high-level principle? How do student designers conceive of the excess analogs? What makes student designers prefer one analog over other analogs during ideation? All these questions motivate investigation in future studies. The only result that did not demonstrate the discussed trend was the number of ideas generated, as shown in Fig. 8. These results were not affected by the number of analogs, suggesting that the quantity is determined by other factors.

5.2 Presence of Noise. An interesting finding was observed in Fig. 8, where the participants generated fewer ideas when they were given additional noise stimuli. Similarly, the number of analog-based ideas in the noise condition decreased by 26%, 42%, 35%, and 33% for the 1-, 2-, 3-, and 5-analog(s) conditions, respectively (Fig. 10). The researchers recognize that the participants in the noise condition were provided a large selection of stimuli (three times more stimuli than no-noise condition), which could cause them to experience cognitive overload during ideation. However, it is important to note that the number of analog-based ideas decreased (Fig. 10), while the number of stimuli-based ideas was not affected in the noise condition (Fig. 9). This implies that the quantity of stimuli in the noise condition was not completely detrimental to student designer's working memory, yet the noise stimuli distracted them from using the analogs to generate ideas.

The effect of noise was not significant in the high-level principle recognition rate (Fig. 11). An interesting finding was that the recognition rate of the all-noise condition was similar to those of the 3- and 5-analogs conditions, and even higher than that of the 1-analog condition. In the all-noise condition, participants received 15 noise products, among which 11 were pure noise and four were noise with elasticity as a surface feature. Accordingly, a hypothetical explanation is that the surface feature of the noise stimuli was as effective as the functional feature of analogs in stimulating analogical reasoning, as exemplar-analogy theory posits [18]. In addition, it is possible that the high-level principle—"store and release energy through elastic deformation"—is sensitive to surface features, as almost every object contains elasticity to some extent. However, the researchers do not have a clear explanation for the factors associated with the recognition of high-level principle, and this could be addressed more clearly in future studies.

Although the understanding of the effect of noise on ideation may be preliminary, the findings have important implications for DbA research and practice. The total number of ideas and analog-based ideas diminished when the student designers received noise stimuli in addition to the analogs. This suggests that the random stimuli consisting of extraneous information are unfavorable in DbA practice, as they could distract the novice designers during ideation. In this study, the level of noise stimuli was predefined, but researchers anticipate that the noise level can be manipulated to some extent by identifying the high-level principle(s), defining a conceptual boundary between the analogs and noise stimuli, and removing noise stimuli that are "far" from the high-level principle. It also appears that presenting a relatively small number of analogs (two or three), with as little as noise as possible, is likely to be highly effective. These motivations call for future studies to investigate strategic DbA methods or software for the selection of analogs.

5.3 Study Limitations and Future Studies. There are several limitations in the study that are important to acknowledge. First, the study showed that the student designers could recognize high-level principle—"store and release energy through elastic deformation"—from the functional feature of the analogs, as well as the surface feature of the noise stimuli. This implies that the noise with surface feature behaves partially as analog and partially as pure noise, and thus posits a limitation in analyzing the noise effect on ideation. Second, the researchers acknowledge that arbitrarily omitting a 4-analogs condition in the study may pose a limitation in fully characterizing the effect of number of analogs, as the trend between the 3- and 5-analogs conditions remains as a blind spot. Third, although compensation is a standard practice in human subject research, there may be a negative effect of tangible rewards on the student designers' ideation results [45]. The tangible and intangible rewards need much consideration to minimize their effects on the participants' design outcomes in design research. Fourth, the study was conducted with a sample of engineering students that represent a skewed gender ratio (79% male and 21% female), low age profile (average 22.6 years old), and limited full-time work experience (4.8 months). Novice designers approach design tasks differently from expert designers [46], which makes the applicability of the study's findings limited to novice designers. Future studies need to consider a larger sample size across diversified gender, age, and expertise levels to gain a better understanding of any demographic covariates impacting the findings.

6 Conclusions

The empirical results presented in this DbA study suggest that ideation is largely dependent on the nature of examples, which can be either an inspiration or a distraction during ideation process, corroborating prior works [44,47,48]. This is consistent with prior literature on both design fixation and inspiration [49,50]. We extend the prior literature by identifying the interaction between analogs and extraneous information and the ratio of the two. In this study, ideation and analog transfer were evaluated by examining the number of ideas (typical in design research) and recognition of high-level principle (more typical in psychology). The effects of analogs and noise on the number of ideas were significant, demonstrating the importance of examples during ideation. Specifically, the number of analog-based ideas increased when the student designers were given multiple analogs, and a saturation point was observed where additional analogs do not increase the quantity of ideas generated. On the other hand, the number of ideas and analog-based ideas decreased when the student designers were given noise stimuli. Based on the empirical findings, the authors anticipate that analog transfer, particularly for novice designers, can be improved by providing them a set of multiple analogs of sufficient quantity to communicate the high-level principle in the absence of noise stimuli to eliminate distraction. As discussed in Sec. 5, several limitations may hinder the finding's applicability and motivate further research to obtain a more extensive understanding of the effects of different types of stimuli on ideation. Yet, the empirical results in this study add to the understanding of the analogs and extraneous information in DbA.

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