Design creativity and the semantic analysis of conversations in the design studio

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The analysis of conversations during design activity can facilitate deeper insights into design thinking and its relation to creativity. A semantic analysis approach was employed to explore the semantic content of communication and information exchange between students and instructors. The goal was to examine design conversations in terms of Abstraction, Polysemy, Information Content and Semantic Similarity measures, and analyse their relation to the creativity of final solutions. These design outcomes were assessed according to their Originality, Usability, Feasibility, Overall Value, and Overall Creativity. Consequently, 35 design conversations from the 10th Design Thinking Research Symposium (DTRS10) dataset were analysed. The main results showed that Information Content and Semantic Similarity predicted Originality, and Information Content alone predicted Overall Creativity. Likewise, Abstraction predicted Feasibility, while Semantic Similarity, Information Content, and Polysemy predicted Overall Value. In context of instructors, Semantic Similarity predicted Usability, and Polysemy predicted Feasibility. For students, Semantic Similarity predicted Overall Value. On the whole, Semantic Similarity and Information Content were the most prolific measures, and therefore could be considered for promoting creativity in the design studio. The implications of using support tools such as automated systems are also discussed.

Keywords: design creativity measures; semantic measures; semantic analysis; design education; design conversations

Introduction

Design problem solving is a complex activity characterised by fluent exchanges of information among designers. One of the difficulties in studying design lies in understanding the content of verbalizations externalized by the designers. The analysis of verbal information generated during the design process can contribute to a better understanding of the communications maintained during these interactions (Gero, 2011; Taura & Nagai, 2013). Moreover, the analysis of verbalizations can aid in gaining a deeper understanding of the relation between the semantic content of the conversations and the creative outcomes that are generated. Due to the complexity of verbal data, an efficient representation of its content is needed for analysis.

Approaches such as semantic analysis are beneficial because they can describe and explore human thinking as a network of interrelated concepts intended for a systematic modelling of design processes. Semantic approaches are often used for modelling a variety of phenomena involved in cognitive psychology such as analogical processing (Gentner & Forbus, 2011). Furthermore, semantic approach studies have been successful in analysing cognitive insight models to gain a more accurate and deep understanding of this phenomenon (Schilling, 2005).

Although interest in the topic has increased over the last decade, only a few studies have explored the semantic content of conversations maintained during the design process. Such analysis represents the use of semantic measures in a network constructed on the basis of verbal data, which can be helpful during design problem solving for the identification, representation, quantification, and modelling of information (Georgiev et al., 2010; Yamamoto et al., 2009). For example, Mabogunje and Leifer (1997) found that nouns verbalized during the process of mechanical design project documentation were strongly related to scores of design solutions. Dong (2009) employed a lexical chain semantic approach to examine linguistic appraisals in design and differentiate discontinuities in agreement during the process of design problem solving.

Since creativity is at the core of design, understanding fundamental semantic representations of human cognition related to creative tasks can help to improve comprehension of design problem solving. Some semantic approach-based studies on design creativity are Georgiev and Georgiev (2018), who investigated changes in semantic measures through time and their relation to underlying cognitive processes such as divergent thinking in creative problem solving (Georgiev & Georgiev, 2018), and Taura and colleagues (2012), who explored semantic-based analysis in virtual creative concept generation. Consequently, exploring how semantic information generated during the design process is related to the resulting creative outcomes is a promising research direction, mainly for design education researchers. Subsequently, a study based on the semantic analysis of verbalizations, maintained between students and instructors could improve comprehension of the nature of conversations in the design studio and their relation to design creativity.

The main goal of the present study was to employ a semantic approach to analyse the design conversations of a substantial number of participants in a design studio environment. In addition, an examination of the relationship of fundamental phenomena-based semantic measures to the creativity of the design outcomes was conducted. Accordingly, the research questions are: i) how does the semantic approach, measured by Polysemy, Abstraction, Information Content, and Semantic Similarity, contribute to the analysis of the content in design conversations; ii) how are these measures related to the creativity of the produced outcomes, measured by Originality, Usability, Feasibility, Overall Value, and Overall Creativity; and iii) how does the relationship between the semantic measures and creativity in the final outcomes differ between students and instructors. To address these questions, the industrial design subset of the 10th Design Thinking Research Symposium (DTRS10) dataset (Adams & Siddiqui, 2013) was used.

The method implemented in this study has several advantages. First, it employs a series of semantic measures which allow the underlying phenomena in design to be quantified from a cognitive perspective. These measures used to investigate creativity in design problem solving are: Polysemy, which denotes the co-existence of several meanings; Abstraction, which stands for the generalization of specific words characterised by detailed information; Information Content, which represents the amount of information conveyed by a specific unit of language in a certain context; and Semantic Similarity, which is used to quantify the strength of semantic relationships between two instances of language (Georgiev & Georgiev, 2018).

Second, it applies a systematic and domain-independent representation of words (i.e. WordNet database, used in previous studies analysing the design process (Kan & Gero, 2018; Taura et al., 2012). Third, compared to existing semantic analysis approaches used in the context of design conversations (e.g. Dong, 2009), the proposed measures are faster to compute. Fourth, previous works on design creativity that employ semantic analysis typically rely on short experiments based on laboratory data (e.g. Chiu & Shu, 2007; Nomaguchi et al., 2019) or computational simulations (e.g. Taura et al., 2012). None of these works focus on long-term research in natural environments such as the design studio and include a limited number of participants.

Dimensions of Design Creativity

Assessment of design creativity

Creative thinking is the ability to make substantial discoveries and inventions, articulate uncommon thoughts, experience reality from unusual perspectives and change existing views in a critical sense (Csikszentmihalyi, 1997). It is also defined as the cognitive ability to generate ideas that are uncommon and of high quality (Hong & Milgram, 2008), and imaginative and surprising (Guildford, 1981). In problem solving, creative thinking is understood as a cognitive process through which known and familiar problems are restructured generating innovative ideas (Smith & Linsey, 2011). Parkhurst (1999) refers to this construct as the exhibition of the ability or quality while developing solutions to problems that have been solved differently, or when producing original and novel outcomes.

Creativity, which is used to describe someone’s attitude to and ability for creative thinking (Kamplis & Valtanen, 2011), is recognized as an essential component of design. This is because design problems are ill-structured, complex, unique, and non-routine (e.g., Goel & Pirolli, 1992; Simon, 1981). Since their initial goals and requirements are not completely formulated, dealing with design problems imply that an unknown number of solutions will be generated (Pretz, Naples & Sternberg, 2003; Rittel & Webber, 1984). Therefore, in addition to knowledge and skills the generation of design solutions demands creativity.

Although theories of design creativity are scarce in the literature (e.g., Taura & Nagai, 2013), various studies focusing on its assessment can be identified. Some of these works centre on the creativity of the designer, while others investigate the creativity of either the process or the product. When the assessment of design creativity is concerned with the outcome, studies often operationalise creativity in terms of originality, usability, feasibility, and value. Originality, known as one of the central features of creativity, is defined as "the quality of being new and different in a good and appealing way" (Merriam-Webster, 2020). Moldovan et al. (2011) describe product originality in terms of newness, uniqueness, and difference from what already exists. An original product is also expected to be surprising and interesting (Derbaix & Vanhamme, 2003). The production of original outcomes is characteristic in problem-solving tasks involving creativity, such as design (Bourgeois-Bougrine et al., 2017).

Independent of their originality, creative designs can also be valuable and useful (Sarkar & Chakrabarti, 2011). Usability can be understood in terms of the product/outcome's efficiency and performance. Useful designs must respond to requirements and needs as specified by the task or design brief (Siang et al., 2018). To be valuable, design products must have some merit. Furthermore, to be feasible, creative designs must not remain simply creative ideas, but potentially be materialized in real practice (Kreitler & Casakin, 2009). In the present study, originality, usability, feasibility, and value were used to assess the creativity of design outcomes produced by students.

Design education and creativity

The encouragement, development, and assessment of creativity is an essential goal of design education, in particular, of the design studio (Boucharenc, 2006). The design studio is an exceptional educational setting for forging and promoting the creativity of future designers.

In that environment, students acquire theoretical and practical knowledge while generating concepts and ideas for their design products (Cross, 1983). During design sessions—also known as design reviews or design critiques—students learn to think and behave as professional designers while producing idea solutions and reflecting on the creativity of their outcomes (Christensen & Ball, 2016). On the other hand, instructors evaluate and criticize the ideas and design outcomes, suggesting appropriate changes and actions to improve them (Demirbaş & Demirkan, 2003).

Critique sessions are vital for training students to develop their creative idea solutions ability, while simultaneously supervising their progress. Critique sessions can adopt different modalities, including personal review, group review, and juries (Goldschmidt et al., 2015). The main goal of a personal review is to provide feedback to students, whereas the group review is more participative and aims at exposing students to alternative views from colleagues. Occasionally, guest professionals are invited to participate in sessions that are usually conducted in the middle and at the end of a semester. Since design critiques expose fundamental aspects of the design process, in the present study they are considered as the most relevant environments for investigating interactions between students and instructors.

The type of information involved in such dialogues, during the review sessions, can affect the creativity of the design (Uluoğlu, 2000). However, the type of knowledge that is generated and communicated during these interactions, and how it contributes to the enhancement of different aspects of design creativity, is yet to be addressed. This is where semantic analysis approach becomes useful, and it can help in studying the contents of design conversations. Therefore, this work has explored, identified, and classified the semantic content of communications generated in review sessions, and has analysed potential relations with the creativity of design outcomes produced by students in the design studio.

Semantic Analysis in Design

Semantic content of the verbalizations, produced during design problem solving, is an indicator of the information generated and exchanged by the designers. Such content can be quantified, analysed, and compared by means of semantic networks (Taura & Nagai, 2013). Several approaches based on this tool have been developed recently to investigate the communication of information in design thinking (Georgiev & Georgiev, 2018; Georgiev et al., 2010; Cash et al., 2014). It is during the design activity that the process of discussing a problem and searching for a solution can be understood as a dynamic semantic network (Georgiev & Georgiev, 2018). The major advantages of using semantic networks for analysing real conversations are: i) applicability of the method for exploring cognitive processes, and ii) robust computation of a number of objective semantic measures, including information theory measures (described below). Semantic measures are grounded in the existing experimental research on design creativity, cognitive psychology, and linguistics (Taura et al., 2012; Ward et al., 2004; Fauconnier & Turner, 2003).

Recently, semantic approaches that use natural language processing, such as lexical chain analysis, have been used to inspect topics that emerged during design problem solving (Dong, 2009). These methods have been mostly successful at specifying forms of language for expressing judgments, as well as identifying semantic resources in linguistic assessments in the context of design conversations (Dong, 2009). Nevertheless, while they facilitate a better understanding of design problem-solving processes, they fail to specifically investigate design creativity. To address this gap, we employed an alternative semantic analysis approach instead of the usual classic method (Mabogunje & Leifer, 1997; Hill et al., 2001; Dong, 2009). The proposed approach is not computationally demanding and uses measures of intrinsic phenomena in design. It is based on four semantic measures that are employed to quantify processes involved in design problem solving, these are: Polysemy, Abstraction, Information Content, and Semantic Similarity.

Polysemy

This measure is defined as potential of a word to have multiple meanings (Taura et al., 2012). Words can range from having a single meaning (e.g., the noun “aunt”) to many (e.g., the noun “right” has eight meanings). Hence, polysemy is identified as manifestation of the flexibility of meaning potential in human thinking (Fauconnier & Turner, 2003; Georgiev & Taura, 2014). This measure can reveal the multiplicity of significations in a design object (Dabbeeru & Mukerjee, 2011). Moreover, it can be a source of creative inspiration, allowing for the exploration of different meanings of related concepts (Zhang & Saunders, 2014). Taura et al. (2012) showed that polysemy correlates significantly with originality of the ideas generated in a task synthesizing new design ideas from two initial concepts. In another study, Georgiev and Taura (2014) found that polysemy is the main feature of successful ideas (i.e., those that were considered in the final solution) discussed in design conversations.

Abstraction

This semantic measure is defined as the ability to generalise specific instances that have a higher level of detail in information. Hence, abstraction can be understood as a kind of thinking in which common features of specific instances are identified and removed to reduce their detail to the essential features (Saitta & Zucker, 2013). It is well known that abstract, compared to specific ways of thinking, can lead to novel and open-ended ideas (Ward et al., 2004; Welling, 2007; Saitta & Zucker, 2013); consequently, abstraction is a central characteristic of creative idea generation (Welling, 2007). Abstracting visual information from external sources can help in enhancing design creativity (Casakin & Goldschmidt, 1999; Goldschmidt, 2011). Moreover, generation of many original ideas is encouraged by the availability of abstract stimuli such as text (Gonçalves et al., 2012).

Information content

Information content is considered as a fundamental phenomenon of human language and thinking. It is defined as the amount of information transmitted by a specific unit of language in a certain context (Georgiev & Georgiev, 2018). For example, in this study nouns are a unit of language. Information Content measures the degree of informativeness of a unit. Thus, units with higher Information Content have a lower probability of occurrence in more general contexts (Meymandpour & Davis, 2016). In design, sharp drops in Information Content are found to be effective in quantifying design fixation while generating new ideas (Gero, 2011). Measuring entropy, i.e. lack of or gradual decline into disorder, based on Information Content in linkography, has been useful in detecting high and low scores in creativity during design sessions (Kan & Gero, 2017). Moreover, dissimilar levels of Information Content demonstrate different degrees of usefulness of solutions for designers in context of function-based models of design (Sen et al., 2010).

Semantic similarity

This is a measure that can be employed to quantify the strength of semantic relationships between words. In fact, the most typical measures used in natural language processing are those that are concerned with semantic similarity (e.g., Resnik, 1995). These rely on an “is-a” taxonomy that enables the measurement of how equal two words are, and how thoroughly they represent human similarity in judgments.

In a study conducted by Hill et al. (2001), semantic similarity in documents was employed to compute the affinity between two topics in design. Furthermore, it was used to represent the concept generation process and model design creativity (Taura et al., 2012). In a recent work, Georgiev and Georgiev (2018) demonstrated that semantic similarity could be helpful in identifying and representing the degree of divergence and convergence in design thinking. Nomaguchi et al. (2019) related this measure to the novelty of a design as an outcome of combining two initial concepts. Despite these studies, literature regarding semantic analysis of connections between verbalizations and design creativity is limited, and therefore, an aim of this study was to extend research in this direction.

Departing from existing literature (e.g., Taura et al., 2012; Ward et al., 2004; Gero, 2011; Han et al., 2018; Nomaguchi et al., 2019), it is expected that semantic measures will be useful in analysing the content of design conversations and predicting the creativity of design outcomes. Considering the participants' expertise, focus, and interest, it is also proposed that differences will be found between students and instructors cognitive representations developed during their conversations and the creativity of their design outcomes.

Method

The information analysed in this study is based on 35 design review conversations from the 10th Design Thinking Research Symposium (DTRS10) dataset (Adams & Siddiqui, 2013). DTRS10, themed "Design Review Conversations," was held at Purdue University in October 2014. Participants shared a common dataset, including single viewpoint videos, transcribed protocols (written as verbatim), and work products (artefacts such as work reports, presentations, and written feedback) of *in situ* design review conversations in authentic design settings, gathered over a period of three months (Adams & Siddiqui, 2013; Adams, 2015). The DTRS10 data focused on the nature of design reviews and instructor–student interactions across different contexts and perspectives (Adams, 2015) including a series of critique sessions carried out in the design studio. From all the available datasets corresponding to a variety of disciplines (e.g., service design, choreography design, or mechanical engineering) industrial design was selected for this study for its richer content, continuous process, and more sessions and participants than other datasets. Industrial design conversations consisted of more than 59 000 words, from which more than 8100 nouns were identified. Therefore, this was considered appropriate for the methodology employed in this work.

A series of 35 design sessions were carried out in a design studio space over a period of nine weeks. They lasted around 15 minutes each, and 12 students (six each from the undergraduate and graduate class), all majoring in Industrial Design, participated. Students were engaged in two to five design review conversations. A group of two experienced design teachers (with extensive design coaching experience) and 16 guest experts took part as instructors in the individual sessions (one teacher and 10 guest experts participated in the conversations with the undergraduates, and another teacher and six guest experts were involved in sessions with the graduates). One was excluded from the group of students, owing to incomplete data.

Real-world design review conversations represent an exceptional source of data for understanding the constructs of design thinking. During the sessions, the instructors discussed and provided critique to students while developing a solution for a real client. The task of the junior students was to design ‘impromptu’ seating places. The main design requirements were to envision solutions which supported collaborative work environments and would be versatile in the industry (for a design example, see Figure 1). The task of the graduate students was to design a space ‘Outside the Laundry Room’. The goal was to explore the laundry process of homeowners. A main design requirement was to develop solutions that might enhance the laundry experience (Adams & Siddiqui, 2014). For both junior and graduate students, design solutions were developed individually.

The assessment of the creativity metric was performed by two experienced independent referees with at least 20 years of teaching experience in the design studio. They did not participate in the design conversations or the data collection. A 5-point Likert scale ranging from 1 (low) to 5 (high) was used. The referees were requested to assess the creativity of the design outcomes produced by the students by means of the following five factors described and justified in sub-section assessment of design creativity: Originality (how dissimilar the solution is from standard solutions in the context of this study); Usability (efficiency, performance, and response to practical needs); Feasibility (technology/materiality), Overall Value (merit compared to standard solutions), and Overall Creativity (based on Amabile's Consensual Assessment Technique [CAT], 1996) which is a reliable measurement tool used by expert evaluators to assess the general creativity of products according to their knowledge).

Cohen’s κ was run to determine whether there was agreement between the two referees in their assessments (Cohen, 1988). Table 1 depicts substantial and significant agreement for all assessed variables. According to Landis and Koch (1977), values of kappa above 0.61 represent substantial agreement, while values above 0.81 represent almost perfect agreement.

Table 1. Cohen's kappa evaluation of agreement between the two referees

	Originality	Usability	Feasibility	Overall Value	Overall Creativity
Kappa	0.883	0.780	0.885	0.644	0.872
Sig.	0.000	0.000	0.000	0.000	0.000

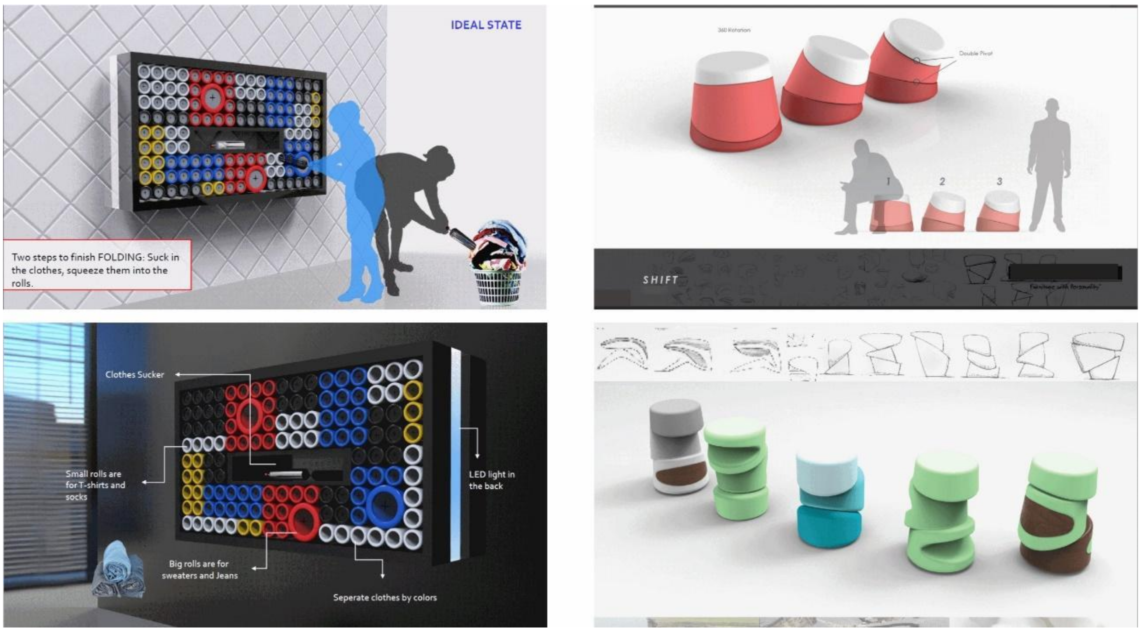

Figure 1. Examples of a design outcome by a graduate student (left) and a junior student (right) for two different design tasks

The sequence of design conversation for each student was analysed as a whole by computing the semantic measures from constructed graphs based on existing information-theoretic formulas (Resnik, 1997; Blanchard, 2008). These graphs are based on conversation transcripts, in which participants exchange and share ideas about the design task. For the sake of automating the calculations, standard natural language processing tools were used to extract nouns from the design conversations. These included the Natural Language Toolkit (NLTK) (Bird et al., 2009), TextBlob library (Loria, 2016), and WordNet 3.1 (Miller, 1998). Thereafter, a method based on Python scripts and dedicated software (WordGraph 3.1, a toolset in Wolfram Mathematica, cf., Georgiev & Georgiev, 2018) was employed to calculate the outlined semantic measures for these nouns. The four semantic measures of Polysemy, Abstraction, Information Content and Semantic Similarity were calculated as average values of all the conversations between students and instructors (Figure 2).

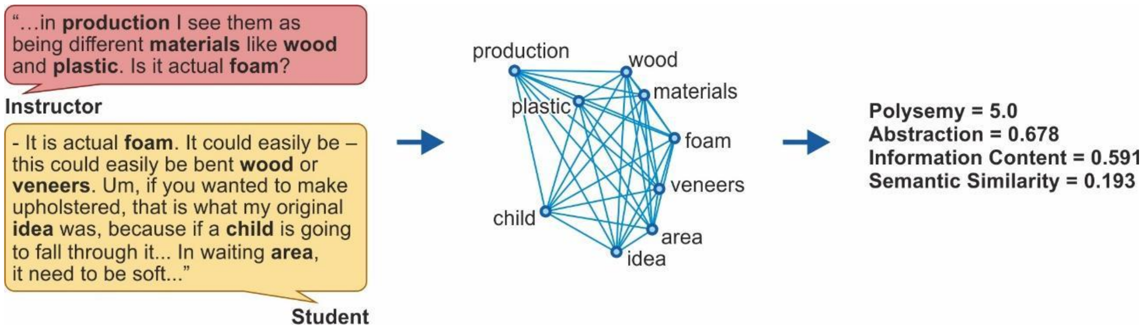

Figure 2. An example of a conversation between an instructor and an undergraduate student illustrating the use of semantic measures

The semantic approach considered in this study included the following subsequent steps: First, to construct semantic networks of nouns the data obtained from DTRS10 (Adams & Siddiqui, 2013) were cleaned to remove any indications of non-verbal expressions (e.g., 'laughter' or names) from the original transcripts. Second, the textual data was processed using part-of-speech tagging (identifying parts of speech) with the Natural Language Toolkit (Bird et al., 2009) to extract singular and plural nouns. Aided by Python scripts, all the identified nouns were processed by converting plurals into singular, discarding a small number of nouns that were not listed in the WordNet database (eight in total, approximately 0.2%).

WordNet is a large lexical public access internet database meaningfully related words and concepts are represented in a network by the means of conceptual semantic and lexical relations (Miller, 1998). The following is an example of four measures that were computed with WordNet 3.1. It uses a network composed of word nodes (connected in an "is-a" hierarchy, e.g., "car" is a "motor_vehicle"), meaning nodes (terminal nodes representing all the meanings of a word node), and direct links between the nodes (Georgiev & Georgiev, 2018).

The semantic measures of Polysemy, Abstraction, Information Content, and Semantic Similarity are illustrated in Figure 3 (a, b, c, and d, respectively), and are explained as follows:

Polysemy was measured by the number of direct links between a word node (e.g., “carriage”) and its associated meaning nodes, counting the number of meanings of the word node (Taura et al., 2012; Georgiev & Taura, 2014). For example, the node “carriage” has five meaning nodes: “passenger_car,” “rig,” “posture,” “machine_part,” and “stroller” (Figure 3a).

In this study we adopted the simplest possible measure of Abstraction (Georgiev & Georgiev, 2018) by calculating the distance of a word to the most abstract word in the tree. Abstraction is the normalized fraction of the distance of shortest path from the root word node to a word node by the maximal shortest path from the root in the network. Abstraction accounts for how generalized the word node is compared to the most specific instance (Georgiev & Georgiev, 2018). For example, the shortest path length of “carriage” to the root node “entity” is six (Figure 3b).

In addition, we endorsed Blanchard et al.’s (2008) Information Content measure as it was successful in analysing design problem solving (Georgiev & Georgiev, 2018). Information Content is measured as a normalized fraction of the number of leaves of the word node, and the maximal number of leaves in the network (Blanchard, 2008; Georgiev & Georgiev, 2018). For example, the Information Content of “carriage” is 0.686 and that of “car” is 0.635 (Figure 3c). There are many well-known semantic similarity measures, for example, path-based, Leacock–Chodorow, Wu–Palmer, Resnik (see Georgiev & Georgiev, 2018; Georgiev et al., 2010) some of which have been employed in a design context (e.g., Taura et al., 2012; Yamamoto et al., 2009). In the present study we adopted Resnik’s (1995) semantic similarity measure since it proved successful in analysing design conversations (Georgiev & Georgiev, 2018). Accordingly, Semantic Similarity of two-word nodes, say B and C, was measured by the Information Content of the lowest common subsumer (LCS) of two words, say ‘A’ (Resnik, 1995) quantifying how alike the two-word nodes are. (e.g., the LCS of “carriage” and “ship” is “vehicle”) (Figure 3d).

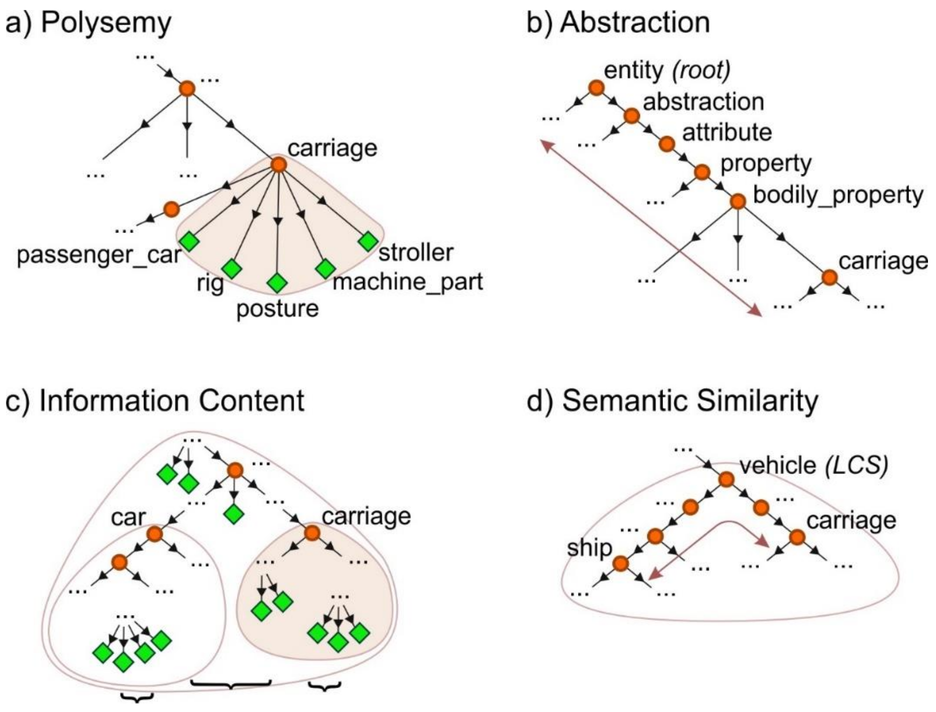

Figure 3. Examples of semantic measures (round nodes are word nodes, and diamond nodes are meaning nodes)

Results

Collective contribution of students and instructors

To explore the relation between the four semantic measures and the five creativity variables for the collective contribution of all parties in the design conversations, a Spearman correlation analysis was conducted and reported along with descriptive statistics in Table 2. Significant correlations between Polysemy and Usability, and Polysemy and Feasibility were observed. Further significant correlations were found between Abstraction and Feasibility, Information Content and Originality, and Information Content and Overall Creativity. Finally, Semantic Similarity was observed to correlate with Overall Value.

Table 2. Descriptive statistics and Spearman correlations for all conversations between semantic measures and creativity variables of the outcomes

Variable	Mean	Std. Dev	Min	Max	Originality	Usability	Feasibility	Overall Value	Overall Creativity
Polysemy	5.410	0.329	4.949	5.809	0.015	0.618**	0.615**	0.471	-0.100
Abstraction	0.709	0.007	0.699	0.720	-0.410	0.135	0.860***	0.014	-0.404
Information Content	0.700	0.008	0.688	0.714	.657**	-0.213	-0.471	0.176	0.800***
Semantic Similarity	0.189	0.010	0.174	0.201	0.076	0.490	0.450	0.695**	-0.152
Notes: N = 11; * p <.1, ** p <.05, *** p <.01									

To investigate whether the creativity of the design products could be predicted from the different semantic measures, several stepwise multiple regression analyses were performed with the four semantic measures as predictors, and five creativity factors as dependent variables.

A multiple regression was run to predict Originality from Polysemy, Abstraction, Information Content, and Semantic Similarity. The stepwise model significantly predicted Originality, $F(2, 9) = 8.620$, $p =.008$, adj. $R^2 =.657$. Information Content and Semantic Similarity variables added statistical significance to the prediction, $p =.003$, and $p =.031$, respectively (See Table 3, Regression 1). The results indicate a positive effect of Information Content and Semantic Similarity together on the Originality of the outcomes.

A second multiple regression was conducted to predict Feasibility from the four semantic measures. It was found that the stepwise model predicted Feasibility, $F(1, 10) = 19.270$, $p =.001$, adj. $R^2 =.658$, which was statistically significant. Abstraction contributed significantly to this prediction, $p =.001$, which proved a positive effect on Feasibility. See Table 3 (Regression 2) for regression coefficients and standard errors.

A further multiple regression explored the contribution of the four semantic measures on Overall Value. The stepwise model significantly predicted Overall Value, $F(3, 8) =$

17.235, p =.001, adj. R^2 =.866. Polysemy, Information Content, and Semantic Similarity variables added significantly to the prediction, p =.002, p =.006, and p =.049, respectively (See Table 3, Regression 3). A negative effect of Polysemy and a positive effect of Information Content and Semantic Similarity were observed on Overall Value.

Finally, multiple regression was run to predict Overall Creativity from the semantic measures. It was found that the stepwise model significantly predicted Overall Creativity, F(1, 11) = 13.087, p =.005, adj. R^2 =.567. Only Information Content contributed to the prediction, p =.005, which indicated a positive effect on Overall Creativity (See Table 3, Regression 4).

Table 3. Results of regression analyses for Originality, Feasibility, Overall Value, and Overall Creativity

Variable	Regression 1: Originality		Regression 2: Feasibility		Regression 3: Overall Value		Regression 4: Overall Creativity	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Constant	-125.192	30.972	-89.467	21.264	-56.555	13.225	-60.577	17.633
Polysemy					-2.682**	1.155		
Abstraction			131.635 ***	29.987				
Information Content	162.186***	39.469			62.178***	16.975	91.090***	25.179
Semantic Similarity	79.536**	31.079			161.651***	35.248		
Notes: N = 11; * p <.1, ** p <.05, *** p <.01								

In sum, the results of the collective input of students and instructors to the design conversation showed that Information Content and Semantic Similarity predicted Originality, and Information Content contributed to Overall Creativity. Furthermore, Abstraction predicted Feasibility, while Semantic Similarity, Information Content, and Polysemy influenced Overall Value. However, we expected each of the parties to have a different contribution to the conversation, meaning different relations between the semantic content of their verbalizations and the creativity of the design outcomes. Therefore, in the following section we analysed the individual contributions of students and instructors to the design conversations.

Creativity variables and semantic measures in verbalizations: Individual contribution of instructors and students

To explore the individual verbalizations of students and instructors in the design conversations, the relations between the four semantic measures and the five creativity variables were analysed separately for each group. Spearman correlation analyses were performed and reported along with descriptive statistics in Table 4 for instructors, and Table 5 for students.

For the instructors, the results showed significant correlations between Feasibility and all four semantic measures. Notably, the correlation in case of Information Content was negative, while correlations at level $p < .1$ were observed between Polysemy/Semantic Similarity and Usability.

For the students, Semantic Similarity was observed to correlate with Overall Value. Correlations at level $p < .1$ were observed between Polysemy and Overall Value and between Abstraction and Overall Creativity.

Table 4. Descriptive statistics and Spearman correlations for instructors

Variable	Mean	Std. Dev	Min	Max	Originality	Usability	Feasibility	Overall Value	Overall Creativity
Polysemy	5.605	0.439	5.048	6.508	-0.098	0.526*	0.749***	0.291	-0.089
Abstraction	0.665	0.012	0.643	0.682	-0.007	0.316	0.605**	0.209	-0.019
Information Content	0.696	0.015	0.674	0.716	0.178	-0.306	-0.626**	0.007	0.226
Semantic Similarity	0.194	0.011	0.174	0.213	-0.098	0.522*	0.698**	0.360	-0.133
Notes: N = 11; * p <.1, ** p <.05, *** p <.01									

Table 5. Descriptive statistics and Spearman correlations for students

Variable	Mean	Std. Dev	Min	Max	Originality	Usability	Feasibility	Overall Value	Overall Creativity
Polysemy	5.714	0.557	4.639	6.990	-0.084	0.227	0.489	0.504*	-0.196
Abstraction	0.662	0.012	0.640	0.676	-0.414	0.220	0.453	0.234	-0.541*
Information Content	0.684	0.022	0.645	0.710	0.247	0.011	-0.036	-0.176	0.344
Semantic Similarity	0.200	0.020	0.161	0.246	0.185	0.409	0.155	0.723***	-0.026
Notes: N = 11; * p <.1, ** p <.05, *** p <.01									

Further regression analyses were conducted to analyse the individual contributions of instructors and students to the design activity. A multiple regression was performed to predict Usability from Polysemy, Abstraction, Information Content, and Semantic Similarity. The stepwise model significantly predicted Usability, $F(1, 10) = 7.190$, $p = .023$, adj. $R^2 = .418$. Semantic Similarity added to the prediction, $p = .023$. Regression coefficients and standard errors are reported in Table 6 (Regression 5). The results showed a significant positive effect of Semantic Similarity on Usability.

Another multiple regression tested the contribution of the four semantic measures on Feasibility. The stepwise model significantly predicted Feasibility, $F(1, 10) = 10.219$, $p = .010$, adj. R^2 =.505. Polysemy added to this prediction, p =.010 (See Table 6, Regression 5). The results showed a positive effect of Polysemy on Feasibility.

Table 6. Results of regression analyses for instructors for Usability and Feasibility

Variable	Regression 5: Usability		Regression 6: Feasibility	
	Coeff.	S.E.	Coeff.	S.E.
Constant	-8.821	4.385	-6.253	3.177
Polysemy			1.798***	0.563
Abstraction				
Information Content				
Semantic Similarity	60.357**	22.509		
Notes: N = 11; * p <.1, ** p <.05, *** p <.01				

A final multiple regression was run to predict Overall Value from the four measures. It was observed that the stepwise model significantly predicted Overall Value, F(1, 10) = 5.736, p =.038, adj. R^2 =.364. Semantic Similarity had a significant input to the prediction, p =.038 (See Table 7, Regression 7). The results suggested a positive effect of Semantic Similarity on Overall Value.

Table 7. Results of regression analyses for students for Overall Value

Variable	Regression 7: Overall Value	
	Coeff.	S.E.
Constant	-2.154	2.146
Polysemy		
Abstraction		
Information Content		
Semantic Similarity	25.731**	10.744
Notes: N = 11; * p <.1, ** p <.05, *** p <.01		

In summary, Semantic Similarity was found to predict Usability for instructors, and Polysemy predicted Feasibility, while for students, Semantic Similarity predicted Overall Value.

Figure 4 summarizes all the regression-based relations between the semantic measures and the creativity variables identified during the design conversations.

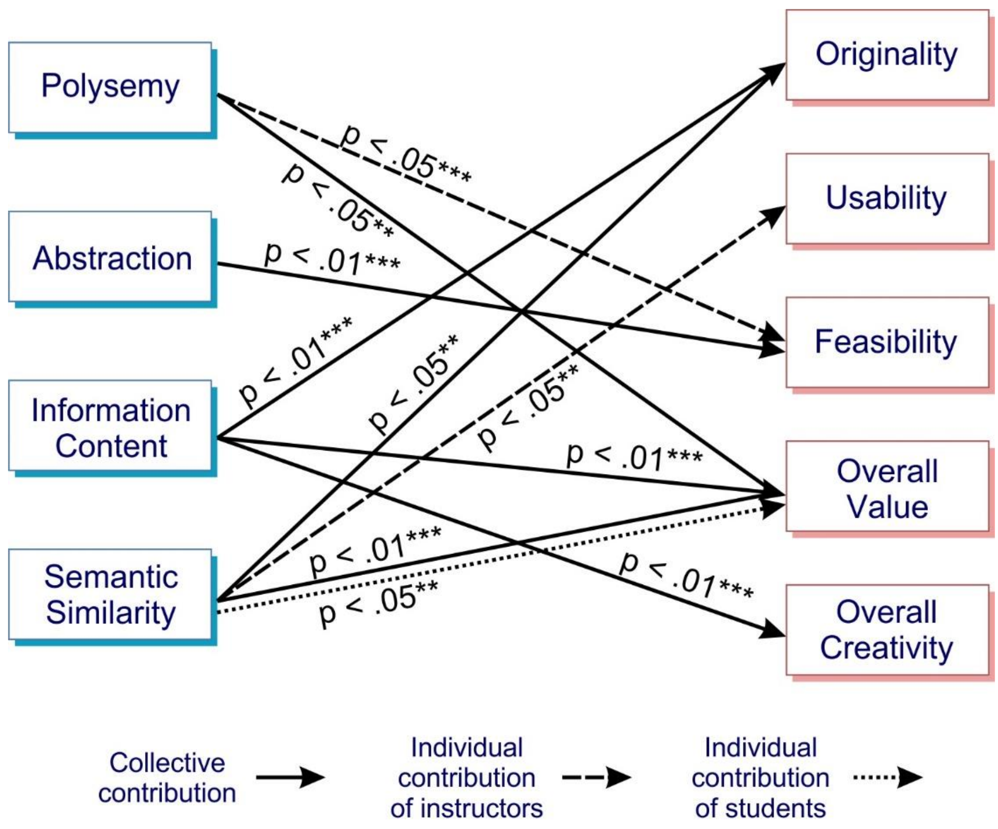

Figure 4. Regression-based relations among semantic measures and creativity variables for collective and individual contributions in the conversations between instructors and students. Arrows indicate prediction.

Discussion

Collective contribution of students and instructors to design conversations

Semantic measures, Originality, and Overall Creativity

The findings revealed that together Information Content and Semantic Similarity had a significant positive effect on the Originality of final solutions. Further, Information Content was also found to have a significant positive effect on Overall Creativity. This finding is in line with Gero (2011), who showed that a significant drop in Information Content was related to design fixation (defined as a contrasting feature of creativity). Georgiev and Georgiev (2018) also observed that an increase in Information Content led to an increase in the generation of successful ideas.

The results suggesting that an increase in Semantic Similarity contributed to an increase in Originality reflected the importance of this measure in enhancing design creativity. This finding might seem unusual as similarity seems to be counter-intuitive to originality. However, Dumas and Dunbar (2014) found that semantic similarity could be used to measure the originality of an idea. Assessing originality in terms of semantic distance is becoming popular in empirical studies on creativity (Acar & Runco, 2014), and it is also aligned with theoretical views of creativity that see original solutions as a development from what is already known (Steinberg, 2003).

The results also showed that Information Content was the only significant predictor of Overall Creativity. However, previous studies found significant relations between Creativity (measured as the originality of the produced ideas) and Polysemy (Taura et al., 2012), as well as Abstraction (Ward et al., 2004). Considering that conversations characterized by high Information Content had a low probability of occurrence, it is proposed that specific and uncommon language could be encouraged in design sessions to support the generation of Original and Overall creative outcomes.

Semantic measures, Feasibility, and Overall Value

It was observed that solutions characterized by higher Feasibility were the outcome of design conversations that involved high levels of Abstraction. This finding suggested that fluency in abstract words (e.g., “vehicle” is more abstract than “carriage”) might contribute to design outcomes that could be materialized in practice. While previous research indicated that a relation between Creativity and Abstraction (Taura et al., 2012; Ward et al., 2004) might exist, no other studies connecting Feasibility with Abstraction were found in the literature. One of the reasons that Abstraction was related to Feasibility could be the nature of the tasks, which were conceptual, instead of real design practice. It is possible that since these tasks were mainly focused on the early stages of the process (which was of major interest from an educational perspective), technical and practical issues might not had been rigorously considered. Hence, specific language in terms of discussing the relation of Information Content and feasibility of the design outcome was not used.

Semantic Similarity and Information Content, together with Polysemy (with a negative contribution) were found to effect the Overall Value of the design outcomes. This suggests that with an increase of Semantic Similarity and Information Content and a decrease of Polysemy in conversations, there was an increase of the Overall Value of the design outcomes. The findings regarding Semantic Similarity were, to some extent, related to the study of Georgiev et al. (2008), who found this measure to be positively related to the self-perceived assessment of the quality of the design outcomes.

Hence, as a general recommendation it is proposed that employing instances that are close to one another, rich in content, and less polysemous could enhance the chances that designers working in a specific context (i.e., design students and teachers or professional designers) would perceive a design outcome of higher value and possibly more original. It should be noted, however, that Polysemy may play different roles for the cases of Overall Value and Feasibility, as discussed in the next section.

Individual contribution of students and instructors to design conversations

To elaborate further upon the individual input of students and instructors to the design conversations, the relations among the semantic measures and the creativity variables are discussed separately for each party. The results showed that for the instructors, semantic measures were related to Usability and Feasibility, whereas for the students a connection was observed with the Overall Value of the final solution. This could possibly be because of differences in expertise causing students to mainly focus on concepts and ideas, and instructors to be concrete and practically oriented. In this sense, the behaviour of students who lack developed design abilities (Cross, 2004) could be considered as novices while, instructors who have master design knowledge and skills could be seen as experts.

It is also remarkable that the semantic measures of verbalizations, generated by both students and instructors separately, were neither associated with Originality nor with the Overall Creativity of the design. This contrasts with a previous analysis about their collective contribution, where Information Content and Semantic Similarity predicted Originality. Hence, this may indicate that design originality could benefit from the collaborative work of students and instructors.

Further analyses indicated that for instructors, Semantic Similarity contributed to the Usability of the design outcomes. As previously noted, this semantic measure was found to be positively related to the quality of the produced solutions (Georgiev et al., 2008). It is therefore proposed that using a lexicon with instances that were close to one another helped instructors to transmit their knowledge to the students more clearly and efficiently, with a probable input in the learning process. This is in line with findings of previous studies on design studio education, where the instructor guided student's learning by providing scaffolding and structure (Sawyer, 2017).

Moreover, it was observed that design conversations of the instructors involving high levels of Polysemy contributed to design outcomes characterized by high Feasibility. The lexical ambiguity of their conversations reflected by Polysemy might have been used to deal with the fuzzy aspects of the design in search of Feasibility, characteristic in the conceptual stages of the design process

In the case of the students, Semantic Similarity was found to predict the Overall Value of the design solutions. It is proposed that the use of similar instances, characterised by Semantic Similarity, helped them in expanding their conceptual jargon from known to unfamiliar related terms. It is possible that using substitute-related nouns played a role in producing less standard and more valuable solutions (e.g., “wood” and “veneer” in Figure 2). On the other hand, no significant relations were observed among the remaining creativity and semantic variables. Similar to novice designers, students did not possess developed and integrated knowledge structures (Casakin, 2012); consequently it could be inferred that their input to enrich the conversation through the design sessions was modest. Regarding the role of students in design conversations, previous studies showed that they tended to produce conventional ideas (Starkey et al., 2016), while they were unable to deal with concept generation challenges (Chen, 2016) as well as to focus on operational aspects of the solution (Casakin & Kreitler, 2008).

Overall, it is possible that based on their knowledge, skills, and level of expertise, instructors were more task-oriented and therefore their semantic verbalizations were mainly associated with creativity variables such as Feasibility and Usability. In contrast, the verbalizations of the novice students (who can be considered as more intuitive than systematic designers), were mainly related to more conceptual aspects of the task.

Conclusions

In this study, we investigated the validity and benefits of employing a semantic approach to analyse design conversations in the studio, and the relation of this approach to design creativity. For this purpose, Abstraction, Polysemy, Information Content, and Semantic Similarity were used as major semantic measures. These were relatively easy to compute and helped gain a better understanding of the nature of design verbalizations by students and instructors. The approach employed proved to be valid for analysing and capturing the semantic content of different dialogues, as well as exploring the importance of semantic content for design creativity. Generally, it was found that the semantic measures have dissimilar contributions to the different variables of design creativity.

It is also interesting that when the verbalizations of instructors and students were analysed individually, they showed a distinct input to design creativity compared to their conversations together. Semantic measures of the instructors were mainly related to Usability and Feasibility, whereas for students, the focus was set on the Overall Value of the outcome. This suggests that the personal goals of designers regarding the creativity aspects they seek may have an impact on the type of language used in conversations.

Major challenges for future studies relate to understanding educational approaches focusing on the analysis of semantic measures from design studio conversations. One direction could be implementing systems for analysing dialogue in real time, aimed at identifying semantic measures of designers (e.g., students and instructors), and anticipating their contribution to creative outcomes. The system could be manipulated according to the intended design goals, such as producing original or feasible solutions.

The present study should be considered as an explorative work based on a small sample of participants. Building upon the present findings, we intend to further explore the importance of the semantic approach for design creativity. Hence, a future work would include designers from other disciplines such as engineering and architecture, with different levels of knowledge and expertise.

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