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# When users become innovators: The role of pre-innovation community experience in a 3D printing platform

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## Abstract

When users become innovators, they have the potential to transfer their own experiences into useful applications, but most still fail to do so. A possible way how users can increase their innovation success is to engage with their target community before becoming an innovator. We study the role of pre-innovation community experience on Thingiverse, a platform used to share innovative designs for 3D printers. We show i) that pre-innovation community experience is associated with higher innovation success, ii) that quantity, quality and relatedness of pre-innovation community experience matter for innovation success, and iii) that the effects of pre-innovation community experience work to a large extent through efforts invested in innovations and the use of recombinant innovations.

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*Keywords*: User innovation, Makerspaces, Communities, Platforms, 3D Printing

*JEL Classification*: O31, O32

## 1. Introduction

User innovation is becoming an increasingly important complement to producer innovation (Baldwin and Von Hippel, 2011), key driver of organizational emergence (Shah and Tripsas, 2007, De Jong et al., 2015) and promoter of social welfare (Gambardella et al., 2016). Yet, the transition from user to innovator is challenging and often fails. Many users never become innovators (von Hippel, 2017) and few of their innovations become successful (de Jong et al., 2018, De Jong et al., 2015). Innovation is risky (Baldwin et al., 2006) and identifying an innovative opportunity for the first time is most difficult (Baron and Ensley, 2006). Not surprisingly, scholars and practitioners share a strong interest in understanding when users become innovators and what factors are linked to this transition.

Communities have been found to be important enablers of user innovation because innovation processes are collaborative and knowledge is shared (Dahlander and Frederiksen, 2012). For instance, Franke and Shah (2003) report that users in the sports industry that developed consumer innovations were receiving important support from their communities. The question remains however, what happens in the community before users actually start innovating - and does the experience gathered then matter for the user innovation process and outcomes?

In this study, we investigate the *specific activities* that take place in a community *before* users develop their first innovation. In this way, we provide insights into the role of community experience prior to the first innovation. Specifically, we investigate 1) the relationship between pre-innovation community experience and innovation success, 2) the attributes of pre-innovation community experience fostering this relationship, and 3) the innovation choices through which pre-innovation community experience relates to innovation success.

Experience with other community members' work inspires users to reuse these designs for their own developments (Haefliger et al., 2008, Kyriakou et al., 2017). Researchers have also shown that individuals' experience of communicating with their community determines the types of projects users work on (Foss et al., 2016), lowers uncertainty about the value of the idea (Autio et al., 2013), and motivates them to act upon their ideas (Shah and Tripsas, 2007). Although these scholars all share the overall idea, that the key in the creation of successful innovation is the experience that individuals gather from their community, the underlying mechanisms remain unclear. In light of this shortcoming, Franke and Shah (2003) state that "a refined understanding of the mechanisms that govern exchange relationships within these communities needs to be developed" (p. 175).

To address this issue, we draw on user innovation and innovation management theory, which offer promising frameworks to investigate the relationship between pre-innovation community experience and innovation success. One of the core premises in user innovation theory is that voluntary user communities are typically governed by a culture of free information sharing and general reciprocity, which enables users to share and collect information, feedback and even other members' work free of charge (Harhoff et al., 2003). We specifically argue that quantity, quality, and relatedness of pre-innovation community experience will positively shape users' likelihoods of being a successful first-time innovator. Further, the experience gained through other members' designs and feedback, will increase users' likelihoods to reuse this information and develop recombinant designs and to invest effort to also share their ideas in an appropriate manner, thereby achieving higher chances of innovation success.

We examine the relationship between pre-innovation community experience and innovation success in an online community context - more specifically, the largest community on 3D printing, Thingiverse. Communities on 3D printing are of particular interest to organizations as they combine the benefits of both off- and online communities. Similar to open source software communities, users in 3D printing communities exchange comments on other users' work, as well as share and further develop designs in the form of digital files (Kyriakou et al., 2017). Three-dimensional printing technology also allows generating physical objects as the digital files that function as blueprints for innovations, can be transformed into 3D, thereby providing enhanced space for innovation. The context of Thingiverse is particularly advantageous to explore the factors that enable and shape the first transition of becoming a successful innovator given that users' behavior prior, during and after the first innovation can be observed.

Our empirical findings offer important contributions to knowledge about the activities and experiences prior to innovating and the generation of successful innovation in community-based innovation systems. We identify two theoretical implications beyond those of existing research on the effects of pre-community experience on innovation and the importance of user communities for organizations (Franke et al., 2013, Von Krogh and Von Hippel, 2006). First, we identify a positive relationship between a user's collects, practices and comments and the chances for successful innovation as well as that quantity, quality and relatedness are key factors strengthening this relationship. In doing so, we show that the impact of community experience on innovation success depends on the extent to which individuals gather information as well as the type of information they receive. Second, we identify effort invested in the innovation and the use of recombinant innovations to be key mechanisms through which community experience relates to innovation success. Our research thereby highlights that although information and designs are freely revealed in communities (Hippel and Krogh, 2003), given the norm of general reciprocity in voluntary communities, the innovations of those users who invest more effort in sharing their own innovations and thereby supposedly increase their ease of use, and those who acknowledge and recombine other users' designs have higher innovation success.

## 2. Theory and hypotheses

In the traditional, producer-centered perspective, organizations represent the primary source of innovation (Schumpeter, 1934). Accordingly, innovation management research considers innovation success as organizations' successful launch of new products, services or business models and their sales in the market (Leiponen and Helfat, 2010).

In the user innovation perspective instead, innovation is created by users, e.g. products, services or more generally artifacts, that are novel and useful (Von Hippel, 1986, 1988, 2017). In this stream of research, scholars have conveyed the idea that innovation success relates to the diffusion of innovations. Diffusion occurs peer-to-peer such as when innovation is shared with others in a community (De Jong et al., 2015), from user to manufacturer (Baldwin et al., 2006), or, through an entrepreneurial venture (Shah and Tripsas, 2007). But because user innovators typically lack motivation or commercial interest to invest costs and effort to diffuse their innovations, innovations are often not adopted by others (de Jong et al., 2018). In other words, because many users do not innovate for commercial reasons but for self-rewards, e.g. for personal use, enjoyment or because they like to help others, their innovations are often not adopted (von Hippel, 2017).

This is particularly problematic, because innovations developed by users typically address important needs that cannot be fulfilled by manufacturers (Von Hippel, 1994, 1988). If shared with others, user innovations would be of high value to others as for example shown in household sector studies in Finland and Canada. In Finland, 61% of innovators estimated that their innovations would be valuable to some or many other users (De Jong et al., 2015); in Canada 85% of innovators expect their innovations to be valuable to others, at least in some specific aspects (De Jong, 2013). In extension of this self-reported approach, our study considers an innovation successful when *other* users verifiably demonstrate their appreciation of the innovation via positive feedback or innovation adoption (de Jong et al., 2018). The consideration of innovation as something valuable to others, i.e. when it passes social evaluation such as accepting, adopting or using an innovation, has long been a consideration in innovation research (Landau et al., 1986).

User innovation occurs in many sectors including sports equipment (Hienerth, 2006), juvenile products (Shah and Tripsas, 2007) or medical devices (Von Hippel, 1988). Not surprisingly, user innovations have the potential to increase social welfare (Gambardella et al., 2016). Because of the significance but challenging nature of becoming an innovator, scholars want to learn more about the factors associated with user innovation. Studies on innovators' characteristics have found that technical skills, educational background, age and gender are associated with being an innovator (Von Hippel et al., 2012). Other studies have also considered the social context in which users engage and found collaboration to be an important determinant of innovation and its diffusion (De Jong et al., 2015, Dahlander and Frederiksen, 2012).

To that end, several studies have demonstrated that collaborative environments such as communities have become a more and more important enabler of innovation, for both users and organizations. For example, collaboration in communities has been linked to innovation diffusion via new venture creation (Halbinger, 2018). Communities have successfully solved scientific problems for organizations (Jeppesen and Lakhani, 2010), developed sophisticated software products in peer-to-peer collaboration (Benkler and Nissenbaum, 2006) and even disrupted whole industries (Hienerth, 2006), while being at the same time more efficient innovators than producers (Hienerth et al., 2014). The strength of innovation processes of communities resides in the access to a diversity of information from comments, questions, and solutions of other community members to specific, ready-to use ideas and designs, typically free of charge.

These studies demonstrate that user communities facilitate important innovation-related outcomes. Yet, another stream of research shows that communities enable innovation-related support and assistance during the prototyping process (Franke and Shah, 2003) and share their work for others to (re-)use (Haefliger et al., 2008). Significantly less attention has been paid to how a user's experience with the community prior to innovating matters for innovation success by taking the actual mechanisms in this relationship into account.

We emphasize on understanding the role of community experience prior to innovating, i.e. how the experience collected in a user community prior to innovating promotes the success of the resulting innovation. The behavior of users in communities centers on production and distribution of information. We explore the mechanisms and factors related to information sharing that may shape the role of community experience on innovation success. In the following, we develop a theoretical framework on the relationship between community experience and innovation success by taking experience attributes and innovation choices into account, as illustrated in Figure 1.

----------------------- INSERT FIGURE 1 HERE ---------------------------

### 2.1. Pre-innovation community experience and innovation success

Interaction and experience in communities provides benefits for user innovation. Even successful innovators who have innovated alone are enabled by their affiliation to wider communities (Uzzi and Spiro, 2005). User communities typically evolve around common interests on hobbies, products, tools and practices. Members exchange information and ideas and provide feedback to one another (Franke and Shah, 2003). Yet, not all users in those communities innovate, let alone do so successfully. Typically only some users actively contribute to communities (Lakhani and von Hippel, 2003) and will thereby collect experience. We argue that collecting experience in communities prior to innovating will have beneficial effects for innovation development.

We consider three ways of collecting community experience: 1) via communication, 2) via accessing and learning about other members' work, and 3) by using other members' work.

The first form of community experience refers to participating in discussions on current topics and technologies, posting questions and solutions, sharing ideas and commenting on each other's work (Jeppesen and Laursen, 2009, Autio et al., 2013). Researchers have mainly considered this form of experience when investigating community experience and for example found that this form of experience shapes the type of projects users pursue (Foss et al., 2016).

But because new communication and design platforms allow for new forms of community interaction, community experience is no longer limited to communication in the sense of commenting and writing. Communities have features and technologies allowing users to visualize their ideas and engage in trial-error processes through virtual prototyping and experimenting (Thomke, 1998, D'Adderio, 2001). This implies first, that users have direct access to other users' work and second, that users can actually make use of these works and apply them for their own purposes – which in turn, represents success of the focal user's innovation as others start using it. In other words, users are not limited to collect community experience through communication only, but can also gather experience via collecting and employing other users' ideas and works.

The first two forms of experience, communication and accessing other members' work are important for innovation success because through the familiarization with and discussion of other community members' innovations, users get access to a variety of information. This includes information on other users' needs, their solutions to those problems and insights into new trends and technologies prevailing within and outside the community (Autio et al., 2013, Haefliger et al., 2008, Franke and Shah, 2003).

Accordingly, when users gain community experience prior to innovating, they have a better understanding of the community's preferences on design features and modules and learn what their peers consider functionally novel and useful. Sharing knowledge promotes the adoption and usage of innovation (Kogut and Zander, 1992, Gallivan, 2000), and user communities are no exception to that. Community experience provides information advantages and important innovation-related knowledge that users will apply when designing their own innovation. The result is innovation that is most likely appreciated and well-liked by others.

With the third form of experience, using other members' work, a new aspect comes into play: by trying out other members' designs, users gain important insights into *what* the design is and *how* to develop it. This aspect is important because users gain experience on both the outcome, the innovative design itself, and on the process of developing an innovation. This increases their chances of successfully transitioning from user to innovator as designers learn from one another and this will influence their subsequent actions (Baldwin et al., 2006).

All of the above will make individuals with community experience not just aware of potential opportunities for innovation but more importantly, enhances their chances to implement them as they gain insights on the development process as well. The experience with others in a community is also important as the innovation-inherent uncertainty is reduced (Autio et al., 2013). This is an essential aspect of community experience because it lowers the threshold to innovate, which is of particular relevance when users become innovators for the first time. Designing an innovation is costly, demands effort and it is highly uncertain how other users will react to it (Baldwin et al., 2006). When innovation-related ideas and information has been exchanged in the community before actually innovating, it is very likely that this also conducive for increasing its adoption afterwards (de Jong et al., 2018). Thus we hypothesize:

*H1: Pre-innovation community experience is positively associated with innovation success.*

### 2.2. Attributes of community experience: The moderating role of quantity, quality and relatedness

Not all experiences are equal. While some users are actively working with their communities, which enables them to gain insights from their peers' designs, others may visit the community just to copy other members' work and leave the community once they have achieved their goal (Hippel and Krogh, 2003). Not surprisingly, users' innovations vary in terms of success, most likely because the innovation designs developed are made on the basis of varying degrees of experience, including the extent to which users have gathered community experience, the value thereof, as well as how relevant the experience is with regards to the first innovation that they develop subsequently.

These aspects of the experience gathered by a potential innovator refer on the one hand to the quantity, the sheer amount of experience that an individual gathers through a series of events in a given time period, and on the other hand to the quality of experience, that is the degree to which an innovation that a user encounters has received high ratings and acceptance. Apart from that, relatedness, the degree to which an innovation is relevant and related to the focal innovation is an important aspect.

*Quantity of community experience.* The extent to which users collect experiences, i.e. the quantity, is important because when individuals accumulate experience in a series of events, they improve their performance referring to an experience curve effect (Ellis, 1965, Harlow, 1949). Conceptually, this is closely related to learning curve effects as each repetition offers an opportunity to learn with diminishing returns over time (Yelle, 1979). When individuals work on tasks repeatedly, they become more efficient and effective every time they engage in it. At the same time, they gather more information relevant for the task at hand, which is particularly important for successfully developing an innovation for the first time as innovation-related activities are inherently uncertain. For example, researchers have shown that inventors develop patents of higher value when they repeatedly engage in collaboration with others (Breschi and Lenzi, 2016, Samila and Sorenson, 2017). Arguably, the more often users engage and familiarize themselves with the developments existing in the community, the better they get in understanding what is appreciated by others in the community. When gathering more and more information on other users' work they increase their knowledge pool that they can access when developing their own innovation. By doing so, they increase chances of success because of the sheer amount of information that they have on other users' preferences regarding functionality, design features and gaps in the market. This can serve as a basis of inspiration and knowledge for their own innovation.

Further, more experience makes individuals better in using equipment to address needs, and thus better in solving a task. Learning derived from experience occurs in iterative, dynamic ways (March, 2010). In that vein, users equipped with toolkits were enabled to learn about preferences via iterations of the innovation design process until the optimal innovation outcome was reached (Von Hippel and Katz, 2002). This indicates that the amount of individuals' experience may have a conducive effect given the sheer scope of the knowledge base they can draw on for innovation. In other words, the bigger the pool of information on other users' developments, comments and insights that users earn in experiencing the community pre-innovation, the higher are chances to develop an innovation that matches needs and preferences and thus, is valued and adopted by others. Thus we hypothesize:

*H2a: The relationship between pre-innovation community experience and innovation success is positively moderated by the quantity of pre-innovation community experience.*

*Quality of community experience.* Yet, not every community experience is equally helpful for innovation success. We expect that specifically high quality experience will enhance the effect of pre-innovation community experience on innovation success. This is because high quality innovations developed by users who are ahead of a trend have been shown to be of extraordinary value. Their innovations address user needs that are to date unmet, i.e. no market offering is existing in the market and thus, these innovation have high market value (Lilien et al., 2002, Von Hippel, 1986). Notably, these innovations exist in a variety of communities (Autio et al., 2013, Jeppesen and Laursen, 2009).

Information about these valuable innovations will positively bias users before they become innovators themselves. First, they receive advanced insights on relevant user needs that have potential to successfully develop into a new market or industry. The kayak surfing industry for example, had its origin in developments by highly advanced users referred to as lead users (Hienerth, 2006). Second, because these users are typically technically skilled, their innovations and design functionalities are relatively sophisticated. Thus, experiencing those developments before becoming an innovator is conducive to developing equally or even more advanced designs. Third, because of the high levels of technical sophistication, these innovations will inform users in the community about the (high) standards of manufacturing in terms of what is considered well designed and aesthetically pleasing to others.

Experience with other users' high-quality innovations will allow the focal user to draw on high-quality information that will provide the basis from which she will start innovating. Accordingly, if other users in a community engage with these high-end designs, they will get a better understanding of up-to-date technologies and needs in the market, resulting in a beneficial effect of community experience on innovation success. Thus, we hypothesize:

*H2b: The relationship between pre-innovation community experience and innovation success is positively moderated by the quality of pre-innovation community experience.*

*Relatedness of community experience.* A third attribute that we expect to enhance the relationship between pre-innovation community experience and innovation success is the relatedness of the experience and the focal innovation. As stated by Nonaka (1994), innovation sparks a related flow of information and knowledge creation, prompting a "sequence of innovations" in the wider innovation system. Further, related innovation "artifacts" provide a common basis from which individuals can economically manage their efforts and attention in problem-solving activities (Carlile, 2002), suggesting benefits for subsequent innovation development. This leads to the assumption that in community-based innovation systems, experiencing other members' innovation prior to innovating may be more advantageous for related innovation developments. For example, in free open-source software communities, members who earned experience with their community and communicated with other members on a specific topic, pursued also projects in that area, allowing them to effectively work on sub-problems within that field (Foss et al., 2016). The prior experience with the community creates a form of bias inducing individuals to follow related paths (Simon, 1973) and this in turn, allows individuals realizing increasing returns from innovating in a related domain. This suggests that if experience is earned in a related domain, learning effects are likely higher and innovations more successful.

Users who focus on related domains when communicating with their community and collecting information, can be expected to develop expert knowledge in that area. Presumably, they develop a deeper understanding of the designs and technologies used in that domain, making them better innovators. They will gain a better understanding of user needs and aesthetics in that domain as well as what is considered technologically valuable. This will enable them to generate an innovation that is more tailored to current demands – an aspect that will likely increase the chances of developing an innovation that is valuable to others. For example, in special interest groups, information that is more related to the focal individual's domain is more valuable for developing an innovation than information received outside that domain (Franke and Shah, 2003).

Finally, the costs of transferring experience from one domain to a related domain are decreasing with proximity. Thus, because individuals with much experience in a special area can be expected to have increasing returns from innovating in a related domain, we hypothesize:

*H2c: The relationship between pre-innovation community experience and innovation success is positively moderated by the relatedness of pre-innovation community experience.*

### 2.3. Innovation choices: The mediating role of effort invested and recombinant innovation

We expect that community experience is associated with innovation choices (choices regarding how and what to innovate) and that these choices will matter for innovation success. For example, because experience equips individuals with cognitive frameworks that are substantially different from those of individuals without the experience, the business opportunities that experienced individuals develop are different with respect to the process of development and opportunity type (Baron and Ensley, 2006). Accordingly, the experience that users collect in the community will affect their choices related to both innovation process and outcomes. Experiencing how much effort others invest in the process of developing and sharing their innovations will be important for users when deciding how to develop their own innovations. Similarly, the existing innovation projects may spark ideas to use (parts of) existing innovations to create their own innovative projects. In other words, the pre-innovation community experience will function as templates for innovation type and process.

On the one hand, these templates may be used subconsciously. Users may follow other users' approach of innovating and use parts of their innovation projects without realizing. Yet, this may help them to successfully develop an innovation. On the other hand, they may consciously observe what other members in the community do and are able to identify success factors. Either way, successful innovation would entail first, usability, that is investing effort to increase ease of use, because ease of use has been linked to diffusion and adoption (Rogers, 2003). Second, besides usability, successful innovation also incorporates the aspect of novelty (von Hippel, 2017), or the combination of existing resources (Schumpeter, 1942), recombinant innovation.

*Effort invested.* Users engaging in a community typically face a culture of free revealing, i.e. users share their innovations with others in the community for free (Harhoff et al., 2003). The scale and scope of this phenomenon is well documented. Detailed studies on open-source software communities (Raymond, 1999, Von Krogh and Von Hippel, 2006) or sports equipment communities (Hienerth, 2006) have shown that users share innovation-related information, advice and fully developed designs for free. More generally, in network-based innovation systems members are inspired to share their developments with other members of the network as they expect to receive valuable information in return (Ryall and Sorenson, 2007, Van der Vegt et al., 2006). This is because communities are typically ruled by a norm of general reciprocity, an expectation, that if a user shares information, the favor will be returned, i.e. others will also reveal their innovations and support, comment and further enhance other users' work (von Hippel, 2017).

To be consistent with others' behavior and to follow the norm of reciprocity triggers individuals wanting to make sure to be aligned and inform their peers in the best possible way (Cialdini, 2001). In other words, others will invest effort and time to share their work with the community and will do their best to make it accessible and understandable for others. This will be appreciated by the community and may prompt the shared innovations to be more successful. This is because when users have interacted with their community, they have a tendency to invest effort and give back to the community (de Jong et al., 2018).

Prior community experience thus serves as a template and will lead users to follow other users' example when developing their innovation. The effort invested will in turn act as a vehicle for increased innovation success because more users will be able to understand, appreciate and further enhance the shared innovation. Ease of use typically attracts users to further adopt designs (Fogliatto et al., 2012). Thus, we hypothesize:

*H3a: The relationship between pre-innovation community experience and innovation success is positively mediated by effort invested in the innovation.*

*Recombinant innovation*. Researchers from various disciplines have considered experience to be core for the recombination of knowledge (Argote, 1999, Shane and Venkataraman 2000). At the same time, knowledge recombination has been seen as essential for innovation (Schumpeter, 1942, Henderson and Clark, 1990). Researchers have argued that innovative ideas are the result of combining previously unconnected information pieces stemming from various experiences such as user demands, technology trends and market developments (Baron, 2006, Baron and Ensley, 2006). In turn, knowledge combination is an important source for innovation success (Hargadon and Sutton, 1997, Hsu and Lim, 2008) and competitive advantage (Grant, 1996).

Accordingly, we expect community experience to be linked with innovation that is based on recombination, i.e. recombinant innovation, which in turn will relate to innovation success. Recombinant innovation occurs based on spillover effects that are typical in communities (Harhoff et al., 2003). Users in a community see what others are doing and consciously or subconsciously, this experience serves as a template for their choice as to how to develop their innovation project.

The experience users gain from looking at, experimenting and working with other users' innovations will bias them to using and combining design pieces into a new, recombinant innovation. For example in software development, reusing code is a common practice and core to innovation (Haefliger et al., 2008). Similarly, in 3D communities where users work with digital artifacts, they typically reuse "models" for innovation (Kyriakou et al., 2017). In other words, users recombine pieces of existing designs in a new way. For organizations, this is a common approach to achieve innovation success (Leiponen and Helfat, 2010).

In the community context, we expect this innovation choice to be conducive for innovation success. First, if an individual user combines parts of innovation projects from other users, she can build on existing knowledge and user bases and synthesize insights. This will enable her to not just use the existing information on the innovation itself, but also to focus and follow up in depth on (subsequently) discovered user needs and technologies. In other words, she can build on the knowledge and innovation of other users and subsequently refine and integrate these information pieces in her project. The feedback that the prior innovations received in the community will provide the focal individual with a better understanding of what might be desired and well-liked in the community enabling successful innovation. Moreover, when innovation is combined, the sheer amount of users following the innovation are most likely higher given that two or more project domains have been united into a new one.

Lastly, if the focal user builds on existing innovations, recombinant innovations are less uncertain, effortful and costly. Experience with other users' work will prompt the focal individual to understand relatively fast what is required in the community, allowing her to quickly address the needs in the community. Being ahead with their innovations will provide them with an advantage in the sense that many in the community will be interested in the innovation and adopt it. Thus, we hypothesize:

*H3b: The relationship between pre-innovation community experience and innovation success is positively mediated by recombinant innovation.*

## 3. Empirical setting

### 3.1. The 3D printing community Thingiverse

We test our hypotheses in the context of the online community of the Thingiverse platform, a website for user generated content on open source hardware designs. Members of the Thingiverse community create and share digital design files primarily related to 3D printing for free. Three-dimensional printing is a computer controlled process in which digital files are transformed into physical objects (Kyriakou et al., 2017). Because the community provides free access to designs, ideas and information on user needs and technological trends as well as promotes support and assistance among users via discussion forums and posts, the community is widely accepted by makers and the wider "do-it-yourself" community of household sector innovators.

Besides its wide usage, the context of the Thingiverse community is particularly beneficial for our investigation because individuals join the community on a voluntary basis. Since users decide how much time they want to invest on the various activities (e.g. commenting, collecting, copying or modifying designs), the community contains users with varying scale and scope of community experience. This means they vary in the extent and depth in which they interact with other members and their innovations.

Further, this practice produces variety among members, allowing us to observe those individuals who are "just" users, those who directly innovate without collecting any community experience, and those who first collect community experience and then become innovators. The core advantage of this setting is that it allows observation of activities in chronological order, that is, we observe individuals' activities in a line of sequence, thereby allowing us to investigate the effect of pre-innovation community experience on innovation success. Although many user innovation scholars have demonstrated the importance of communities in user innovation, most studies do not allow for this chronological investigation (Franke and Shah, 2003). Further, they typically focus in their final sample on innovators only (De Jong et al., 2015) thereby not providing a clear distinction between when and how the experience gathered within the community occurred in the user's innovation process.

### 3.2. Data and variable description

We obtained all 1,086,989 3D models that have been uploaded to Thingiverse the platform until June 14th, 2018 and profiles of 702,924 users that have registered on the platform and for which we observed activity. The 3D models uploaded on Thingiverse are called things and we will be using this notation in the following.

As this paper focuses on the role of pre-innovation community experience, we track user behavior from the time the user registers their account until the time of the first user innovation. We define innovations as the uploading of unique new things on the platform and do not consider customizations (Kyriakou et al. 2017) as innovations as these are just minor adaptions of existing designs such as changes in the length of an object. Overall, we observe 146,301 users that have created at least one thing on Thingiverse. For these users, we observe both their pre-innovation community experience, i.e. all observable activities on Thingiverse from the time of registration until the upload of the first thing, as well as success measures and characteristics of their first innovation. One observation in our dataset therefore captures the pre-innovation period as well as the first innovation for all users that eventually innovate. Variables definitions and summary statistics are reported in Table 1 and Table 2 shows pairwise correlations.

----------------------- INSERT TABLE 1 AND TABLE 2 HERE -----------------------

We construct three kinds of variables: measures of innovation success, variables measuring pre-innovation experience and observable characteristics of the innovations.

### *3.2.1 Success measures*

Thingiverse reports a wide range of success measures for each thing. *Views* is the cumulative number of users that visited a thing's website on the Thingiverse platform and *Downloads* measures how often the files of the 3D model have been downloaded. In contrast to many other platforms, Thingiverse is relatively open in that viewing and downloading of things does not require registration, but all following success measures require registration. Similar to social media platforms, you can like a thing and *Likes* measures the total number of likes a thing got. If users want to bookmark things, they can add them to individual collections and *Collects* is the cumulative number a thing has been added to user collections. If users decide to make a copy of a thing by printing it on a 3D printer, they can share the outcome on the thing's site and *Copies* counts the number of times a report of a copy has been created. Finally, users can also create recombinant innovations by using one or more existing things as a basis for their own innovations and *Derivatives* counts the number of times a thing has been used in follow-up innovations.

All success measures are count measures and as success is highly dispersed, we take the logarithm. To ensure that things for which success measures take the value 0 are not dropped because of the non-defined logarithm of 0, we always add 1 before taking the logarithm. We only observe the value of success measures at the time of the crawl, which favors older things as they had more time to attract attention and generate success. In all regressions for which the dependent variable is one of the measures of innovation success, we therefore control for the linear and squared term of the days since a thing has been posted as well as the release year, the release month and the weekday of the release.

In addition to these specific measures of innovation success, we also generate a joint measure of innovation success. To do this, we first standardize each of the six success measures discussed above by subtracting their mean and dividing by their standard deviation and then take the mean of these standardized values to generate the variable *InnovationSuccess*.

### *3.2.2 Measures of pre-innovation community experience*

We are also able to observe multiple ways in which individuals engage with the Thingiverse community before publishing their first innovation.

First, users on Thingiverse are able to create individual collections to which they can add things that are of interest to them. We create the dummy variable *CollectExp* that takes the value one if a user added things to collections after signing up on Thingiverse and before publishing their first own thing. We expect that exploring other designs can be a key learning mechanism for creating your own things. Other items can serve as a source of inspiration and given that success measures for each thing are prominently displayed, users can also infer what kind of design characteristics could increase the success of their own innovations.

Second, we construct the dummy variable *CopyExp* that measures if a user created a print of an existing thing and shared their results with the community. Printing objects on 3D printers is far more challenging than printing on a regular printer and many prints initially fail. This is as 3D printers need to be calibrated precisely to achieve satisfactory results, because 3D printers are far from standardized and users need to gather experience to operate them successfully, and because the choice of the printing material also greatly influences results. By experiencing these challenges themselves, users can gain valuable knowledge for creating their own models. Important insights could be to experience which kind of geometries work well and what are minimum size thresholds.

A third way to engage with the community is to engage in discussions with other community members. The dummy variable *CommentExp* takes the value one if a user has been writing a comment in the discussion forums that are attached to each thing and to each make of a thing. As creating new 3D models can be a highly complex task, engaging in discussions with other community members can be a promising channel to acquire new knowledge that can then be directly applied in own innovation efforts.

On top of these specific measures of pre-innovation community, we also create *PreInnoExp* as a joint measure of pre-innovation community experience that takes the value of one if the user experienced at least one of the three types of pre-innovation community experiences.

While we have so far operationalized pre-innovation community experience as a dummy variable, we do now want to disentangle community experience into the three components quantity, quality, and relatedness.

First, we count the number of times a user has gathered pre-innovation community experience and create the variable *PreInnoExpQuantitiy*. As the quantity of pre-innovation community experience is highly dispersed, we measure it as the logarithm of the number of pre-innovation experiences (we add one to avoid losing observations without pre-innovation community experience).

Second, we want to measure the average quality of the 3D objects through which the pre-innovation community experience has been made. This is possible as the kinds of community experience that we introduced above are always linked to a specific 3D object on the platform. We therefore create the variable *PreInnoExpQuality* as follows. First, we run six regressions, in which we regress the six measures of innovation success on the linear and squared term of the days since a thing has been posted as well as the release year, release month and the weekday of the release. We then take the residuals from these regressions, standardize them by subtracting their mean and dividing by their standard deviation, and generate the variable by taking the mean of these six standardized success measures.

Third, we create the variable *PreInnoExpRelatedness* to measure the relatedness of pre-innovation community experience. We create a relatedness measure by comparing the category of the focal innovation with the categories of the things through which the pre-innovation community experience was collected. The most basic approach would be to check if any of the prior experience falls in the same category as the focal category, but this is problematic if you have a lot of categories (in our case 80), as only experience in the focal category counts and all other experience is treated as unrelated. We use the following approach to create a continuous relatedness measure. We start by generating a vector for each user, where one column represents the experience in each of the N categories. We then calculate pairwise correlations between all categories, which results in an NxN matrix. Higher values in this matrix indicate that more users are co-engaging in the two categories. We then calculate relatedness as the weighted sum of all prior experiences.

### *3.2.3 Measures for innovation characteristics*

For our third research question, we are interested in identifying innovation characteristics that could mediate the relationship between pre-innovation community experience and innovation success. We would observe a mediation effect if pre-innovation community experience is associated with changes in the use of certain innovation characteristics, if these innovation characteristics in turn affect innovation success, and if the association between pre-innovation community experience and innovation success becomes weaker once we control for these innovation characteristics. We identify two possible ways how the mediation could work: through effort invested and through recombinant innovations.

Recombinant innovations are innovations that are built on the base of existing innovations. This kind of innovation might be a powerful way to re-use elements from successful innovations instead of starting the search process for an innovative design from scratch. We create the dummy variable *RecombinantInnovation* that equals one if the creator of the thing lists at least one existing thing as an ancestor. We think that pre-innovation community experience can increase the use of recombinant innovations as users that engage more before their own innovation get to know more other innovations and are therefore more likely to find innovations that are a useful base for their own innovation. But they should also be more likely to find out that many successful innovations are recombinant innovations as this is displayed prominently on Thingiverse and might therefore invest more effort in searching for existing innovations as a base for their own innovation.

Effort invested is operationalized with the variable *DescriptionLength,* which measures the logarithm of the number of characters for a thing's description. This measure should be a good proxy for effort as it is more work to write a longer description of your innovation. In addition, this measure could not only reflect more effort invested in writing about a project, but also more effort invested in developing the thing itself. If you develop a more complex project, you are also more likely to also write a longer description. We again believe that pre-community experience can trigger users to invest more effort in their innovations. First, if users interact more with their community and see more thing descriptions, they will start valuing more complete information about projects and will become more likely to reciprocate by investing more into the writing about their own innovation. Similarly, more engaged users will see many ideas, which makes it likely that they will not just reinvent another basic thing, but will go for greater challenges and work on more complex and also more promising projects.

#### *3.2.4 Control variables*

Finally, we introduce the control variables. First, we use the variable *DaysToInnovation* to capture the logarithm of the number of days between a user's registration on Thingiverse and the day when the first innovation was uploaded. This variable should proxy for forms of user activity that are unobserved by us but vary with the time spent on the platform. This could for example be learning from viewing or downloading things or direct messages exchanged with creators of things. Second, the choice of license is also an innovation characteristic that could be associated with innovation success. We consider two characteristics of licenses: *NonCommercialInnovation* is a dummy variable equal to one if the license prohibits commercial use of the innovation and *OpenLicense* a dummy equal to one if the license can be used without any restrictions.

In addition to the control variables that are explicitly reported in the regression results, we also control for fixed effects on the level of the 80 different categories available on Thingiverse and on the level of the thing's release year, release month, and the weekday of the release. These fixed effects are helpful to account for between-category and between-year differences in overall innovation success. Finally, as we already mentioned in section 3.2.1, in all innovation success regressions, we control for the linear and square term of days since the thing was first posted to control for different exposure lengths that things have had.

### 3.3. Estimation approach

As we already explained in section 3.2, one observation in our dataset captures a user's pre-innovation period as well as the success of her first innovation. In all models except one mediation test, our dependent variables will be different measures of innovation success and our main independent variables will be different measures of pre-innovation community experience.

In this paper we are interested in identifying the effect of pre-innovation experience on the subsequent success of the first innovation. One key advantage for identification is that we do not have selection problems stemming from prior performance feedback as we are examining the performance of the first innovation. If we would also include the success of follow-up innovations, it would be likely that those who perform better in their first innovation would be encouraged by their success and would be more likely to release follow-up innovations than those that did not do well with their first innovation.

One concern for identification is that unobserved quality of innovators could influence both pre-innovation community experience and innovation success and we would therefore have an omitted variable bias. The bias could work in two ways. First, worse innovators could need more help from the community and would therefore collect more pre-innovation experience before being able to launch their first innovation. Lower innovator quality would therefore lead to more pre-innovation experience and lower innovation quality and effects would therefore be underestimated. Second, better innovators could also have lower costs to engage with the community. Higher innovator quality would then lead to more pre-innovation experience and to higher innovation quality and our effects would therefore be underestimated. As we do not know if any of the two potential effects exists and which of those effects dominates, we are conservative in not claiming evidence for a causal link between pre-innovation community experience and innovation success.

For three reasons, we are optimistic that our findings are still informative. First, we control for cohort-based differences in innovator quality by controlling for release year, release month, and weekday fixed effects. Second, we examine the relationship between pre-innovation community experience for all combinations of six different measures of innovation success and three different measures of pre-innovation community experience plus index measures for innovation success and pre-innovation community engagement. Third, we do not only consider the direct effects of pre-innovation community experience on innovation success but also the mediating role of quantity, quality, and relatedness of experience as well as the mediating role of two innovation characteristics. We would expect that the potential biases would be less pronounced for these indirect effects.

## 4. Results

We conduct three different sets of analyses to explore the relationship between pre-innovation community experience and innovation success. As a baseline, we establish a generally strong and positive correlation between pre-innovation community experience and innovation success. We then show, that this relationship is driven by the quantity, quality and relatedness of pre-innovation community experience. Finally, we show that pre-innovation community experience is associated with more effort invested in innovations and more use of recombinant innovation and that these innovation characteristics act as mediators for the relationship between pre-innovation community experience and innovation success.

### 4.1. The relationship between pre-innovation community experience and innovation success

We test our first hypothesis on the expected positive relationship between pre-innovation community experience and innovation success with the models presented in Table 3. In columns (1) to (6), we use the six different measures of innovation success as dependent variables and resort to the joint measure of innovation success in columns (7) and (8). We measure pre-innovation community experience in columns (1) to (7) by adding the three dummy variables for experience regarding collection of things, creating copies of things, and commenting on things and in column (8) by using the joint measure for all three types of pre-innovation experience. We also control in all models for the days between the registration of the user and their first innovation, the license type (non-commercial and open), linear and squared term of the days since a thing has been posted, as well as category, release year, release month, and release day fixed effects.

----------------------- INSERT TABLE 3 HERE -----------------------

Our results provide strong support for hypothesis 1. Nearly all measures of pre-innovation community experience are positive and significant, with the only exemption being the insignificant coefficient for comment experience in model (5). The coefficients are also economically meaningful. As the dependent variable in models (1) to (6) is the logarithm of the success measures, and the measures of pre-innovation experience are dummy variables, we can approximately interpret the coefficients as percentage changes in the dependent variable if the experience dummy turns one. The precise interpretation would be that the percentage change equals $100 \times (\exp(coefficient) - 1)$, so the relationship between collect experience and views in column (1) would for example be 21.5%. The largest relationship are the 34.3% between collect experience and number of collects in column (4) and the smallest one the 5.3% relationship between comment experience and the number of downloads in column (2). It is interesting to note that the effect sizes for views, downloads, likes, and collects are larger than the effect sizes for copies and derivatives. When we collapse the different success measures into one success index in column (7), we can observe that the relative effect sizes are higher for collect experience, lowest for comment experience, and intermediate for copy experience. We finally also aggregate all measures of experience in column (8) and find again a positive and significant relationship.

When we look at the control variables, the results for days between the registration of the user and their first innovation are inconsistent, with coefficients ranging from negative and significant to positive and significant. Both non-commercial as well as open licenses show generally positive and significant effects. The positive effects for non-commercial licenses might at first look puzzling as this type of license restricts usage in that it does not allow commercial use. But it can be explained by users protecting their better innovations stronger as they might like to keep their own options for commercialization open and as they might not want others to freeride on their own innovations.

### 4.2. Mechanisms of pre-innovation community experience

In our second hypothesis, we expect that the positive relationship between pre-innovation community experiences is positively moderated by the quantity, quality, and relatedness of pre-innovation community experience. We test this hypothesis in model (2) of Table 4. From now on, we will only report results for the joint measures of innovation success and for pre-innovation experience, but results remain consistent if we run the disaggregated models. In model (2), we add quantity, quality, and relatedness of the pre-innovation community experience to the baseline model from column (1) that repeats model (8) from Table 3.

----------------------- INSERT TABLE 4 HERE -----------------------

We find strong support for hypothesis 2 as the coefficients for the quantity, quality, and relatedness of pre-innovation community experience are all positive and significant. While the success index as the dependent variable does not allow a direct interpretation in terms of economic significance, we can compare the relative magnitude of the effects by multiplying the coefficients with the standard deviations of the respective variables. Doing this, we get a value of 0.084 for relatedness, 0.076 for quality, and 0.035 for quantity. Therefore, relatedness and quality of pre-innovation community experience seem to be the strongest predictors for innovation success.

### 4.3. The mediating role of innovation characteristics

In our third hypothesis, we expect that effort invested in the innovation and the use of recombinant innovations mediate the relationship between pre-innovation community experience and innovation success. To find support for this hypothesis, three necessary conditions have to be fulfilled: we need a positive relationship between pre-innovation community experience and the use of the innovation characteristics, the innovation characteristics have to be associated positively with innovation success, and the relationship between pre-innovation community experience and innovation success has to become weaker once we control for the innovation characteristics.

We start by examining the first condition, i.e. if pre-innovation community experience is positively related with longer description lengths and the creation of recombinant innovations. We test these relationships in Table 5. In models (1) and (2) our dependent variable is description length and in models (3) and (4) we substitute it with the use of a recombinant innovation. In models (1) and (3), we look at the base effect of pre-innovation community experience, while we add quantity, quality, and relatedness of pre-innovation experience in models (2) and (4).

----------------------- INSERT TABLE 5 HERE ---------------------------

Our results show that pre-innovation community experience has indeed a positive and significant relationship with the innovation characteristics. Having pre-innovation experience is associated with a 36.5% longer description and with an 8.9% higher probability that the innovation is building on existing innovations. Quantity, quality, and relatedness of pre-innovation community experience show also a positive and significant relationship with the innovation characteristics, except the insignificant coefficient for the relationship between quality and recombinant innovation in model (4).

Next, we have to check if the innovation characteristics are positively related with innovation success. To do this, we go back to Table 4, where model (3) and (4) are including the description length and the use of a recombinant innovation. All coefficients are positive and significant, i.e. these innovation characteristics are positively associated with innovation success. The second necessary condition for our mediation hypothesis is therefore also confirmed.

Finally, we check if the relationship between pre-innovation community experience and innovation success is weakened once we control for innovation characteristics. Comparing the coefficients for pre-innovation community experience in models (1) and (3) in Table 4, we see that the effect size in model (3) becomes 37.1% smaller. Similarly, if we compare the coefficients for quantity, quality, and relatedness of pre-innovation community experience between model (2) and (4), we see that the effect sizes went down by 12.7% (quality), 29.3% (relatedness), and 60.8% (quantity). The third condition for our mediation hypothesis is therefore also fulfilled.

As all necessary conditions for the mediating role of description length and recombinant innovations are fulfilled, we find strong support for our third hypothesis. The type of mediation is a partly mediation and not a full mediation, as we still find a positive (but reduced) and significant relationship between pre-innovation community experience and innovation success.

## 5. Discussion and conclusion

This study demonstrates that pre-innovation community experience matters for innovation success and the underlying mechanisms that shape this relationship. First, our findings have important implications for scholars in user innovation research. Research has shown that user innovators receive important information in voluntary communities (Franke and Shah, 2003). Central to this research is on the one hand examining the likelihoods of being an innovator based on individual characteristics such as technical skills, gender and age (Von Hippel et al., 2012). On the other hand, given that individuals are already innovators, this research examines the factors that promote the diffusion and adoption of their innovations by particularly highlighting the supportive role of the community (De Jong et al., 2015, de Jong et al., 2018). In sum, this literature has documented first, the attributes linked to user innovation and second, that users share information and innovative developments in communities for free thereby promoting adoption. Our study contributes to this research as it considers the role of community experience *prior* the transition from user to innovator. This is important as becoming an innovator entails risks (Baldwin et al., 2006) and the initial identification of an innovative opportunity is difficult (Baron and Ensley, 2006). As a consequence, innovation often fails and many users never innovate (von Hippel, 2017).

Our first important finding is that collecting experience from the community prior to innovating is beneficial for innovation success. We elaborate on this finding and further identify that the more community experience a user earns, that is the more a user collects, practices and comments on other members' work, the higher the chances for successful innovation. Further, we find quality and relatedness of experience to be key factors to strengthen the effect of community experience on innovation success. We show that the impact of community experience on innovation success depends on the extent to which individuals gather information as well as the type of information received. Finally, we identify effort invested in the innovation and use of recombinant innovation as key mechanisms through which community experience relates to innovation success. Our research thereby highlights that although information and designs are freely revealed in communities (Hippel and Krogh, 2003), given the norm of general reciprocity in voluntary communities, the innovations of those users who invest effort in sharing their own innovations and thereby supposedly increase their ease of use, and those who acknowledge and recombine other users' designs, have higher innovation success.

Second, our findings also speak to organizational scholars interested in innovation management supported by communities. Researchers have argued that overall economic and social benefits could be increased if users and producers would collaborate by complementing one another in their innovation endeavors (Gambardella et al., 2016). To date, researchers have highlighted that open source software communities are particularly appropriate to offer the best for 'both worlds' because code can be easily shared, duplicated, amended and further developed online (Hippel and Krogh, 2003). But because communication and design tools are becoming increasing digitized and powerful, we believe that this effect is no longer just limited to software communities, but also applies to communities dealing with physical objects.

Digital technologies have enabled communities to collaborate increasingly through online platforms and work on projects that go beyond software. Powerful design tools allow locally dispersed individuals to virtually prototype by using advanced software technologies (D'Adderio, 2001) and facilitate innovation-related information transfers (Vaccaro et al., 2009). This has major benefits for any organization interested in enhancing its innovation potential as the range and possibilities of collaboration opportunities with communities are expanded with tools and infrastructures that allow new forms of collaboration. On the one hand, a community that generates successful innovations can fuel an organization's innovation pipeline. This represents a major benefit in markets that have become increasingly competitive and dynamic. User communities and internet-based platforms provide effectively and efficiently access to the innovations that their users develop. On the other hand, when a community produces successful innovation, it will retain and attract more users – a relevant aspect for organizations to increase their installed base of users of their products. User communities generate complementary assets to organizations' market offerings, which is important to increase their customer base (Dahlander and Wallin, 2006, Dahlander and Magnusson, 2005). Furthermore, communities attract more users when the innovations developed in their community are well-received and valuable to other users. Thus, when communities are able to produce successful innovations, their customer base and platform traffic most likely will increase. This in turn is interesting from the perspective of advertising-based markets as this offers new business models for organizations to "skim off profit".

Finally, because of the collaborative nature of innovation processes in user communities (Dahlander and Frederiksen, 2012), they present a novel and successful alternative to concentrated innovation models in organizations since they are highly informative as to how organizations should develop innovations and organize their processes (Hippel and Krogh, 2003). To that end, because our study demonstrates the importance of gaining experience in the community, this matters also to communities and platforms with user generated content such as Wikipedia and YouTube.

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**Figures and tables**

**Figure 1: Effects of pre-innovation community experience**

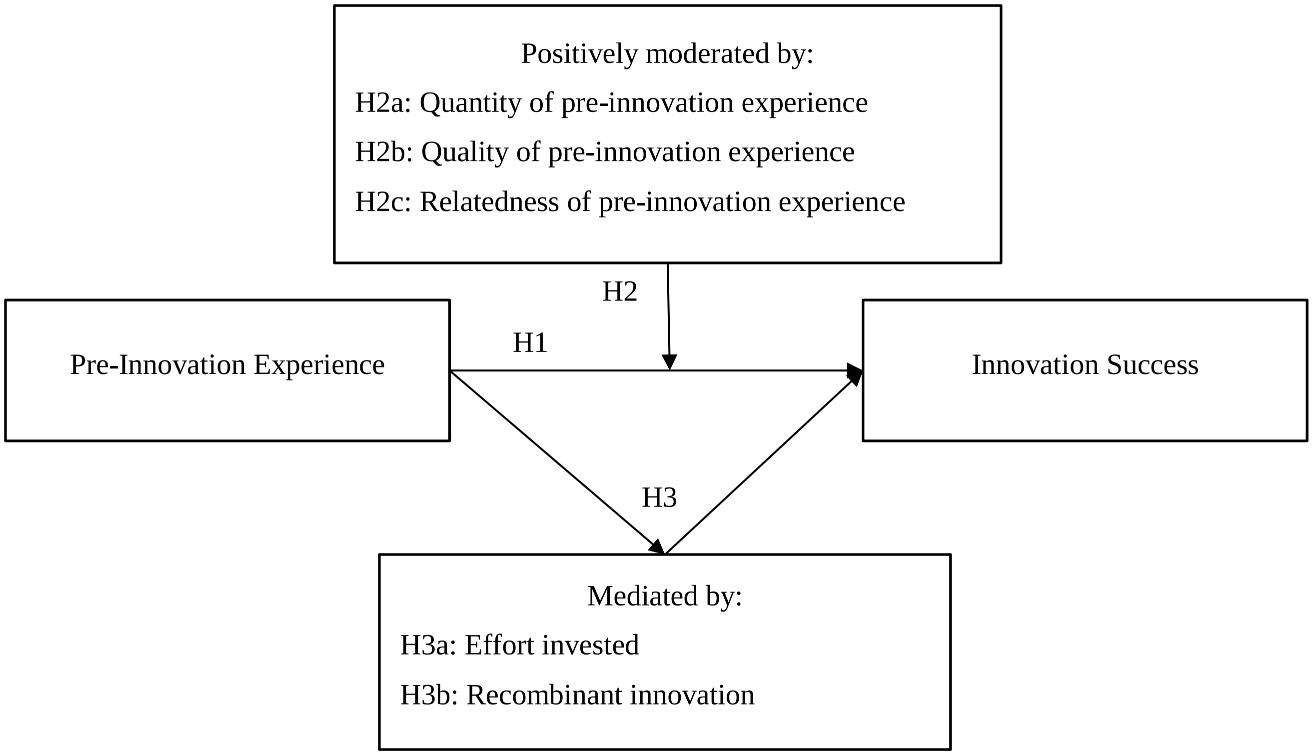

**Table 1: Variable definitions and summary statistics**

| Variable | Definition | Dummy | Logarithm | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|---|
| *Innovation Success* | | | | | | | |
| Views | Number of views of thing | | X (+1) | 5.95 | 1.61 | 0.69 | 13.62 |
| Downloads | Number of downloads of thing | | X (+1) | 4.79 | 1.38 | 0 | 12.52 |
| Likes | Number of likes of thing | | X (+1) | 1.93 | 1.42 | 0 | 10.05 |
| Collects | Number of collects of thing | | X (+1) | 2.13 | 1.52 | 0 | 10.13 |
| Copies | Number of copies of thing | | X (+1) | 0.18 | 0.49 | 0 | 7.23 |
| Derivatives | Number of derivatives of thing | | X (+1) | 0.09 | 0.33 | 0 | 3.43 |
| SuccessIndex | Mean of the standardized values of the six variables above | | | -0.09 | 0.78 | -1.64 | 6.74 |
| *Pre-Innovation Experience* | | | | | | | |
| CollectExp | At least one thing added to collection before release of first thing | X | | 0.53 | 0.50 | 0 | 1 |
| CopyExp | At least one thing printed before release of first thing | X | | 0.17 | 0.38 | 0 | 1 |
| CommentExp | At least one comment made before release of first thing | X | | 0.19 | 0.40 | 0 | 1 |
| PreInnoExp | At least one pre-innovation experience before release of first thing | X | | 0.61 | 0.49 | 0 | 1 |
| *Attributes of Experience* | | | | | | | |
| PreInnoExpQuantity | Number of pre-innovation experiences | | X (+1) | 1.75 | 1.91 | 0 | 9.61 |
| PreInnoExpQuality | Average quality of pre-innovation experiences | | | 1.44 | 1.49 | -1.57 | 7.21 |
| PreInnoExpRelatedness | Average relatedness of pre-innovation experiences | | | 0.34 | 0.30 | 0 | 1 |
| *Innovation Choices* | | | | | | | |
| DescriptionLength | Length of the thing’s description in characters | | X (+1) | 4.93 | 1.21 | 0 | 11.09 |
| RecombinantInnovation | Thing derived from at least one prior existing thing | X | | 0.15 | 0.35 | 0 | 1 |
| *Controls* | | | | | | | |
| DaysToInnovation | Days from user registration until release of first thing | | X (+1) | 3.48 | 2.17 | 0 | 8.15 |
| NonCommercialLicense | Thing’s license prohibits commercial use | X | | 0.18 | 0.38 | 0 | 1 |
| OpenLicense | Thing’s license does not impose any restrictions | X | | 0.04 | 0.20 | 0 | 1 |

N=146,290

**Table 2: Pairwise correlations**

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Innovation Success* | | | | | | | | | | | | | | | | | | | |
| Views | 1 | 1.00 | | | | | | | | | | | | | | | | | |
| Downloads | 2 | 0.91 | 1.00 | | | | | | | | | | | | | | | | |
| Likes | 3 | 0.82 | 0.77 | 1.00 | | | | | | | | | | | | | | | |
| Collects | 4 | 0.82 | 0.77 | 0.94 | 1.00 | | | | | | | | | | | | | | |
| Copies | 5 | 0.49 | 0.51 | 0.56 | 0.56 | 1.00 | | | | | | | | | | | | | |
| Derivatives | 6 | 0.37 | 0.38 | 0.38 | 0.39 | 0.45 | 1.00 | | | | | | | | | | | | |
| SuccessIndex | 7 | 0.90 | 0.89 | 0.91 | 0.91 | 0.72 | 0.59 | 1.00 | | | | | | | | | | | |
| *Pre-Innovation Experience* | | | | | | | | | | | | | | | | | | | |
| CollectExp | 8 | 0.03 | 0.00 | 0.10 | 0.12 | 0.05 | 0.03 | 0.07 | 1.00 | | | | | | | | | | |
| CopyExp | 9 | 0.06 | 0.02 | 0.09 | 0.10 | 0.06 | 0.03 | 0.07 | 0.21 | 1.00 | | | | | | | | | |
| CommentExp | 10 | 0.04 | 0.01 | 0.06 | 0.07 | 0.03 | 0.03 | 0.05 | 0.20 | 0.38 | 1.00 | | | | | | | | |
| PreInnoExp | 11 | 0.06 | 0.02 | 0.12 | 0.15 | 0.06 | 0.05 | 0.09 | 0.86 | 0.37 | 0.40 | 1.00 | | | | | | | |
| *Attributes of Experience* | | | | | | | | | | | | | | | | | | | |
| PreInnoExpQuantity | 12 | 0.05 | 0.01 | 0.11 | 0.14 | 0.06 | 0.05 | 0.08 | 0.76 | 0.38 | 0.37 | 0.74 | 1.00 | | | | | | |
| PreInnoExpQuality | 13 | 0.05 | 0.02 | 0.12 | 0.14 | 0.07 | 0.05 | 0.09 | 0.69 | 0.32 | 0.26 | 0.78 | 0.59 | 1.00 | | | | | |
| PreInnoExpRelatedness | 14 | 0.06 | 0.02 | 0.10 | 0.14 | 0.06 | 0.05 | 0.09 | 0.76 | 0.33 | 0.37 | 0.91 | 0.64 | 0.66 | 1.00 | | | | |
| *Innovation Choices* | | | | | | | | | | | | | | | | | | | |
| DescriptionLength | 15 | 0.27 | 0.18 | 0.31 | 0.33 | 0.16 | 0.14 | 0.28 | 0.12 | 0.14 | 0.16 | 0.16 | 0.16 | 0.15 | 0.16 | 1.00 | | | |
| RecombinantInnovation | 16 | 0.08 | 0.05 | 0.10 | 0.11 | 0.07 | 0.08 | 0.10 | 0.11 | 0.15 | 0.16 | 0.14 | 0.17 | 0.11 | 0.15 | 0.12 | 1.00 | | |
| *Controls* | | | | | | | | | | | | | | | | | | | |
| DaysToInnovation | 17 | -0.12 | -0.16 | 0.00 | 0.01 | -0.02 | -0.01 | -0.06 | 0.27 | 0.25 | 0.31 | 0.35 | 0.34 | 0.27 | 0.30 | 0.11 | 0.11 | 1.00 | |
| NonCommercialLicense | 18 | 0.08 | 0.04 | 0.11 | 0.11 | 0.06 | 0.02 | 0.08 | 0.04 | 0.03 | 0.01 | 0.04 | 0.05 | 0.04 | 0.03 | 0.13 | -0.04 | 0.03 | 1.00 |
| OpenLicense | 19 | 0.02 | 0.02 | 0.01 | 0.01 | 0.00 | 0.02 | 0.02 | -0.02 | 0.00 | 0.00 | -0.01 | -0.02 | -0.02 | -0.01 | 0.01 | -0.02 | -0.01 | -0.10 |

N = 146,290

**Table 3: The relationship between pre-innovation experience and innovation success**

| | (1) Views | (2) Downloads | (3) Likes | (4) Collects | (5) Copies | (6) Derivatives | (7) Success Index | (8) Success Index |
|---|---|---|---|---|---|---|---|---|
| CollectExp | 0.195*** | 0.138*** | 0.230*** | 0.295*** | 0.0520*** | 0.0250*** | 0.121*** | |
| | (28.22) | (25.82) | (31.82) | (38.48) | (20.15) | (14.05) | (32.66) | |
| CopyExp | 0.127*** | 0.0639*** | 0.160*** | 0.171*** | 0.0469*** | 0.0119*** | 0.0769*** | |
| | (14.34) | (8.86) | (16.62) | (16.73) | (12.04) | (4.41) | (14.93) | |
| CommentExp | 0.111*** | 0.0521*** | 0.0666*** | 0.0836*** | 0.00639 | 0.00883*** | 0.0398*** | |
| | (12.68) | (7.48) | (7.22) | (8.49) | (1.79) | (3.48) | (8.12) | |
| PreInnoExp | | | | | | | | 0.158*** |
| | | | | | | | | (41.70) |
| DaysToInnovation | -0.00461** | -0.000751 | 0.00797*** | 0.0101*** | 0.00118 | 0.00240*** | 0.00286** | 0.00357*** |
| | (-2.82) | (-0.58) | (4.50) | (5.41) | (1.80) | (5.28) | (3.12) | (3.96) |
| NonCommercialLicense | 0.377*** | 0.270*** | 0.362*** | 0.369*** | 0.0824*** | 0.0258*** | 0.188*** | 0.188*** |
| | (44.10) | (38.17) | (38.80) | (37.52) | (21.77) | (10.57) | (37.61) | (37.64) |
| OpenLicense | 0.0908*** | 0.101*** | 0.0689*** | 0.0765*** | 0.00810 | 0.0233*** | 0.0500*** | 0.0477*** |
| | (5.95) | (8.06) | (4.09) | (4.27) | (1.27) | (4.55) | (5.60) | (5.33) |
| *N* | 146281 | 146281 | 146281 | 146281 | 146281 | 146281 | 146281 | 146281 |
| $R^2$ | 0.448 | 0.540 | 0.191 | 0.208 | 0.067 | 0.042 | 0.291 | 0.291 |

*Notes*: OLS point estimates with t-values based on robust standard errors in parentheses. All specifications control for the linear and squared term of the days since a thing has been posted, for category (80), release year (11), release month (12), and release day (7) fixed effects, and a constant but these terms are not reported. Asterisks denote significance levels (*** p<0.001, ** p<0.01, * p<0.05).

**Table 4: The role of elements of pre-innovation experience and the mediating role of innovation choices**

| | (1) Success Index | (2) Success Index | (3) Success Index | (4) Success Index |
|---|---|---|---|---|
| PreInnoExp | 0.158*** | -0.169*** | 0.0994*** | -0.135*** |
| | (41.70) | (-13.63) | (27.17) | (-11.40) |
| PreInnoExpQuantity | | 0.0184*** | | 0.00722*** |
| | | (13.25) | | (5.43) |
| PreInnoExpQuality | | 0.0510*** | | 0.0445*** |
| | | (26.94) | | (24.70) |
| PreInnoExpRelatedness | | 0.280*** | | 0.198*** |
| | | (17.55) | | (12.92) |
| DescriptionLength | | | 0.163*** | 0.162*** |
| | | | (104.79) | (103.87) |
| RecombinantInnovation | | | 0.154*** | 0.150*** |
| | | | (29.79) | (29.13) |
| DaysToInnovation | 0.00357*** | 0.00347*** | -0.000558 | 0.0000340 |
| | (3.96) | (3.83) | (-0.65) | (0.04) |
| NonCommercialLicense | 0.188*** | 0.185*** | 0.145*** | 0.144*** |
| | (37.64) | (37.22) | (30.53) | (30.31) |
| OpenLicense | 0.0477*** | 0.0511*** | 0.0416*** | 0.0441*** |
| | (5.33) | (5.74) | (4.86) | (5.16) |
| *N* | 146281 | 146281 | 146281 | 146281 |
| $R^2$ | 0.291 | 0.296 | 0.355 | 0.358 |

*Notes*: OLS point estimates with t-values based on robust standard errors in parentheses. All specifications control for the linear and squared term of the days since a thing has been posted, for category (80), release year (11), release month (12), and release day (7) fixed effects, and a constant but these terms are not reported. Asterisks denote significance levels (*** p<0.001, ** p<0.01, * p<0.05).

**Table 5: The relationship between pre-innovation experience and thing characteristics**

| | (1) Description Length | (2) Description Length | (3) Recombinant Innovation | (4) Recombinant Innovation |
|---|---|---|---|---|
| PreInnoExp | 0.311*** | -0.135*** | 0.0891*** | -0.0566*** |
| | (48.43) | (-6.47) | (50.23) | (-8.50) |
| PreInnoExpQuantity | | 0.0496*** | | 0.0267*** |
| | | (21.74) | | (33.17) |
| PreInnoExpQuality | | 0.0394*** | | 0.000236 |
| | | (12.16) | | (0.24) |
| PreInnoExpRelatedness | | 0.385*** | | 0.126*** |
| | | (14.49) | | (14.08) |
| *N* | 146281 | 146281 | 146281 | 146281 |
| $R^2$ | 0.111 | 0.115 | 0.055 | 0.065 |

*Notes*: OLS point estimates with t-values based on robust standard errors in parentheses. All specifications control for category (80), release year (11), release month (12), and release day (7) fixed effects, but coefficients of these fixed effects and of the constant are not reported. Asterisks denote significance levels (*** p<0.001, ** p<0.01, * p<0.05).