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SEMANTIC NETWORK DIFFERENCES ACROSS ENGINEERING DESIGN COMMUNICATION METHODS

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ABSTRACT

Engineering designers have a variety of methods at their disposal when it comes to communicating an idea (e.g., Linguistic, Pictorial, Virtual). Studies have explored how these methods affect the idea generation process, revealing that some methods can induce design fixation and reduce creativity. Moreover, studies reveal that depending on the communication methods and a receiver's familiarity with the idea conveyed, the amount of relevant information transmitted can vary. Hence, based on previous studies, it is hypothesized that different communication methods and a receiver's familiarity can impact a receiver's ability to construct and interpret the information conveyed. To test this hypothesis, an experiment is conducted in which multiple methods are used to communicate different product ideas to individuals (N=370). Participants are asked to describe the products in their own words and provide details about their functions. A text-mining approach is used to analyze the semantic structure of their responses. The results reveal that dissemination methods can affect the consistency of participants' responses, as well as the diversity of words used to describe a product idea or provide details about its functions. This knowledge can help designers in the selection of an appropriate method given the design intention and help them leverage different methods to maximize communication effectiveness during the different stages of the design process.

Keywords: Engineering Design, Design, Text-mining, Creativity, Crowdsourcing, Creativity

1. INTRODUCTION

Due to the complexity of the engineering design process and its nonlinearity, it is challenging to manage the information flow among team members [1]. As presented by Zhao and Tucker [2], Shannon's Information Theory [3] shares a lot of similarities with the idea dissemination process in engineering design. For example, as shown in Fig. 1, an idea is envisioned by designer A (sender) and then communicated to designer B (receiver) through the aid of a dissemination method. The effectiveness of this process can be quantified by its entropy. *Entropy* is defined as "*the amount of freedom of choice we have in constructing messages*" [4]. This means, the higher the entropy, the higher the freedom of choice a receiver (e.g., designer B) has to interpret the message from the sender (e.g., designer A). Therefore, the amount of information that a sender can transmit to a receiver relies heavily on the idea dissemination methods used. By selecting a dissemination method, designers can impact the effectiveness of the communication process [5]. Failure to identify and recognize the appropriate way of communicating ideas with others is a major source of confusion, which tends to hinder the effectiveness of knowledge transfer [6]. Therefore, it is important to balance the tradeoffs between possible information loss and the dissemination methods implemented to communicate a design idea effectively.

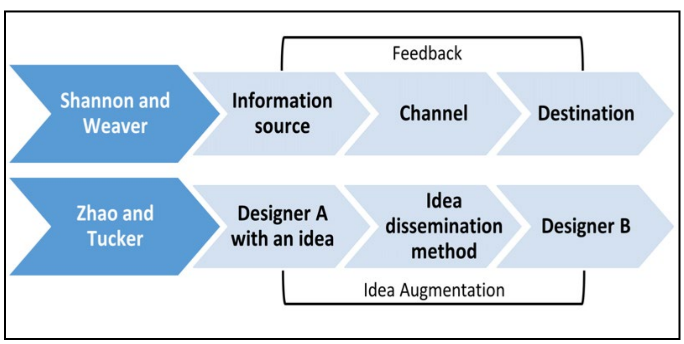

FIGURE 1. COMPARISON OF INFORMATION THEORY AND THE ENGINEERING DESIGN PROCESS [2]

The authors' previous work aimed to explore the entropy of different communication methods, and its results show that *Linguistic* communication methods (i.e., textual description of a product) transmit less relevant information, compared to *Virtual* methods (i.e., 3D CAD models) [2], [7]. These findings can help designers choose the appropriate communication method based on their design needs. For example, researchers have found that low entropy methods (e.g., 3D CAD models) can promote design fixation and reduce creativity [8]. Hence, they should not be used in the initial stages of the design process [2].

Studying the impact that *Linguistic*, *Pictorial*, and *Virtual* communication methods may have on the degree of freedom of a receiver to construct and interpret the information transmitted (i.e., entropy) would help designers promote effective communication and successful design solutions at different stages of the design process. Moreover, besides the communication methods, the stage of the design and the receiver's familiarity can also contribute to the effectiveness of communication [9]. While, the authors' previous studies showed a general ranking hierarchy of different idea dissemination methods from the point of view of the amount of relevant information they convey [7], there is still a need to better understand how different methods and the familiarity of a receiver to the domain of study, impact his/her ability to construct and interpret the information transmitted.

In order to address the existing knowledge gap this work seeks to (1) quantify the effect of *Linguistic*, *Pictorial*, and *Virtual* communication methods (i.e., textual descriptions, 2D drawings, and 3D CAD models) on a receiver's ability to construct and interpret the product idea transmitted, as well as the (2) impact that the receiver's own familiarity with a product has on his/her ability to construct the idea conveyed. In order to quantify these effects, (i) the variety, (ii) consistency, and (iii) semantic complexity of receivers' responses, when describing a product and its function(s) are evaluated using Semantic Network Analysis. In the text-mining community, researchers have frequently implemented Semantic Network Analysis to efficiently extract knowledge from unstructured textual data [10], [11]. Specifically, this work aims to test the hypotheses that (h_1) the number of vertices, (h_2) the density, and (h_3) the diameter of a semantic network constructed from participants' responses depends on the dissemination method used and the receiver's familiarity with the product idea. These hypotheses can be mathematically expressed as follows:

(h_1) h_o: $V(M) = V(K)$ vs. h_a: $V(M) \neq V(K)$

(h_2) h_o: $\rho(M) = \rho(K)$ vs. h_a: $\rho(M) \neq \rho(K)$

(h_3) h_o: $\varnothing(M) = \varnothing(K)$ vs. h_a: $\varnothing(M) \neq \varnothing(K)$

Where,

- $V(M)$ and $V(K)$ are the number of vertices for the semantic network M and K, respectively. For M and K in the set of network graphs $\{\mathbf{G}\}$, $M \neq K$.
- $\rho(M)$ and $\rho(K)$ are the density of the semantic network M and K, respectively.
- $\varnothing(M)$ and $\varnothing(K)$ are the diameter of the semantic network M and K, respectively.

These hypotheses are established on previous research that has found that different idea representations methods (e.g., 2D drawings, physical prototypes) can influence the quantity and originality of ideas produced during the idea generation process [12]–[14]. They are also founded on previous research that has explored the differences between novices and experts while generating and evaluating ideas [15]. The number of vertices of a semantic network captures the variety of words used to construct the idea transmitted. A network with more vertices indicates that, on average, individuals used a more extensive and diverse set of words. The variety of words used to construct the idea transmitted relates to the freedom of choice receivers had to interpret the product idea. Moreover, variety is frequently assessed when evaluating the effectiveness of the idea generation process and the creativity of idea sets [16]. In addition, both the diameter and density of a network provides information about how interconnected these words are, and how sparse the network is. A network with a small diameter and low density indicates less consistency and agreement between the responses, which also relates to the freedom of choice receivers had to interpret the product idea. Knowing how different dissemination methods affect the diversity and consistency of receiver's responses when constructing and interpreting the product idea transmitted, can help designers leverage different methods to maximize communication effectiveness during the different stages of the design process. For example, more diversity might help explore the design space during the idea generation stages, while more consistency might help reduce mistakes during the development phases [8].

2. LITERATURE REVIEW

2.1 Communication Methods

Owen and Horvath [17] proposed a classification of dissemination methods for engineers as (i) *Linguistic*, (ii) *Pictorial*, (iii) *Virtual*, (iv) *Symbolic*, and (v) *Algorithmic*. This work uses this taxonomy, focusing on the first three methods since the effectiveness of *Symbolic* and *Algorithmic* relies on an individual's knowledge of the symbols and equations used (e.g., GD&T [18]). *Linguistic* representations can have two sub-categories, verbal and textual [17]. In this work, *Linguistic* textual communication is explored. As one of the most commonly used communication methods, textual communication demonstrates its usefulness in the execution stage for a team [19].

Pictorial representations are often inexpensive and easy to create [20], especially at the beginning of the design process [21]–[24]. However, this type of communication may introduce confusion because it only provides fundamental features of a product, such as the shape and the size of an object [20]. As the fidelity of the sketches increases, more details could be communicated [25],[26], but it may require professional training to create detailed sketches [27]. *Pictorial* communication is fast and provides richer content than *Linguistic* representations. *Pictorial* methods (e.g., sketches) are often recommended to use in the early design stages to help designers disseminate their ideas [2]. *Virtual* communication methods, such as 3D CAD models, allow designers to observe an idea from various perspectives [28]. However, it requires a relatively long learning process to create a prototype using this technique [29], [30], compared to the other communication methods. Furthermore, studies have shown that 3D CAD models can promote design fixation and reduce creative thinking [8]. For a detailed review of the different dissemination methods in Engineering Design see Refs [2] and [7].

Several studies have explored how different idea representations method can affect the idea generation and selection process. The study by Toh et al. [12] shows that individuals that interacted with a physical prototype of a product example, produced ideas that were less novel and useful than those who were exposed to a *Pictorial* representation of the product that had a textual description. However, other studies have shown that individuals exposed to textual examples of conceptual designs, generate less diverse and novel ideas [13]. Studies have also shown that the use of 2D product examples can have adverse effects on the idea generation process since its promoted design fixation [14], [31]. Viswanathan and Linsey's [32] study also indicate that while participants exposed to physical prototypes generated a more significant number of ideas, both the *Pictorial* and *Virtual* methods caused the same amount of design fixation. Design fixation can also be affected by the expertise level of a designer [13], [32] . Similarly, studies have shown that prior knowledge and an individual's familiarity with an idea can affect the effectiveness of a dissemination method [7], [9], [33].

Even though researchers have explored how various idea communication methods can impact the design process, they focus on exploring the effects of *Linguistic*, *Pictorial*, or *Virtual* representation without any comparison between all the methods. Moreover, most of these studies concentrate on uncovering the effects of unique methods in the context of idea generation. Hence, from an idea dissemination and information theory point of view, it is still unclear how these methods can impact a receiver's ability to construct and interpret the information conveyed. In a previous study, the authors compare the effectiveness of *Linguistic*, *Pictorial*, and *Virtual* communication methods when it comes to conveying relevant information of a product [2], [7]. Their work showed that more relevant information was conveyed to participants exposed to the *Virtual* and *Pictorial* communication methods than those who were exposed to the *Linguistic* method. However, it is still unclear how much information the receivers were able to construct from the product idea transmitted since in that work the authors only analyzed the responses to the close-ended, multiple-choice questions and the proportion of correct responses when asked to identify certain product features (e.g., material, weight, shape). This analysis might have introduced some bias in the findings since it only analyzed questions that constrained the participants' responses.

Knowing how communication methods impact a receiver's ability to construct and interpret the information transmitted can help guide designers on the selection of appropriate methods to optimize the idea dissemination process. Hence, in this work, the authors analyze the participants' responses to a series of open-ended questions to determine how different dissemination methods and a receiver's familiarity with the idea, affect a receiver's ability to construct and interpret the information transmitted. Understanding the influences various communication methods have on a receiver's ability to construct and interpret the information transmitted can help designers leverage different dissemination methods to maximize the communication effectiveness during the different stages of the design process.

2.2 Text-mining in Engineering Design

With the use of text-mining techniques, researchers have been able to extract knowledge from unstructured textual data that have allowed them to inform the product development process by identifying target customers and lead users, quantifying changes in user preferences, and estimating the market favorability of new and existing product [34]–[40]. For example, Tuarob and Tucker [34], [35] present a method to recognize product features and relevant customers' opinions from textual data found in social media platforms. Inspired by this method, Lopez et al. [37] developed a data-mining driven approach to assess market favorability of new product ideas based on the favorability of existing product features.

In addition, with text-mining methods, such as Semantic Network Analysis, researchers have been able to generate visually synthesized solutions for creative design purposes [10], [11]. While the abstractness of semantic network graphs can introduce errors and inaccuracies when using only visual inspections [41], the use of network graphs statistics (e.g., density, diameter) help researchers to objectively analyze semantic networks and extract valuable knowledge from them [42], [43]. For example, Chiu and Shu used semantic networks to developed a method to retrieve cross-domain knowledge to improve biomimetic design [44]. Guo et al. [45] utilized semantic understanding to help engineers effectively search cases during the case-based reasoning process in engineering design. Similarly, researchers have started implementing text-mining techniques to assess and evaluate the novelty and usefulness of new ideas. For example, Gosnell and Miller [46], [47] presented a method for evaluating new design concepts by just using single-words adjectives and implementing a semantic similarity approach.

Thanks to the advantages of text-mining techniques, engineering designers and researchers have been able to extract valuable knowledge from unstructured textual data. Similarly, this work takes advantage of text-mining techniques to extract knowledge from the participants' responses. By implementing Semantic Network Analysis and calculating descriptive network statistics, the semantic structures of participants' responses to a series of open-ended questions are analyzed. This is done with the objective to better understand how different communication methods and a receiver's familiarity with an idea can affect a receiver's ability to construct and interpret the information of a product idea transmitted.

3. METHOD AND EXPERIMENT

To test the hypotheses introduced in Section 1, an experiment was conducted to test the effects that different communication methods and the familiarity of a product have on an individual's ability to construct and interpret the product information transmitted. In order to mimic the heterogeneity of the stakeholders involved in the design process, the crowdsourcing platform Amazon Mechanical Turk (AMT) was used to recruited engineering and non-engineering participants. Several designs and engineering researchers have already taken advantage of the flexibility offered by AMT [48]–[51]. Individuals on this experiment were given a monetary compensation of $0.20 for just participating. In addition, based on the amount of information that participants provided in the open-ended questions, they were offered additional compensation of up to $1. For this study, only individuals with an approval rate of 95% or greater participated in the experiment.

This is the same experiment introduced in the authors' previous work [7]. However, as stated in section 2.1, in that work the authors only analyzed the close-ended, multiple-choice questions, which constrained the participants' responses. Hence, in this work, the authors analyze participants' responses to a series of open-ended questions to determine how different dissemination methods and a receiver's familiarity with the idea, affect a receiver's ability to construct and interpret the information transmitted.

3.1 Products and Dissemination Methods

In this study, information about a familiar and an unfamiliar product was presented to participants with the objective to evaluate the effects that receivers' familiarity with the product ideas has on their ability to construct and interpret the information transmitted. Specifically, participants were presented information about a (i) *TV remote controller* and a (ii) *coffee percolator*. While the individuals might know about both of these products, the coffee percolator is a less familiar product than the TV remote controller [52]. The responses of the participants when asked about their familiarity with these products, confirmed that coffee percolators are less familiar products than the TV remote controllers [7]. Furthermore, in this work, the effects of *Linguist*, *Pictorial*, and *Virtual* communication methods were assessed (i.e., textual description, 2D drawings, and 3D models). For this work, participants were

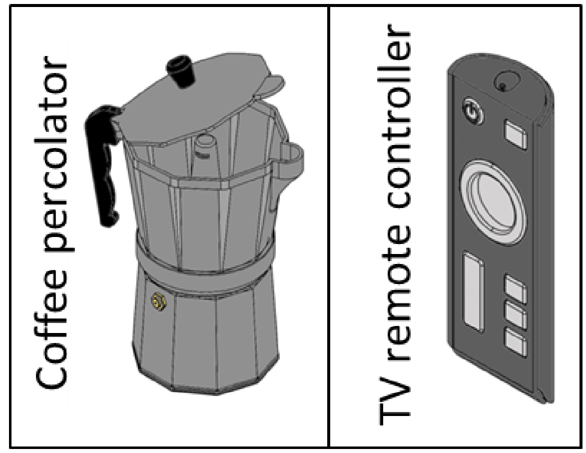

FIGURE 2. DRAWING OF PRODUCTS [7]

presented with information about the two products only using one communication method. In addition, to reduce any order effects, the order of the products was randomized.

To reduce the bias that selecting the textual descriptions used for the *Linguistic* method might have introduced, the textual descriptions used in this experiment were collected from a pilot study (see details at [7]). The textual descriptions of: "*Coffee Maker*", "*Coffee Pot*", "*Espresso Maker*", "*Coffee Percolator*", "*TV Controller*", "*TV Remote*", "*TV Clicker*", and "*Remote Controller*" were selected and shown to participants exposed to the *Linguistic* method. In this experiment, multiple textual descriptions were evaluated in order to mitigate the possible effects that certain words might have on participants' responses. However, each participant exposed to the *Linguistic* method was only shown one textual description from each product.

Figure 2 shows the isometric view drawings of the products that were presented to the participants exposed to the *Pictorial* method. For the *Virtual* method, participants were exposed to a set of 3D CAD models of the products (Coffee percolator: psu.app.box.com/v/CAD2, TV remote controller: psu.app.box.com/v/CAD1). These CAD models allow participants to rotate and interact with the virtual products in real-time.

3.2 Questionnaire

Participants were asked to first complete a (i) *Product Information* questionnaire. Afterward, they were asked to complete a (ii) *Communication Method* questionnaire, a (iii) *Product Familiarity* questionnaire, and a (iv) *Demographics and Experience* questionnaire. In the *Product Information* questionnaire, participants were presented with both multiple choice and open-ended questions. Figure 3 shows the *Product Information* questionnaire. In the authors' previous work, the participants' responses to the multiple choice questions of the *Product Information* questionnaire, as well as their responses to the *Communication Method*, *Product Familiarity*, and *Demographics and Experience* questionnaires, were analyzed.

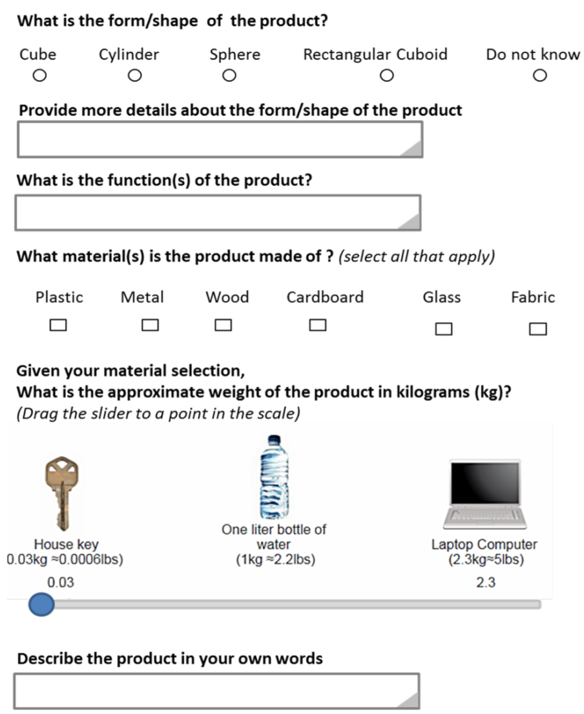

FIGURE 3. PRODUCT INFORMATION QUESTIONNAIRE

In this work, however, only the responses from the open-ended questions of "*What is (are) the function(s) of the product?*" (Q1) and "*Describe the product in your own words*" (Q2) are analyzed (see Fig. 3). Participants' responses for *"Provide more details about the form/shape of the product*" were not analyzed since the previous multiple-choice question may have biased their responses (e.g., using the same multiple-choices). For more details about the experimental design and protocol, readers are referred to the authors' previous work [7].

4. RESULTS & DISCUSSION

The response to the open-needed questions Q1 and Q2 (see sections 3.2) of 370 participants (192 females) that correctly responded the quality control questions and spent more than 10 secs reading the instructions was analyzed in this work. The Mann-Whitney U test indicates that participants reported being significantly more familiar (*p-value*<0.001) with TV remote controllers (M=6.55, Men=7, SD=0.78), than with coffee percolators (M=3.87, Men=4, SD=2.07). This shows that the TV remote controller is a more familiar product than the coffee percolator (for more descriptive statistics of the other questionnaires see [7]).

Before analyzing the open-ended responses of participants, symbols (e.g., !, @, $, ?) and common English stop words (e.g., the, for, a, and) were removed from the textual data. In addition, Porter's stemming algorithm [53] was implemented to disambiguate the words used by participants. In the text-mining literature, these pre-processing steps are common since they help reduce the noise inherent in textual datasets [36], [37], [54], [55]. After these pre-processing steps, a semantic network was created from the participants' responses to each of the questions and given the different communication methods and product used. The semantic networks are constructed by identifying all bigrams in the pre-process textual dataset. Figure 4 shows the semantic networks generated from participants' responses when asked to describe the coffee percolator in their own words (Q2), given the different dissemination methods. For visualization proposes only the top 30 most frequently used bigrams are illustrated in the graphs. These semantic networks were generated with the pre-process textual data (i.e., all the symbols and common English stop words were removed before stemming the words). From these graphs, it is clear that participants were describing a product that related to coffee (e.g., the stemmed word "coffe" is shown with the most number of vertices in all the networks). Furthermore, these graphs

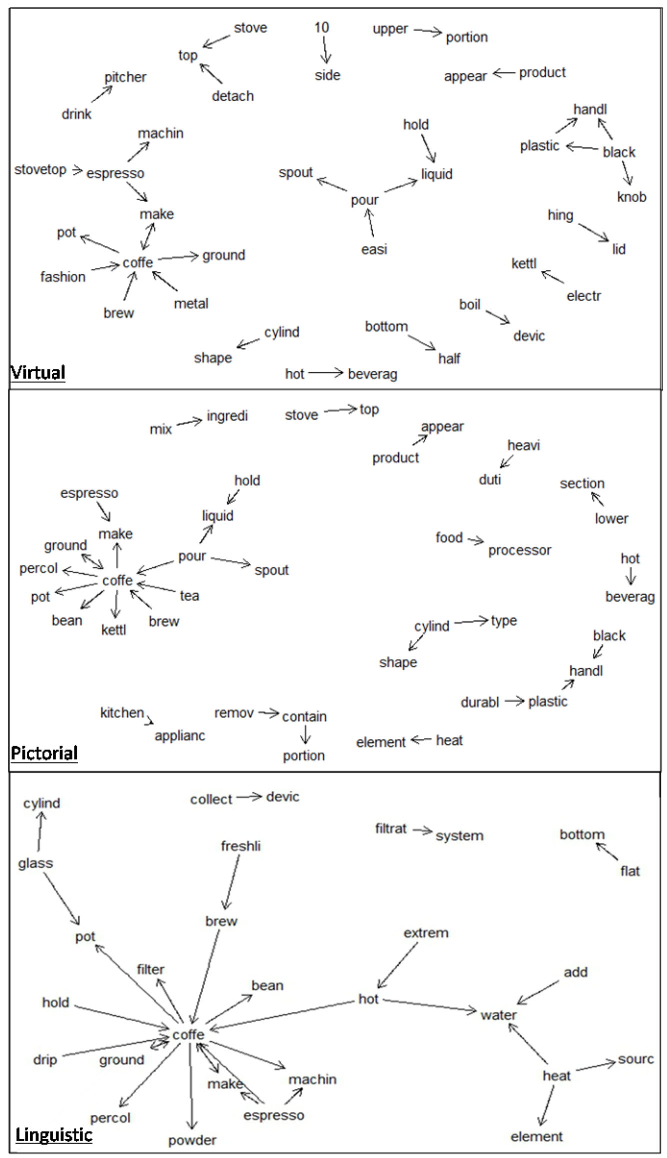

FIGURE 4. REPRESENTATION OF SEMANTIC NETWORKS

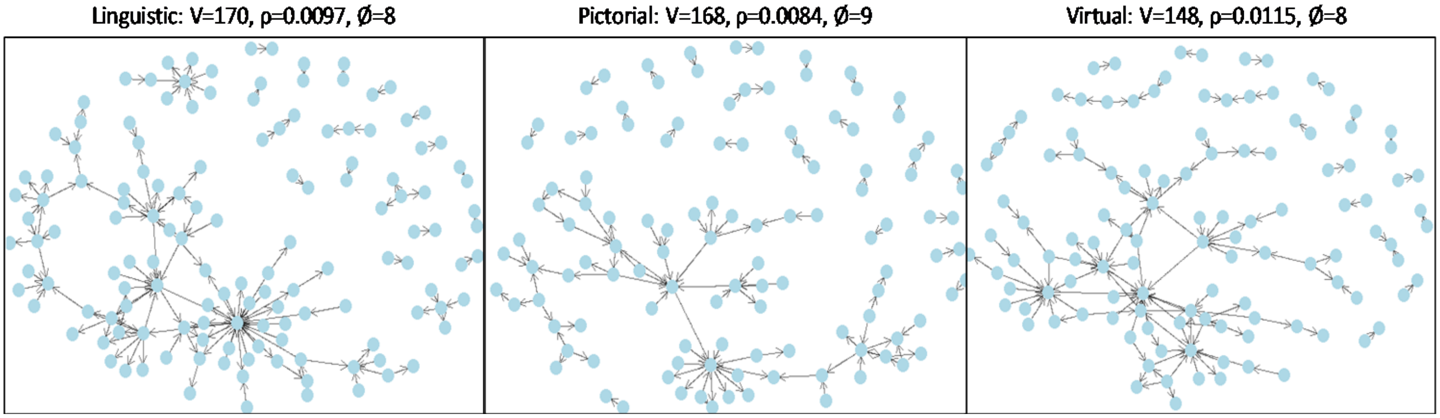

FIGURE 5. SEMANTIC NETWORKS FROM Q2 RESPONSES GIVEN THE DIFFERENT DISEMINATION METHODS

illustrate the value of using semantic network statistics to compare between participants' responses that were exposed to different communication methods since just performing visual analyses of the network would be prompt to human bias. Moreover, the networks shown in Fig. 4 contain only V=30 vertices, while the full networks shown in Fig. 5 have at least V=148 vertices, which makes it harder to inspect them visually.

Figure 5 shows the semantic networks from participants' responses when asked to describe the products in their own words (Q2), given the *Linguistic*, *Pictorial*, and *Virtual* methods. The nodes of these graphs represent the words, which are not illustrated for visualization purposes. From this figure, it can be seen how the number of vertices (V), the density (ρ), and the diameter ($Ø$) of the networks differ. However, to test if there was any significant difference between the networks and to test the hypotheses introduced in Section 1, a permutation test was performed. This test allows us to evaluate if the difference between the descriptive statistics (i.e., V, ρ, $Ø$) of two networks is due to random chance or due to the underlying structure of the networks. This was achieved by performing 10,000 re-sampling permutation tests.

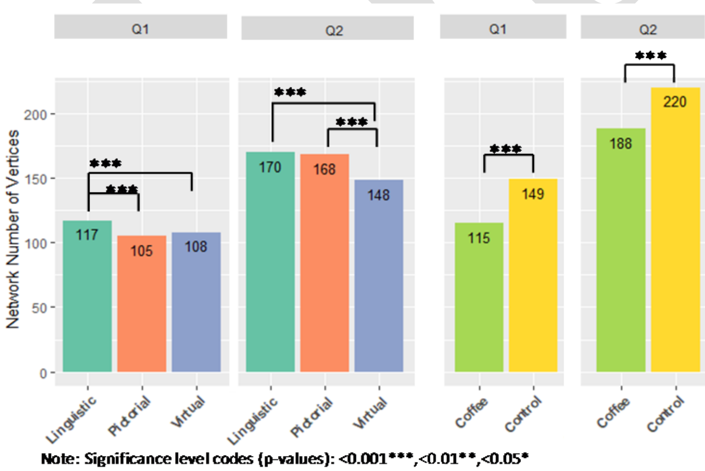

FIGURE 6. NUMBER OF VERTICES OF SEMANTIC NETWORKS

words (i.e., Q2), the semantic network from the responses for the TV remote controller has a larger number of vertices (V=220) than the network from the coffee percolator (V=188, *p-value*<0.001). In addition, the network from participants' responses that were exposed to the *Linguistic* method had a significantly larger number of vertices (V=170), than the network from participants' responses that were exposed to the *Virtual* method (V=148, *p-value*<0.001). The network from participants' responses that were exposed to the *Pictorial* method also had a notably larger number of vertices than the network from the *Virtual* method (*p-value*<0.001).

These results provide evidence to reject h_1 since the number of vertices of the semantic networks was different between the methods and the product ideas participants were exposed. These results reveal that participants that were exposed to the *Linguistic* and *Pictorial* methods used a larger and more diverse set of words when responding to the questions compare to the participants exposed to the *Virtual* method. Similarly, participants used a larger and more diverse set of words for the familiar product (i.e., TV remote controller) than for the unfamiliar one (i.e., coffee percolator).

4.2 Semantic Networks' Density and Diameter

Figure 7 shows the bar plots for the density and diameter of the semantic networks generated from participants' responses given the different methods and products. The permutation test indicates that when the participants were asked to provide details about the function(s) of the products (i.e., Q1), the semantic network generated from participants' responses exposed to the *Virtual* method was significantly denser (ρ=0.017) than the networks from the *Pictorial* (ρ=0.0167, *p-value*<0.001) and *Linguistic* methods (ρ=0.0145, *p-value*<0.001). Similarly, the network from the *Pictorial* method was significantly denser than the *Linguistic* method (*p-value*<0.001). When asked to describe the products in their own words (i.e., Q2), again, the network generated from the participants' responses that were exposed to the *Virtual* method was significantly denser (ρ=0.0115) than the networks from the

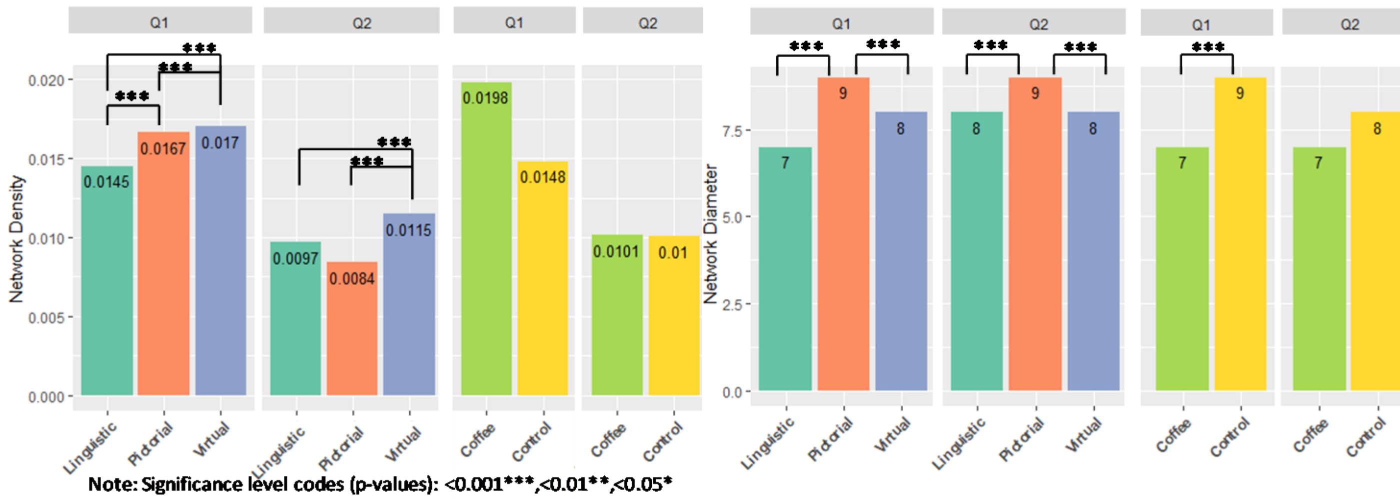

FIGURE 7. DENSITY AND DIAMETER OF SEMANTIC NETWORKS

Pictorial (ρ=0.0084, *p-value*<0.001) and *Linguistic* methods (ρ=0.0097, *p-value*<0.001). Regarding the diameter of the network, for both questions, Q1 and Q2, the network generated from participants' responses that were exposed to the *Pictorial* method was remarkably greater than for the networks of the *Virtual* and *Linguistic* method. In addition, when the participants were asked to provide more details about the function(s) of the product (i.e., Q1), the network from the responses about the TV remote controller had a larger diameter ($Ø$=9) than the network for the coffee percolator ($Ø$=7, *p-value*<0.001).

These results help to reject h_2 and h_3 since they indicate that the density and the diameter of the semantic networks were different depending on the method and the product idea participants were exposed. The networks from the participants that were exposed to the *Linguistic* and *Pictorial* were less dense than the network from the *Virtual* method, which demonstrates that these networks were sparser. These results reveal that participants exposed to the *Virtual* method showed more consistency and agreement on their responses, followed by the participants exposed to the *Pictorial* and *Linguistic* methods, respectively. However, the responses of participants that were exposed to the *Pictorial* method had longer semantic structures since the network generated from these participants had a larger diameter.

4.3 Implications for Engineering Design

In summary, the results of this work indicate that:

- Participants used a larger and more diverse set of words when responding to the questions related to a familiar product compared to an unfamiliar product.

- Participants exposed to the *Linguistic* method used a greater number and diversity of the words in their responses than participants exposed to *Pictorial* and *Virtual* methods.

- Participants exposed to the *Linguistic* method shows less consistency in their responses than participants exposed to *Pictorial* and *Virtual* methods.

Assuming that all participants were equally motivated to provide as many relevant details on the open-ended questions as possible (i.e., they were all offered the same extrinsic monetary rewards), the number and diversity of words used in their responses can be attributed to the creativity of participants, the amount of relevant information transmitted by the method, or participants' familiarity with the product idea transmitted. For example, the larger and more diverse set of words used to describe the TV remote controller can be attributed to participants' familiarity with the product idea. Even if the dissemination method does not provide enough relevant information about the product, thanks to individuals' familiarity with the product, they would be able to fill in the information gap with their prior knowledge. This is supported by studies supporting that individuals are good at reconstructing mental relationships from the previous outcomes and the information given [56], [57]. The differences between designers use of prior knowledge to fill information gaps when presented with familiar vs. unfamiliar product ideas have some important implications for the engineering design process. A better understanding of how designers' prior knowledge might help them fill information gaps can guide designers in the selection of an appropriate method that maximizes communication effectiveness during the different stages of the design process. For example, when communicating an idea of a familiar product, a designer might want to provide more details to avoid errors due to the receiver filling possible information gaps (e.g., making assumptions).

With regards to the effects of the different methods on the number and diversity of words used by participants, it can be explained either by the creativity of participants or the amount of relevant information transmitted by the method. The results reveal that participants exposed to the *Virtual* method showed more consistency and agreement on their responses, followed by the participants exposed to the *Pictorial* and *Linguistic* methods, respectively. However, the results from the authors' previous study indicate that the *Virtual* method is able to convey more relevant information than *Linguistic* since participants exposed to this method tended to provide a correct response for the multiple-choice questions more frequently than those exposed to the *Linguistic* method. Hence, the number and diversity of words used by participants exposed to the *Linguistic* method cannot be attributed to the amount of relevant information transmitted by the method. The results of the previous work and the ones presented here indicate that the consistency of participants' responses was dependent on the entropy of the method they were exposed. Moreover, studies also indicate that *Virtual* methods can increase design fixation [35]. Hence, the smaller and less diverse set of words used by the participants exposed to the *Virtual* method can be attributed to possible design fixation to the product features shown. This possible fixation effects might have caused a decrease in the diversity of words, which can have a significant implication on the early stages of the design process when ideas are generated.

Knowing how *Linguistic*, *Pictorial*, and *Virtual* dissemination methods affect the diversity and consistency of receiver's responses when constructing and interpreting an idea transmitted, can help guide designers in the selection of an appropriate dissemination method given their design intention. For example, during the idea generation process, having a wide range of diversity and variety when constructing and interpreting an idea transmitted can help designers explore the design space for more novel ideas (e.g., brainstorming). Hence, *Linguistic* idea dissemination methods should be promoted. In the developing phases, consistency might be needed to help reduce mistakes; hence, *Virtual* methods should be promoted.

5. CONCLUSION

The design process is nonlinear and involves the dissemination of information across multiple entities with different experiences and expertise. While designers have a variety of methods at their disposal to disseminate an idea, different methods can provide the receivers with a different degree of freedom to construct and interpret the information been transmitted (i.e., entropy). Therefore, failure to identify and recognize the appropriate way of communicating ideas with other designers may lead to confusion, which tends to hinder the effectiveness of the idea dissemination process.

Studies have explored how different dissemination methods can impact the idea generation process. However, these studies have not compared the effects of these methods from an idea dissemination and information theory point of view. Hence, it is still unclear how different dissemination methods and a receiver's familiarity affect a receiver's ability to construct and interpret the information transmitted. Balancing the tradeoffs between possible information loss and the dissemination methods implemented is the key to communicate a design idea effectively.

In light of this, an experiment was conducted in which different dissemination methods were used to communicate information about an unfamiliar and familiar product to both engineers and non-engineers' participants. In this work, Semantic Network Analysis was used to mine valuable knowledge from participants' responses to a series of open-needed questions that asked them to describe and provide details about the function(s) of the product ideas transmitted. In the authors' previous work, the amount of relevant information different dissemination methods provided and how informative

Finding from Lopez et al. [7]	Finding from this work
• Participants on the pilot study provided more textual descriptions for the familiar product. • The textual descriptions frequently used by participants in the pilot study were perceived as more informative than the textual descriptions that were less frequently used.	• Participants used a larger and more diverse set of words when responding to the questions related to the familiar product compare to the unfamiliar product.
• The *Linguistic* method was perceived as less informative than *Pictorial* and *Virtual* methods.	• Participants exposed to the Linguistic method used a greater number and diversity of the words in their responses than participants exposed to Pictorial and Virtual methods.
• Participants shown the *Linguistic* method tended to have more incorrect answers than participants shown the *Pictorial* and *Virtual* methods.	• Participants exposed to the Linguistic method shows less consistency in their responses than participants exposed to Pictorial and Virtual methods.

TABLE 1. SUMMARY OF STUDIES FINDINDS

these methods were perceived and explored by analyzing participants' responses to close-ended, multiple choice questions. Table 1 shows a summary of the authors' previous work that relates to the finding of this work, which was a continuation of the former (see Table 3 Ref. [7]). The findings of both studies are in agreement, revealing that product idea familiarity and the dissemination method used can impact the amount of information transmitted to a receiver.

The results of this work reveal how different dissemination methods affect the diversity and consistency of receiver's responses when constructing and interpreting a product idea transmitted. This knowledge can help designers maximize communication effectiveness during the different stages of the design process. While this work provides empirical evidence on the impact that *Linguistics*, *Pictorial*, and *Virtual* dissemination method have on the receiver's ability to construct and interpret the information transmitted, several limitations exist. First, not all existing dissemination methods were explored. For example, physical prototypes were not used in this work, even though studies have shown that they can help in the idea generation process [32]. Researchers should explore the effects of other idea dissemination methods on designers' ability to construct and interpret the design idea transmitted. Furthermore, while studies have shown that the responses of laboratory participants are no significant differences from online participants [58], [59], the crowdsourcing method used in this work may have compromised the validity of the experiment. Nonetheless, the knowledge gained from this work can help designers in the selection of an appropriate idea dissemination method given their design intentions, as well as help them leverage different methods to maximize communication effectiveness during the different stages of the design process.

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REFERENCES

[1] M. Muszynska, K., Dermol, V., Trunk, A., Đakovic, G., & Smrkolj, "Communication management in project teams–practices and patterns.," *Manag. Intellect. Cap. Innov. Sustain. Incl. Soc.*, p. 1359–1366., 2015.

[2] V. Z. Zhao and C. . Tucker, "Categorization of Information Loss during the Dissemination of Design Ideas," *in Proc. ASME Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf., 2018 .p.1-11.*, 2018, pp. 1–15.

[3] C. E. Shannon, "A mathematical theory of communication," *ACM SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 5, no. 1, pp. 3–55, 2001.

[4] C. E. Shannon and W. Weaver, "The mathematical theory of communication," 2002.

[5] R. L. Daft, R. H. Lengel, and L. K. Trevino, "Message equivocality, media selection, and manager performance: Implications for information systems," *MIS Q.*, pp. 355–366, 1987.

[6] D. De Long and P. Seemann, "Confronting Conceptual Confusion and Conflict in Knowledge Management," 2000.

[7] Z. V. Zhao, C. E. Lopez, and C. S. Tucker, "Evaluating the impact of idea diseeminations methods on information loss," *J. Comput. Inf. Sci. Eng.*, 2019.

[8] B. F. Robertson and D. F. Radcliffe, "Impact of CAD tools on creative problem solving in engineering design," *CAD Comput. Aided Des.*, vol. 41, pp. 136–146, 2009.

[9] B. Macomber and M. C. Yang, "The role of sketch finish and style in user responses to early stage design concepts," in *ASME Int. Design Eng and Technical Conf.*, 2011, pp. 567–576.

[10] L. Chen, P. Wang, F. Shi, … J. H.-… of the D. 2018 15th, and undefined 2018, "A COMPUTATIONAL APPROACH FOR COMBINATIONAL CREATIVITY IN DESIGN," *designsociety.org*.

[11] K. Fu, J. Chan, J. Cagan, K. Kotovsky, C. Schunn, and K. Wood, "The meaning of 'near' and 'far': the impact of structuring design databases and the effect of distance of analogy on design output," *J. Mech. Des.*, vol. 135, no. 2, p. 021007, 2013.

[12] C. A. Toh, S. R. Miller, G. Kremer, and E. Okudan Kremer, "The Impact of Team-Based Product Dissection on Design Novelty," *Artic. J. Mech. Des.*, 2014.

[13] C. Cardoso, M. Goncalves, and P. Badke-Schaub, "Searching for Inspiration During Idea Generation: Pictures or Words?," in *International Design Conference*, 2012.

[14] J. S. Linsey, I. Tseng, K. Fu, J. Cagan, K. L. Wood, and C. Schunn, "A Study of Design Fixation, Its Mitigation and Perception in Engineering Design Faculty," *J. Mech. Des.*, vol. 132, pp. 041003-1–12, 2010.

[15] S. Ahmed and B. T. Christensen, "An In Situ Study of Analogical Reasoning in Novice and Experienced Design Engineers," *J. Mech. Des.*, vol. 131, no. 11, pp. 111001–1, 2009.

[16] J. J. Shah, S. M. Smith, and N. Vargas-Hernandez, "Metrics for measuring ideation effectiveness," *Des. Stud.*, vol. 24, no. 2, pp. 111–134, Mar. 2003.

[17] R. Owen and I. Horváth, "Towards product-related knowledge asset warehousing in enterprises," in *Proceedings of the 4th international symposium on tools and methods of competitive engineering, TMCE*, 2002, vol. 2002, pp. 155–70.

[18] K. Paige, M. M. A., & Fu, "Spatial Demonstration Tools for Teaching Geometric Dimensioning and Tolerancing (GD&T) to First-Year Undergraduate Engineering Students.," in *Proceedings of the ASEE Annual Conference and Exposition, June 25 - 28,*

Columbus, Ohio, 2017, pp. 25–28.
[19] R. Ocker, J. Fjermestad, S. R. Hiltz, and K. Johnson, "Effects of four modes of group communication on the outcomes of software requirements determination," *J. Manag. Inf. Syst.*, vol. 15, no. 1, pp. 99–118, 1998.
[20] E. Sagan and M. Yang, "Perception and interpretation: points of focus in design sketches," in *ASME 2012 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2012, pp. 763–772.
[21] E. Robbins and E. Cullinan, *Why architects draw*. MIT press, 1994.
[22] V. Goel, *Sketches of thought*. MIT Press, 1995.
[23] B. F. Robertson and D. F. Radcliffe, "Impact of CAD tools on creative problem solving in engineering design," *Comput. Des.*, vol. 41, no. 3, pp. 136–146, 2009.
[24] M. Suwa, J. Gero, and T. Purcell, "Unexpected discoveries: How designers discover hidden features in sketches," in *Visual and spatial reasoning in design*, 1999, vol. 99.
[25] A. McGown, G. Green, and P. A. Rodgers, "Visible ideas: information patterns of conceptual sketch activity," *Des. Stud.*, vol. 19, no. 4, pp. 431–453, 1998.
[26] P. A. Rodgers, G. Green, and A. McGown, "Using concept sketches to track design progress," *Des. Stud.*, vol. 21, no. 5, pp. 451–464, 2000.
[27] C. A. Cory, "Utilization of 2D, 3D, or 4D CAD in construction communication documentation," in *Information Visualisation, 2001. Proceedings. Fifth International Conference on*, 2001, pp. 219–224.
[28] Y. Baba and K. Nobeoka, "Towards knowledge-based product development: the 3-D CAD model of knowledge creation," *Res. Policy*, vol. 26, no. 6, pp. 643–659, 1998.
[29] H. Salzman, "Computer-aided design: limitations in automating design and drafting," *IEEE Trans. Eng. Manag.*, vol. 36, no. 4, pp. 252–261, 1989.
[30] R. F. Hamade, H. A. Artail, and M. Y. Jaber, "Evaluating the learning process of mechanical CAD students," *Comput. Educ.*, vol. 49, no. 3, pp. 640–661, 2007.
[31] M. Perttula and P. Sipilä, "The idea exposure paradigm in design idea generation," *J. Eng. Des.*, vol. 18, no. 1, pp. 93–102, 2007.
[32] V. Viswanathan and J. Linsey, "Physical examples in engineering idea generation: an experimental investigation," in *Proceedings of the 2nd International Conference on Design Creativity Volume 1*, 2012, pp. 23–32.
[33] A. Akmajian, A. Farmer, L. Bickmore, and R. Demers, *Linguistics: An introduction to language and communication*. 2017.
[34] S. Tuarob and C. S. Tucker, "Discovering next generation product innovations by identifying lead user preferences expressed through large scale social media data," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASME*, 2014, pp. DETC2014-34767.
[35] S. Tuarob and C. S. Tucker, "Quantifying Product Favorability and Extracting Notable Product Features Using Large Scale Social Media Data," *J. Comput. Inf. Sci. Eng.*, vol. 15, no. 2, p. 0321003, 2015.
[36] S. Tuarob and C. S. Tucker, "Automated Discovery of Lead Users and Latent Product Features by Mining Large Scale Social Media Networks," *J. Mech. Des.*, vol. 137, no. 7, pp. 1–11, 2015.
[37] C. E. Lopez B., X. Zheng, and S. R. Miller, "Linking Creativity Measurements to Product Market Favorability: A Data-Mining Approach," in *Volume 2A: 43rd Design Automation Conference*, 2017, p. V02AT03A013.
[38] N. Hu, N. S. Koh, and S. K. Reddy, "Ratings lead you to the product, reviews help you clinch it? the mediating role of online review sentiments on product sales," *Decis. Support Syst.*, vol. 57, no. 1, pp. 42–53, 2014.
[39] Y. Park and S. Lee, "How to design and utilize online customer center to support new product concept generation," *Expert Syst. Appl.*, vol. 38, no. 8, pp. 10638–10647, 2011.
[40] T. Hou, B. Yannou, Y. Leroy, and E. Poirson, "Mining changes of user expectations over time from online reviews," *J. Mech. Des. (accepted manuscript)*, 2019.
[41] W. van. Atteveldt, *Semantic network analysis : techniques for extracting, representing and querying media content*. BookSurge, North Charleston, SC, U.S.A, 2008.
[42] F. Shi, L. Chen, J. Han, and P. Childs, "Implicit knowledge discovery in design semantic network by applying Pythagorean means on shortest path searching," in *ASME Int. Design Eng. Technical Conf. and Computers and Inf in Eng. Conf.*, 2017, p. V001T02A053.
[43] F. Shi, L. Chen, J. Han, and P. Childs, "A data-driven text mining and semantic network analysis for design information retrieval," *J. Mech. Des.*, vol. 139, no. 11, p. 111402, 2017.
[44] I. Chiu and L. H. Shu, "Biomimetic design through natural language analysis to facilitate cross-domain information retrieval," 2007.
[45] Y. Guo, Y. Peng, and J. Hu, "Research on high creative application of case-based reasoning system on engineering design," *Comput. Ind.*, vol. 64, no. 1, pp. 90–103, Jan. 2013.
[46] C. A. Gosnell and S. R. Miller, "A novel method for providing global assessments of desing concepts using single-word adjectives and semantic similarity," *Proc. ASME 2014 Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf.*, pp. 1–10, 2014.

[47] C. A. Gosnell and S. R. Miller, "But Is It Creative? Delineating the Impact of Expertise and Concept Ratings on Creative Concept Selection," *J. Mech. Des.*, vol. 138, no. 2, pp. 2110-1,2110-11, 2015.
[48] A. Burnap, R. Gerth, R. Gonzalez, and P. Y. Papalambros, "Identifying experts in the crowd for evaluation of engineering designs," *J. Eng. Des.*, vol. 28, no. 5, pp. 317–337, 2017.
[49] J. H. Panchal, "Using Crowds in Engineering Design – Towards a Holistic Framework," *Proc. 20th Int. Conf. Eng. Des. (ICED 15)*, no. July, pp. 1–10, 2015.
[50] M. L. Dering and C. S. Tucker, "Generative adversarial networks for increasing the veracity of big data," in *2017 IEEE International Conference on Big Data (Big Data)*, 2017, pp. 2595–2602.
[51] C. S. Lopez, C. E., & Tucker, "Human validation of computer vs human generated design sketches," in *Proc. ASME Int. Des. Eng. Tech. Conf. Comput. Inf. Eng. Conf.*, 2018, p. 85698.
[52] A. Häggman, G. Tsai, C. Elsen, T. Honda, and M. C. Yang, "Connections between the design tool, design attributes, and user preferences in early stage design," *J. Mech. Des.*, vol. 137, no. 7, p. 071408, 2015.
[53] P. Willett, "The Porter stemming algorithm: then and now," *Program*, vol. 40, no. 3, pp. 219–223, 2006.
[54] S. Vijayarani, M. J. Ilamathi, and M. Nithya, "Preprocessing Techniques for Text Mining -An Overview," *Int. J. Comput. Sci. Commun. Networks*, vol. 5, no. 1, pp. 7–16, 2011.
[55] C. A. Toh, E. M. Starkey, C. S. Tucker, and S. R. Miller, "Mining for creativity: Determining the creativity of ideas through data mining techniques," in *ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2017, p. V007T06A010.
[56] C. Eckert and M. Stacey, "Sources of inspiration: a language of design," *Des. Stud.*, vol. 21, no. 5, pp. 523–538, Sep. 2000.
[57] S. Caillies, G. Denhière, and W. Kintsch, "The effect of prior knowledge on understanding from text: Evidence from primed recognition," *Eur. J. Cogn. Psychol.*, vol. 14, no. 2, pp. 267–286, Apr. 2002.
[58] T. Buchanan, "Psychological Experiments on the Internet," *Psychol. Exp. Internet*, pp. 121–140, 2000.
[59] W. Mason and S. Suri, "Conducting behavioral research on Amazon's Mechanical Turk," *Behav. Res. Methods*, vol. 44, no. 1, pp. 1–23, 2012.

