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RESEARCH ARTICLE

NOVELTY AND THE STRUCTURE OF DESIGN LANDSCAPES: A RELATIONAL VIEW OF ONLINE INNOVATION COMMUNITIES[1]

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Design artifacts in online innovation communities are increasingly becoming a primary source of innovation for organizations. A distinguishing feature of such communities is that they are organized around design artifacts, not around people. The search for novel innovations thus equates to a search for novel designs. This is not a trivial problem since the novelty of a design is a function of its relationship to other designs, and this relationship changes as each design is added. These relations between artifacts affect both consumption and production. Moreover, these relations form a landscape whose structure affects the emergence of novelty. We find evidence for our theorizing using an analysis of over 35,000 Thingiverse design artifacts. This work identifies the differential effects of different forms of novelty, visual and verbal, on subsequent innovation, and identifies the differential effects of different degrees of structure in the landscape on novelty.

Keywords: Novelty, design landscape, visual novelty, verbal novelty, structure, search, online innovation community, innovation, design artifacts, 3D printing

Introduction

Online innovation communities (OICs) such as Propellerhead, Threadless, and ccMixter are gaining so much popularity that some of the biggest holders of intellectual property, such as IBM, Microsoft, and Apple, are embracing them in their strategic product offerings, donating copyrighted software for others to build upon, and encouraging their employees to participate (Lakhani & Panetta, 2007). OICs allow participants to share and distribute their artifacts in order to build product, technology, or service innovations (Antikainen, 2011; Debaere et al., 2018). A distinguishing feature of such communities is that they are organized around the designed artifacts[2] instead of the focus in many other communities on participant profiles (Stanko, 2016).

[1]Brian Butler was the accepting senior editor for this paper. Jan Recker served as the associate editor.

[2]For the remainder of the paper, we use the terms *design artifacts, designs*, and *artifacts* interchangeably.

Participants in OICs are primarily novelty-seekers (Hirschman, 1980; Kyriakou et al., 2017). Searching for novelty in an OIC equates to a search for novel designs (Brem et al., 2019; Dean et al., 2006; Füller et al., 2011; Hutter et al., 2015). Such a search is not trivial because designs have relations with other designs, in particular differences with respect to attributes such as shape and function (Boden, 2009). The set of relations can be described as a design landscape (Levinthal, 1997; March & Simon, 1958; Simon, 1996). Searching through large landscapes where there are many designs requires finding designs that are both close enough to the searcher's interest to be suitable and distant enough from other designs to be novel. This search is made more complex because, as each design artifact is added, the relations change, requiring participants interested in novelty to not just search once, but repeatedly over time (Kyriakou et al., 2017; Stanko, 2016). Finally, searching is conducted for various purposes. In particular, a design may be found and used to solve a problem, a form of consumption, or it may be found and classified as a source of inspiration, then modified, then contributed, a form of production. Searching for a novel artifact to consume suggests criteria that are not just novelty-related, but also use-related, which may be highly personal, such as when a community participant looks for a heart-shape to be 3D printed as a Valentine's gift, or looks for a t-shirt to be silkscreened that complements that participant's existing wardrobe. Searching for a novel artifact to inspire production of future designs suggests additional criteria, such as when the design might appear ready for an improvement that would utilize the particular skills of the participant. Therefore, the relations between artifacts in an OIC are likely to have complex effects on both consumption and production—an effect which calls for empirical study.

A focus on relations between artifacts helps to bridge a gap in the existing literature on OICs in which two streams of research have not yet been integrated. The first stream has focused primarily on measuring properties of artifacts rather than measuring the corresponding relations between the artifacts. For example, the number of images posted for the artifacts (Stanko, 2016), or the number of tags used to describe the artifacts (Flath et al., 2017) were measured rather than the differences in shape or function. The second stream has focused on individual participants' actions that affect the quality of contributions in OICs (Claussen & Halbinger, 2019; Kyriakou et al., 2017). A relational perspective helps extend and integrate the two streams by identifying how participant actions affect the relations between artifacts which in turn affect later participant actions. In sum, we ask: *How do the relations between artifacts affect the production and consumption of novel artifacts?*

To submit our relational perspective to empirical examination, we used new computer graphics and topic modeling methods to analyze the relations between more than 35,000 design artifacts in Thingiverse, a community dedicated to the sharing of novel user-generated digital design files. We distinguish between two forms of novelty—visual and verbal—because of the differences in the manner in which they are cognitively processed. We find that visual and verbal novelty of an artifact have distinct effects on consumption and production. We also consider the *structure* of the relations—the degree to which artifacts are organized. Visually novel artifacts are more likely to be produced in more-structured landscapes, while verbally novel artifacts are more likely to be produced in less-structured landscapes. Extending this view, we find that an artifact that is verbally novel leads to greater consumption and production than a visually novel artifact. Moreover, in comparison to an overall strong preference for novel designs, consumption and production are lower when the artifact is both more visually and verbally novel than other artifacts in the landscape.

These findings suggest that consumers and producers are influenced not only by their individual backgrounds and the attributes of the artifacts, but by the relational distribution of the artifacts throughout the landscape.

Background

Online Innovation Communities

Interest in OICs has surged in both practice and research. Toy manufacturers such as Lego consistently draw from their OICs to identify new products to launch (Antorini et al., 2012), OICs are increasingly becoming the source of new products for medical devices manufacturers (DeMonaco et al., 2019), and many OIC participants have their creations sold in marketplaces like Etsy (Saunders, 2019). Claussen and Halbinger (2019) describe OICs as places to develop not merely successful innovations but also successful innovators; Ye et al. (2012) argue that OICs are critical for novel idea generation; and Gebauer et al. (2013) refer to OICs as rich sources of innovation that offer added value to their participants. In addition, OICs have recently been recognized as not simply important sources of innovation, but also as important settings for scholars to understand innovation processes (Flath et al., 2017).

There has been substantial research attention focusing exclusively on the unique qualities of OICs (Dean et al., 2006; Fichter, 2009; Filitz et al., 2015; Gebauer et al., 2013; Huang et al., 2012; Jarvenpaa & Lang, 2011; Papadakis et al., 2014). In this research, an OIC is defined as a loosely coupled organization of participants in which designed artifacts, instead of profiles of the participants, are central to the organization (Flath et al., 2017; Jarvenpaa & Lang, 2011). Participants engage with the artifacts in a variety of ways: publicly reacting to the artifact by providing comments, votes, or likes; manufacturing a digital artifact into a physical object (e.g., on a 3D printer); downloading an artifact into a private workspace; or reusing an artifact to make modifications resulting in a new artifact (Flath et al., 2017; Riedl & Seidel, 2018; Stanko, 2016).

OICs are to be distinguished from other online knowledge production communities such as those focused on open source software, travel advice (Scott & Orlikowski, 2014) and Wikipedia (Kane & Ransbotham, 2016). First, OICs do not have a singular production goal, and output is often assessed based on the novelty of the artifacts produced, rather than the amount and quality of knowledge integrated (Dahlander & Frederiksen, 2012; Jarvenpaa & Lang, 2011; Stanko, 2016). Second, software development communities are organized around team-based projects (Crowston et al., 2012), whereas OICs are organized around artifacts made by individuals. Third, the creation process is one in which OICs promote, reward, and focus explicitly on adding novel content (Stanko, 2016). In OICs, the average novelty of the designs in the community is important because the presence of novelty excites participants and makes it more likely they will remain active (Kyriakou et al., 2017). In this respect, OICs are different from many platform ecosystems in which app developers are motivated only to improve their own products, not the products of others (Boudreau, 2012).

Prosumption in Online Innovation Communities

Much of the prior research on OICs has focused on either consumption or contribution separately, using two different theoretical streams. In the consumption stream, research has found such predictors of artifact consumption as the artifact's complexity, social feedback on the artifact, and the appearance of the artifact on the front page (Hautz et al., 2010; Li et al., 2016; Stanko, 2016). In the contribution stream, research has focused on community participants including participants' characteristics (Claussen & Halbinger, 2019; Li et al., 2016), behavior (Bateman et al., 2011), effort creating the artifact (Kankanhalli et al., 2005; Ye et al., 2016), and specific forms of social exchange (Faraj & Johnson, 2011; Füller et al., 2011; Wasko & Faraj, 2005). The two different streams are generally independently researched.

While these two streams have helped to identify important factors, their independence makes it difficult to see that, in OICs, contribution and consumption are often undertaken as parts of the same process and affect each other. OICs are marketplaces in which consumers may be contributors, and vice versa. For example, Kyriakou et al. (2017) describe how participants both consume an existing design artifact by selecting and downloading it, and then become contributors by modifying and uploading the modified artifact. Similarly, contributors often consume (e.g., select, view, download, and 3D print) others' designs in the process of getting inspiration (Stanko, 2016). Therefore, in OICs, many contributions of new artifacts are preceded by consumption, and much consumption is conducted that will lead to subsequent contributions. Consequently, we recognize this interrelationship by examining both behaviors as a function of the other behavior, referring to both behaviors collectively as *prosumption* (Ritzer et al., 2012; Toffler, 1980). We define prosumption in OICs as the total of participant activities with respect to the artifact, including selection, downloads, likes, incorporation into a material good, reuse of existing artifacts, and the creation of new artifacts.

Search and Design Landscapes

A design landscape or design space is the name given by search researchers to the abstract territory in which design search takes place (Baldwin et al., 2006). Search is a common paradigm for understanding problem solving by postulating it as a process of exploring a space (Majchrzak & Malhotra, 2019; March & Simon, 1958; Simon, 1996). Subsequently, many scholars have framed innovation as a search problem (Katila, 2002; Kornish & Ulrich, 2011; Martin & Mitchell, 1998; Rosenkopf & Nerkar, 2001; Stuart & Podolny, 1996; Terwiesch & Xu, 2008).

A design landscape includes a collection of artifacts, while a particular artifact corresponds to a single point in the design landscape (Baldwin & Clark, 2000; Bell & Newell, 1971; Murmann & Frenken, 2006). Design landscapes are searched by seekers. As they search, the design landscape gets "mapped"; that is, the seekers come to understand the properties of a large number of design alternatives (Baldwin et al., 2006; Lee & Butler, 2019).

Search researchers generally assume that seekers search the design landscape before either selecting an existing solution or proposing a new solution (Brunswicker et al., 2018; Levinthal, 1997; Simon, 1978). Consequently, the design landscape and the manner in which it is searched affect prosumption. When a seeker searches for an artifact, the novelty of the artifacts in the design landscape itself is likely to have consequences for which artifacts are discovered and selected, hence prosumed. In an OIC in which artifacts are so numerous as to prohibit display at one time, the design landscape is often not fully known to actors (Shah et al., 2003). Consequently, participants in a large design landscape have been observed to start their search with a large number of artifacts, skimming them according to search heuristics and then selecting a subset on which to focus their attention (Kornish & Ulrich, 2011; Nelson, 1961; Riedl & Seidel, 2018).

Search heuristics are often implicit (Edelkamp & Schroedl, 2011), personalized (McGown et al., 1998; Visser, 2006), and satisficing (Simon, 1991). As designers differ substantially in the way they search the design landscape (McGown et al., 1998; Visser, 2006), it is important to understand how attributes of the design landscape can affect their actions.

The existence of novel artifacts in the design landscape also depends on the actions of participants. Therefore, actions associated with prosumption—how participants decide which designs to create and use—sculpt the design landscape. This sculpting is not simply of individual artifacts but the relations between artifacts indicating which gaps inviting novelty insertion have been filled and which are still available. These relations help participants "represent differences between the desired and the present" (Visser, 2006, p. 7). Just as the structure of physical landscapes constrains and encourages certain physical explorations (Davies, 1992), the structure of design landscapes will encourage or discourage certain design explorations that lead to the creation of novel artifacts (compare to design as exploration; Gero, 1998; Logan & Smithers, 1993; Navinchandra, 2012).

A Relational Perspective

In the search literature, the novelty of a design added to the design landscape is defined by the extent to which the design is introduced in a relatively underutilized part of the design landscape (Kornish & Ulrich, 2011; Visser, 2006). Looking in underutilized parts of a landscape helps searchers to resolve a tradeoff. On the one hand, if a participant adds a design to the design landscape which is identical to designs that already exist, the introduction of the new design is unlikely to offer additional value to others using the designs since the design will not introduce novelty in the design landscape; as such, a random search process will be sufficient to identify a novel design. On the other hand, if all participants create designs that are completely different from existing designs, a random search process is again likely to be sufficient since designs will be distributed throughout the landscape. Consequently, searchers look for parts of a landscape in which there are gaps or a relative lack of existing designs.

A search for gaps makes the search a relational one; gaps are not found by looking at one artifact but by understanding how artifacts differ from one another. By relational, we refer to relations between artifacts which yield a measure—for example dissimilarity. An exemplar of the relational view comes from McKinney and Yoos (2010), who offered a distinction in how information is examined by identifying the "token view" and the "syntax view." The token view is one in which people are assumed to evaluate a piece of information about an individual artifact, not for its relational characteristics to other artifacts, but for the artifact itself. In contrast is what they call the syntax view, which focuses on "the measurable relationship between tokens that reduces entropy" (p. 332). McKinney and Yoos found only 2 out of 60 information systems papers that took the syntax view, while the remainder took the token view. *We suggest that the design landscape serves as a source for information not just about individual artifacts, but also about relations between artifacts.*

The relational view is consistent with how novelty has been defined in most studies, where an artifact is considered as novel when it is more rare, unusual, or uncommon *in relation to* existing artifacts in the design landscape (Connolly et al., 1993; Dennis et al., 2013; MacCrimmon & Wagner, 1994). Novel artifacts tend to provide superior value (Brown & Eisenhardt, 1995), have been repeatedly demonstrated to be stimulating and capturing the attention of people (Hirschman, 1980; Schweizer, 2006), and have higher economic value (Kaplan & Vakili, 2014). There is no creative work without novelty (Dean et al., 2006; Rietzschel et al., 2010), as novelty serves as its key distinguishing feature (Franke et al., 2014; Mueller et al., 2011). Similarly, in OICs, most participants are interested in identifying and creating novel artifacts (Stanko, 2016).

Assessing novelty in this relational manner has been examined in the literature in two different ways. In the first way, the novelty of an artifact is judged in relation to how uncommon it is *in the mind of the rater*, known as psychological novelty (Boden, 2009). However, such an assessment is difficult to compare between raters (Criscuolo et al., 2017; Danneels & Kleinschmidt, 2001; Garcia & Calantone, 2002; Huy & Vuori, 2015) because of their different experiences (von Hippel, 1986). In the second way, the novelty of an artifact is judged by how uncommon the artifact is in the overall population of preexisting artifacts (Dean et al., 2006)—a time-dependent concept referred to as *historical novelty* (Boden, 2009). Since, in the context of OICs, the novelty of an artifact refers to the extent that the artifact has not been expressed before at that point in time (Kankanhalli et al., 2005; Magnusson et al., 2003), we focus on historical novelty, viewing it as a relational, time-dependent concept (North, 2013).

Two Forms of Novelty Affecting Search

Novelty-seeking participants are likely to exhibit curiosity, practice differentiation, and engage in learning (Arentze & Timmermans, 2005; Hirschman, 1980; Schweizer, 2006). To satisfy the need for novelty, participants will search the design landscape by skimming pages of artifact information such as images and descriptions, or by using search filtering when available (Faraj et al., 2011; Hildebrand et al., 2013; Stanko, 2016; Zhang et al., 2013). This search process involves making comparisons about the information between existing designs, and between existing designs and designs being formulated in the minds of the participants. Since novelty can be identified by participants based on preferences for certain types of information (Pisula, 2009; Potts, 2012; Schweizer, 2006), the types of information that participants are likely to search for when seeking novelty are important to understand.

Past literature distinguishes between two attributes of artifacts that are likely to inform participants. The first describes the *visual* nature of the design, such as the pictures, sketches, shapes, and sizes depicted in the design. The second describes the *verbal* nature of the design, such as textually based design descriptions explaining the purpose, function, and meaning of the design (Mayer & Sims, 1994; Paivio, 1991). Participants attend differently to—and independently of—these two types of information (Sadoski & Paivio, 2013). Visual information is processed in parallel, sensory, visceral, holistic fashion. That is, when viewing a design, the individual is likely to see a complete image and formulate a holistic sensory perspective of it, such as "a jumping candle" or "a flying car." In contrast, verbal information is processed sequentially as words are presented, activating an associative structure. That is, when reading about the intended functional use of a design, the individual is likely to formulate a series of associations such as "the car will be useful to reduce commutes between cities, but create a commuter mess within a city" (Mayer & Sims, 1994; Paivio, 1991). Therefore, in understanding how search occurs within a design landscape, the verbal and visual attributes of the designs are likely to be used differently.

Theory Development

Design Landscape Structures as Antecedents of Novelty

Participants in OICs searching to create novel designs are likely to act similarly to market innovators (Alexander, 1997; Potts, 2012; White, 1981), looking for gaps in the existing design landscape. How these gaps can be identified and depicted has been the subject of much research related to ontology, organization, and structure (Burton-Jones et al., 2005; Johnson et al., 2015; McKinney & Yoos, 2010). The structure of a design landscape can be defined via categorizations that depict relations between artifacts or participants' conceptualizations (Malerba, 2007; Potts, 2012; White, 1981). That is, categorization schemes indicate the extent to which participants and their designs are similar on some information dimension (Simon, 1962). These categorizations can reduce search costs because designs with similar characteristics can be identified (Chan et al., 2018; Porac & Thomas, 1990). Since creators are looking for opportunities and gaps for novelty, categorization can help them identify the gaps with greater ease.

The degree to which structure is conveyed—such as through categorization—has been described as ranging from entropy (i.e., randomness, or chaos) to negentropy (i.e., order, or organization) (McKinney & Yoos, 2010). In systems theory, entropy is defined as the randomness of the elements of a system (von Bertalanffy, 1950), depicting all systems as moving toward an entropic state. Prior literature on innovation has also suggested that a lack of structure motivates participants to create novel designs, because a lack of structure indicates an immature market, attracting entrants with novel designs (Malerba, 2007; White, 1981). We suggest, then, that participants are likely to be affected by the apparently random distribution of designs—indicative of a lack of structure—in the design space. Participants should then use this structure (or lack thereof) to identify gaps in the design landscape, which they can target when creating new designs.

Search costs are different for verbal and visual attributes (Mayer & Sims, 1994; Sadoski & Paivio, 2013). Therefore, it is likely that the structure of visual information in the design landscape will be processed differently than the structure of verbal information in the design landscape. We examine the possible differences below.

In OICs, verbal information not only can be searched in more sophisticated ways than visual information, but linguistically, verbal stimuli are generally more organized—hierarchically and categorically—than visual information (Landau et al., 1988). Participants carry extensive hierarchically organized linguistic categories which allow them to flexibly formulate different sentences with the same meaning, or similar sentences with different meanings (Bock & Levelt, 1994; Greenfield, 1991). However, when these structures are similar to the structure of the design landscape, they are likely to impair the creation of novel designs.

For example, some searchers may look in categories that have well-articulated ontological structures. They may look for gaps in designs for games by searching such descriptors as the number of players, the game purpose, the rules, and the skills needed. In such a well-structured ontology, provided there are designs distributed throughout this ontology, obvious gaps may be harder to locate (Gilhooly et al., 2007). Such a structure may inhibit the creativity of the designer because any design generated is likely to land on the defined points of the ontology, and hence be less novel. In contrast, for a product category where a deep and well-structured ontology does not already exist—for example, "bobble headed look-alikes"—gaps should be easier to locate. As such, we suggest

Proposition 1A: *Participants will contribute less verbally novel artifacts in highly structured design landscapes.*

By contrast, the ontology of visual information is not well-articulated in practice. For example, there is less ontological agreement about differences between two shapes than differences between two functional uses of a design. This lack of visual ontological structure makes findings gaps difficult since the definition of a gap is not clear, such as whether a shape which shares some attributes of another shape is novel or not. Moreover, visual search is performed configurationally, and can proceed bottom-up as well as top-down (Bruce & Tsotsos, 2009). Finally, searching for visual information is accomplished differently from searching for verbal information. Visual stimuli are more readily skimmed as they accelerate the translation between different perceptual modalities (Gonçalves et al., 2012; Malaga, 2000), in contrast to verbal information which is processed linearly. Consequently, any structure accorded visual attributes may help the searcher in identifying gaps. For example, if the existing designs in a product category of "fasteners" show few if any fastener designs that exhibit playful-like visual information such as squeaks, surprise movements, and unexpected expansion elements (by contrast to the ubiquity of such qualities in the product category of toys), then this marked difference in the density of fasteners with and without playful-like visual information can indicate a gap in which novel designs could be inserted. Thus, for visual information, structure is likely to help indicate the presence of gaps for novel insertion.

Proposition 1B: *Participants will contribute more visually novel artifacts in highly structured design landscapes.*

Consequences of Visual and Verbal Novelty on Prosumption

Effects of Verbal and Visual Novelty

We now turn our attention to how participants select artifacts in the design landscape. We have previously argued that artifacts are more likely to be used by participants when they are novel (Arentze & Timmermans, 2005; Hirschman, 1980; Schweizer, 2006). We have also distinguished between two different forms of novelty based on their informational dimensions: artifacts that are verbally novel, and artifacts that are visually novel. Moreover, we have argued that the search costs for visual and verbal information about an artifact are different. Verbal search is likely to be exploiting an ontology, while visual search is likely to exploit sensory associations. We now address the question of how participants find verbally novel artifacts and visually novel artifacts as they search the design landscape.

Because of the different search processes for visual and verbal information, we expect that participants will develop novelty assessments separately for visual and verbal attributes. Given that OIC participants are likely to be drawn to novel artifacts, they will develop heuristics through interacting with the design landscape that allows them to identify artifacts as either visually novel or verbally novel, even though they are unlikely to have examined all designs in the design landscape. Moreover, given the differential search costs that participants will incur when using visual or verbal information, we propose that the visual and verbal novelty of a design will have distinct positive effects on its prosumption:

Proposition 2A: *The greater an artifact's visual novelty, the more likely that the artifact will be prosumed*.

Proposition 2B: *The greater an artifact's verbal novelty, the more likely that the artifact will be prosumed*.

Relative Strength of Visual and Verbal Novelty

When searching the design landscape, the different search heuristics for verbal and visual novelty may not only lead to separate assessments affecting participants' actions, but also to differences in the relative strengths of those effects. As discussed in reference to Proposition 1B, there is a much more organized normative structure for the verbal information of design artifacts, including functional descriptions, as well as product categories, subcategories, and ontologies. Consequently, it should be easier to search for, and find, verbally novel artifacts.

There may be additional reasons why verbal novelty has a stronger effect on prosumption than visual novelty. Faulkner and Runde (2009) suggest that, while visual depictions represent the physical form of an artifact, verbal descriptions present the social function of an artifact, and thus descriptions will have a greater influence than visual depictions on prosumption. Additionally, verbal descriptions of designs should be more elaborate because of the ease with which common non-novel terms can be discovered (Pirolli, 2007). Because verbal terms can be easily combined, verbal novelty may be easier to locate through such combinations, helping participants search for novel designs. Finally, participants may be more confident in a design found through sophisticated search engines using verbal information, knowing that the search engine is examining the entirety of the corpus (Purcell et al., 2012).

In contrast to the value of verbal information in conducting searches for novel designs, visual novelty is assessed through an incomplete, idiosyncratic, and manual search of designs, and consequently is unlikely to instill such a level of confidence. Therefore, we expect that visual novelty will have a smaller, albeit still significant influence on a participant's decision to prosume an artifact. In sum, we suggest

Proposition 3: *Verbal novelty will have a stronger effect on artifact prosumption than visual novelty.*

Effects of Combined High Visual and High Verbal Novelty

As visual and verbal novelty attributes are assessed separately by participants, their combined assessment for any particular artifact is not known. However, we suggest that the two attributes may have an additive, or catalyzing effect on prosumption. Past literature has suggested that visual novelty is used as a clue in understanding verbal novelty (Landau et al., 1988). That is, individuals often understand what an object does from how it looks.

However, identifying a design that has both high visual and high verbal novelty is likely to be quite difficult because novelty creates uncertainty, leading associated search costs to increase (Arentze & Timmermans, 2005; Boudreau et al., 2016). In such extreme cases, the search costs may exceed the time and effort that participants are willing to put into the task. A search for high visual and high verbal novelty requires simultaneously examining both visual and verbal information in the design landscape, which can lead to missing essential information, or selectively focusing on one type of information without regard to the other type of information (Mayer & Moreno, 2003). For example, if a design has both high visual and high verbal novelty, it may suffer from the dilemma describe by Hargadon and Douglas (2001, p. 478): "Purely novel actions and ideas cannot register because no established logics exist to describe them." Consequently, participants may experience higher perceptions of risk (Rubenson & Runco, 1995), failure (Simonton, 1984), uncertainty (Metcalfe, 1986), and social rejection (Nemeth, 1986) when interacting with designs that are both visually and verbally novel. Similarly, Stanko (2016) suggested that highly novel artifacts will be difficult to reuse because community participants will not anticipate benefits from their use.

Moreover, a novel verbal representation and a novel visual representation may not always be aligned with each other, thus further increasing search costs (Mannucci, 2017; Orlikowski, 2002). For example, a design of a windmill-shaped object may not provide enough meaning to the object if it is verbally referred to as a telescope. This suggests that the co-occurrence of high levels of visual and verbal novelty may have diminishing returns on artifact prosumption:

Proposition 4: *Visual and verbal novelty will have a negative interacting effect on artifact prosumption.*

Research Design and Methodology

Research Setting

Our research was conducted on Thingiverse, following prior studies describing the site as an exemplar of OICs because of its focus on novel artifacts (Flath et al., 2017; Kyriakou et al., 2017; Stanko, 2016). Thingiverse stems from the maker movement, a technology-based contemporary extension of the Do-It-Yourself culture that enjoys creating new devices, as well as tinkering with existing ones. Makers are typically interested in product design and engineering-oriented projects related to electronics, robotics, and 3D printing (Wikipedia, 2017). Makers have a strong focus on using and learning practical skills and applying them to reference designs, making the context ideal for the study of processes enabled by digital technologies (Pentland et al., 2020).

Technologies such as 3D printing provide access to a wide array of new products, as they offer the possibility of customizing products, creating products for highly segmented markets, or even for markets of one (Gershenfeld, 2005; Ihl & Piller, 2016). In addition, diminishing costs of access to these technologies permit continuous experimentation and have contributed to the democratization of production processes.

To test our propositions, we collected data for 4.5 years using Thingiverse's Application Program Interface. We started collecting design artifacts uploaded when the first design was created in Thingiverse. Our dataset includes 35,727 product designs after excluding designs that were automatically created. We collected digital content data, including titles, text descriptions, and tags, as well as all 3D digital representations of the designs available in Thingiverse. In addition, we collected data on whether designs were downloaded, and when new designs were uploaded. The designs examined were created by 8,759 participants, in 79 product categories ranging from toys and household items, to quadcopters and prosthetics.

Measuring Novelty and Structure

We measured novelty and structure by creating dissimilarity matrices that captured the visual and verbal differences across artifacts. For the measure of novelty, we used the dissimilarity matrices to identify the most similar preexisting design. For the structure measure, we used the dissimilarity matrices to calculate the additive inverse of entropy of all the artifacts in a product category. The processes for the creation of the dissimilarity matrices, as well as the measurement of novelty and structure measures, are described in detail below.

Visual Dissimilarity Matrix

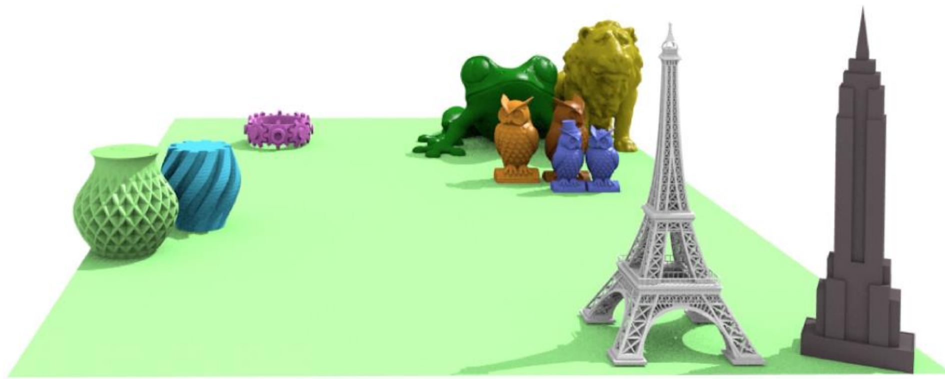
A matrix containing more than 638 million visual dissimilarity measurements between all designs available was created, making it possible to determine how dissimilar a newly created design was from all preexisting designs at the time of its introduction. The algorithm for visual dissimilarity between any two given designs was developed purposefully for this research. It was based on a variation of a computer graphics method for calculating the shape differences between product designs (Kazhdan et al., 2003). The algorithm represented each 3D design based on spherical harmonics, obtaining rotation and scale-invariant characterizations that can be used to calculate dissimilarities that represent visual changes rather than changes in perspective. This technique is analogous to the way audio waveforms are decomposed into frequencies using Fourier analysis. Objects can be composed of smaller objects of different sizes: for example, spheres of different dimensions. The count of these spheres forms a signature of the object that is invariant to rotation and scale. Figure 1 shows an example of the visual dissimilarity between ten designs in our dataset, which can be used to derive novelty measures of designs depending on the time they were introduced in the community.

Specifically, Figure 1 presents an example that demonstrates how the visual dissimilarity measure performs with a series of designs. 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 dissimilarity matrix across all designs in our example is also reported. To create Figure 1, we used multidimensional scaling to decrease the number of dimensions to two in order to embed the designs on a plane in a way that respects the calculated dissimilarities between them. The 3D product designs shown were placed at the projected coordinates. Animal designs, building designs, and vase designs clustered together, as was desired.

Verbal Dissimilarity Matrix

Another dissimilarity matrix based on the verbal differences between designs was used to derive measures of verbal novelty. The verbal differences between designs were calculated using topic modeling on the text associated with each of the designs (Wang & Blei, 2011). Similar types of semantic analysis have been used in the information systems and strategy literature to measure verbal differentiation (Guo et al., 2017; Johnson et al., 2015; Kaplan & Vakili, 2014). Topic modeling permits the discovery of latent topics in a collection of product descriptions. As each product description is composed of a mixture of topics, we can measure the differences between designs according to their differences in topic composition. The more dissimilarity in topics between a new design and preexisting designs, the greater the novelty of that new design with respect to its description.

Specifically, topic modeling was carried out using the standard techniques of preprocessing through stemming and removing stopwords. In stemming, inflected or derived words are reduced to their word stem (Paice, 2014), which helps to treat words with the same stem as synonyms (e.g., robot and robots). Stopwords are words that are very common or insignificant (i.e., articles, prepositions) and are filtered out before processing natural language data (Wilbur & Sirotkin, 1992). Similar to prior studies, we found it most useful to constrain the number of topics to 100 (Blei & Lafferty, 2007; Hall et al., 2008; Kaplan & Vakili, 2014). Another matrix containing more than 638 million verbal dissimilarity measurements between all designs was then created. The longitudinal data collected allowed us to examine how novel each new design description was relative to preexisting design descriptions at the time that the design was introduced.



Dissimilarity Measures Between Designs

		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	<0.00					
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

Figure 1. Examples of Visual Differences among Designs

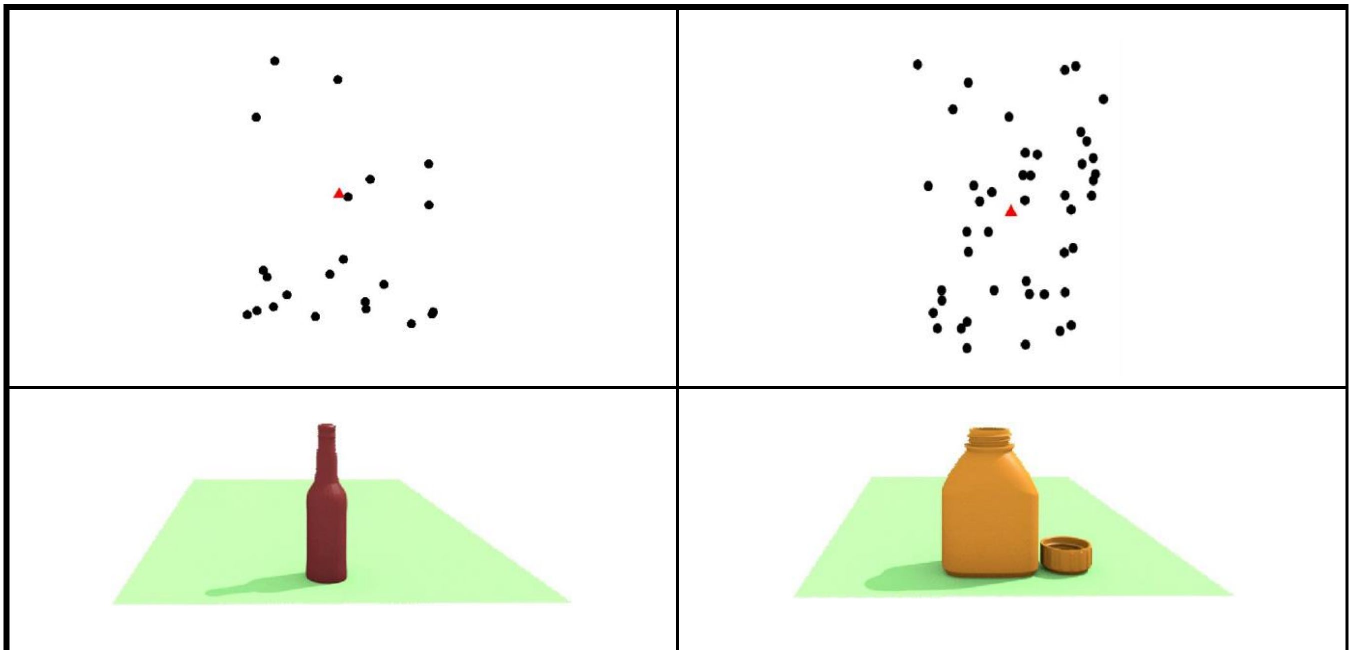
Variables to Test P1: Effects of Verbal and Visual Structure on Verbal and Visual Novelty

Dependent Variables: Degree of Visual and Verbal Novelty of a Contributed Design

Contribution of a design is one side of the prosumption of artifacts in Thingiverse. Our propositions predict the degree of novelty of the contributed design. Using the dissimilarity matrices described above, we operationalized the degree of each type of novelty for each artifact at the time that the artifact was introduced. The dissimilarity matrix was used to determine the dissimilarity between any newly proposed design and the *most similar preexisting design*, which was consistent with previous approaches (Reehuis et al., 2013). For illustration purposes, two bottle designs submitted in Thingiverse are also compared in more detail, as an example of the visual novelty measure (Figure 2).

On the left side is a beer bottle design submitted by participant *MNinventer* in January, 2012. The design was 3D printed once and was never reused by another participant for a subsequent creation. The visual novelty of the beer bottle design—the design's dissimilarity to the closest preexisting product design—was 0.09, as a nearly identical product design preexisted. By contrast, participant *CreativeTools* created a 3D printable bottle and screw cap in March, 2013 (Figure 2, right). The design was manufactured 70 times and was reused 33 times in subsequent creations within the community. The visual novelty of the 3D printable bottle and screw cap was 0.23.

The top of Figure 2 depicts the parts of the design landscape where these two designs were introduced. The design landscape visualization is the result of multidimensional scaling from the original dissimilarity matrix. Each part of the design landscape is shown at the same scale. The two focal designs are depicted as red triangles in the middle of each figure. Even though the part of the design landscape that the second



Beer Bottle		3D Printable Bottle and Screw Cap	
Visual Novelty	0.09	Visual Novelty	0.23
Reuse	0	Reuse	33
Makes	1	Makes	70

Figure 2. Illustrative Difference in Visual Novelty for Two Designs in the Same Category

bottle was introduced into was much more populated than the corresponding part of the design landscape for the first bottle, the second bottle was more novel. The bottom of Figure 2 provides a summary of the visual novelty and prosumption measures. This dissimilarity measure provides a way of not only comparing individual designs in local context, but also a way of characterizing the entire design landscape by considering properties of the matrix, described next.

Independent Variables of Visual and Verbal Design Landscape Structure

Using the dissimilarity matrices described earlier, we measured structure as the additive inverse of the entropy among designs in the visual and verbal dissimilarity matrices. As entropy is a measure of lack of order, structure is operationalized as the additive inverse of entropy (Figure 3) by applying Blau's entropy index (Blau, 1977; Daniel et al., 2013). Figure 3 shows a graphic depiction of the structure for high and low degrees of structure.

Variables for P2-P4: Effect of Visual and Verbal Novelty on Artifact Prosumption

Dependent Variable: Prosumption

Two types of design prosumption were measured: *makes* and *reuse*. Reuse was measured by determining the number of times a design was referenced as the basis for another design introduced in the community. Community participants who build upon a design acknowledge it by citing the original design. Makes was measured as the number of times that participants indicated that they had manufactured a design on a 3D printer. When community participants download a Thingiverse design to manufacture it, typically on a home 3D printer, they post a picture of the manufactured end product and link it to the original design to show the end quality of the produced artifact and for attribution to the creator. In our analysis, self-use instances were not counted; for the same reasons self-citations are often excluded from measures of scholarly impact (Hyland, 2003). These indicators were binarized to indicate the presence or absence of makes or

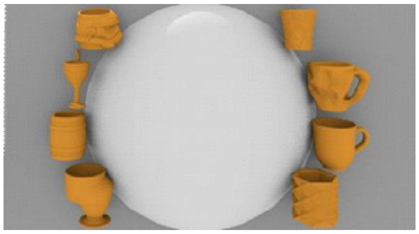
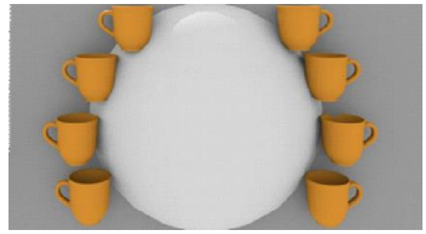
Structure Level	
Low	**High**
	

Figure 3. Examples of Structure

reuse. In addition to the logit binomial models reported on these two measures, we also used and report the results of Poisson regressions on the original counts (Appendix A).

A potential limitation of the makes and reuse measures is that, similar to academic and patent citations, both rely on participants' willingness to cite artifacts they took inspiration from or manufactured. The authors observed while analyzing Thingiverse that the participants, similar to many online and open source communities, consistently provide credit to others when using preexisting artifacts. This observation was supported by a *post hoc* test using the visual dissimilarity algorithm that showed that less than 1% of all designs posted were identical to preexisting designs without citing them, and a qualitative examination of those designs showed that most of those designs where simple designs such as cubes and spheres. Nevertheless, despite Thingiverse community norms, it is possible that the number of participants that decide to manufacture a design and then post a picture of the newly manufactured design to show the quality of the end result and acknowledge its use underestimates the actual use of the design. In order to alleviate this concern, we additionally examined alternative measures of use that require less effort from the participants including the number of *likes* of each design and the number of *downloads* of each design. Downloads as a measure alleviates underestimation concerns, as they are tracked automatically, but the level of commitment is less. We also considered combinations of all four variables. In all cases, our results were robust to alternative hypotheses (Appendix A).

Independent Variables of Visual and Verbal Novelty

The visual and verbal novelty of artifacts calculated previously as dependent variables for Proposition 1 were used as the independent variables in this analysis.

Control Variables for Tests of All Propositions

In line with other studies, we measured several control variables. The first control was the participant's *community experience*, calculated by counting the number of prior creations made by the individual (Claussen & Halbinger, 2019; Crowston et al., 2012; Hann et al., 2013; Ransbotham & Kane, 2011; Ren et al., 2015). We included tenure to control for the possibility that designs by long-standing participants would be more likely to be prosumed than designs from participants with shorter tenure (Arguello et al., 2006; Faraj et al., 2015). *Tenure* was operationalized as the number of days between the first design of the participant and the day that the participant's design being analyzed was created. Our third control variable, the number of *preexisting designs* controlled for the possibility that designs that were introduced earlier in the history of the community would be considered more novel. In addition, we accounted for *effort* and the time-on-task participants devoted to creating their creations by measuring the number of tags and pictures associated with each design (Dimoka et al., 2012; Kauffman & Wood, 2006; Ye et al., 2012; Yi et al., 2017). In order to capture potential effects of community *demand* (Eisenman, 2013), we divided the number of likes within the category of the product with the number of preexisting designs within the category, after controlling for the overall number of designs in Thingiverse. All control and independent variables were log-transformed due to skewed distributions and were normalized by scaling between zero and one.

Results

Descriptive statistics of all the variables are presented for all four propositions (for Proposition 1, in Appendices B and C), and for Propositions 2–4, in Appendix D). It is important to

Table 1. Propositions and Tests Performed

	Proposition	Test	Robustness Tests
P1A	Participants will offer less verbally novel artifacts in highly structured design landscapes.	Ordinary least squares (OLS) regressions using visual and verbal novelty as dependent variables	• Introduced category fixed effects • Alternative measure of verbal novelty based on ConceptNet
P1B	Participants will offer more visually novel artifacts in highly structured design landscapes.		
P2A	The greater an artifact's visual novelty, the more likely that the artifact will be prosumed.	Logit binomial regressions using makes and reuse as dependent variables	• Poisson models of makes and reuse • Examined downloads and likes as alternative variables • Constructed variables from a series of combinations of these variables
P2B	The greater an artifact's verbal novelty, the more likely that the artifact will be prosumed.		
P3	Verbal novelty will have a stronger effect on artifact prosumption than visual novelty.	Coefficient of verbal novelty compared to coefficient of visual novelty	• Average marginal effects (AME) of visual and verbal novelty on makes and reuse • Additional AME analysis using downloads and likes as dependent variables
P4	Visual and verbal novelty will have a negative interacting effect on artifact prosumption.	Logit binomial regressions using makes and reuse as dependent variables	• Poisson models of makes and reuse • Examined downloads and likes as alternative variables • Constructed variables from a series of combinations of these variables • Two lines test of U-shaped relationships

note that, as conceptualized, visual novelty and verbal novelty have a relatively low correlation (Pearson's $R = 0.16$, $p < 0.001$). In order to test for potential issues of multicollinearity in our analyses, we computed variance inflation factors (VIFs), which quantify the severity of multicollinearity in regression analyses. All VIFs were well below the 2.5 threshold (Allison, 2012), and are reported on the descriptive statistics tables. Variables were added in a step-wise fashion to the models. In Table 1, we show which tests were conducted for which propositions.

Test of P1: Effect of Visual and Verbal Structure of the Landscape on Visual and Verbal Novelty

In order to test our propositions related to the role of the design landscape structure on the creation of verbally and visually novel designs (Proposition 1), we performed a series of ordinary least squares (OLS) regressions (Table 2). We report exact p-values in parentheses (Mertens & Recker, 2020), and standard error terms in braces in all results tables. Models 1 and 3 show the effects of the control variables used. The number of *preexisting designs* had a negative effect on both visual and verbal novelty, whereas *tenure* had a positive effect only on the creation of verbally novel designs. Also, both novelties had a positive effect on each other.

Models 2 and 4 included *visual and verbal structure* and were used to test Proposition 1. Visual structure had a positive effect on visual novelty. In sharp contrast, verbal structure had a negative effect on verbal novelty. We also introduced category fixed effects which did not meaningfully alter our results. Another concern was that the text associated with each design in Thingiverse would contain noise; ideally, we want the measure of dissimilarity to reflect the function of the design. To ensure that our results were robust to different ways of measuring dissimilarity between descriptions, we used the corpus of ConceptNet, a knowledge graph that describes general human knowledge and how it is expressed in natural language (Speer & Havasi, 2012). We extracted the semantic meaning of the terms associated with each of the designs in Thingiverse by using ConceptNet. For example, instead of using the term *screwdriver*, we used terms such as *screwing screws*, *pry*, and *open a can of paint*. Next, we reran our topic modeling measures, creating a third matrix containing 638 million semantic dissimilarity measures, computing a new measure of verbal novelty based on the corpus of ConceptNet. Our results were once again not significantly altered when using this alternative measure of verbal novelty.

Table 2. Multiple Regressions for Verbal and Visual Novelty

	Verbal Novelty	Model 1	Model 2		Visual Novelty	Model 3	Model 4
	Constant	0.44*** (< 2e-16) {0.002697}	0.42*** (<2e-26) {0.002934}		Constant	0.25*** (< 2e-16) {0.002800}	0.44*** (< 2e-16) {0.005990}
Control	Community Experience	-0.11*** (< 2e-16) {0.011020}	-0.11*** (< 2e-16) {0.010972}	Control	Community Experience	0.01 (0.1655) {0.009573}	0.01 (0.1032) {0.009398}
Control	Designer Tenure	0.07*** (< 2e-16) {0.002660}	0.07*** (< 2e-16) {0.002658}	Control	Designer Tenure	0.00 (0.6279) {0.002331}	0.00 (0.4173) {0.002288}
Control	Designer Effort	1.56*** (< 2e-16) {0.023970}	1.55*** (< 2e-16) {0.023876}	Control	Designer Effort	0.41*** (< 2e-16) {0.021886}	0.41*** (< 2e-16) {0.021484}
Control	Preexisting Designs	-0.08*** (< 2e-16) {0.002938}	-0.09*** (< 2e-16) {0.002983}	Control	Preexisting Designs	-0.14*** (< 2e-16) {0.002468}	-0.13*** (< 2e-16) {0.002443}
Control	Demand	0.09*** (< 2e-16) {0.015550}	0.10*** (< 2e-16) {0.015488}	Control	Demand	0.03* (0.0194) {0.013497}	0.03† (0.0547) {0.013250}
Control	Visual Novelty	0.07*** (< 2e-16) {0.006087}	0.08*** (< 2e-16) {0.006109}	Control	Visual Novelty	0.05*** (< 2e-16) {0.004582}	0.05*** (< 2e-16) {0.004498}
P1A	Verbal Structure		-0.04*** (< 2e-16) {0.002073}	P2B	Verbal Structure		0.23*** (< 2e-16) {0.006202}
	DF	35,720	35.719		DF	35,720	35,719
	F-Stat	1,342.00	1,207.00		F-Stat	820.40	922.60
	Adjusted R^2	**0.18**	**0.19**		**Adjusted R^2**	**0.12**	**0.15**

N = 35,727; ***p < 0.001; **p < 0.01; *p < 0.05; †p < 0.10

Test of P2 and P3: Effect and Strength of Visual and Verbal Novelty on Artifact Prosumption

We performed a series of logit binomial and ordinary least squares (OLS) regressions to test Propositions 2–4. Logit binomial regression models are essentially binary choice models and were used in the models where prosumption was the dependent variable. The results of the series of logit binomial regression models are shown in Table 3. We started by inserting the control variables, which are shown in Models 5 and 10. All control variables were significant in expected ways.

P2 posited that visual and verbal novelty had distinct effects on the artifact's prosumption. To test Propositions 2–3, we used Models 6–8 and 11–13, which included visual and verbal novelty. Both visual and verbal novelty had a positive effect on prosumption (P2), while verbal novelty had a higher effect on prosumption than visual novelty (P3). Beyond the coefficients of visual and verbal novelty reported in Table 3, the average marginal effects (AME) of visual and verbal novelty were positive, and the difference between them significant (p-values < 0.001). As an additional robustness test for P3, we calculated the average marginal effect (AME) of visual and verbal novelty on a series of count variables, namely the number of times a design was reused, the number of times it was made, the number of times it was downloaded, and the number of times it was liked. Verbal novelty also had a significantly higher marginal effect in all types of artifact prosumption than visual novelty when using these alternative dependent variables (Figure 4, all p-values < 0.001).

We explored the distinction between reuse and makes by using a series of seemingly unrelated regressions (SUR), which allowed us to meaningfully compare the coefficients between reuse and makes models (Zellner, 1962). We estimated the SUR model and then used simultaneous tests for

Table 3. Logistic Models for Prosumption

		Makes				
		Control	**Main Effects**			**Interaction**
		Model 5	**Model 6**	**Model 7**	**Model 8**	**Model 9**
	Constant	0.897*** (5.853-15) {0.11493}	0.239† (0.0668) {0.22307}	0.742*** (6.63e-09) {0.12797}	0.119 (0.3965) {0.14069}	-0.02 (0.63829) {0.15355}
Control	Community Experience	1.681*** (< 2e-16) {0.15404}	1.776*** (< 2e-16) {0.15466}	1.680*** (< 2e-16) {0.15409}	1.775*** (< 2e-16) {0.15470}	1.785*** (< 2e-16) {0.15491}
Control	Designer Tenure	0.511*** (< 2e-16) {0.04259}	0.447*** (< 2e-16) {0.04301}	0.501*** (< 2e-16) {0.04259}	0.447*** (< 2e-16) {0.04301}	0.445*** (< 2e-16) {0.04301}
Control	Designer Effort	11.120*** (< 2e-16) {0.37729}	9.599*** (< 2e-16) {0.39871}	10.967*** (< 2e-16) {0.38084}	9.492*** (< 2e-16) {0.40119}	9.541*** (< 2e-16) {0.40161}
Control	Preexisting Designs	-3.009*** (< 2e-16) {0.12495}	-1.712*** (< 2e-16) {0.12767}	-2.896*** (< 2e-16) {0.13144}	-2.634*** (< 2e-16) {0.13365}	-2.657*** (< 2e-16) {0.13373}
Control	Demand	1.160*** (1.99e-07) {0.22307}	1.091*** (9.08e07) {0.22218}	1.153*** (2.25e-07) {0.22264}	1.086*** (9.82e-07) {0.22184}	1.087*** (9.58e-07) {0.22182}
P2	Verbal Novelty		0.946** (< 2e-16) {0.08774}		0.936*** (< 2e-16) {0.08782}	1.351*** (< 2e-16) {0.15866}
P2	Visual Novelty			0.269** (0.00551) {0.09676}	0.218* (0.0247) {0.09701}	1.169*** (0.00022) {0.31627}
P4	Verbal * Visual Novelty					-1.817** (0.00157) {0.57487}
	DF	35,721	35,720	35,720	35,719	35,718
	AIC	38,171.00	38,055.00	38,165.00	38,052.00	38,044.00
	Wald ÷2	**2,286.32**	**2,404.50**	**2,294.03**	**2,408.55**	**2,419.58**

N = 35,727; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; †$p < 0.10$

		Reuse				
		Control	**Main Effects**			**Interaction**
		Model 10	**Model 11**	**Model 12**	**Model 13**	**Model 14**
	Constant	-0.146 (0.310) {0.14403}	-0.981*** (9.82e-09) {0.17115}	-0.351* (90.0334) {0.16591}	-1.133*** (1.31e-09) {0.18680}	-1.386*** (5.93e-11) {0.21176}
Control	Community Experience	-0.366 (0.189) {0.27890}	-0.245 (0.378) {0.27805}	-0.370 (0.1855) {0.27923}	-0.250 (0.370) {0.27834}	-0.242 (0.38472) {0.27858}
	Designer Tenure	0.490*** (3.01e-15) {0.06207}	0.409*** (7.07e-11) {0.06266}	0.488*** (4.05e-15) {0.06208}	0.408*** (7.75e-11) {0.06267}	0.406*** (9.10e-11) {0.06267}
	Designer Effort	9.901*** (< 2e-16) {0.44774}	8.331*** (< 2e-16) {0.47529}	9.32*** (< 2e-16) {0.45212}	8.217*** (< 2e-16) {0.47824}	8.250*** (< 2e-16) {0.47845}
	Preexisting Designs	-3.012** (< 2e-16) {0.15821}	-2.659*** (< 2e-16) {0.16314}	-2.865*** (< 2e-16) {0.16851}	-2.546 (< 2e-16) {0.17227}	-2.570*** (< 2e-16) {0.17227}
	Demand	1.043*** (1.22e-05) {0.23840}	0.980*** (4.00e-05) {0.23862}	1.043*** (1.22e-05) {0.23844}	0.981*** (3.94e-05) {0.23864}	0.978*** (4.09e-05) {0.23844}
P2	Verbal Novelty		1.180*** (< 2e-16) {0.12816}		1.165*** (< 2e-16) {0.12830}	1.678*** (1.37e-12) {0.23681}
	Visual Novelty			0.353* (0.0105) {0.13806}	0.281* (0.042) {0.13838}	1.458** (0.00208) {0.47356}
P4	Verbal * Visual Novelty					-2.154** (0.00929) {0.82801}
	DF	35.721	35,720	35,720	35,719	35,718
	AIC	22,094.00	22,009.00	22,089.00	22,007.00	22,002.00
	Wald ÷2	**1,068.57**	**1,155.47**	**1,075.14**	**1,159.61**	**1,166.42**

N = 35,727; ***p < 0.001; **p < 0.01; *p < 0.05; †p < 0.10

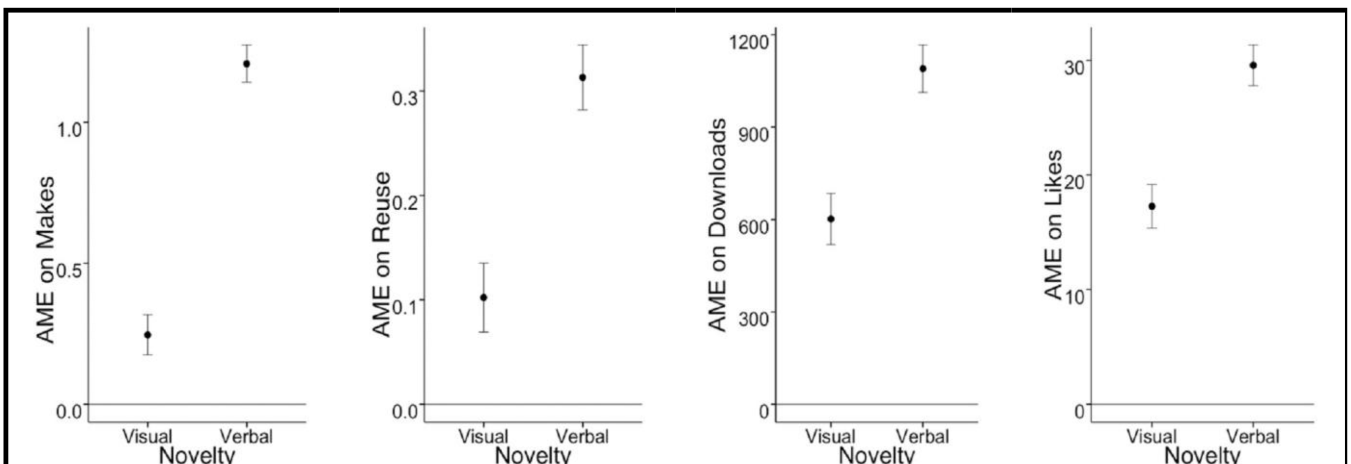


Figure 4. Average Marginal Effects to Test Proposition 2

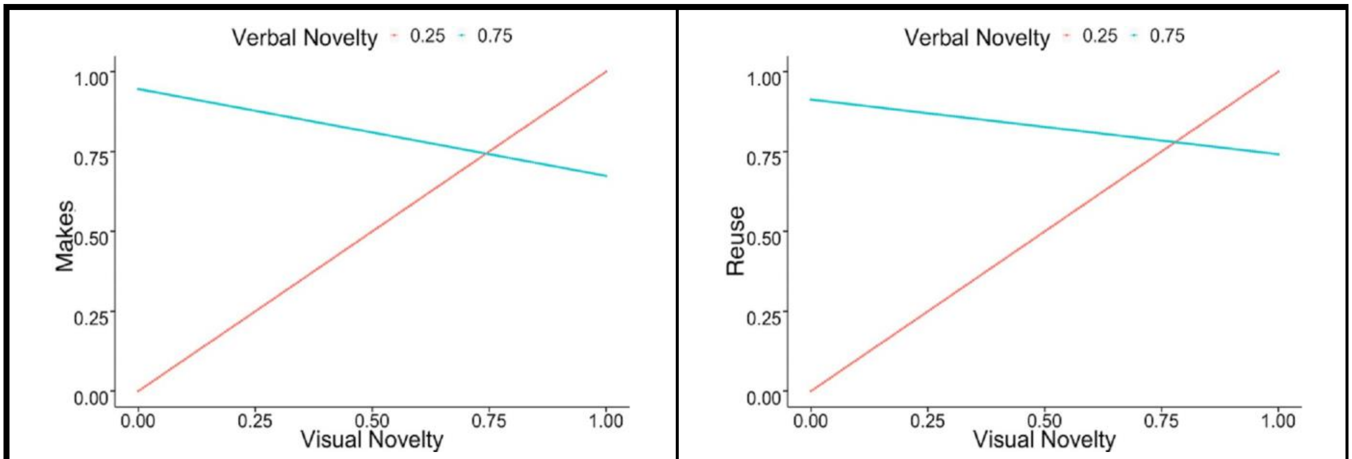


Figure 5. Interaction Between Visual and Verbal Novelty

general linear hypotheses to contrast the obtained coefficients (Hothorn et al., 2008). All control variables, besides the number of preexisting designs, have a stronger effect on makes than on reuse (Appendix E). In addition, verbal novelty had a higher effect on makes than on reuse.

Test of P4: Interaction Effect of Visual and Verbal Novelty on Prosumption

To test Proposition 4, we introduced the interaction between *visual and verbal novelty* in Models 9 and 14 (Table 3). Our results suggest that designs with high degrees of both *visual and verbal novelty* were prosumed less than designs that don't exhibit high degrees of both types of novelty. Figure 5 demonstrates how high visual novelty will foster prosumption when an object has low verbal novelty, but attenuate the prosumption of designs with high verbal novelty. In an effort to understand better how the interplay between visual and verbal novelty affects prosumption, we performed a tipping point analysis (Laursen, 2011). This analysis revealed that the point where the interaction between visual and verbal novelty started having diminishing returns to makes was slightly below average ($tipping\_point_{makes} = 0.48$), whereas the tipping point related to reuse was slightly above average ($tipping\_point_{reuse} = 0.52$).

In order to examine alternative explanations to our results regarding the effects of visual and verbal novelty on prosumption, we explored the option of introducing quadratic terms in our models. However, the alternative explanations of (1) a curvilinear effect of visual novelty on prosumption and (2) a curvilinear effect of verbal novelty on prosumption were not supported, as they did not pass the two lines test of u-shaped relations. Thus, these tests did not support a Goldilocks interpretation (i.e., that too little novelty and too much novelty are worse than some just-right amount of novelty). Instead, the more novelty along a particular attribute the better, caveated by the interaction we found between the two different types of novelty. Figure 5 shows the effects of the interaction between visual and verbal novelty on prosumption.

Discussion

Summary of Findings

Our findings derive from a relational perspective on OICs, based on the relations between designs. The set of relations forms a collectively searchable design landscape. Searches involve not simply looking for individual artifacts, but also gaining a broader understanding of the relations among the design artifacts within the landscape. We examined the effect of the structure of the design landscape on the production of novel designs, and then examined the effects of novel designs on four indicators of prosumption: makes, reuses, downloads, and likes. We focused on two of these—makes and reuses—because the processes that produce both of these demand substantial commitments of time from participants. Results for downloads and likes are shown in Appendix A; they are consistent with findings for makes and reuse. Because artifacts are displayed in two modes—verbally and visually—and each mode is associated with different search costs, we distinguished relations among artifacts into those based on visual information and those based on verbal information.

We examined the prosumption of over 35,000 Thingiverse designs. We find that the structure of the design landscape affects whether a new design will be novel, but in different ways for verbal and visual information. Since verbal information is more hierarchically organized in OICs, we theorized that the lack of structure allows participants to be more creative. In stark contrast, as visual information is inherently less organized, we theorized and found empirical evidence that any visual structure will help to identify gaps.

We also find that the novelty of a design artifact affects all indicators of prosumption in a similar way. In addition, despite past research claiming the predominance of visual representations in design (Gonçalves et al., 2012), we find that novelty in terms of verbal information has a stronger effect on prosumption than novelty in terms of visual information. Moreover, we find that when artifacts have high novelty with respect to both verbal and visual information, the likelihood of prosumption is decreased. Next, we suggest a framework based on our findings, and then we discuss the theoretical and managerial implications of this study.

An Integrative Framework Based on a Relational Perspective

We offer a framework integrating the two streams of research in OICs: the effects of attributes of individual artifacts on prosumption (Flath et al., 2017; Stanko, 2016), and the effects of participants' individual characteristics on contributions (Claussen & Halbinger, 2019; Kyriakou et al., 2017). Our framework is graphically summarized in Figure 6.

By focusing on a relational perspective, both streams can be integrated, and the value of each for both streams can be extended. Our integrative framework in Figure 6 also underscores the distinct effects of verbal and visual information in general, and verbal (see the arrow marked A in Figure 6) and visual novelty (arrow B) in particular. We encourage future researchers to reconsider describing digital artifacts simply as "novel" since we found such distinctive differences between the prosumption of artifacts that are highly novel visually, highly novel verbally, and highly novel both visually and verbally. Our framework in Figure 6 also emphasizes the differential effect of design landscape structure when that structure is defined by verbal (arrow C) or visual information (arrow D). Thus, we encourage future researchers to consider the relations within and between the artifacts, the design landscape as a whole, and the designers (arrow E) when explaining prosumption in OICs. Figure 6 underscores how contribution and consumption are often so interrelated in OICs that research examining one or the other may not be fully describing how either occurs.

To be more precise, this interrelationship involves three aspects of the search process. First, as participants search the landscape to find novel designs to *consume*, they develop an understanding of the landscape's structure useful for identifying existing gaps where novel designs can be contributed. Second, *contribution* often relies on first searching for preexisting designs to reuse (a consumption process) and then modifying the design (a production process). Third, the structure of the *design landscape* is collectively shaped as more designs are contributed, affecting future searches.

Our framework also extends existing research focused on designed artifacts (Claussen & Halbinger, 2019; Kuk & Kirilova, 2013; Kyriakou et al., 2017; Stanko, 2016). The notion that individual artifacts affect participants' behavior can alternatively be framed in terms of search: the search for innovation is a relational process involving people and artifacts in which the landscape plays a crucial role. Participants' experiences affect the creation of novel design via the search process. That is, certain participants may contribute in the design landscape in a particular way—they create within specific product categories—which may help other participants to gain a better understanding of the creator's particular niche, which can in turn help participants perform more efficient searches to identify and create novel designs. We suggest that by combining the study of relations within and between *artifacts, individuals,* and *design landscapes,* as shown in Figure 6, a richer understanding of innovation in OICs can be pursued.

A key assumption of the past research that frames creative processes as search in a design landscape is that the designs are already there and are *simply* to be located in the landscape (Visser, 2006). Desired designs are, however, often not readily available: novel designs have to be constructed (Gero, 1998; Logan & Smithers, 1993; Navinchandra, 2012). Through our integrative framework, participants search the design landscape, trying to identify a satisficing design among those readily available, and to identify gaps in the design landscape "to represent differences between the desired and the present" (Visser, 2006, p. 7). Our integrative framework may then help to explain when consumers become contributors: as they search the design landscape for a particular artifact and discover a gap, they may be motivated to contribute. Thus, the actions of participants may not be just the result of an internal drive for challenge (Ye et al., 2016), nor just a result of seeking acclaim in the community, but instead may be driven by an iterative process of design landscape search, gap discovery, and contribution.

Implications for Research on OICs

While the attractiveness of a design depends on its relations with other designs, past literature has primarily looked at how

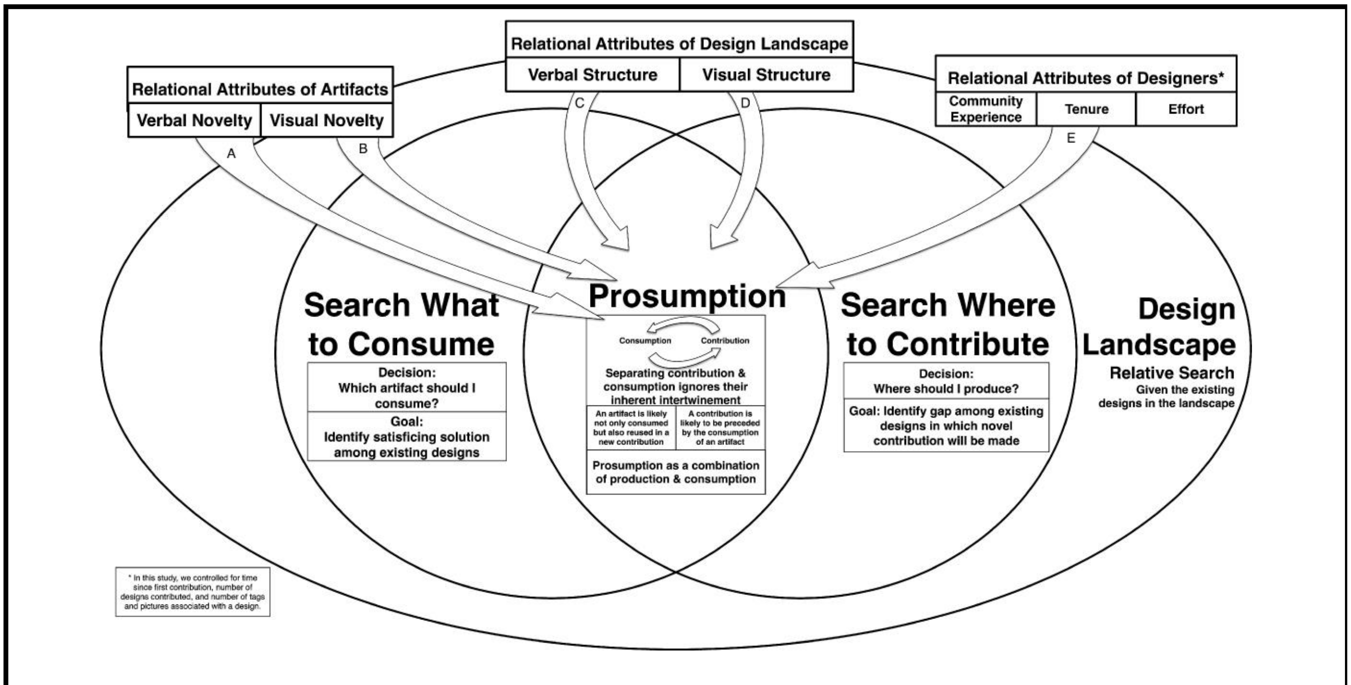


Figure 6. A Relational Perspective on Prosumption in Online Innovation Communities

each participant's individual characteristics support their search processes, rather than where they should search in the landscape (Erat & Krishnan, 2012). Using the metaphor of "digging for golden carrots" (Taylor, 1995, p. 872), Erat and Krishnan argue that "past studies have primarily looked at how hard each agent digs for the golden carrot, rather than where they dig! (2012, p. 610). In addition, to the best of our knowledge, literature related to search on design landscapes (Kauffman, 1993; Levinthal, 1997; March, 1991) has not been applied to OICs. In the next section, we describe two specific contributions we have made to the study of innovation in OICs.

The Relational Perspective

Our first contribution is to view OICs from a relational perspective. Our perspective is *relational* in that it focuses on relations between, rather than values of, attributes. In this study, the focus has been on the relations between attributes of artifacts, specifically dissimilarities in shapes and semantics. These relations form design landscapes that invite search: artifacts are compared to other artifacts. The actions participants take are influenced by the relations between the preexisting designs in the landscape. In particular, participants in online innovation communities are drawn to novelty, which is discovered through searching the landscape. Novelty is dependent on the continuously changing structure of the landscape. This changing structure is the eventual result of participants' contributions: new artifacts that are novel in relation to other artifacts and thereby gradually shape the landscape.

Generally, this study is one illustration of how a relational perspective can be used to study OICs. In this study, the perspective is applied in several ways. Relations between artifacts form the landscape on which participants search. The novelty that participants seek is based on this landscape: a new design artifact's novelty is assessed in relation to the collection of preexisting design artifacts within the design landscape. Something that will be considered novel if contributed now might not be considered novel if contributed in the future, because in the meantime other similar artifacts might have been added. As community participants continue adding new artifacts in an eternally evolving design landscape, designs that are novel may be imitated by others, creating the need to examine novelty temporally by measuring novelty based on the relation of one artifact to the collection of preceding artifacts.

Additionally, our relational perspective has implications for identifying new characteristics of individuals which may influence their activities. For example, building on the distinctions made by McKinney and Yoos (2010), some participants may focus on ferreting out the structure of the design landscape—the patterns in the relations between artifacts—while other participants may focus on attributes of individual artifacts. Identifying the relationally oriented individuals in a community may be particularly important since such individuals may be swayed less by how well individual artifacts are presented and more by the overall structure of the landscape. This is conceptually similar to a phenomenon discovered in Wikipedia (Kane et al., 2014): editors who shaped articles were interested in the patterns in the article, whereas editors who corrected articles were primarily interested in expressing an individual thought and leaving. This suggests the possibility that this tendency to seek out relations versus individual artifactual attributes may be an under-explored characteristic of online community participants.

Examining the Multifaceted Nature of the Design Landscape

Our second contribution is that, through our relational perspective, we have shown that different artifact attributes have affect participants' activities in distinct ways. Past research has argued that any representational theory should accommodate the dual functionality of artifact attributes (Paivio, 1990). We have distinguished between the visual and verbal information about artifacts, showing that these independent attributes have distinct yet interacting effects on prosumption. Table 4 shows the different results when each of the four cells are treated as different independent variables.

For some researchers in marketing and creativity, novelty is often seen as trading off with practicality (Amabile, 1996; Tian et al., 2001; Toyama & Yamada, 2012). Moreover, research specifically on idea generation suggests that the ideas that are least similar to others are not generally the most practical ones (Kornish & Ulrich, 2011). Our study provides additional insights to such past findings by providing evidence that, while novelty in OICs leads to practical solutions (evident from its effect on downloads and makes of designs), the interaction of visual and verbal novelty may indeed impede practicality. An artifact that is novel with respect to more than one artifact attribute may introduce a high search cost for participants, impeding their efforts to understand and evaluate a product (Akhlaghpour et al., 2013; Allen & Parsons, 2010; Oswick & Robertson, 2009). In sum, our work underscores the importance of moving to a perspective in which artifacts are characterized by more than one of their attributes and relation between these attributes is examined in explaining participant behavior.

In contrast to past findings suggesting equal weights across visual and verbal information (Paivio, 1990), we find that verbal information has a greater effect than visual information on decisions about which artifacts get prosumed in OICs. The stronger effect of verbal novelty deserves further exploration. There may be an implicit bias in the search process because of the current inability of most search processes to allow for searching through visual content. That is, most searching, even of visual content, still largely relies on textual descriptions. However, as immersive visual multimedia content continues to gain attention (e.g., virtual reality, augmented reality, mixed reality) and is shared in OICs, it may soon become pivotal for communities to permit visual search of their artifacts. The insights of this study about how both artifact attributes and the landscape affect prosumption can serve as initial guidelines for the development of search tools that consider multiple artifact attributes.

Examining the multifaceted nature of the design landscape required us to develop measures of visual novelty; quantifying novelty was a difficult problem to solve, especially for visual attributes, and itself a field of study (Wachs et al., 2018). We introduced a combination of computer graphics and natural language processing methods as an important methodological step in operationalizing novelty beyond perceptual measures to objective relational measures. More broadly, this introduces to the study of OICs empirical design landscapes—landscapes constructed from empirical data about artifacts—as an alternative to simulated landscapes constructed from random distributions (e.g., Brunswicker et al., 2018; Levinthal, 1997).

Implications for Online Knowledge Production Communities

We studied a specialized form of online knowledge production communities, the online innovation community. The increasing attention paid by practitioners to these OICs has led to a growing body of research (Di Gangi et al., 2010; Dong & Wu, 2015; Friesike et al., 2018; Füller et al., 2011; Gebauer et al., 2013; Kyriakou et al., 2017; Li et al., 2016; Riedl & Seidel, 2018; Stanko, 2016; Ye et al., 2016; Zhang et al., 2013). Given this growth, it may be time to assess similar and dissimilar results about prosumption in different types of knowledge production communities.

The effect of relations between artifacts may be applied beyond OICs. One study of Wikipedia focused on the importance of the maturity of an article in attracting readers but not editors (Kane & Ransbotham, 2016), while another focused on the types of trajectories of articles that correlate to quality (Arazy et al., 2020). A relational perspective might study the relationship between these ideas together by conjecturing that

Table 4. Value of Examining Artifact Attributes Separately

Attribute	Visual	Verbal
Structure of Product Category	Increases novelty	Decreases novelty
Novelty of Artifact	Less important than verbal Negatively interacts with verbal	More important than visual Negatively interacts with visual

that the way an artifact evolves will be in relation to surrounding artifacts and that these relations affect the rate of growth, the quality of the artifact, and the collection of artifacts. In open source software, task modularity is a relational construct describing any individual task within a landscape of tasks. The well-documented finding that, in open source software communities, task modularity helps to motivate and focus the community (Howison & Crowston, 2014; Shah et al., 2003; von Krogh et al., 2012; Zhang et al., 2013) may reflect that modular tasks are more easily discoverable and, therefore, more likely to be prosumed. Thus what on the surface would seem to be three very different types of knowledge production communities—wikis, open source software projects, and OICs—can be more easily analyzed for their similarities when viewed from a relational perspective.

Managerial Implications

From a managerial viewpoint, our study provides practical advice on building and managing OICs (Antikainen, 2011; Geilinger et al., 2020). Managers, such as those moderating communities at Threadless or Lego, may want to encourage participants to create artifacts as novel as they want on one attribute (with respect to visual or verbal information), but counsel caution about being highly novel on both attributes. Additionally, as communities begin to include other kinds of sensory representations, including the auditory and the haptic, these representations may not be complementary with respect to novelty: they may come to interfere with one another.

By describing how patterns of existing knowledge affect the acquisition of future knowledge, tools for searching and retrieving information from these systems should be developed to help participants identify these patterns, or present previously unobserved patterns (Poppe et al., 2017; Ren et al., 2006; Ren et al., 2015). It is possible that such tools might affect the structure of the design landscape. For example, it may be that, over time, tools (such as the metamodels described in Kyriakou et al., 2017) may evolve to parameterize more of the design landscape, thus affecting its structure.

Limitations

Our measure of verbal novelty is based on the textual descriptions provided by the creators when uploading their designs. As each product description is composed of a series of topics, we measured the differences between designs according to their differences in topic composition. This allowed us to create a continuous variable measuring verbal novelty, under which designs that had a dissimilar topic composition to any preexisting design were considered as verbally novel. Our measure of verbal novelty overcomes many of the limitations of dissimilarity measures used in past literature, such as the difficulty of training raters (Dean et al., 2006), the assumption that raters have a common base of experience (Boden, 2004; von Hippel, 1986), and the inconsistency of raters (Dean et al., 2006; Garcia & Calantone, 2002). While our verbal novelty measure is drawn from widely accepted natural language processing (NLP) methods to measure differences between text corpora (Allan et al., 1999; Kaplan & Vakili, 2014; Vosoughi et al., 2018) and is of interest in its own right, it can also be seen as a proxy measure of functional novelty. Future research can further explore the development of direct measures of functional novelty (Kittur et al., 2019). Such measures might be used to discover the extent to which new inventions shift away from the functions of parent artifacts, or add functions to the functions of their parents. Each of these processes might affect prosumption differently.

Our measures of visual and verbal novelty are based on the novelty of an artifact at the time it was created. These measures were used as dependent variables in the first part of the paper, and as the predictors in the latter part of the paper. In line with prior research, the novelty of an artifact is based on the novelty exhibited historically at the time it was created, not at the later time that another participant engaged with the artifact. This is justifiable in creative communities in general and OICs in particular. Participants are conscious of the historical novelty of artifacts, as evidenced by the fact that participants often request the deletion of copycats of previously uploaded designs (Kyriakou et al., 2017). In addition, the time-series data show that participants acknowledge and strongly support historical novelty by liking, collecting, downloading, and reusing original designs, rather than imitative designs. In other types of communities where reuse is minimal, a novelty measure that takes into account the actions of later participants may plausibly be more appropriate, especially if the time of creation is not visible to participants or if participants don't value the historical novelty of artifacts.

Our findings suggest that, even though participants are unlikely to be able to search all designs in Thingiverse, comparative content affects their propensity to create novel designs. These findings are surprising since community participants are unlikely to know 35,000 or more designs in Thingiverse. We argued that this is possible because the structure of the design landscape provides sufficient information about the additional designs not searched so that, when used along with the comparative content, novelty can be heuristically assessed. There may be a range of alternative explanations to consider in future research, such as information gained from high-status participants, offline conversations, or extensive experience with narrow product categories. Thus, our results call for an exploration of additional explanations of how participants are able to assess novelty. Moreover, the correspondence between the objective novelty we measured and the degree of novelty perceived by different participants is not known.

We assume that the creator of a design is affected by the design landscape prior to uploading a design. While we conducted sensitivity analyses to determine if time lags affected our results and found no effect, experiments using search logs and eye movement data could determine what a participant is viewing when looking at the design landscape. Moreover, characteristics of the participants such as demographics, expertise built outside the community, and social capital undoubtedly affect individual design decisions and the emergence of novelty (Boden, 2004; Johnson et al., 2014; Kudaravalli et al., 2017). These characteristics, if integrated theoretically with our model on the role of novelty in the community, might help to provide a more comprehensive picture of how community interest is sustained and how novelty emerges. Future research might also examine how our theory may apply in other types of online communities, as well as shed light on the role that the open source hardware context may play in the phenomena observed in our study.

Conclusion

This study used a relational view to better understand online innovation communities. The negative interaction of visual and verbal novelty on both production and consumption, and the opposing effects of structure on visual and verbal novelty, indicate that participants are influenced by the relations between preexisting artifacts and collectively engaged in complex search processes.

There is much work yet to be done to understand the way a landscape of artifacts evolves as a result of the cumulative decisions of many individuals. Moreover, as online innovation communities and other communities add new artifact attributes—for example, haptic representations that communicate the texture of an artifact—the interference and contradictory effects of these additional attributes should be considered as aspects of the perpetually increasing richness of the landscape. More broadly, this work might serve as the basis for a new subfield of information systems focused on landscapes rather than individual users or artifacts.

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Appendices

Appendix A. Robustness Tests Results for Prosumption Measures

		Makes	Reuse	Downloads	Likes	Makes + Reuse	Makes + Reuse + Downloads	Makes + Reuse + Downloads + Likes
	Dependent Variable	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21
	Family	Poisson	Poisson	Poisson	Poisson	Quasi Poisson	Quasi Poisson	Quasi Poisson
	Constant	0.442*** (4.19e-11) {0.06697}	-1.699*** (< 2e-16) {0.15009}	5.347*** (< 2e-16) {0.0029190}	0.868*** (< 2e-16) {0.017865}	-4.312*** (< 2e-16) {0.19891}	-4.302*** (< 2e-16) {0.15763}	-4.414*** (< 2e-16) {0.11881}
Control	Community Experience	1.014*** (< 2e-16) {0.06929}	-0.355† (0.080432) {0.20287}	0.623*** (< 2e-16) {0.0032112}	0.450*** (< 2e-16) {0.017998}	0.552* (0.01472) {0.22661}	0.576** (0.00121) {0.17796}	0.504*** (6.29e-05) {0.12592}
Control	Designer Tenure	0.585*** (< 2e-16) {0.02085}	0.545*** (< 2e-16) {0.04566}	0.331*** (< 2e-16) {0.0008388}	0.507*** (< 2e-16) {0.004917}	0.562*** (< 2e-16) {0.06127}	0.483*** (< 2e-16) {0.04751}	0.496*** (< 2e-16) {0.03406}
Control	Designer Effort	4.822*** (< 2e-16) {0.06535}	5.173*** (< 2e-16) {0.12771}	6.566*** (< 2e-16) {0.0014476}	5.284*** (< 2e-16) {0.014886}	5.010*** (< 2e-16) {0.18307}	5.734*** (< 2e-16) {0.10935}	5.501*** (< 2e-16) {0.09081}
Control	Preexisting Designs	-2.675*** (< 2e-16) {0.05067}	-2.074*** (< 2e-16) {0.11429}	-1.438*** (< 2e-16) {0.0021921}	-0.167*** (< 2e-16) {0.014411}	-2.430*** (< 2e-16) {0.15090}	-2.115*** (< 2e-16) {0.11928}	-1.036*** (< 2e-16) {0.09335}
Control	Demand	1.370*** (< 2e-16) {0.05145}	1.049*** (< 2e-16) {0.12779}	1.114*** (< 2e-16) {0.0023925}	1.159*** (< 2e-16) {0.015548}	1.250*** (3.54e-15) {0.15879}	1.205*** (< 2e-16) {0.12695}	1.180*** (< 2e-16) {0.09995}
	Verbal Novelty	2.033*** (< 2e-16) {0.07876}	2.122*** (< 2e-16) {0.17531}	2.479*** (< 2e-16) {0.0034159}	2.167*** (< 2e-16) {0.019516}	2.068*** (< 2e-16) {0.23327}	2.173*** (< 2e-16) {0.18461}	2.170*** (< 2e-16) {0.13408}
	Visual Novelty	1.525*** (< 2e-16) {0.16066}	1.248*** (0.000487) {0.35769}	1.890*** (< 2e-16) {0.0068993}	1.462*** (< 2e-16) {0.039618}	1.408** (0.00309) {0.47597}	1.527*** (4.83e-05) {0.37567}	1.501*** (3.65e-08) {0.27249}
	Verbal * Visual Novelty	-2.156*** (2.09e-15) {0.27170}	-1.134† (0.059310) {0.60106}	-1.194*** (< 2e-16) {0.0114419}	-0.465*** (3.71e-12) {0.066872}	-1.732* (0.03098) {0.80281}	-1.498* (0.01740) {0.62998}	-0.917* (0.0457) {0.45870}
	DF	35,718	35,718	35,718	35,718	35,718	35,718	35,718
	AIC	130,202.00	37,628.00	23,263,707.00	867,055.00	3,185.80	4,356.90	8,747.30
	Wald $\div_2$	**13,623.98**	**2,872.52**	**14,788,820.00**	**214,143.30**	**146.88**	**271.70**	**543.97**

N = 35,727; ***p < 0.001; **p < 0.01; *p < 0.05; †p < 0.10

Appendix B. Means and Correlations for Verbal Novelty

	Mean	s.d.	1	2	3	4	5	6	7	VIF
1. Community Experience	0.03	0.08								1.18
2. Designer Tenure	0.43	0.33	0.39*** (0.0000)							1.2
3. Designer Effort	0.04	0.03	0.01* (0.0304)	0.13*** (0.0000)						1.06
4. Preexisting Designs	0.50	0.29	0.04*** (0.0000)	-0.01* (0.0387)	-0.15*** (0.0000)					1.19
5. Demand	0.01	0.05	-0.01 (0.2110)	0.03*** (0.0000)	0.06*** (0.0000)	-0.13*** (0.0000)				1.02
6. Visual Novelty	0.22	0.14	0.00 (0.6282)	0.03*** (0.0000)	0.17*** (0.0000)	-0.32*** (0.0000)	0.06*** (0.0000)			1.15
7. Verbal Structure	0.36	0.40	-0.02*** (0.0004)	0.01† (0.0730)	0.02**** (0.0000)	-0.25*** (0.0000)	0.06*** (0.0000)	0.19*** (0.0000)		1.08
8. Verbal Novelty	0.50	0.17	0.00 (0.7763)	0.17*** (0.0000)	0.37*** (0.0000)	-0.22*** (0.0000)	0.08**** (0.0000)	0.16*** (0.0000)	0.02*** (0.0000)	✓

N = 35,727; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; †$p < 0.10$

Appendix C. Means and Correlations for Visual Novelty

	Mean	s.d.	1	2	3	4	5	6	7	VIF
1. Community Experience	0.03	0.08								1.19
2. Designer Tenure	0.43	0.33	0.39*** (0.0000)							1.23
3. Designer Effort	0.04	0.03	0.01* (0.0304)	0.13*** (0.0000)						1.17
4. Preexisting Designs	0.50	0.29	0.04*** (0.0000)	-0.01* (0.0387)	-0.15*** (0.0000)					1.09
5. Demand	0.01	0.05	-0.01 (0.2110)	0.03*** (0.0000)	0.06*** (0.0000)	-0.13*** (0.0000)				1.02
6. Verbal Novelty	0.50	0.17	0.00 (0.7763)	0.17*** (0.0000)	0.37*** (0.0000)	-0.22*** (0.0000)	0.08*** (0.0000)			1.22
7. Visual Structure	0.12	0.11	-0.02** (0.0031)	-0.01† (0.0627)	0.02*** (0.0000)	-0.13*** (0.0000)	0.03*** (0.0000)	0.03*** (0.0000)		1.02
8. Visual Novelty	0.22	0.14	0.00 (0.6282)	0.03*** (0.0000)	0.17*** (0.0000)	-0.32*** (0.0000)	0.06*** (0.0000)	0.16*** (0.0000)	-022*** (0.0000)	✓

N = 35,727; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; †$p < 0.10$

Appendix D. Means and Correlations for Prosumption

	Mean	s.d.	1	2	3	4	5	6	7	8	VIF	VIF
1. Community Experience	0.03	0.08									1.20	1.18
2. Designer Tenure	0.43	0.33	0.39** (0.0000)								1.23	1.21
3. Designer Effort	0.04	0.03	0.01* (0.0304)	0.13*** (0.0000)							1.17	1.17
4. Preexisting Designs	0.90	0.10	0.05*** (0.0000)	0.01* (0.0308)	-0.13*** (0.0000)						1.22	1.18
5. Demand	0.01	0.05	-0.01 (0.2110)	0.03*** (0.0000)	0.06*** (0.0000)						1.03	1.02
6. Visual Novelty	0.13	0.08	0.00 (0.7763)	0.03*** (0.0000)	0.17*** (0.0000)	-0.32*** (0.0000)	0.06*** (0.0000)				1.17	1.14
7. Verbal Novelty	0.50	0.17	0.00 (0.6282)	0.17*** (0.0000)	0.37*** (0.0000)	-0.22*** (0.0000)	0.08*** (0.0000)	0.16*** (0.0000)			1.24	1.22
8. Reuse	0.10	0.30	0.01 (0.1569)	0.05*** (0.0000)	0.15*** (0.0000)	-0.12*** (0.0000)	0.06*** (0.0000)	0.07*** (0.0000)	0.12*** (0.0000)		✓	
8. Makes	0.81	3.51	0.03*** (0.0000)	0.06*** (0.0000)	0.14*** (0.0000)	-0.11*** (0.0000)	0.08*** (0.0000)	0.06*** (0.0000)	0.10*** (0.0000)	0.29*** (0.0000)		✓

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

Appendix E. Simultaneous Tests for Prosumption Measures

		Reuse | Makes		
		Estimate	Std. Error	z-value
Control	Community Experience	-0.38*** (< 2e-16)	0.03	-11.57
	Designer Tenure	-0.04*** (9.55e.08)	0.01	-5.34
	Designer Effort	-0.86*** (< 2e-16)	0.08	-11.33
	Preexisting Designs	0.24*** (< 2e-16)	0.03	9.07
	Demand	-0.08† (0.0718)	0.05	-1.80
H1	Verbal Novelty	-0.10*** (0.000175)	0.03	-3.75
	Visual Novelty	-0.08 (0.152)	0.05	-1.43
H3	Verbal * Visual Novelty	0.12 (0.248)	0.10	1.16

N = 35,727; ***p < 0.001; **p < 0.01; *p < 0.05; †p < 0.10