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# Copy, transform, combine: exploring the remix as a form of innovation

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## Abstract
The reuse of existing knowledge is an indispensable part of the creation of novel ideas. In the creative domain knowledge reuse is a common practice known as "remixing". With the emergence of open internet-based platforms in recent years, remixing has found its way from the world of music and art to the design of arbitrary physical goods. However, despite its obvious relevance for the number and quality of innovations on such platforms, little is known about the process of remixing and its contextual factors. This paper considers the example of Thingiverse, a platform for the 3D printing community that allows its users to create, share, and access a broad range of printable digital models. We present an explorative study of remixing activities that took place on the platform over the course of six years by using an extensive set of data on models and users. On the foundation of these empirically observed phenomena, we formulate a set of theoretical propositions and managerial implications regarding (1) the role of remixes in design communities, (2) the different patterns of remixing processes, (3) the platform features that facilitate remixes, and (4) the profile of the remixing platform's users.
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## Introduction
### Background and motivation
The origin of innovations has been a central theme in management research for several decades (Rosenberg, 1982; von Hippel, 1988; Van de Ven *et al.*, 1999; Hargadon, 2003; Simonton, 2004; Usher, 2011). A major objective of this stream of inquiry is to gain a better understanding of the process of innovation and its determinants to improve the generation of novel ideas in real-world organizations in the hope that these may ultimately result in successful products and services. A research topic that has received the interest of both academics and practitioners in this context is the role of existing innovations in the creation of new ones. The traditional understanding of innovation is usually associated with an "Aha! moment" (Berkun, 2010; Birkinshaw *et al.*, 2012) – that is, a spontaneous epiphany, as most famously captured in Isaac Newton's falling apple that led him to understand the concept of gravity. In contrast to this intuitive but also naïve view on innovation, there is a common understanding among scholars that innovations do not emerge in isolation but are at least to some extent recombinations of previously existing building blocks (Schumpeter, 1942; Van de Ven, 1986; Nelson and Winter, 1982; Weitzman, 1998; Arthur, 2009; Salter and Alexy, 2014).

Driven by the advent of open platforms and communities on the internet, it has only been in recent years that the concept of innovation through recombination has gained further attention (Lessig, 2008; Khatib *et al.*, 2011; Tuite and Smith, 2012; Cheliotis *et al.*, 2014; Sapsed and Tschang, 2014; Oehlberg *et al.*, 2015; Dasgupta *et al.*, 2016; Stanko, 2016). Online platforms with openly licensed content and data make it increasingly easy to share and access a wide range of user-generated ideas (Lee *et al.*, 2010; Kane and Ransbotham, 2012; Leonardi, 2014; Payton, 2016). These platforms thus

offer a promising starting point for innovators who apply existing ideas to novel settings, recombine them in new ways, or extract parts to integrate them into their own creations. The theoretical concept describing this process is known in the literature as "knowledge reuse" (Markus, 2001; Majchrzak *et al.*, 2004). Thus far, knowledge reuse has been explored primarily in the context of open-source software (Haefliger *et al.*, 2008; Sojer and Henkel, 2010) and crowdsourcing projects (Bayus, 2013). The corresponding studies provide valuable insights into the importance of reuse in practice and some of its driving and inhibiting factors. However, little is known about the occurrence of the phenomenon itself, that is, the different forms of reuse and the existence of generalizable reuse patterns. Furthermore, although prior work has considered the design of platforms for idea generation (Leimeister *et al.*, 2009), research regarding information systems as enablers of knowledge reuse remains sparse (Couger *et al.*, 1993; Sambamurthy and Subramani, 2005; Mitchell and Subramani, 2010). This lack of scholarly knowledge stands in sharp contrast to the evident potential of IT artifacts to support users' creativity (Markus, 2001; Huysman and Wulf, 2006; Aragon *et al.*, 2009; Müller-Wienbergen *et al.*, 2011).

### Research objective and contribution

The present study investigates knowledge reuse in open online communities. Here, "remixing" – an established term in the music domain – is very often used to describe the phenomenon of repurposing existing materials to create something new. A contemporary example of a remix is the "cronut," a pastry developed as a hybrid of a croissant and a donut. Although such examples of remixes are omnipresent in today's culture and economy, it is difficult to study or even quantify the phenomenon because designers, artists, inventors, and companies are usually reluctant to disclose their sources of inspiration. As a resolution to this issue, we base our work on publicly available data from *Thingiverse*, the largest online community for 3D printable models. In recent years, the availability of low-cost 3D printers has opened manifold possibilities for consumers to become designers and producers of everyday items. On the internet, 3D printing (Berman, 2012; Lipson and Kurman, 2013) has fostered the growth of a vivid community of "makers" (Dougherty, 2012; Anderson, 2013) who share their designs with others. In the case of Thingiverse, users are required to publish their designs ("Things") under an open license that allows others to remix them into new Things. Furthermore, users who remix a Thing are obliged to credit their source. Our dataset comprises information on the online activities of makers over the course of six years and the creation of more than 200,000 different 3D models. As the data originate from actual user activity, they are not prone to response-rate bias (Edelman, 2012) or desirability effects (Ganster *et al.*, 1983). This allows us to not only collect data from a large and diverse range of remixes and users but also gain insights into the creative acts surrounding the platform.

Our study at the intersection of IS and innovation management addresses the following overarching research question: *What are the characteristics and determinants of remix-based innovation in open online communities?* In more detail, the contribution that we make is fourfold. *First*, we shed light on the role that remixing plays in open online communities with regard to the available content, other activities on the platform,

and its appeal to users. *Second*, we analyze the process of remixing in detail to reveal the patterns into which remixing processes can be grouped. A *third* contribution is the identification of platform features that enable specific forms of remixing. *Fourth*, our empirical evidence suggests the existence of different user types, each associated with characteristic remixing preferences. Because of the lack of well-established theory explaining the creative process behind remixing, we strive for theory generation rather than theory confirmation (Gregor, 2006; Müller *et al.*, 2016). Our study accordingly follows a quantitative exploratory approach in which we use a large dataset (Hey *et al.*, 2009), which leads to a set of propositions to guide future research on an under-researched topic that bears tremendous importance for our understanding of creativity in the digital age.

The remainder of the paper is organized as follows. The next section presents the theoretical foundations by reviewing the existing body of literature on knowledge reuse and remixing. After introducing our research methodology, we continue with the quantitative analyses. We then conclude with a discussion of our main findings, the theoretical and managerial implications of our study, its limitations, and an outlook on opportunities for further research.

## Literature review

Recombining existing ideas into something new has long been a research topic in the management discipline (Rosenberg, 1982; Weitzman, 1998; Hargadon, 2003; Usher, 2011; Allen and Henn, 2007; Dodgson *et al.*, 2013). Recently, researchers' interest in the phenomenon of recombinations has increased with the advent of online platforms for knowledge sharing. The corresponding studies typically use the concepts of *reuse, recombination* and *remixing* interchangeably. In the following subsections, we provide an overview of the literature along the following four major research strands (see Table 1): (1) *relevance*, the role of recombinations for innovation; (2) *process*, the mechanisms of recombinations; (3) *platform*, the role of IT for recombinations; and (4) *people*, individual and environmental factors of recombinations.

### Relevance: the role of recombinations in innovation

The "centrality of remix[ing]" (Benkler, 2009, p. 337) as a fundamental building block of anything new is often highlighted in the literature (Olsson and Frey, 2002; Nerkar, 2003; Navarra, 2005; Arthur, 2009; Cunningham, 2009; Brynjolfsson and McAfee, 2014; Thorén *et al.*, 2014; Strumsky and Lobo, 2015). The concept can be traced back to Schumpeter (1942), who argued that any innovation is essentially a combination of existing factors. Identifying how such new combinations lead to a novel insight has since been viewed as "the 'holy grail' of innovation research" (Gruber *et al.*, 2013, p. 837). Furthermore, the integration and recombination of knowledge have been described as core tasks and fundamental assets of any organization (Ciborra, 1996; Sambamurthy and Subramani, 2005; Romer, 2008). Intra-firm knowledge, its flow and its reuse are considered key factors in the formation of competitive advantages (Galunic and Rodan, 1998; Watson and Hewett, 2006; Carnabuci and Operti, 2013). The underlying assumption – that innovations come to life by merging formerly separate ideas (Leenders and Dolfsma, 2016) – has

**Table 1** Related work on recombining for innovation

| Research stream | Main research topics | Typical research settings | References | Dominant disciplines |
|---|---|---|---|---|
| Relevance | • Theorizing, defining, and modeling innovation<br>• Recombining within organizations<br>• Constraints to the combination of ideas | • Economies<br>• Organizations<br>• Firms | Schumpeter (1942), Nelson and Winter (1982), Galunic and Rodan (1998), Weitzman (1998), Ciborra (1996), Olsson and Frey (2002), Carnabuci and Operti (2013), Navarra (2005), Watson and Hewett (2006), Arthur (2009) | • Economics<br>• General management |
| Process | • Understanding the process of knowledge reuse<br>• Analyzing and evaluating the process<br>• Investigation of recombination output | • (Open source) software development<br>• Patents<br>• Scientific citation analysis<br>• Innovation case studies | Rothenberger et al. (1998), Fleming (2001), Katila and Ahuja (2002), Majchrzak et al. (2004), Haefliger et al. (2008), Cunningham (2009), Schoenmakers and Duysters (2010), Garud et al. (2013), Sapsed and Tschang (2014), Arts and Veugelers (2015), Kaplan and Vakili (2015), Oehlberg et al. (2015), Strumsky and Lobo (2015), Wirth et al. (2015), Mukherjee et al. (2016) | • General management<br>• Technology and innovation management |
| Platform | • Knowledge management systems<br>• Enablement and support of creative work<br>• Sharing and reuse in online communities | • Organizational memory systems<br>• Online communities<br>• Crowdsourcing | Couger et al. (1993), Markus (2001), Hewett (2005), Huysman and Wulf (2006), Shneiderman (2007), Leimeister et al. (2009), Mitchell and Subramani (2010), Faraj et al. (2011), Müller-Wienbergen et al. (2011), Yu and Nickerson (2011), von Krogh (2012), De Waal and Knott (2013), Thorén et al. (2014), Payton (2016) | • Information systems<br>• Computer science |
| People | • Individual-level characteristics of inventors<br>• Recombination in teams<br>• Recombining in different environments | • (Open source) software development<br>• Organizational memory systems<br>• (Resource-constrained) firms | Markus (2001), Hertel et al. (2003), Baker and Nelson (2005), Lenhart and Madden (2005), Bock et al. (2006), Perretti and Negro (2007), Bayus (2013), Gruber et al. (2013), Hwang et al. (2014), Senyard et al. (2014), Sonenshein (2014), Sojer et al. (2014) | • Information systems<br>• General management<br>• Technology and innovation management |

not changed over the past 75 years. Therefore, the ways in which recombining takes place in different settings remain a vibrant research topic (Salter and Alexy, 2014; Sapsed and Tschang, 2014; Mukherjee et al., 2016).

One of the contexts in which the reuse of knowledge has been investigated is that of scholarly knowledge production. Mukherjee et al. (2016), for example, analyzed 17.9 million papers from Web of Science regarding the combination and reuse of references. Their results show that the top 5% of publications use a combination of highly conventional references with a small number of unconventional ones. Recently, open online platforms (e.g., Wikipedia, YouTube, GitHub) have become another subject of research (Cheliotis and Yew, 2009; Di Gangi and Wasko, 2009; Ransbotham and Kane, 2011; Dabbish et al., 2012; Susarla et al., 2012; Benlian et al., 2015; Spagnoletti et al., 2015). These platforms foster the sharing of knowledge among large user groups (Bayus, 2013; Blohm et al., 2013) and are hence considered important tools for enabling recombinations (Schoenmakers and

Duysters, 2010; Yu and Nickerson, 2011; Hwang et al., 2014). Moreover, many platforms explicitly promote the sharing and recombination of existing content, encouraging users to make their contributions freely available, often under an open license (von Hippel and von Krogh, 2003, 2006; Cheliotis et al., 2007). Although the relevance of recombinations is often mentioned, particularly with regard to open online platforms, little is known about the extent to which remixes contribute to overall platform activities.

### Process: mechanisms of recombinations
The innovation process includes invention, development, and implementation phases, where the sequence of events and actions is not necessarily ordered. Herein, invention denotes the emergence of an idea with recombination as its key mechanism (Garud et al., 2013). According to Majchrzak et al. (2004, p. 174), a "reuse-for-innovation process" comprises the following three major activities: (1) the

reconceptualization of the problem and decision to search for ideas to reuse, (2) the evaluation of found ideas, and (3) the development of the selected idea.

The process that lets people recombine existing knowledge into something new has been studied in a variety of research settings, with patent citations being by far the most prominent example. Similar to scholarly articles, patents cite one another, and an analysis of these citations can be used to understand the context of a patented invention (Albert *et al.*, 1991; Almeida, 1996). Patent citation analyses support the hypothesis that inventing is a process of recombination (Fleming, 2001; Katila and Ahuja, 2002; Strumsky *et al.*, 2012; Arts and Veugelers, 2015; Guan and Liu, 2015; Strumsky and Lobo, 2015). Strumsky and Lobo (2015), for instance, analyzed US patent data and patent technology codes. Their quantitative study shows that inventions are rarely created from scratch but are usually a combination of existing components. Breakthroughs or radical innovations are made possible by allowing the recombination of distant and diverse knowledge (Kaplan and Vakili, 2015; Nakamura *et al.*, 2015). Schoenmaker and Duysters (2010) examined 157 individual patents from a pool of 300,000 and found that in contrast to conventional wisdom, radical inventions are based on existing building blocks more often than non-radical ones. Further, patent citations reveal that small serial innovators prosper if they are able to intensively recombine knowledge in one area of expertise (Corradini *et al.*, 2016). Although patent citations help address many research questions, they also have several downsides. In particular, they do not show the actual inspiration of an invention but instead show its general context (Karki, 1997; Nelson, 2009). Moreover, they are limited to patentable insights.

Another research stream has studied the knowledge-reuse process in the context of software engineering. The sharing and combination of code is a widespread development approach in open-source development projects (Lakhani and von Hippel, 2003; Haefliger *et al.*, 2008; Dabbish *et al.*, 2012). Haefliger *et al.* (2008) conducted a multi-case study based on data from six open-source projects. Interviews with developers and an analysis of the source code itself revealed that code reuse helps improve productivity and quality in software development (Rothenberger *et al.*, 1998; Vitharana *et al.*, 2010). In recent years, several platforms for knowledge sharing among software developers have emerged, such as GitHub for source code and Stackoverflow for questions surrounding software development in general. However, despite the rapid proliferation of these and many other online communities, studies of the underlying reuse processes remain sparse (Garud *et al.*, 2013).

Investigating innovation network structures is another promising approach to studying the process of recombining existing knowledge (Kyriakou *et al.*, 2012; Papadimitriou *et al.*, 2015). Cheliotis and Yew (2009) analyzed recombination patterns by examining the reuse of songs and samples by musicians. More recently, Oehlberg *et al.* (2015) and Wirth *et al.* (2015) examined designs in online maker communities in order to reveal basic remixing patterns. However, beyond these initial findings, there is a need for a deeper understanding of innovation networks to gain further insights into the recombination process (Seshadri and Shapira, 2003; Cheliotis and Yew, 2009; Kyriakou and Nickerson, 2013; Fordyce *et al.*, 2016; Leenders and Dolfsma, 2016).

## Platform: the role of IT for recombinations

The increasing complexity of work has led to a greater appreciation of knowledge and knowledge processing (Huysman and Wulf, 2006). Tools that activate and support the creation and utilization of ideas are crucial to innovation (Romer, 2008; Leimeister *et al.*, 2009). IT is well suited to play a key role in knowledge management, as technology allows for knowledge or ideas to be stored, managed, shared, and reused (Markus, 2001; Shneiderman, 2007; von Krogh, 2012). To foster creativity, information systems need to support users in extending their personal knowledge (Müller-Wienbergen *et al.*, 2011). Hewett (2005), for instance, considered the problem of designing a creative problem-solving environment by conceptualizing a virtual workbench based on concepts from psychology. His findings suggest that information systems should offer the possibility to create user-expandable repositories of reusable objects, which may then be combined into new solutions. Online communities extensively exploit this idea by allowing users to create, share, and remix content (Lee *et al.*, 2010; Leonardi, 2014; Payton, 2016). Yu and Nickerson (2011) experimentally evaluated a "human-based genetic algorithm," that is, an idea-generation system in which users have to combine each other's ideas. The results show that designs of later iterations score significantly higher in terms of originality and practicality. The possibility of reusing knowledge is hence a cornerstone of crowd-generated ideas (Yu and Nickerson, 2011; Bayus, 2013; Hwang *et al.*, 2014), and the fluidity of knowledge is a fundamental characteristic of these communities (Faraj *et al.*, 2011). However, although there is broad agreement among researchers on its general importance, the creative recombination of knowledge is an often neglected area in the field of IS (Couger *et al.*, 1993; Seidel *et al.*, 2010). In fact, there is little research on how an IT-based platform can support and spur knowledge sharing (Markus, 2001; Huysman and Wulf, 2006), and even less is known about how IT shapes reuse practices (Mitchell and Subramani, 2010).

## People: individual and environmental factors of recombinations

Individual and environmental factors influence not only *if* but also *how* the recombination of existing knowledge occurs (Markus, 2001). Younger people, for example, have internalized remixing into their habits concerning content creation (Lenhart and Madden, 2005; Payton, 2016). Further, Perretti and Negro (2007) demonstrated that Hollywood teams create more innovative recombinations if the team comprises both novices and experienced filmmakers. In general, employees expand their ability for creative reuse when they are assigned resources and responsibilities (Sonenshein, 2014). Gruber *et al.* (2013) investigated the relationship between inventors and their inventions by using more than 30,500 patents filed at the European Patent Office together with survey data on the inventors. Their results showed that individuals with a scientific background, for instance, generate broader patents in terms of technological domains than engineers (Gruber *et al.*, 2013). Entrepreneurs' use of remixing, particularly in resource-poor environments, is known as "bricolage" and offers an attractive option for resource-constrained firms to innovate (Ciborra, 2002; Baker and Nelson, 2005; De Waal and Knott, 2013). Senyard *et al.* (2014) found support for this view based on a panel study

with 658 founders from Australia. Specifically, the results show that the recombination of available resources has a strong positive effect on innovativeness. The underlying motivational processes are similar to those of other social communities and teams (Hertel *et al.*, 2003; Sojer and Henkel, 2010; von Krogh *et al.*, 2012). These include ideational inducements (i.e., software should be free to modify and to redistribute) and career concerns (i.e., signaling talent to potential employers) (Hertel *et al.*, 2003). In general, these motivations may be categorized into intrinsic (e.g., ideology) and extrinsic (e.g., career improvement) motivations (Leimeister *et al.*, 2009; von Krogh *et al.*, 2012). Programmers have a general understanding of ethical reuse and license terms. In cases of wrongful reuse, developers either lack license information or are forced by external factors (Sojer *et al.*, 2014). Collaborative norms that help govern and regulate have been shown to positively affect individuals' knowledge-seeking behavior (Bock *et al.*, 2006). Because users differ in so many ways – for example, regarding their experience or interests – it is important to understand the characteristics of remixing platform users to better answer and meet a user population's needs (Seidel *et al.*, 2010; Müller-Wienbergen *et al.*, 2011; Stanko, 2016).

## Methodology

Against the backdrop of our literature review, we conclude that more empirical research is needed to shed light on research questions concerning the relevance of remixes for innovation, the remixing process, the role of IT-based platforms, and the profile of remixing individuals. For this purpose, we explore remixing based on a real-world dataset collected from Thingiverse, an online 3D printing community that allows its users to share and remix three-dimensional models of physical objects. Because of the sheer size and diversity of the dataset, a structured analytical approach is required (Müller *et al.*, 2016), which we describe in the following subsections. To prepare and process the data, we primarily used the statistical software environment *R* (Ihaka and Gentleman, 1996; R Core Team, 2016) and drew upon functionalities from extension packages for data manipulation (Wickham and Francois, 2016), network analysis (Csardi and Nepusz, 2006), and visualization (Gu *et al.*, 2014; Wickham, 2009). In addition, we used "Gephi" to create visualizations of family trees (Bastian *et al.*, 2009).

### Extraction and filtering

Thingiverse supports two file formats for 3D designs on its platform: STL and OpenSCAD. STL files directly represent an object's geometry information by specifying the complete surface of an object as a polygon mesh in three-dimensional space. In contrast, OpenSCAD files describe the generation of 3D models by using a scripting language. This programmatic approach facilitates the parametrization of designs, which simplifies their customization by other users. In addition to the actual model data, Thingiverse records meta-information on Things, such as the name, a unique ID, the creator, the date of publication, a list of descriptive tags, and user comments. Furthermore, a Thing is associated with dynamic data, such as the number of likes, views, downloads, and confirmed makes. Finally, remix relationships between designs are available as lists of a model's immediate ancestors and descendants, which are referred to as "Parents" and "Remixes."

These data from Thingiverse were collected by using a custom-made web crawler implemented in C#. We extracted information on 216,541 Things created between November 2008 (the establishment of the platform) and October 2014. From this set, we excluded 378 Things that violated Thingiverse's terms of services (e.g., weapons or sex toys) and 13 Things that had been removed because of copyright issues. Another 3054 Things were removed, as they were not published under an open license and were hence not remixable. Note that Thingiverse made open license publishing mandatory in 2012. The final filtered dataset comprises 213,096 Things, with 116,659 of these being remixes.

### Preprocessing and statistical analyses

In the second step, we used the available information on direct remix relationships to reconstruct higher-order relationships through repeated merge operations. To facilitate further analyses, we introduce the concept of *generations*. While some Things ("isolated designs") have neither ancestors nor descendants, others are part of larger family trees spanning multiple generations. In the latter case, we determined the generation of every design within Thingiverse, which indicates its position within a remixing path (i.e., a sequence of remixes that build upon each other). All Things without a direct ancestor are assigned the generation 0 and subsequent remixes of these Things take on a generation value incremented by 1. For remixes with multiple parents, these parents may belong to different generations. In such cases, the remix is assigned the highest generation value reflecting the longest path to a generation 0 ancestor (see Figure 1).

The annotation of processed genealogical information facilitates subsequent analyses involving remix depth and repeated remixing chains. In the following sections, we initially explore the importance of remixing within the platform based on descriptive statistics of Thing characteristics and remix activity. Subsequently, we use network analysis and visualization to explore the remix process in detail. To create genealogical trees of Thingiverse categories that meet aesthetic criteria (e.g., balanced vertex distribution, limiting of edge crossings) while facilitating interactive exploration, we rely on a force-directed layout (Di Battista *et al.*, 1999; Jacomy *et al.*, 2014). To visualize inter-category remixes, we use a circular chord diagram representation of transition matrices. From the qualitative visualizations, we extract and describe distinct remix patterns, which are in turn mathematically coded and quantified across the whole platform. A similar coding is proposed to objectively categorize remix complexity. Finally, we apply regression modeling to identify key influence factors on remix likelihood (logistic regression) and user growth dynamics (linear regression).
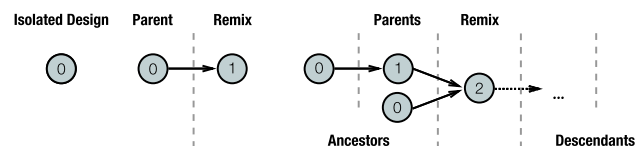


**Figure 1** Concept of remix relationships and generations.

## Results

This section presents our empirical results categorized along the four research topics discussed in the literature review section: (1) the practical relevance of remixes, (2) the structure of the remix process, (3) the features of a remix-enabling IT platform, and (4) the characteristics of remixing individuals.

### Relevance: remixes of 3D designs on Thingiverse

Table 2 provides descriptive statistics associated with the remixes in our dataset. It becomes evident that remixes exhibit large differences concerning the number of tags (ranging from 0 to 129), their origin (ranging from 1 to 10 parents), and the length of the remix chain (one-hop remixes vs. up to 13 evolutionary stages). The same holds true for individual Thing-related metrics, such as page views, file downloads, or makes (i.e., user-reported successful prints). Moreover, we find considerable differences in the magnitude of "attention" metrics (views, downloads) and "engagement" metrics (comments, makes).

Next, we consider the extent of remixing activities relative to the total number of designs available on the platform; that is, we compare remixes with isolated designs. Figure 2 depicts the relevance of remixes within the community on the basis of the following three different metrics: (1) the number of Things, (2) the total number of downloads, and (3) the total number of makes.

The *number of Things* describes the quantity of designs available on the platform and therefore reflects its size in terms of offered content. The 86,728 isolated designs without any remix relationship account for 40.7% of all available

Things, whereas remixes account for 54.7%. The remaining 4.6% are remix parents without incoming relations (generation 0). The data reveal that the number of remix parents in one generation is always smaller than the number of remixes in the following generation that built upon them. This illustrates that the possibility of remixing facilitates the emergence of a host of new designs based on other designs.

The *total number of downloads* measures the general activity on the platform of both registered and unregistered users. Here, remixes account for 29.8% of the total number of downloads. Clearly, this number is lower than the remix share of the number of designs, but it should be noted that remixes emerge later in time and often in a highly customized manner. The share of almost 30% of total download activity suggests that remixes play an important role on not only the supply side but also the demand side of the platform.

The *number of reported makes*, again, represents the effect beyond the platform itself in terms of 3D-printed objects. On Thingiverse, remixes account for 29.6% of all reported makes.

### Process: different patterns of remixing

A remix on Thingiverse is a three-dimensional design that includes references to all other designs on which it is based. In its simplest form, a previously isolated Thing is remixed into a single new one. This simple form of remixing can be described as a *linear evolution*. It is not uncommon for such remix behavior to occur in a daisy-chain fashion in which an isolated design leads to a remix, which in turn leads to another remix. With regard to our full dataset spanning all of Thingiverse's categories, we find that 113,439 remixes are

**Table 2** Remix characteristics ($N = 116,659$ remixes)

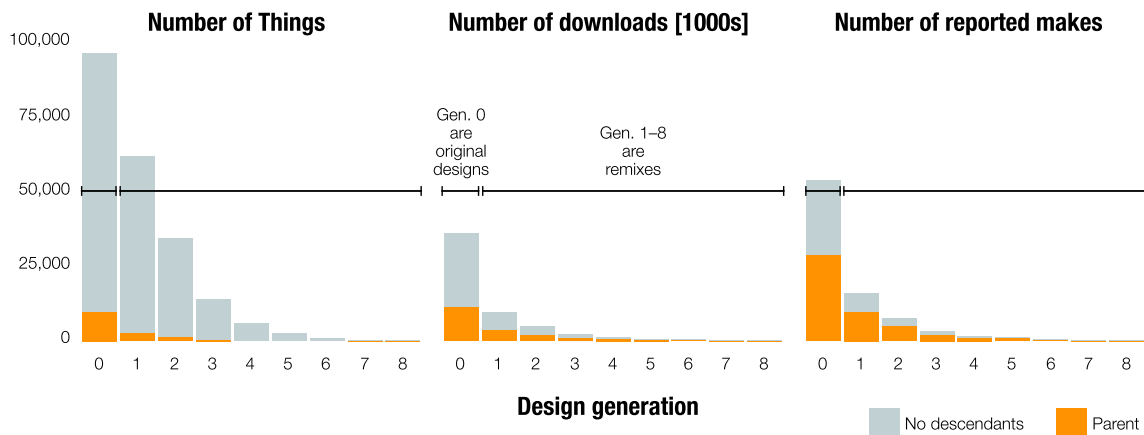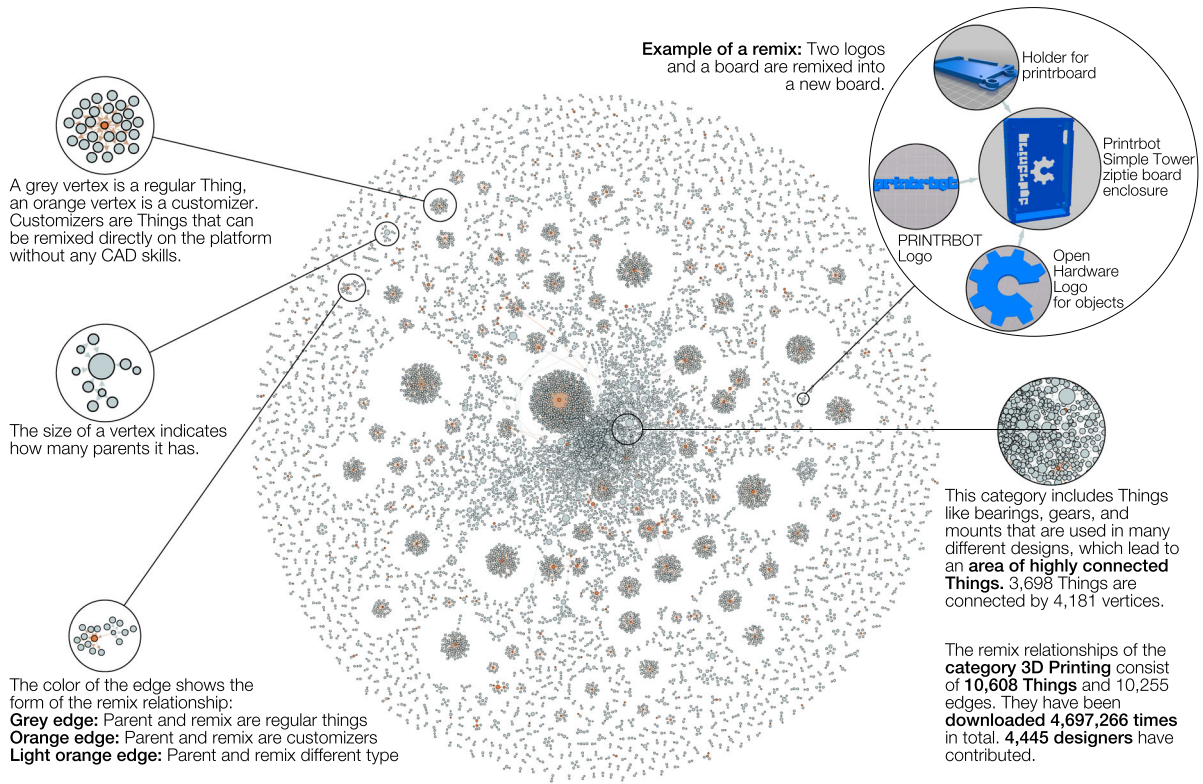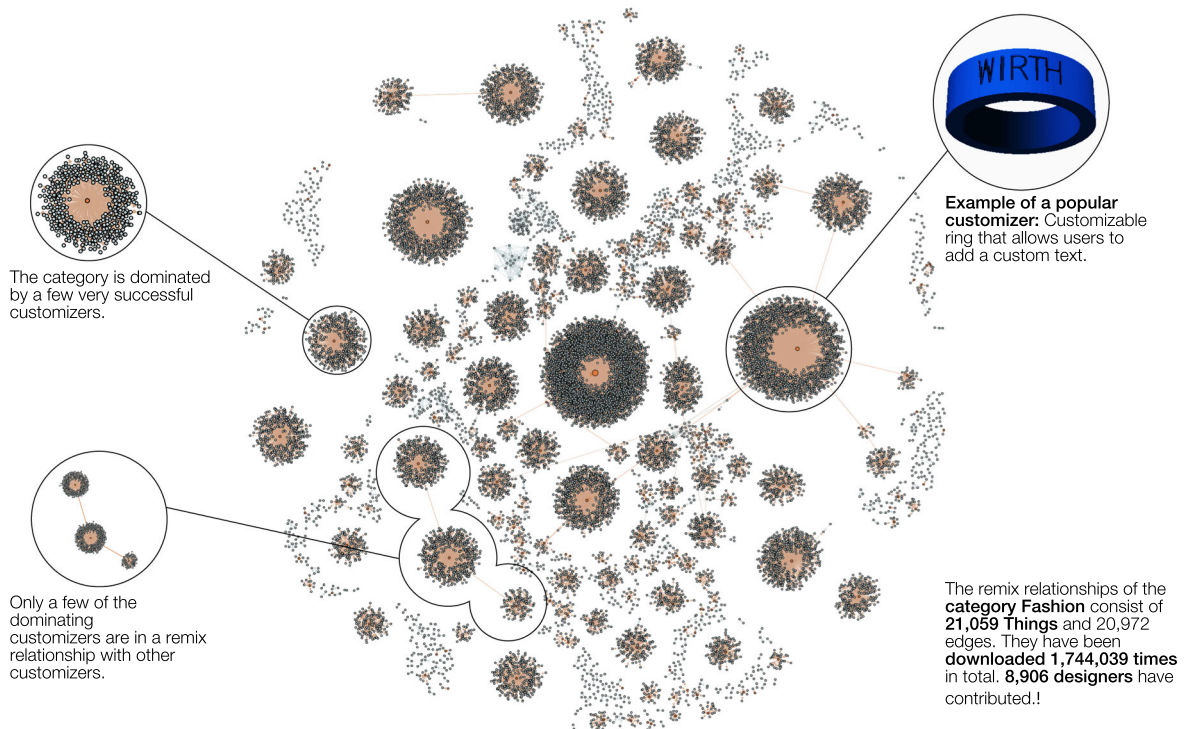| Variables | Mean | SD | Min | Median | Max |
|---|---|---|---|---|---|
| Tags | 1.52 | 2.08 | 0 | 1 | 129 |
| Parents | 1.04 | 0.32 | 1 | 1 | 10 |
| Generation | 1.81 | 1.14 | 1 | 1 | 13 |
| Views | 621.29 | 3188.86 | 0 | 132 | 392,333 |
| Downloads | 130.77 | 754.67 | 0 | 31 | 87,527 |
| Likes | 4.74 | 33.18 | 0 | 0 | 2512 |
| Comments | 0.42 | 3.28 | 0 | 0 | 364 |
| Makes | 0.19 | 2.19 | 0 | 0 | 268 |



**Figure 2** Total number of Things available on the platform, downloads performed, and makes actually reported by designers per generation (Things beyond the 8th generation are omitted).

A grey vertex is a regular Thing, an orange vertex is a customizer. Customizers are Things that can be remixed directly on the platform without any CAD skills.

The size of a vertex indicates how many parents it has.

The color of the edge shows the form of the remix relationship:
**Grey edge:** Parent and remix are regular things
**Orange edge:** Parent and remix are customizers
**Light orange edge:** Parent and remix different type

**Example of a remix:** Two logos and a board are remixed into a new board.

Holder for printrboard

Printrbot Simple Tower ziptie board enclosure

PRINTRBOT Logo

Open Hardware Logo for objects

This category includes Things like bearings, gears, and mounts that are used in many different designs, which lead to an **area of highly connected Things**. 3,698 Things are connected by 4,181 vertices.

The remix relationships of the **category 3D Printing** consist of **10,608 Things** and 10,255 edges. They have been **downloaded 4,697,266 times** in total. **4,445 designers** have contributed.

**(a)** Network structure of all Things in a remix relationship in the category "3D Printing"



The category is dominated by a few very successful customizers.

Only a few of the dominating customizers are in a remix relationship with other customizers.

**Example of a popular customizer:** Customizable ring that allows users to add a custom text.

The remix relationships of the **category Fashion** consist of **21,059 Things** and 20,972 edges. They have been **downloaded 1,744,039 times** in total. **8,906 designers** have contributed.!

**(b)** Network structure of all Things in a remix relationship in the category "Fashion"

**Figure 3** Things and intra-category remix relationships for different Thingiverse categories. **a** Network structure of all things in a remix relationship in the category "3D Printing", **b** Network structure of all things in a remix relationship in the category "Fashion".

part of linear evolution paths. However, our analysis indicates that this is only one of several remix relationships. Figure 3 shows the intra-category remix relationships for the Thingiverse categories "3D printing" and "fashion." Non-linear remixing paths may be found in virtually any other Thingiverse category, but these two exemplary categories are specifically chosen because they show obvious structural differences, contain a wide variety of Things and are popular on the platform. The resulting network structures show the subset of Things that are themselves either a remix or its ancestor; all isolated designs are omitted. The figures highlight the diversity and complexity of remix relationships between Things beyond purely linear evolutions. We distinguish and describe eight compound remix patterns grouped in the following two fundamentally different classes: (1) *convergent remixes* characterized by remix relationships with several parents and (2) *divergent remixes* characterized by remix relationships with several children.

### Convergent remixes
Remix relationships exist between a "child" (i.e., the remix itself) and its "parents" (i.e., the Things the remix is based on). When we apply this family analogy to remix relationships, a *convergent remix* is defined to reflect a relationship in which a child inherits from at least two parents. Convergent remixes are hence viewed from the perspective of the children. The simplest form of a

convergent remix is a *merge* in which two formerly unrelated Things are remixed into a new design. For example, Thingiverse lists individual designs for the mascots of both the Republican and the Democratic Party of the United States, the elephant and the donkey. These two unrelated Things have been remixed/merged into a "debate coin" that shows one of the mascots on each side. To create Things through convergence, designers merge and integrate designs and concepts in various ways that may formally be distinguished from each other by using the respective relationship between remix $x$ and its set of parents $P_x$. In total, we thus distinguish between four patterns of convergent remixes (see Table 3).

### Divergent remixes
A second class of remixes that we found is the *divergent remix*. In these cases, a single design is the source for several new ones. In contrast to convergent patterns, divergent remixes are about inspirational variety stemming from the same source. Applying the family analogy, a divergent remix may be described as a relationship in which a single parent has at least two children. Divergent remixes are hence viewed from the perspective of the parent. The simplest form of a divergent remix is a *fork*, that is, a single design resulting in two remixes. For example, a Thingiverse user created a bottle opener based on a 25-cent coin, which was later remixed by two other designers. The first designer altered the design to reduce

**Table 3** Convergent remix patterns ($x, y \in$ set of Things $\mathbb{T}$; $P_x$: set of parents of Thing $x$; $P_x^2$: set of grandparents of $x$)
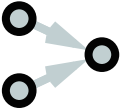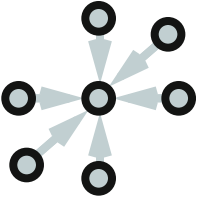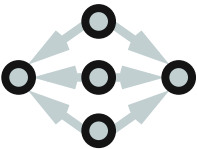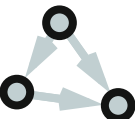
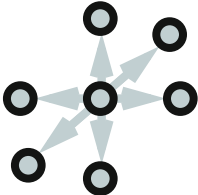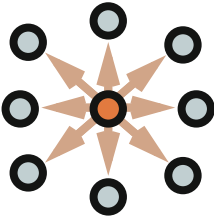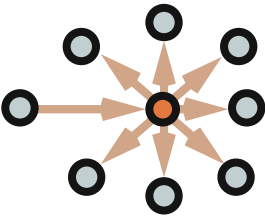| Pattern | Description | Formalization | Count |
|---|---|---|---|
| *Merge* | Here, two distinct Things are remixed into a new Thing. The resulting merge contains aspects of both previously unrelated Things | $\{x : |P_x| = 2\}$ | 2345 |
| *Compilation* | A new Thing can be a "best-of" compilation of a variety of ideas that were previously unrelated. Therefore, a great number of culled Things are compiled together into a single Thing. In large compilations, the influence of a single predecessor may be difficult to identify | $\{x : |P_x| \geq 3\}$ | 898 |
| *Siblings* | In some cases, several creators combine the same parents into independent new Things. These new Things are not connected directly but share the same ancestors. This remix pattern can lead to multiple discoveries, a situation in which similar Things are developed by different people | $\{x, y : |P_x \cap P_y| \geq 2\}$ | 819 |
| *Retrospect* | A retrospect combines the features of several generations of ancestors. Thus, it not only is a remix of a single Thing but goes back in time and creates a best-of from multiple generations. To qualify as a retrospect, a remix has to borrow from at least two generations | $\{x : |P_x \cap P_x^2| \geq 1\}$ | 773 |

**Table 4** Divergent remix patterns ($x \in$ set of Things $\mathbb{T}$; $c \in$ set of customizers $\mathbb{C}$; $C_x$: set of children of Thing $x$; $P_c$: set of parents of customizer $c$)

| Pattern | Description | Formalization | Count |
|---|---|---|---|
| Fork | In this pattern, a concept reaches a crossroads and forks into two new Things. The initial design seems to cause different associations that are the basis for remixes | $\{x : |C_x| = 2\}$ | 2241 |
| Bouquet | Some Things turn out to be suitable for remixing and hence are remixed overproportionately. A bouquet of derivatives emerges | $\{x : |C_x| \geq 3\}$ | 3159 |
| Customizer | A customizable Thing allows users to easily adapt it to their personal preferences. In the context of Thingiverse, a customizer can be adjusted within the frame of a few given parameters. It is therefore predestined to be remixed. This fact leads to a relatively high number of customized derivatives | $\{c : |P_c| = 0\}$ | 1545 |
| Template Builder | This is a pattern in which a non-customizable Thing is remixed into a customizer. A user decides that a certain design would serve the community better if it were easily customizable. Thus, a template builder acts as a springboard and links an original idea and its descendants | $\{c : |P_c| \geq 1\}$ | 727 |

material usage during printing, whereas the other designer changed the form of the bottle opener so it can be mounted to a bicycle frame. Again, we distinguish between four distinct patterns of remixes within this class (see Table 4).

*Category transitions*
Every Thing on Thingiverse is assigned a category, which allows users to browse and find familiar designs; example categories include "household," "toys and games," and "art." Remixes occur both within a single category and across multiple categories. While the majority of remixes remain within the same category as their respective parents, approximately 8% of remixes transfer knowledge from one domain to another. An example of a cross-category remix is the "Cable Organizer" from the "household" category that is based on "Mr. Jaws," a stylized shark from the "models" category. The cable organizer uses the shark's teeth to hold cables in place.

Figure 4 shows all category-spanning remixes in a compact chord diagram (Gu *et al.*, 2014). Here, the color indicates the category of the parent (i.e., the origin of the inspiration). The visual depiction suggests that relationships between categories are highly unbalanced. On the one hand, there are *donating categories* that provide inspiration for remixes in other categories but receive few remix inflows. The category "learning," for example, is displayed in green with a total of 624 remixes transferring knowledge from "learning" to "hobby." In contrast, only 24 remixes move in the opposite direction, as highlighted by the dotted outlines. Other examples of donating categories are "tools" and "art." On the other hand, there are *absorbing categories* that heavily rely on other categories for inspiration while providing only limited inspiration themselves. Examples of absorbing categories are "hobby" and "household." In sum, the analysis indicates that the exchange of knowledge between categories is not mutually beneficial but skewed toward absorbing categories.
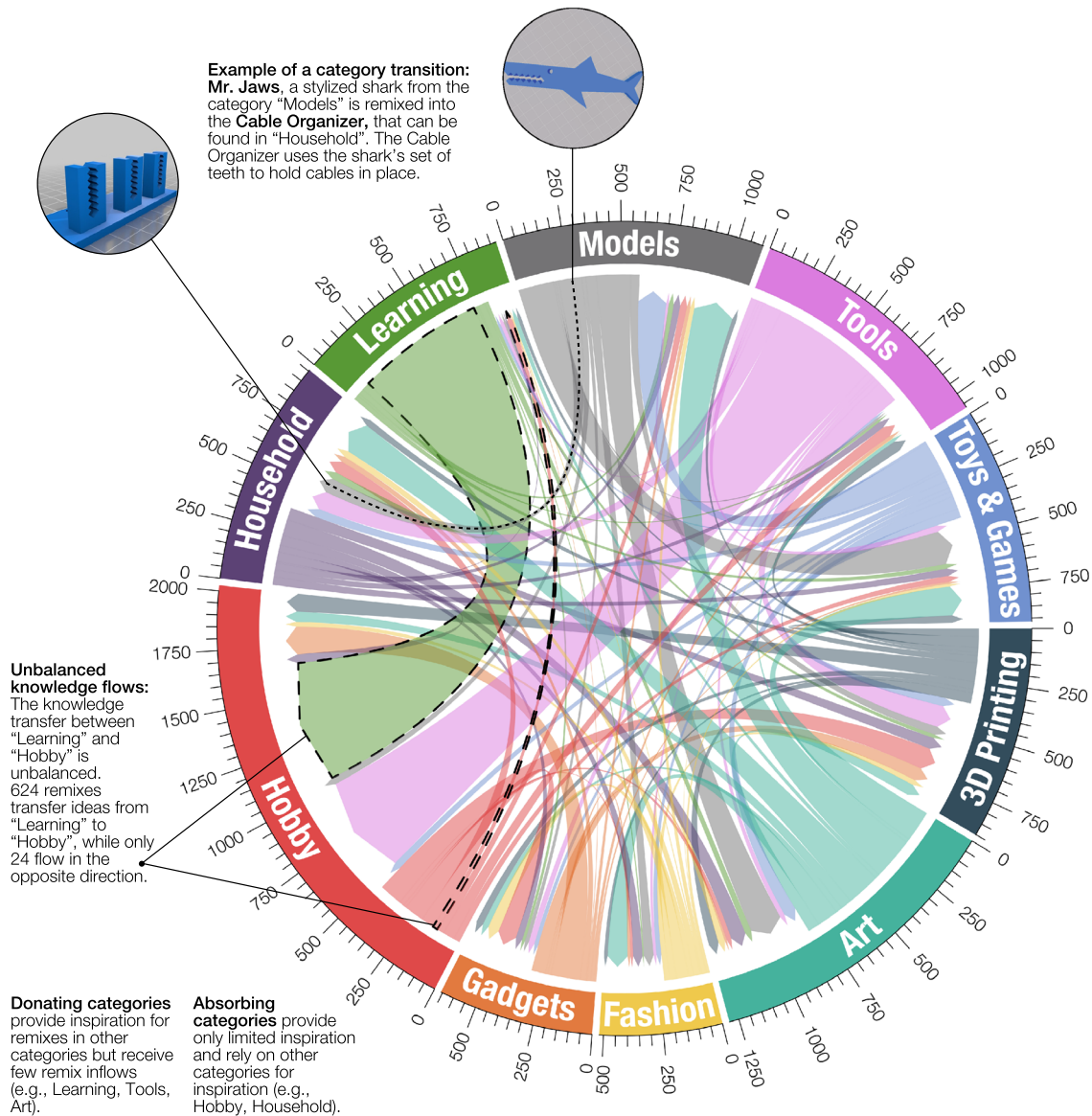
**Figure 4** Category transitions.

## Platform: IS features facilitating remixing

Fostering user activity is a key objective of any online platform. In the case of Thingiverse, user activity includes the exploration of available designs and the creation of new designs in addition to remixing. To support these activities, Thingiverse offers tools and assistance to help create new Things and navigate platform contents (categories, tags, and featured designs). Furthermore, Thingiverse relies on standardized file formats and offers customization capabilities, both of which facilitate reuse activity. This section analyzes drivers of the remix propensity of individual designs. Furthermore, we show that Thingiverse succeeds in facilitating both basic and sophisticated remixing.

### Exploration pathways: finding Things to remix

Remixes are by definition based on one or more building blocks. Thingiverse offers users several ways to find Things to remix. Because the platform operators are interested in

supporting the creation and utilization of remixes, it is important to understand which factors increase the likelihood that a Thing will serve as a source of inspiration.

Based on our previous analysis, natural candidates include whether a Thing is a remix itself and, if so, to which generation it belongs, how many parents it has, whether it was created from a customizer, or whether the Thing itself is a customizer. In addition to these aspects, we also consider the following variables: How long has a Thing been available on the platform? Is it categorized or tagged? Is the design labeled as a component and hence meant to primarily serve as an input for other designs (e.g., gear or a toolkit)?[1] How many designs have been published by the designer? To shed light on the influence of these factors, we set up a logistic regression model. We start with an unrestricted variable list with all *static* Thing characteristics, the author information, and additional logarithmic transformations of dispersed numeric variables.[2] Note that this list does not consider

**Table 5** Explorative pathway regression (dependent variable: "Thing was remixed")

| Independent variables | 5 Variables | 10 Variables | Minimum BIC |
|---|---|---|---|
| Is a customizer | 4.200*** (0.065) | 4.190*** (0.064) | 4.230*** (0.065) |
| Is a customizer remix | −3.810*** (0.062) | −3.570*** (0.063) | −3.550*** (0.064) |
| Is a remix | 0.865*** (0.023) | 0.695*** (0.025) | 0.678*** (0.026) |
| Log(Days Online) | 0.650*** (0.012) | 0.592*** (0.012) | 0.649*** (0.014) |
| Log(#Tags) | 0.554*** (0.012) | 0.511*** (0.012) | 0.603*** (0.025) |
| Has been featured | | 0.820*** (0.038) | 0.872*** (0.039) |
| Has $\geq$ 2 parents | | 0.479*** (0.049) | 0.457*** (0.049) |
| Main category: 3D-Printing | | 0.463*** (0.025) | 0.463*** (0.031) |
| Log(#Designs by Author) | | 0.196*** (0.009) | 0.197*** (0.009) |
| #Designs by Author | | −0.001*** (0.000) | −0.001*** (0.000) |
| Verified by Thingiverse | | | 1.170*** (0.188) |
| Main category: Gadgets | | | 0.314*** (0.044) |
| Main category: Toys & Games | | | 0.276*** (0.044) |
| Main category: Hobby | | | 0.172*** (0.039) |
| Is uncategorized | | | −0.198*** (0.033) |
| Main category: Household | | | −0.192*** (0.039) |
| Is titled as component | | | 0.142*** (0.040) |
| #Tags | | | −0.021*** (0.005) |
| Constant | −6.920*** (0.074) | −7.080*** (0.079) | −7.460*** (0.088) |
| Nagelkerke $R^2$ | 0.351 | 0.364 | 0.368 |
| $C$ statistic | 0.882 | 0.889 | 0.890 |
| BIC | 72,989 | 71,685 | 71,398 |
| Observations | | 213,096 | |

\*$p < 0.1$; \*\*$p < 0.05$; \*\*\*$p < 0.01$.

dynamic success metrics (e.g., the number of views or downloads), as they will likely have a confounding effect – we cannot tell from snapshot data whether something is remixed often because it is viewed often or vice versa. Based on this full variable set, we perform backward stepwise model selection based on BIC values (Venables and Ripley, 2013). For comparison, we include forward-selected models with 5 and 10 independent variables. The results of the three models (coefficients, odds ratios, and quality measures) are presented in Table 5. The five main factors influencing remix likelihood identified by the 5-variable model are (1) whether the Thing is a customizer, (2) whether it is a customizer remix, (3) whether it is a remix itself, (4) the log number of days online and (5) the log number of tags. Together, these five independent variables result in a Nagelkerke $R^2$ of 0.351 with a $C$ statistic of 0.882. The more complex models are able to further increase the scores slightly while achieving a lower BIC, with a Nagelkerke $R^2$ of 0.368 and a $C$ statistic of 0.890 for the full model.

The statistical results indicate that the longer a Thing has been available on the platform, the greater its likelihood of being remixed. Similarly, customizers are far more likely to be remixed, which is understandable, as they provide a simple tool for designers of all experience levels. A customizer remix may already be too specific to serve as a meaningful input for a subsequent remix. However, a non-customizer remix is more likely to be remixed. Unsurprisingly, uncategorized Things are less likely to be remixed because these things are more difficult to find when designers browse categories. Similarly, the number of descriptive tags positively influences the remix likelihood. As the number of tags a Thing has increases, it becomes better connected. Designs that were featured by the platform enjoy greater

visibility, leading to greater remix activity. Moreover, Things with verified compatibility and Things that have several parents are more readily adopted as a base for a new design. Component Things indeed serve as platforms for subsequent remixes with a correspondingly higher remix likelihood. The results also indicate the existence of category effects. The "3D printing" category, for example, includes many functional components that are meant to serve as building blocks for new designs. Other categories with an increased remix likelihood include "toys & games", "gadgets", and "hobby", whereas "household" Things are less likely to be remixed. Finally, Things created by authors who have several other models on the platform tend to be remixed more often. By and large, the connectedness of a Thing has a strong influence on its likelihood of being remixed – a finding that we refer to as "exploration pathways."

*From shallow to deep: enabling remix complexity*
As described above, remixes can have either one or several parents, which may stem from the same category as the remix, from a different category than the remix, or from multiple parent categories, if several parents exist. We use these properties of a remix to determine the complexity of the preceding remixing process. Because there is no generally accepted definition of complexity among scholars, it is commonly described by using real-world examples (Johnson, 2009). In these examples, complexity is often deduced from the interaction and interconnectedness of objects (Johnson, 2009). The depth (Nakamura *et al.*, 2015; Katila and Ahuja, 2002) and breadth of a recombining process (Majchrzak *et al.*, 2004; Enkel and Gassmann, 2010; Kaplan and Vakili, 2015) are two general criteria to differentiate combinations (Hwang
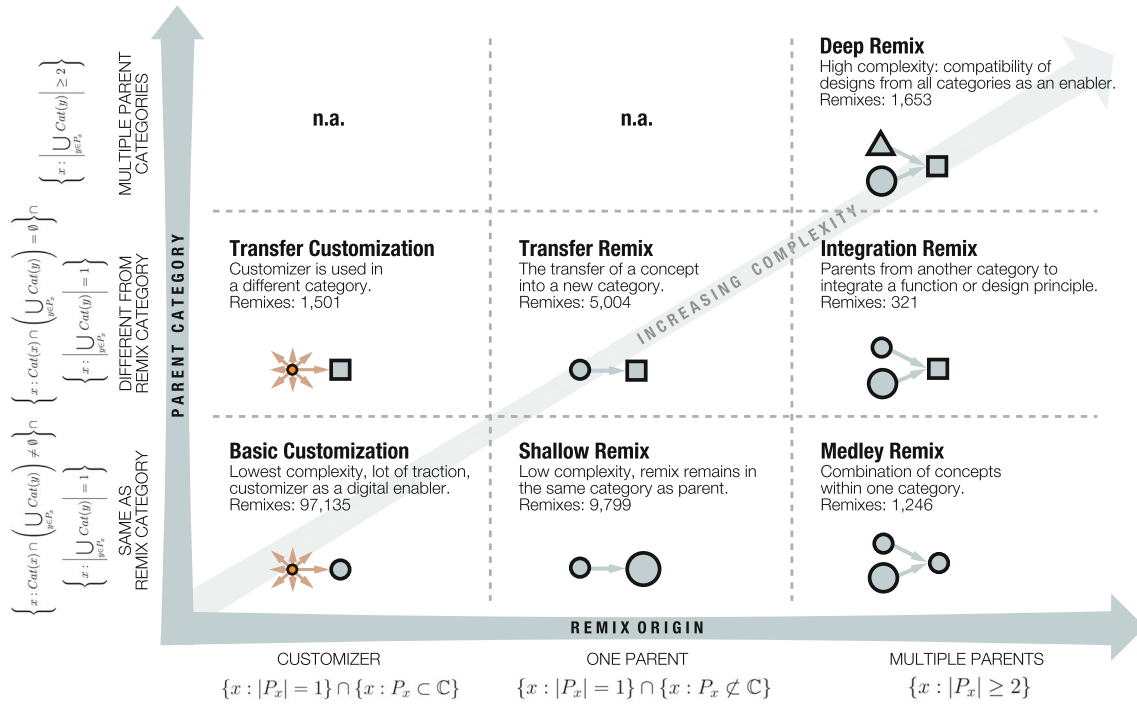
**Figure 5** Remix-complexity matrix.

et al., 2014). In our case, we differentiate remixes along the following two dimensions that represent the criteria mentioned above and are objectively measurable in our dataset: *remix origin* and *parent category*. We use these two dimensions to construct the remix complexity matrix shown in Figure 5. This figure also reports the number of occurrences for each complexity level, highlighting the fact that both very simple and very complex remixes occur on the platform.

The left two entries in our matrix describe the simplest form of remixing, that is, customization by means of a customizer. Designers are able to easily adapt a customizer to their personal preferences within a few given parameters. These adaptations are performed directly on the platform, and no knowledge of computer-aided design is needed. A popular example of a customizer is a smartphone case that allows one to select a phone model and change the pattern on the back of the case. Customizer remixes are by far the simplest and most popular form of remixes on Thingiverse. The platform enables this form of remixing by providing all the tools needed to directly remix on the website. It is therefore reasonable that the "basic customization" yields the most remixes. If the remix of a customizer is categorized differently from the customizer itself, we refer to a "transfer customization."

"Deep remixes" – the combination of several parents from several categories – can be found 1653 times in our dataset. These complex recombinations are not directly enabled by a tool that the platform provides. However, they are enabled by the rules that govern the activities on the platform. All designs in all categories are uploaded in a standardized file format. Consequently, they are inherently compatible. The designs across all categories are also uploaded under an open license that explicitly enables remixing. If designers encounter several Things that inspire them, they do not need to find out whether remixing them is possible from a technological or legal perspective.

Between the extremes, we differentiate intermediate complexity levels. "Shallow remixes" represent a relatively low threshold of originality. That is, all a designer has to do is find a single design to adapt. A "medley" denotes a remix that combines the concepts of several Things from the same category in a best-of manner. A "transfer remix" takes a concept from one category and applies it to another. Finally, the "integration remix" describes a remix in which parents from one category are combined into a Thing in a different category.

The fact that the platform includes remixes showing a broad range of complexity highlights its attractiveness to users with different levels of expertise. Novices without 3D modeling experience, for instance, may easily start with building customizer remixes. In contrast, experts may create complex combinations from downloadable designs using the CAD tool of their choice.

### Person: user population

The final dimension of the remix phenomenon that we want to explore is that of the individual user. To better understand Thingiverse's user population, Table 6 provides summary statistics for the top ten designers, ranked according to their number of views (other metrics yield very similar orders). The leading trio attracted more than one million design views each and jointly accumulated 1.4 million downloads. Regarding the corresponding Thing categories, the data show that the top ten designers are all active in multiple categories. Three of them created designs in all 11 categories.

In addition to success measures, we also consider design behavior. It turns out that among the top ten designers, remix shares vary greatly between 0.04 and 0.77. This suggests that there are fundamentally different pathways to success – both original designers and skilled remixers can become successful designers. Customizers, however, are rarely used by

**Table 6** Top designers (sorted by total number of design views; maximum and minimum values highlighted)

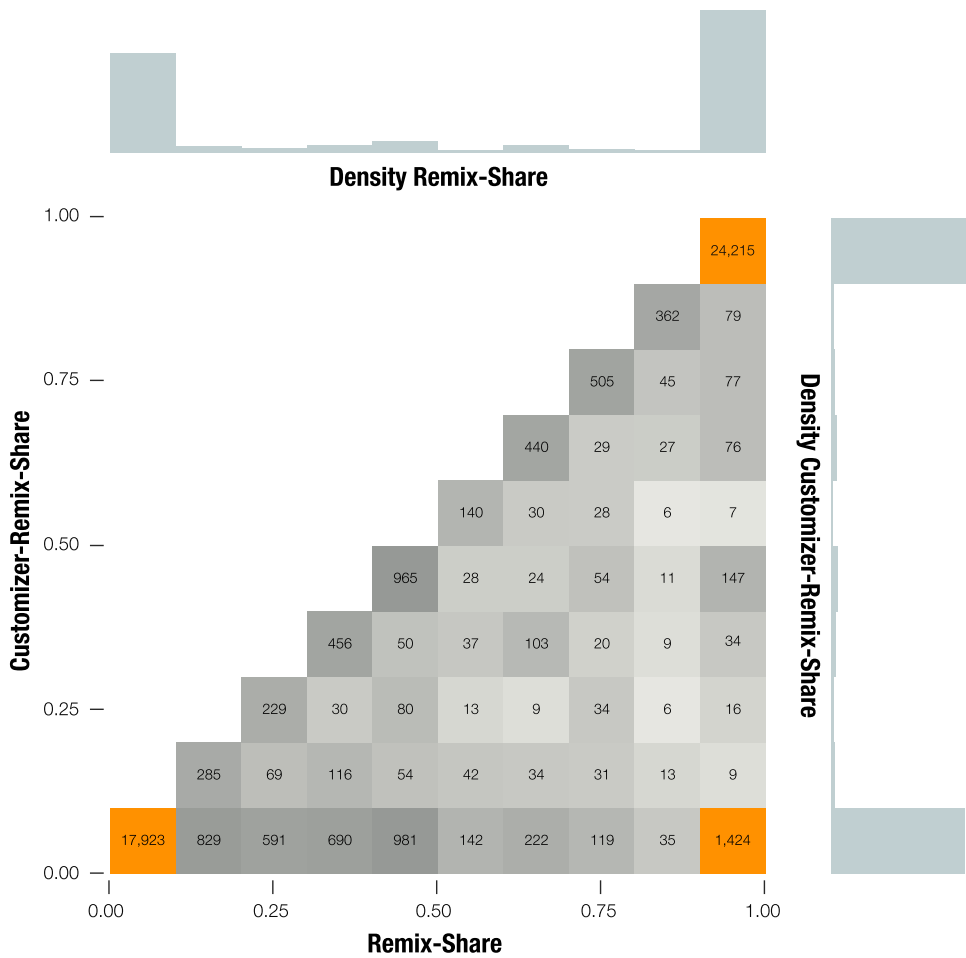| # | Author | Designs | Views | DLs | Likes | Makes | Comments | Categories | Remix share | Customizer-remix share |
|---|--------|---------|-------|-----|-------|-------|----------|------------|-------------|------------------------|
| 1 | MakerBot | 334 | 3.89 M | 774 k | 39,230 | 1859 | 2084 | **11** | 0.11 | **0** |
| 2 | Emmett | 64 | 2.05 M | 433 k | 20,770 | 1601 | 1601 | 10 | **0.77** | 0.03 |
| 3 | Tbuser | 248 | 1.09 M | 209 k | 7639 | 568 | 976 | 9 | 0.56 | **0.14** |
| 4 | Dutchmogul | 186 | 0.98 M | 140 k | 12,506 | 331 | 1244 | **6** | 0.19 | 0.01 |
| 5 | Cerberus333 | 474 | 0.92 M | 157 k | 10,634 | 944 | 1319 | 9 | **0.04** | **0** |
| 6 | MakeALot | 164 | 0.88 M | 183 k | 9140 | 490 | 1030 | 9 | 0.27 | 0.01 |
| 7 | PrettySmallThings | 56 | 0.80 M | 148 k | 6006 | 247 | 353 | **6** | 0.30 | **0** |
| 8 | TheNewHobbyist | 83 | 0.71 M | 71 k | 6282 | 198 | 372 | **11** | 0.33 | 0.06 |
| 9 | Walter | 125 | 0.70 M | 112 k | 13,939 | 264 | 367 | 7 | 0.33 | 0.03 |
| 10 | MakerBlock | 172 | 0.70 M | 147 k | 3912 | 167 | 550 | **11** | 0.41 | 0.02 |



**Figure 6** Number of users for different remix- and customizer-remix-shares.

this group, which stands in contrast to the overall user population, in which customizer remixes are the dominant form of remixing.

*User segments*
Having identified these fundamental differences in design behavior among top designers and between the general population and this elite group, we use the designers' remix and customizer shares to segment the designer population, as shown in Figure 6. The density function of remixing behavior

(see the histogram at the top of the figure) mimics a bathtub curve. Accordingly, most designers fall into one of the following two stereotypes: *never-remix designers*, who do not make use of the possibility of remixing at all, and *always-remix designers*, who base all their designs on other designers' creations. We find a similar split with respect to customizer usage (see the histogram on the right) as follows: one subgroup does not use customizers at all, whereas the second group completely relies on the provided customization function.
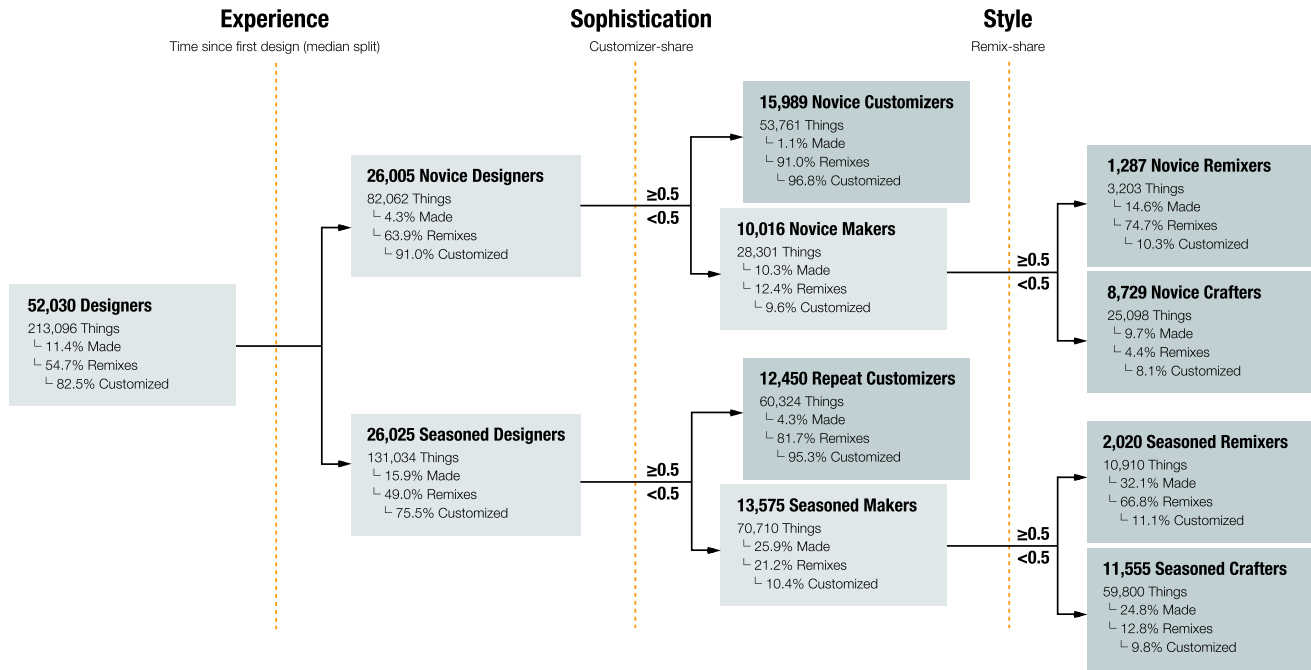
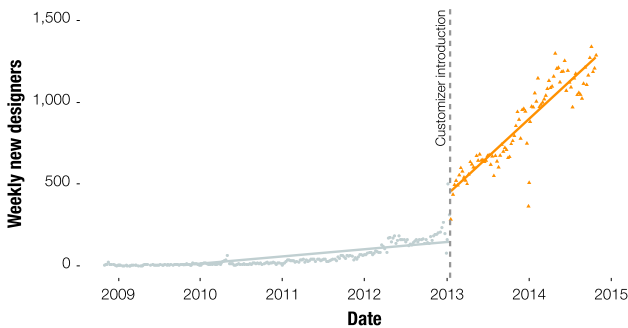**Figure 7** Taxonomy of Thingiverse's user base.



**Figure 8** Weekly growth of Thingiverse's designer base.

We next leverage these insights to develop a classification scheme for Thingiverse's user base. In addition to using the remix share as a proxy for design style and customizer-remix share as a proxy for design sophistication, we consider the time since users' first design on the platform as a proxy for experience. Applying a median split on the time and share splits at 50%, we obtain the taxonomy presented in Figure 7.[3] Using the percentage of reported makes as a measure of design appeal, we again find that remixing and isolated

designs are equally suitable design strategies for creating successful Things. Interestingly, among the successful designers, there are fewer remixers than designers of isolated Things. Platform experience is also beneficial to design success. Finally, the percentages also confirm that mere customization will seldom yield successful Things, which makes sense because customizers are such an easy way to create that many users would rather build their own Thing instead of reusing that of someone else.

*Population growth dynamics*
Having understood the composition of Thingiverse's user base, we now take a dynamic perspective to assess how this structure emerged over time. Figure 8 illustrates the weekly number of designers committing their first design. The growth of the user base essentially breaks down into two distinct segments – a very gradual increase from 2009 until late 2012 and rapid growth since the beginning of 2013. This drastic shift coincides with the introduction of customizers on the platform, which opened the platform to non-experienced users.

To quantify these effects, we apply a linear regression of the weekly number of new designers $Y_i$ on the week index $i$ since the platform's creation and a dummy variable $C_i$

**Table 7** Platform growth regression (dependent variable: "weekly new designers")

| | | |
|---|---|---|
| Time of observation (in weeks) ($\beta_1$) | 0.834*** | (0.071) |
| Time of observation * Customizer available ($\beta_2$) | 7.947*** | (0.270) |
| Customizer available ($\beta_3$) | −1476.153*** | (71.761) |
| Constant ($\beta_4$) | −41.974*** | (9.200) |
| Observations | 318 | |
| Adjusted $R^2$ | 0.971 | |
| Residual SE | 68.618 (df = 314) | |
| F Statistic | 3530.478*** (df = 3; 314) | |

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

indicating the availability of the customizer feature on the platform, that is, $Y_i = \beta_1 \cdot i + \beta_2 \cdot i \cdot C_i + \beta_3 \cdot C_i + \beta_4$. The $\beta_1$ and $\beta_4$ coefficients apply to all observations, whereas the $\beta_2$ and $\beta_3$ coefficients apply only to observations after the introduction of the customizer ($C_i = 1$). The regression results are reported in Table 7 and confirm the posited twofold effect as follows: The weekly user join rate instantly increased by approximately 300 new weekly designers ($\beta_2$ introduction week – $\beta_3$). Second, the slope of the growth trend increased by 1000% from 0.8 to 8.8. These findings also hold if we consider only designers who have repeatedly published Things. In general, the constant growth of the join rate may be attributed to bandwagon effects of more activity on the platform originating from accumulating designs and users. The jump in the user base may in part be attributed to media attention and publicity that went along with the customizer introduction and the opportunity of unsophisticated users to be able to contribute to Thingiverse. Given the large size of the customizer segments (Figure 7), we surmise that indeed the second effect played a central role; that is, the customizer introduction allowed Thingiverse to access a previously untapped and abundant user base.

Overall, the introduction of customizable things has permanently altered Thingiverse's designer population structure by facilitating the emergence of a rapidly growing unsophisticated user segment. This has allowed Thingiverse to attain a dominant position in the market with the largest number of designs and users. Going forward, however, the marked heterogeneity of the user base may pose challenges to community management.

## Conclusions

To date, the phenomenon of remixing has received little attention in the IS discipline. The lack of prior research stands in sharp contrast to the proliferation of open online platforms, which serve as a basis for knowledge sharing and reuse (Sambamurthy and Subramani, 2005; Huysman and Wulf, 2006; Mitchell and Subramani, 2010). To shed light on remixing as a source of innovation in these digital environments, we have chosen an explorative approach using a dataset collected from the world's largest platform for 3D printable designs. In the following subsections, we discuss our study's theoretical and managerial implications, its limitations, and opportunities for further research.

### Implications for research

Regarding theory, the implications of our study are knowledge claims that we formulate as a set of generalized research propositions, P1–5. On the one hand, further explorative research may build on these propositions and iteratively complement them with the ultimate objective of developing a coherent theoretical framework that explains the role of remixing in the innovation process. On the other hand, confirmative studies may use the propositions to generate testable hypotheses in order to obtain further support for our conclusions in different contexts.

A first finding of our study is that remixing can play a central role in open online communities. Our results suggest that more than half of the content on Thingiverse would not be available if the platform did not explicitly support remixing. It is also plausible to argue that this number may even underestimate

the effect because designers self-report remixing. Although this finding is in line with the literature that stresses the importance of recombinations for the development of new ideas, the sheer magnitude of remixes on Thingiverse struck us as remarkable. This is because one could expect that users would receive inspiration from sources outside the platform. If we assume that a user wants to design and print a cup, the inspiration could come from real-world cups, or it could be driven by a specific need. Yet, half of the designs on the platform are based on prior designs on this very platform. Furthermore, our data show that the importance of remixing is evident in all dimensions of the open online community; it can be found in the content quantity, in the appeal and attraction, and in the activity on the platform. The fact that more than half of all designs are directly based on another Thing makes the platform itself of paramount importance in the creative process of its users. Considering these observations, we come to the conclusion that without remixing, a major part of the community's online activities would be missing.

> **P1** Remixes pose a second major source of innovation in open online communities besides the emergence of isolated designs.

Further, we show that remixing on open online platforms occurs in many different forms, and we can distinguish between two perspectives: (1) convergent and (2) divergent remixes. The remix patterns that we describe have merit outside Thingiverse; they describe very basic forms of recombinations that are applicable to other open online platforms. They also extend prior research in the field of human–computer interaction in which Oehlberg *et al.* (2015) reported six common network motifs in remixing graphs. Furthermore, we assume that the remix patterns that we present in this article will be useful outside open online communities. If understanding how combinations of known building blocks can lead to novel insights really is the "holy grail" of innovation research (Gruber *et al.*, 2013), we hope that our study will prove helpful in finding it.

> **P2** Remixes occur in the form of several different, clearly distinguishable paths, including convergent and divergent patterns.

The majority of remixes in our dataset stay within the confines of their parent categories. Nevertheless, some remixes transfer ideas and concepts to other settings. As prior research on patents indicates, recombinations of distant and diverse knowledge allow for breakthrough innovations (Schoenmakers and Duysters, 2010; Kaplan and Vakili, 2015; Nakamura *et al.*, 2015). These category transitions have been shown to be asymmetric; that is, categories either absorb more or donate more knowledge. Knowledge flow and its reuse are considered among the most important competitive advantages (Galunic and Rodan, 1998; Watson and Hewett, 2006; Carnabuci and Operti, 2013). It is therefore essential to gain a deeper understanding of knowledge fluidity. The asymmetry of knowledge flows between categories deserves more attention, particularly when evaluating or incentivizing interdisciplinary cooperation.

> **P3** The co-existence of different design categories allows for cross-category remixes, which are asymmetric, with categories tending to either donate or absorb ideas.

IT artifacts may support the creation and utilization of knowledge by helping people share and reuse ideas (Markus, 2001; Romer, 2008; Shneiderman, 2007; von Krogh, 2012), for example, in the search for inspiration. In the case of Thingiverse, the platform offers various ways to find inspiring designs, which we refer to as "exploration pathways." Among other things, our results indicate that the number of tags on a design positively influences its likelihood of being remixed. Descriptions and metadata therefore play an important role in facilitating remixing because all remixes begin with the discovery of something worth remixing.

To find out more about how IT systems shape reuse, we grouped all remixes according to their complexity. On the basis of a complexity matrix, we can show that Thingiverse enables customizer remixes in a different way than deep remixes. Customizers are IT artifacts that enable simple, shallow remixes right on the platform. Because of their simplicity, customizers are an entry gate to remixing for novice users. They are also a simple tool for anyone who wants to make only a minor change to an existing design. By contrast, complex deep remixes are enabled by the platform's rules and standards to ensure compatibility across all designs. Hewett (2005) called for information systems that offer the possibility to create user-expandable repositories of reusable objects. Thingiverse provides exactly that, and by offering different ways to engage with the platform's content, it attracts both novice and expert users. Couger *et al.* (1993) critically noted that creativity is a neglected subject in the field of IS. Two decades later, this finding still holds some merit (Seidel *et al.*, 2010; Müller-Wienbergen *et al.*, 2011). In an attempt to respond to this research gap, we show how IT systems enable remixing in an open online community. Thus, we extend previous research on IT artifacts that facilitate creativity and support users during the creativity process (Markus, 2001; Huysman and Wulf, 2006; Aragon *et al.*, 2009; Leimeister *et al.*, 2009).

> *P4* The effectiveness of remixing on online platforms and their attractiveness to different user groups is influenced by a variety of platform features for browsing and processing its contents.

The general concept of remixing is common among many peer groups (Lenhart and Madden, 2005; Payton, 2016). This is reflected in the increase of Thingiverse's user base and growth rate after the introduction of the customizer feature, which allows users with no prior design knowledge to remix. However, not all designers remix. Most designers fall into one of the following two categories: they either make extensive use of remixing or do not remix at all. Designers who remix, again, fall into the following two subgroups: those who heavily rely on customizers and those who hardly ever use a customizer. These diverse groups show that there is no "one-size-fits-all" solution to encourage creativity. Rather, users differ and open online platforms need to offer solutions for different user types.

> *P5* To foster innovation in online communities, platforms need to address the needs and interests of different user groups, each characterized by distinct preferences regarding platform features.

## Implications for practice

A deeper understanding of the remixing concept is fundamental for the design and maintenance of creative communities and, in turn, for the generation of ideas and innovations. Against this backdrop, we consider five aspects of our study to be of particular relevance for management practice:

- **Enabling exploration** A community that wants its users to remix existing content must enable them to find content to remix. To enable exploration, platforms must offer different ways to discover their content. On Thingiverse, users can browse Things by keyword search, category, tag, group, and functionality, among others. This multitude of pathways increases the chance that users stumble upon something that inspires them. As the number of pathways that a platform offers increases, so does the likelihood that a design will be remixed.

- **Tools for non-technical users** Remix activity showed a steep incline when Thingiverse introduced the customization feature. This feature allows designers with very little experience to remix designs and thus lowered the barrier of participation. Tools for non-technical users can also be considered a gateway for future designers. The simplicity of the feature allows anyone to have a quick sense of achievement, which may motivate users to become more engaged with the technology.

- **Technological and legal compatibility** Communities can enable users to create highly complex remixes by allowing a large degree of freedom. Two aspects strike us as particularly supportive of deep remixes. On the one hand, all designs on Thingiverse are available in the same file format. They are therefore all technologically combinable. On the other hand, the platform compels users to publish designs under an open license; that is, all designs are also remixable from a *legal* perspective.

- **Different users, different needs** Users differ greatly in the way they employ remixing in their creative processes. Whereas many rely on this form of creation for all designs they produce (i.e., remix-always designers), others shy away from it completely (i.e., remix-never designers). Platform designers must be aware of this dichotomy and offer an environment that caters to both creative stereotypes. A platform design that favors one form over the other runs the risk of discouraging users that have a different workflow.

- **Assessing asymmetric benefits of cooperation** We observed that knowledge flows in the remixing of existing innovations are asymmetric between categories. Consequently, some categories benefit more from these transitions than others. This might lead to discontent, and it would be desirable to assess the situation to align incentives and reputation mechanisms in a way that offers proper rewards for those who provide more benefits for other categories than they receive in exchange.

The creative content generated in open online communities plays an increasingly important role in everyday life. The recent release of the PC operating system Windows 10, for instance, has a built-in tool to open and print 3D designs. Moreover, with "Remix 3D", Microsoft launched an online community solely devoted to remixing 3D designs.

Thingiverse is the largest source for these designs. Designing an information system to best support and enable users to be creative will become a major challenge in IS. The implications for practice that we derive from our exploratory study will hopefully provide a first set of actionable insights for practitioners. However, more research will be needed to understand how to design appropriate platforms.

### Limitations and further research

The research that we conducted is subject to a few limitations. *First*, our dataset is a snapshot of a vibrant platform gathered at one specific point in time. Timestamps (e.g., the date on which a design was created) are available for some but not for all activities. For instance, we do not know when a download occurred. We are thus unable to explain in detail the causality behind what makes a remix successful. *Second*, we looked at only one open online community. It would be interesting to contrast our findings with other communities, particularly those that have a different purpose. *Third*, our study is solely based on data from the platform itself. We did not conduct interviews with designers and can therefore contribute little to our understanding of the motivations behind their actions. Understanding these motivations would be helpful for designing open online platforms in a way that attracts more users. It is also plausible that user motivations vary and that platforms need to attract users with a diverse set of motivations. *Fourth*, the determination of remix complexity uses origin and category as its dimensions. Although this classification is objective and replicable, there are cases in the field in which a shallow remix is more complex than, for example, a deep remix. To detect these edge cases, a manual coding of all remix relationships would be necessary.

Moreover, although we find that remixing is a powerful tool to develop novel solutions within open online communities, we know little about how remixing plays out in other settings. It would be desirable to understand more about the function of remixing as a creativity tool. For instance, we do not know whether our findings in the realm of design are readily transferable to ideation. This would have interesting implications for corporate settings, and more research in this area is needed to gain a deeper understanding. The concept that characterizes open communities is the free revealing and sharing of knowledge. The introduction of intra-firm suggestion systems and idea markets has proved to be a fruitful way to foster the generation of new ideas (Van Dijk and Van Den Ende, 2002; Soukhoroukova *et al.*, 2012). We believe that these concepts can further be improved if they allowed employees to remix the ideas of their colleagues.

The practice of remixing is a fundamental cornerstone of open online communities. We hope that our research will encourage more scholars to investigate the intersection of IS and remixing. Not least, understanding this intersection better from a theoretical perspective will eventually contribute to the design of better platforms. We structured this paper along the following four perspectives of remixing: (1) relevance, the role of remixes on Thingiverse; (2) process, different patterns of remixing; (3) platform, IS features facilitating remixing; and (4) people, user population. We believe that this structure may also be helpful for future

research on how remixing may be encouraged, why users recombine in certain ways, how users can better be educated on remixing options, how remix patterns and the success of a design are connected, and what keeps users from engaging in remixing more intensely. We believe that remixing will be a topic of increasing importance in IS and hope that this article will motivate others to consider this relevant and highly interesting topic.

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## Notes

1  To identify these objects, we checked the title of each Thing for the occurrence of the following terms: "helper", "library", "toolkit", "toolbox", "gear", "mount", "holder", and "bearing".

2  The full variable list is as follows: Category (10 variables), featured on platform, verified by platform, is a remix, is a customizer remix, is a customizer, number of tags, log number of tags, number of parents, multiple parents, Thing generation, is labelled as component, is labelled as parametric, number of days online, log number of days online, number of designs by designer, and log number of designs by designer.

3  Note that we confirmed the validity of categorizing the population along these axes by using a principal component analysis.

4  Things displayed in this article, ThingID (license). Figure 3.a: 408390 (CC BY-SA 3.0), 54311 (CC BY-SA 3.0), 27097 (CC BY-SA 3.0), 18034 (CC BY-SA 3.0); Figure 3.b: 40704 (CC BY 3.0); Figure 4: 405658 (CC BY-NC 3.0), 14702 (CC BY-SA 3.0). Access via thingiverse.com/thing:ThingID.

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