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Novelty in Collective Design

Harris Kyriakou [a] and Jeffrey V. Nickerson [a]
[a] Stevens Institute of Technology

Abstract

An important element for any successful innovation endeavor is novelty. However, novelty is often linked to unpractical solutions. Our study examines 35,727 product designs submitted to the largest 3D printing online community from January 2009 to June 2013, showing how (i) shape novelty, (ii) semantic novelty and (iii) their interaction affect product design usage. We develop both a shape-based and a text-based measure of novelty by identifying designs that are dissimilar to any preexisting design. We find that, counter to theories of creativity, novel designs are used more than their counterparts. In addition, we find that designs that demonstrate both high shape novelty and high semantic novelty are used 4.2 times more than designs with low shape and semantic novelty. In most studies of creativity, novelty is thought to tradeoff with utility: in this community, novel designs have better outcomes. The evaluation of the community members may be acting to highlight designs that are both novel and useful. Implications for theory and the design of online communities are discussed.

Keywords: digital innovation, novelty, online communities, product design, open design, user innovation.

1 INTRODUCTION

Ideas are not creative if they are not novel (Rietzschel et al. 2010). Novelty is the key distinguishing feature in creative work (Franke et al. 2014), beyond ideas that are merely well done (Amabile et al. 2005; Mueller et al. 2011). Novel ideas tend to have higher economic value (Kaplan and Vakili 2014) and novelty may lead to successful products by providing superior customer value (Brown and Eisenhardt 1995).

However the impact of novelty is not always clear. A strong tendency to select feasible and desirable ideas, at the cost of novelty has been identified. Experiments have shown that evaluators have a hard time viewing novelty and practicality as attributes that go hand in hand, often viewing them as inversely related (Rietzschel et al. 2010). When endorsing a novel idea, people can experience failure (Simonton 1984), perceptions of risk (Rubenson and Runco 1995), social rejection (Moscovici 1976; Nemeth 1986), and uncertainty (Metcalfe 1986). Hence, people can also have negative associations with novelty; an attribute at the heart of what makes ideas creative in the first place (Mueller et al. 2011).

Potential benefits exist in mapping product fitness landscapes, in particular for the design of online open innovation platforms that facilitate product design

(Brunswicker and Hutschek 2010; Nambisan 2013). By using repeatable distance measures, it becomes possible to understand the relationship between novelty and design outcomes; in one recent example, string edit distance was used to evaluate differences between programs in a remix community (Hill and Monroy-Hernandez 2012). In another related stream of research, online traces in open source communities have been analyzed using biological sequence analysis tools (Yoo et al. 2012; Zhang et al. 2014). In this paper, we measure the shape and semantic differences between designs in a 3D printing online community. We do this by calculating the distances between all products based on three dimensional shape characteristics and based on their semantic differences. The longitudinal data collected allow us to know at a product's introduction time how novel it was. We also know what the future will hold for many of these products, in terms of how the community will respond to the invention. Therefore, it is possible to measure novelty, and understand its relationship to design usage.

Our findings show that novelty leads to higher design usage. This is surprising, because novelty is often seen as introducing risk: that is, consumers will tend to choose the norm when there are risks that a chosen product will not perform as expected (Campbell and Goodstein 2001). The community studied here is continuously creating and highlighting designs that are both novel and useful, a general goal of all innovation activity. Possible reasons for these findings are discussed, as are the implications for the design of open innovation platforms.

2 THEORETICAL DEVELOPMENT

Novelty is sometimes measured by asking consumers to compare designs (Andriopoulos and Lewis 2009; Martin and Mitchell 1998) or by asking experts in the field to rate the novelty of proposed innovations (Jeppesen and Frederiksen 2006). However, concerns have been raised about the use of subjective methods with respect to novelty, since such novelty assessments assume that the raters have a common base of experience (Von Hippel 1986). Assessing the degree of novelty is difficult (Garcia and Calantone 2002). Boden has pointed out that someone can be personally creative rather than historically creative (2004). That is, a person can do something that is novel and practical from the standpoint of their own experience, but not from the standpoint of history: the individual just didn't know about a previous invention (Dietrich and List 2007; Gershenfeld 2005; Lesser and Storck 2001). In the context of an online community, it is possible to measure novelty from the historical perspective within that community: that is, it is possible to know if the idea was novel in that community, assuming that a measurement system can be found. What are the possible measures?

Technological distance has been used as a way of measuring pairwise distance in patent search research (Fleming 2001; Fleming et al. 2007; Ulrich 1995). Technological distance is based on the classification scheme of patent offices, and hence is dependent upon the accuracy of that tagging. In online communities, tagging is sporadic, and the ontology is not as sophisticated as that used by the patent examiners. In addition, tagging relies on a classification process that evolves over time; ideally, we would like a repeatable distance measure that can be performed in real time, potentially providing instant feedback to members of the community.

Automatic real-time techniques for measuring and generating novelty have also been pursued in the evolutionary computing field (Cuccu and Gomez 2011; Lehman and Stanley 2008). These techniques are based on finding an objective distance measure and then looking for new elements that are far from the existing elements. String edit distance (that is, the number of edits needed to convert one text string to another) is often used when the underlying representation of a product is textual.

2.1 Shape Novelty

In the product design literature, and the design literature in general, products are often discussed in terms of both form and function (Bloch 1995). Forms are most often expressed with photographs or drawings, and function in textual descriptions of products. In some domains such as commodity electronics, forms may not provide many clues to underlying differences in functionality. But in the case of many products, form and function are associated: differences in form often equate to differences in product. Indeed, consumers pay attention to both, using form as a heuristic for evaluating products. And much of the product design process involves discovering the appropriate form for products. Differences in shape will have an impact on the behavior of those interacting with the objects (Creusen and Schoormans 2005; Luchs et al. 2008; Rindova and Petkova 2007). In this study, we focus on two types of novelty, shape and semantic novelty.

In the case of Thingiverse, STL files (coordinates of the faces of objects) of product designs are freely shared and available. They are textual. But they represent 3D objects. There is a challenge in comparing shapes: objects can be rotated or scaled, but the measure needs to recognize their underlying similarity. In addition, similar objects can be constructed with a different CAD package, and the measure needs to be able to see through the superficial differences in text formats. Because of these requirements, it is better to work from a standard representation of the shape to be printed, and then measure the differences between shapes.

The measure is calculated using a variation of a computer graphics method (Kazhdan et al. 2003) for measuring the shape distance between product designs. The algorithm represents each design based on spherical harmonics (Müller 1966), in order to obtain rotation and size invariant characterizations that can be used to calculate distances that fairly represent changes in shape rather than changes in perspective. One way to conceptually understand the technique is to imagine hollow 3D objects, and consider filling these objects with some number of tennis balls, Ping-Pong balls, and pebbles. Objects that are similar will need a similar proportion of balls of different sizes to fill them up. In the studies that follow, a full distance matrix between designs was calculated, making it possible to determine at any time how dissimilar any new design was to the nearest preexisting design. This measure is used as an indication of shape novelty.

2.1.1 The Shape Distance Measure Applied

Figure 1 presents an example, showing how the novelty measure is calculated for a given design. We selected 10 illustrative shapes from the dataset. The designs included (left to right, clockwise): a double twisted vase (light green), a twisted gear vase (light blue), a gear bracelet (pink), a tree frog (green), a Venetian lion (yellow), an owl facing right that has become one of the standards for calibrating 3D printers (light brown), an owl facing left (dark brown), two owls (purple), the Eiffel tower (white) and the Empire State Building (gray). The distances between designs are reported in Table 1.

Figure 1: Shape Comparison Example.

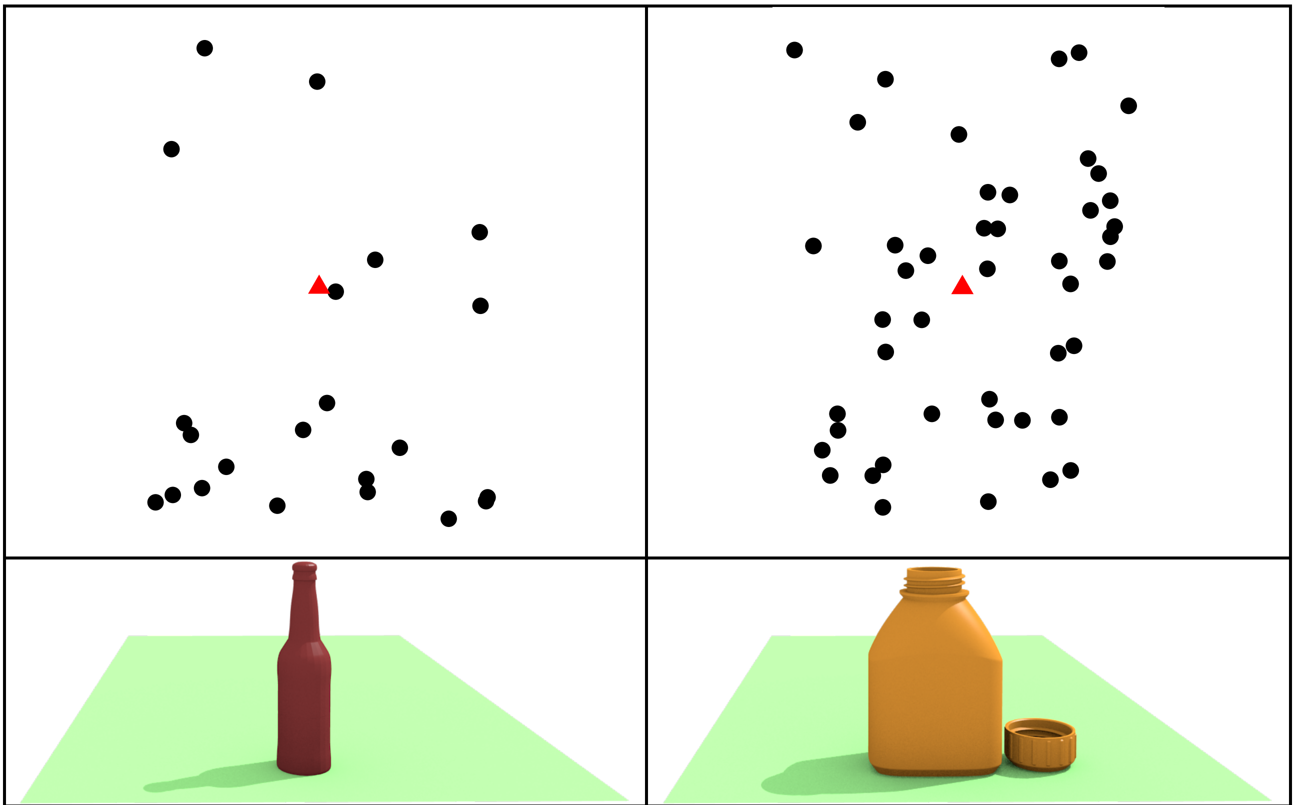
Table 1 Distances between Designs in the Shape Comparison Example.

		1	2	3	4	5	6	7	8	9
1	D. Twisted Vase									
2	Twisted Vase	0.16								
3	Two Owls	0.75	0.72							
4	Owl Face Left	0.71	0.69	0.01						
5	Owl Face Right	0.71	0.69	0.01	0					
6	Tree frog	0.67	0.65	0.41	0.41	0.41				
7	Venetian Lion	0.65	0.62	0.26	0.26	0.26	0.35			
8	Empire State	1.01	0.97	0.5	0.54	0.54	0.67	0.54		
9	Eiffel Tower	0.88	0.87	0.49	0.5	0.5	0.49	0.51	0.54	
10	Gear Bracelet	0.57	0.55	0.7	0.7	0.7	0.64	0.67	0.94	0.91

Assuming that the design that was submitted was a twisted vase (Figure 1, light blue), then the shape of that product design would be compared to all preexisting designs (in this example, nine other designs in Figure 1). The shape distance would be calculated between the design submitted and these nine other designs (Table 1). Since the twisted vase shape is very similar to the double twisted vase (light green) that preexisted, the minimum distance of the twisted vase to any preexisting design is the distance between the two vases (distance=0.16 from its closest neighbor). This closest neighbor distance is a measure of novelty.

We used metric multidimensional scaling to decrease the number of dimensions to two in order to embed the shapes on a plane in a way that respects the calculated distances between them. The 3D product designs shown were placed at the projected coordinates. Animal designs, building designs and vases clustered together, as was desired. Having demonstrated the way the measure works, we now give an example of how it can be used to describe the context of a new invention.

Two bottle designs submitted in Thingiverse are compared in detail (Figure 2). On the left, there is a beer bottle design submitted by *MNinventer* in January 2012. The design was downloaded 230 times and attracted 6 likes, 0 makes and 0 reuses. The novelty metric for the design called *beer bottle* at the time of the post – the design's distance to the closest preexisting product design – was 0.09, because an almost identical product design preexisted.



Beer Bottle		3D Printable Bottle and Screw Cap	
Makes	0	Makes	16
Likes	6	Likes	256
Remixes	0	Remixes	0
Downloads	230	Downloads	8,129
Novelty	0.092	Novelty	0.226

Figure 2: Comparison of Two Product Designs

By contrast, *CreativeTools* contributed a *3D printable bottle and screw cap* in March 2013 (Figure 2, right). The design was downloaded 8,129 times and attracted 256 likes, 16 makes and 0 reuses. The novelty metric for *3D printable bottle and screw cap* at the time of the post was 0.22.

The top of Figure 2 depicts the neighborhood that these two designs were introduced into. The neighborhood visualization is the result of multidimensional scaling from the original large distance matrix. Each neighborhood is shown at the same scale. The designs are in the middle of each figure, and indicated by red triangles. Even though the neighborhood that the second bottle was born into was much more populated than the corresponding neighborhood for the first bottle, the second bottle was more novel. This is an example of a design that is novel in a relatively dense field. The bottom of Figure 2 provides a summary of the novelty and outcome measures. The distance measure provides a way of not only comparing individual designs in local context, but also a way of characterizing the entire design landscape, the task we turn to next.

2.2 Semantic Novelty

Ideas are embedded in vocabularies and therefore shifts in ideas can be detected in shifts in language (Kuhn 1962). Extracting the distance between text documents is anything but new (see Blei 2012; Blei et al. 2003). However, only recently such methods have made their way to management and organization studies (Kaplan and Vakili 2014). Understanding the semantic distance (Rips et al. 1973) between products can allow us to understand the extent to which they differ. In addition, in a longitudinal examination of product designs, we can understand how these designs evolve. Another benefit of quantifying the distance between product designs is that we can measure the degree of *semantic* or *cognitive* (Kaplan and Vakili 2014) novelty of a proposed design upon its introduction. We borrow a computer science technique called ‘topic modeling’ (Wang and Blei 2011) that allows us to discover the latent topics in a collection of product descriptions. As each product description is composed by a series of topics, we can measure the differences between designs according to their differences in topic composition. The designs that are dissimilar to any preexisting design can be characterized as novel.

By introducing these new measures of shape and semantic novelty, we can unpack the relationship between shape and semantic novelty. To develop and validate this approach, we examine the formation of novel ideas in Thingiverse, an open innovation community, where designers freely share their product designs intended for 3D printing.

2.3 Novelty and Design Usage

In order for an invention to be classified as creative, it is expected to possess novelty (Amabile 1996; Finke et al. 1992; Mumford 2003). Novel solutions are shown to emerge from creative thinking processes (Davenport 2013; Woodman et al. 1993), but these processes are surprisingly scarce in organizations (Scott 1987; Staw 1990) despite their importance for organization survival (Massetti 1996). Unfortunately, novelty is also often linked to unpractical solutions. A body of open innovation literature is emerging from fields including information systems, which can serve as a reference discipline for new product development (Nambisan 2003). However, this literature rarely considers how product architectures affect strategic choices (Ulrich 1995; Yoo et al. 2010) and little attention has been given to studying the impact of information systems on product development (Banker et al. 2006; Krishnan and Ulrich 2001). While this literature considers many aspects of open innovation, the dynamics concerning the novelty of digital artifacts have been overlooked.

In pursuit of innovation, organizations have looked outside their borders, but sometimes these open innovation efforts yield little novelty (Jeppesen and Frederiksen 2006; Morrison et al. 2000). Online communities, however, have been shown to discover novel solutions (Faraj et al. 2011). These solutions can be found even by, and especially by, non-experts (Lakhani et al. 2013). Novel solutions can lead to less useful inventions (Fleming 2001) and be misunderstood (Alvesson 1993; Levina and Orlikowski 2009; Weick 1987).

Novelty is desired (Mueller et al. 2011) and novel designs are expected to become popular by attracting more attention than conventional designs. However, the more novel an idea, the more uncertainty can exist about whether it can be reliably reproduced (Amabile 1996). In addition, a strong tendency to select feasible ideas, at the cost of novelty has been identified (Rietzschel et al. 2010). Novelty and practicality are often viewed as inversely related (Mueller et al. 2011). Therefore, we expect that the inherent uncertainty of novel designs lead to their lower overall usage. The aforementioned lead to a three-part hypothesis on novelty:

H1A: Novel designs in terms of their shape will be used less than their counterparts.

H1B: Semantically novel designs will be used less than their counterparts.

H1C: Semantically novel designs with novel shape will be used less than their counterparts

3 RESEARCH DESIGN AND METHODOLOGY

To validate the proposed hypothesis, we collected data from Thingiverse.com. The dataset employed here was extracted using Thingiverse Application Program Interface (API). We wanted to test an as diverse as possible population of designers. We selected 35,727 designs created by 8,759 designers that were uploaded between January 2009, date that the Thingiverse community was created, and June 2nd, 2013, the date we concluded data collection.

The number of downloads has been used as a proxy for usage (Crowston et al. 2004; Wiggins et al. 2009), sales (Chandrashekaran et al. 1999) and market success (Liebowitz 2005). In our study, we used the number of times a design was downloaded as a measure of product design usage. We operationalized the independent variables in the following way. *Shape* and *Semantic Novelty* were measured by determining the distance between any new design and the nearest preexisting design on terms of either shape or semantic similarity. This measure was used as an indication of novelty.

We also included a series of control variables identified in prior literature in our model, to understand the effect of shape and semantic novelty on the final success of a proposed design. In order to control for varying levels of expertise among designers and their embeddedness in the community, we included an experience-related variable. *User Experience* was measured by the number of designs the designer had uploaded to the community prior to that design.

Table 2: Means and Correlations

	Means	s.d.	1	2	3	4	5	VIF
1. Shape Novelty	0.22	0.14						1.14
2. Semantic Novelty	0.05	0.04	0.17***					1.08
3. User Experience	0.03	0.08	0	0.02**				1
4. Time Uploaded	0.22	0.19	0.33***	0.23***	-0.05***			1.23
5. Featured Design	0.09	0.29	0.16***	0.19***	0.02***	0.29***		1.11
6. Usage	502.49	1,771.71	0.10***	0.20***	0.02***	0.12***	0.19***	

N=35,727; ***p<0.001; **p<0.01; *p<0.05

In order to control for designers contributing at different time periods we introduced a time-related variable: *Time Uploaded.* The variable was captured by the number of days between the day that a design was uploaded and the last day of our data collection. A binary variable indicating whether a design was featured in the first page of the community controlled for uneven exposure of designers to specific product designs. All independent variables were normalized within the range 0 to 1. Descriptive statistics of all the variables are presented in Table 2, including variance inflation factors.

4 RESULTS

Table 3: Exponential Regression Models

	Variables	Model 1	Model 2	Model 3	Model 4
	Constant (y-intercept)	4.89***	3.78***	4.00***	3.85***
Novelty	Shape Novelty	2.26***	1.78***	0.72***	0.41***
	Semantic Novelty		2.46***	1.99***	1.66***
	Shape*Semantic Novelty			2.11***	0.56***
Control	User Experience				0.80***
	Time Uploaded				2.07***
	Featured				0.81***
	Adjusted R^2	**0.07**	**0.19**	**0.19**	**0.36**
	Standard Error of the Estimate	1.13	1.06	1.06	0.95
	DF	35,725	35,724	35,723	35,720
	F-statistic	2,733.00	4,132.00	2,786.00	3,279.00

N=35,727; ***p<0.001; **p<0.01; *p<0.05

We used a series of exponential regression models to test our hypothesis and report the results in Table 3, because usage is (i) asymmetric, (ii) continuous and (iii) has only positive extreme values. That is, usage is similar to activity distributions in a large range of online community platforms (Shirky 2008). Model 1 tested only the effect of shape novelty on the usage of a product design. Inconsistent with hypothesis 1A, shape novelty had a significant positive impact on design usage (H1A, ß = 2.26, p

< .001). Model 2 included both shape and semantic novelty (H1B, ß = 2.46, p < .001). Model 3 included the interaction between shape and semantic novelty (H1C, ß = 2.11, p < .001). Although the interaction is positive and significant, the magnitude of the latter is noticeably higher, suggesting that the interaction of shape and semantic novelty has a stronger impact on design usage than shape novelty by itself. Model 4 included all control variables. User experience within the community (ß = 0.80, p<0.001), time that a design was available in the community (ß = 2.07, p<0.001) and whether the design had been featured in the first page of the community (ß = 0.81, p<0.001) had a strong positive and significant impact to the final usage of a proposed design.

These results are inconsistent with the novelty hypothesis, and show that novel designs in both semantic and shape terms are used more. The results from model 4 suggest that designs are more used when they are novel both in terms of their shape and in terms of the semantics used to describe them.

4.1 Shape Novelty, Semantic Novelty and their Interplay

In order to better understand the relationship between novelty and design outcomes, we categorized the designs into 5 categories, ranging from *Very Low* to *Very High* novelty (Figure 3) by splitting them into quintiles based on their novelty scores. *Very Low* novelty designs were designs that were similar to a preexisting design, whereas designs with *Very High* novelty were designs that were relative distant from all preexisting designs. Each of the shape categories had either 7,145 or 7,146 designs and each of the semantic categories ranged from 6,912 designs (*Average* category) to 7,375 designs (*Very Low* category). Figure 3 shows the relationship between shape novelty, semantic novelty and design usage.

Designs with very novel shapes were used 2.4 times more than designs with very low shape novelty. In addition, semantically very novel designs were used 5.8 times more than designs with very low semantic novelty. Pairwise Mann-Whitney tests resulted in p-values<0.001 for all comparisons of shape and semantic categories.

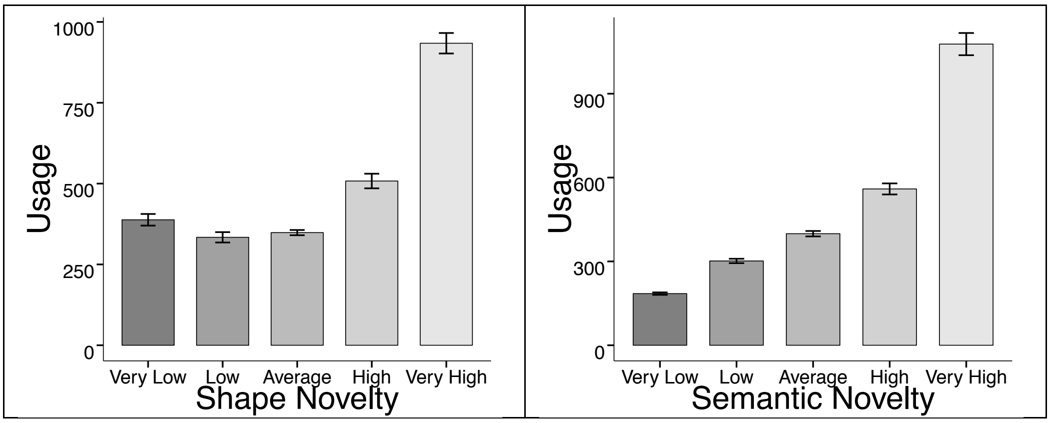


Figure 3: Shape and Semantic Novelty of Designs and Usage. The figures above show the results of pairwise comparisons using t-tests with pooled SD with Holm p-value adjustment method. Error bars represent standard error of the mean.

Next we examined the interaction effects of shape and semantic novelty on the final success of a proposed design. We found that designs that demonstrated high novelty in terms of their shape and high novelty in terms of the semantics used to describe them were more successful than their counterparts. Specifically, designs that were both shape and semantically novel were used 4.2 more than designs with low shape novelty and low semantic novelty (Figure 4). All p-values<0.001 in a pairwise Mann-Whitney test between the four categories. Our results suggest that there is no tradeoff: novelty is rewarded.

5 DISCUSSION

Design is often framed as a form of search (Katila and Ahuja 2002; Sinha and May 1996). If a newly proposed design is close to an existing design, the design is considered as imitative. On the other hand, if the new design is distant from anything preexisting, then it is considered as novel. Past studies have looked at academic citations or patent citations; such citations provide valuable information, but are often far removed from the moment of invention. Online communities provide traces of the inventive process at the individual level as it happens.

Our primary objective for this study was to examine the effect of shape and semantic novelty on design usage. We introduced two new methods measuring the novelty of product designs shared in an online open innovation community. Shape novelty was measured by computing the distance between products as a function of their shape distances. Similarly, we used topic modeling to measure the dissimilarity of the text description accompanying a design to the textual description accompanying any preexisting design. Design usage was measured by examining how often designs were downloaded. These measures were used to calculate the degree of novelty of each design. Novel designs yielded designs that were used more. In the open innovation community discussed, very novel designs at the time of invention in terms of their shape are used 2.4 times more. This last result is particularly noteworthy because in most studies of creativity, novelty is thought to tradeoff with utility: in this community, novel designs yield better outcomes.

Designs that had both high shape novelty and high semantic novelty were 4.2 times more used than design with low shape and semantic novelty. An exponential regression model controlling for factors identified in prior literature suggests that shape novelty, semantic novelty and their interaction have a positive impact on the use of an open innovation design.

We examined the novelty of the designs freely shared in an open innovation community of product designers. Theories of creativity postulate a tradeoff between novelty and utility (Amabile 1996; Cowan and Jonard 2003; Finke et al. 1992; Goldschmidt and Smolkov 2006; Mumford 2003) and a recent remix study found a tradeoff between novelty and reuse (Hill and Monroy-Hernández 2012). But in this case, novel designs were used more than design with low novelty. At least in the 3D printing world, novelty is rewarded more than imitation.

Why might the novelty lead to higher usage? Perhaps designers with access to rapid prototyping tools such as 3D printing devices may be more novelty seeking (Hirschman 1980) than typical consumers.

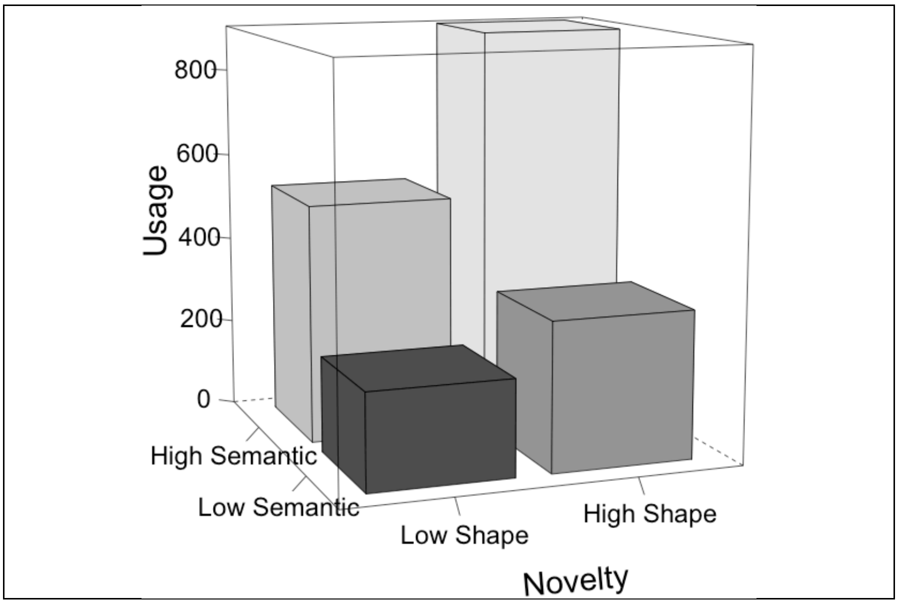


Figure 4: Usage of designs, conditional on shape and semantic novelty. This figure presents the average number of times a design will be downloaded conditional to its own combination of shape and semantic novelty. Designs that combine high shape novelty and high semantic novelty, are downloaded 902.78 times on average, a rate more than 69% higher than the background rate of 533.59. All p-values with a pairwise Mann-Whitney test were <0.001.

It has been suggested that success leads to less successful ideas (Bayus 2013). If that is true, then the Matthew effect (Azoulay et al. 2013) may have a much stronger effect in collective innovation than we might think. Assuming that someone comes up with a novel idea in an open innovation community. As we know, members of his community will be more likely to build upon his work after that (Azoulay et al. 2013). But if this person, becomes fixated to his past ideas which leads him to produce less novel ideas (Bayus 2013), then the community as a whole is likely to suffer from such a behavior.

Another possibility is related to the overall process. Since all designs are visible and openly available, designs that are novel are more likely to attract attention from those who know the domain well (and may already have manufactured previous novel designs), leading to preferential attachment as people seek out the popular designs. This is an argument based on the diffusion of innovations (Rogers 2003), but a diffusion that happens very rapidly. The community effectively filters for both novelty and various forms of utility. This creates a virtuous cycle: designers and consumers alike know what is novel, and know that novelty is rewarded. Designers create more novelty, and consumers reward the products that will meet their needs. The cycle is short, so the communities can innovate at a fast rate. This process provides for loosely coupled collaboration.

In sum, this conjecture states that designers create new ideas, some of which are more novel than others. Novelty is recognized by the community members. This recognition takes the form of digital artifact usage: all this activity rewards innovation by providing motivating feedback and peer-based filtering so that others can easily access the most innovative designs. This conjecture about coordination processes in open innovation communities can be tested through meta-analysis of many online communities, or through experiments in which parts of the process are turned on and off and the effects of those interventions are compared. As part of such experiments, it would be useful to study the effects of providing information about the novelty of a design as it is created.

Specifically, it is possible to automatically calculate a measure of shape-based distance, and provide this measure of novelty back to a designer, so that a designer can know right away what the closest design is, and how novel a potential submission is. Such a measure might help by reducing the number of imitative submissions, encouraging designers to further explore the space. On the other hand, open innovation communities may rely on unintended affordances, and one such affordance may be that users learn through imitation (Majchrzak et al. 2013). There is a potential downside: A tool that provides novelty feedback may set too high a bar on contributions, and frustrate contributors, the same way restrictions on editing on Wikipedia have frustrated new editors (Schneider et al. 2014).

Other complex processes are also at work in such communities. Designers respond to each other's designs, remixing them. These designs may function as anchors in the search space. Designers may build relationships and asynchronously collaborate with each other (Banker et al. 2006), and these collaborations may determine trajectories through the search space. Designs that become popular will become more visible, and thus attract more attention. The types of collaboration possible are dependent on the features made available. For example, some remix communities call for the modification of single previous designs, whereas others allow recombination. This feature might affect the relationship between novelty and design outcomes, and is a possible explanation of the difference in findings between this work and Hill and Monroy-Hernandez's research (2012), which focused on a community with different features. This might be tested through experiments in which designers are randomly assigned one or the other feature set.

Design in open innovation communities is a non-linear ongoing process with feedback loops, and such processes are filled with contingency and noise. Understanding these processes will take effort from many different researchers using a variety of quantitative and qualitative techniques. Nonetheless, simple measures of shape and semantic distances in a product landscapes reveal that novelty is associated with design usage. Further research might seek to understand how far away a design needs to move before it is perceived as novel by community members, and how the density of the neighborhood in which a design will reside will affect outcomes.

Practically, this study suggests that the features of open innovation communities can in some cases facilitate a continuous and productive search through product design space. Designs can be seen by all, and because of that, novelty can be recognized. Risks associated with manufacturing objects can be reduced through features that document the number of people utilizing the designs. In this way the community highlights high novelty and utility design, which in turn provides motivation to designers to create more novel and useful designs. The ability to quickly generate novel solutions and receive feedback may constitute a powerful intrinsic motivator (Lakhani and Wolf 2005). Allowing users to evaluate the novelty of both their ideas and the ideas proposed by others might reduce the effort needed to find promising designs to use or build upon, and in that way accelerate innovation.

6 CONCLUSIONS

Participants in online open innovation communities create artifacts and collectively explore the design space. Because all designs are visible and all contribution history available, it is possible to monitor the evolution of designs, and understand the relationship between novelty and design outcomes. In the case of the 3D printing community studied here, it was possible to objectively measure differences both in form and semantically in the product space. That is, it was possible to see how different every design was from any other design at the time it was introduced into the community, and then see the resulting outcomes.

Designs that were novel were more successful than those that were not. It is possible that collective innovation communities are effective because they allow for the fast discovery of novel and practical designs. That is, product designs will become more visible as the number of other people who have printed, liked, downloaded, cited or printed those designs increases.

The example described demonstrates that at least some online communities are capable of sustained innovation, and this happens through a combination of generative and evaluative activity that makes ideas visible so that others can decide if and how to contribute a new idea or further a preexisting idea. Ideas that were more novel were more likely to become successful in all the ways we measured. In a sense, the community is rewarding designs that are both novel and practical by driving more attention to those designs. These designs will get noticed and imitated, but it is the designs that move further away that are more likely to be noticed. There is a fitness landscape, one in which both the many new ideas and the many evaluations of those ideas come from the community members themselves. It is an engine of collective design.

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