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RESEARCH ARTICLE

COMPARING POTENTIAL AND ACTUAL INNOVATORS: AN EMPIRICAL STUDY OF MOBILE DATA SERVICES INNOVATION[1]

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Firms are increasingly opening up their innovation efforts to allow users to tap into the benefits they can offer, such as mobile data service (MDS) innovation on iOS and Google Android platforms. For this purpose, platforms typically provide toolkits to facilitate user participation, aiming to create an ecosystem for sustainable innovation. However, with the barriers to user innovation and attrition of existing innovators, it could be challenging for firms to attract and sustain users' MDS innovation. With the possible benefits from user innovation, and considering the challenges faced, firms need to understand how to influence potential user innovators to take part and to encourage extant user innovators to innovate again. However, there is a lack of comprehensive research and understanding of what drives users' intentions to innovate services and the differences in the antecedents of such intention between potential and actual user innovators. Further, although prior studies have suggested that toolkits can support user innovation, little research has theorized and empirically tested their influence. Motivated thus, this study proposes a model based on (1) user innovation theory to explain the antecedents (including toolkit support) of user MDS innovation intention and (2) construal level theory to explain the differential effects of the antecedents for actual and potential user innovators. We tested the model through survey data from potential and actual MDS user innovators on Google Android and iOS platforms. We find that trend leadership and anticipated extrinsic reward influence both potential and actual user innovators' intentions to innovate. However, anticipated recognition and toolkit support affect only actual user innovators, while anticipated enjoyment affects only potential user innovators. Interestingly, toolkit support strengthens the influence of anticipated enjoyment for actual user innovators but weakens its influence for potential user innovators. Further, potential user innovators value anticipated extrinsic rewards less than actual innovators do. The implications for research and practice are discussed.

Keywords: User service innovation, mobile data services, user innovation theory, construal level theory, potential and actual user innovators

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Introduction

Firms are increasingly considering end users or consumers as an important source of service innovation (Magnusson et al. 2003; Ordanini and Parasuraman 2011) as they can contribute diverse ideas and first-hand knowledge of their requirements or even carry out the entire innovation (Bogers et al. 2010). Tapping users for innovation allows firms to create new services at reduced costs, improve new service acceptance, and obtain continuous innovation (Lüthje et al. 2005; Ordanini and Parasuraman 2011). Indeed, past research has reported such benefits from user innovation in areas such as banking (Oliveira and von Hippel 2011), library (Morrison et al. 2000), telecom (Magnusson et al. 2003), and mobile (Matthing et al. 2004) services.

In light of these benefits, firms are beginning to open up their innovation efforts to allow users to take part (von Hippel 2005). For example, Apple and Google have provided access to the iOS and Android platforms for users to create applications including mobile data services (MDS) (Ye et al. 2011). *MDS* refers to digital data services available on or accessible via mobile devices (Hong and Tam 2006; Lee et al. 2009), such as mobile banking, gaming, news, mapping, location-based information, and internet surfing. The market for mobile services is growing rapidly with revenues expected to hit U.S. $70 billion by 2017 (Takahashi 2014), of which MDS is an important segment as mobile data revenues surpassed voice revenues during the first quarter of 2014 (Lopes 2014). Further, as MDS applications constitute a highly competitive marketplace (Gupta 2013), innovation in MDS is becoming vital for phone and carrier companies. Unfortunately, such innovation is stifled by the attrition and churn of MDS innovators among different platforms (Burrows 2010; Kim 2010). These challenges prevent host firms and the user base from taking advantage of the benefits of user innovation (Boudreau 2012). Hence, there is a need to understand how to stem the attrition of user innovators and influence potential user innovators to participate in order to ensure the sustainability of these platform ecosystems. Here, we define *potential user innovators* as those MDS users who have basic programming knowledge and some interest/needs in creating MDS innovations in the future, but they have not yet done so. This distinguishes them from pure users who have low or no interest in MDS innovation and *actual user innovators* who have higher interest/needs and have MDS programming skills by virtue of having carried out MDS innovation.

The importance of attracting both groups of user innovators suggests that it is necessary to understand their differing perceptions and innovation antecedents considering that the two groups differ in their experience with the target activity (i.e., innovation activity) (Fiedler 2007). Also, it is noteworthy that MDS innovation differs from previously studied user innovation contexts in several ways. First, user innovators are not expected to have significant prior knowledge to create new MDS applications (Hughes 2011), differing from contexts such as OSS where innovators are most often technically trained and work collectively (Roberts et al. 2006). In MDS innovation, the goal of the host firm is to encourage broad-based public participation (Boudreau 2010, 2012). Yet, such innovation typically faces barriers in the form of lack of deeper technical/programming skills and unfamiliarity about the process of applications development (Moon and Bui 2010), giving rise to the salience of innovation toolkits for such platforms. Second, these user innovators undertake the entire new MDS application creation (Ye et al. 2011) as opposed to users in innovation communities such as Dell Ideastorm who mainly provide and evaluate ideas (Di Gangi and Wasko 2009), again highlighting the importance of toolkits. Third, user innovation of MDS differs from user participation in crowdsourcing initiatives such as the Netflix competition in which there are specific tasks/challenges and specified monetary rewards (e.g., a prize) for which participants compete. With a lack of specified incentives, the expected benefits for user innovators need to be examined in the MDS context. Last, while user innovation of MDS has a degree of overlap with social media application creation in that some social media apps are for mobile devices, MDS typically cover many other services as well.

While these differences suggest the need for specific understanding of user MDS innovation, there are few studies in this area. We reviewed prior related research in Tables A1 (user product innovation) and A2 (user service innovation) in Appendix A.[2] First, we found limited studies on the antecedents of user service innovation (Table A2), and none for MDS innovation. Specifically, among the user level studies, most are experiments comparing the innovations of user innovators with professionals (i.e., those who engage in innovation as their job). For the two survey studies (Franke and von Hippel 2003; Morrison et al 2000), we found that neither examined the effects of expected benefits (as we intend to do) on user innovation and hence covered limited antecedents. Second, previous research on user service innovation has also not captured the role of IT artifacts (i.e., toolkit support), although, as noted above, the influence of innovation toolkits is likely to be salient for user MDS innovation. Of the empirical studies on toolkits, Franke et al. (2008) in Table A1 considered one aspect (access to other's designs) and related

[2]With sparse literature on user service innovation, and service innovation studies drawing on product innovation literature, we reviewed both sets of literature for our study.

it to the quality of design of skis, while Franke and von Hippel (2003) in Table A2 noted that toolkits can serve the heterogeneous needs of users designing open source security software. In other words, we found a gap in conceptualizing, operationalizing, and testing the efficacy of toolkits for user service innovation. Third, there is a lack of studies on potential user innovators (with the exception of Matthing et al. (2006) who note that they may be able to create diverse service ideas), as well as comparing the antecedents for potential and actual user innovation (which we highlighted as important from a practical viewpoint).

Our review shows that user innovation in MDS is a nascent area with a lack of extant theory. This paper, thus, aims to address the knowledge gaps highlighted above and build theory in this emerging area. Hence, a model is developed to answer the following *research questions*: What are the antecedents of users' MDS innovation intention in terms of individual drivers and toolkit support? What are the differences in the effects of the antecedents for potential and actual user innovators? To derive the model, we draw on user innovation theory (Von Hippel 2005) as our overarching lens to explain how individual drivers (user characteristics and expected benefits) and innovation toolkits influence the intention to innovate. We also use construal level theory (Liberman and Trope 1998) to explain the differences between potential and actual user innovators based on their direct experience and resultant psychological distance from the innovation activity. The model is tested through a survey of potential and actual user innovators of MDS applications on iOS and Android platforms. Specifically, the study is expected to contribute to the user and service innovation literature by developing and testing a theoretical model that explains the antecedents of users' intention to innovate MDS and compares the antecedents for potential and actual user innovators. The findings of this study seek to inform practitioners on ways to encourage users to create new MDS for the benefit of the entire user base and the host firm.

Conceptual Foundation

In this section, we introduce the two theories upon which our research model builds. We also review the literature related to innovation toolkits to conceptualize the *toolkit support* construct for our model. The overarching lens for our study is *user innovation theory*, which seeks to explain how users' attributes, motivations, and artifacts influence their innovation behavior (Von Hippel 2005; von Hippel et al. 2011). It is used to identify the antecedents of user MDS innovation for our model. Further, *construal level theory* (Liberman and Trope 1998; Trope and Liberman 2010) can help to understand how various antecedents differentially affect MDS innovation for potential and actual user innovators. It explains the perception differences between the two groups based on their direct experience (or lack) that influences their psychological distance from the target activity (i.e., MDS innovation) in our study.

User Innovation Theory

The premise of user innovation is based on the realization that new ideas do not necessarily emerge from within the research and development function of a firm. Rather, it could be the users of a product or service who have the insights and ideas that lead to innovation (Von Hippel 2005; von Hippel et al. 2011). Users are often well placed to predict fellow customer needs and may also be able to design, build, and distribute their own solutions, as in the case of MDS innovation. Specifically, user innovation theory proposes that *lead userness* of users is related to their likelihood of innovation (Von Hippel 1994; von Hippel et al. 2011). This theory has been applied and tested in several contexts of new product design (e.g., Franke and Shah 2003; Franke et al. 2006; Schreier and Prugl 2008). For example, Schreier and Prugl (2008) found that the degree of lead userness of users positively affects their innovation of sports products.

As per the theory, the concept of lead userness consists of two dimensions: *trend leadership* and *expected benefit* (Franke et al. 2006). Trend leadership refers to the extent to which the user is at the leading edge of important market trends, and so is currently experiencing needs that will later be experienced by many users in that market. For example, the application "Fans for Super Junior," which collects and shares information regarding the Korean band, Super Junior, including their schedule, products, and songs to be launched, was created by one of its loyal fans who experienced the need for it. Subsequently, this application benefitted other fans of this band. With instances of such needs seen in MDS innovation contexts (Kim et al. 2012), we expect trend leadership to be important for users' MDS innovation and therefore include this variable in our model. Expected benefit refers to the anticipated incentives of users from innovating a solution to their needs, which should influence their innovation likelihood (Schreier and Prugl 2008). Therefore, we identify various forms of expected benefits for user innovators to include in our model.

To derive the different forms of expected benefits, we systematically looked through Tables A1 and A2 and grouped the

similar benefits together from the literature (see Table A3).[3] As a result, we identified *anticipated extrinsic reward, anticipated enjoyment,* and *anticipated recognition* as expected benefits for user innovators. We also included tenure (as a proxy for experience) and programming skill from Table A3 as control variables for our study.[4] Apart from the effects of user characteristics (trend leadership) and motivations (expected benefits) user innovation theory can explain the influence of artifacts, such as innovation toolkits, on innovation behavior.

Innovation toolkits are being introduced by firms in order to facilitate user innovation (Franke et al. 2010). Innovation toolkits refer to coordinated sets of design tools that aim to enable users to take part in innovation (Von Hippel and Katz 2002). In the context of our study, Apple provides the Xcode development environment with the iOS software development kit (SDK), while Google provides the Android Studio and SDK that includes various tools intended to facilitate users' innovation activities. Also, the iOS App Store and Google Play Store provide access to and analytics information for each MDS application, including reviews and ratings.

With regard to toolkits, von Hippel and Katz (2002) posited that innovation involves two types of tasks: *need-related tasks* and *solution-related tasks*. They noted that *need-related knowledge* could be sticky to transfer *from users to the firm,* whereas *solution-related knowledge* could be sticky to transfer *from the firm to users*. They advocated that if need-related design tasks are assigned to users and solution-related tasks are assigned to the firm/manufacturer, time and cost of innovation will be reduced. Toolkits were proposed as an effective way for need-related design tasks to be assigned to users such that they can create a custom product or service design according to the unique needs, after which the firm will take the design (e.g., for a semiconductor chip) and manufacture it (i.e., perform the solution-related tasks). However, we extend this idea further for contexts such as user MDS innovation, where the user innovator is not only able to perform the design but also the implementation of the innovation (i.e., both need-related and solution-related tasks). Thus, we posit that the role of the toolkit here is to facilitate the entire innovation process.

To conceptualize the toolkit support construct for our model, we reviewed and summarized the literature on innovation toolkits (see Table A4). By synthesizing the desired features of toolkits from that literature (see Table A5), we derived two aspects of this construct: exploring and experimenting innovation ideas (exploration) and reducing innovation effort (ease of effort). *Exploration* involves being able to extensively search innovation ideas in the market and experiment with their creation through the toolkit. *Ease of effort* refers to ease in collecting information and in designing the innovation with the toolkit. Thus, *toolkit support* is defined as the extent to which the user (potential or actual) innovator perceives that the tools provided facilitate MDS innovation in terms of exploration and ease of effort.

Construal Level Theory

We employ construal level theory (CLT) to explain the differences between potential and actual user innovators based on their direct experience and resultant psychological distance from the innovation activity. CLT proposes that psychological distance influences the way people think about or construe a target object or activity (Trope and Liberman, 2010). The basic premise of CLT is that the more distant an object is from the individual, the higher the construal level, while the closer the object is, the lower the construal level. *Construal level* refers to how an individual mentally interprets or construes information about the target (Trope et al. 2007). A high-level construal refers to abstract and general interpretations of the target, while a low-level construal refers to detail-oriented and concrete interpretations. For example, a low-level construal of an activity as "playing ball" could be seen as a high-level construal of "having fun," where details such as the ball are omitted (Trope and Liberman, 2010).

As per the theory, *psychological distance* refers to the "egocentric" perception of how far an object or activity is from the self in terms of time, space, social distance, and hypothetical alternatives to reality (Trope and Liberman 2010). Liberman and Trope (2014) define four dimensions of psychological distance: *time/temporal* (time distance from object or event; the object belongs to the past or future), *spatial* (geographical distance from object or event), *social* (distance to others; they are similar/dissimilar, familiar/unfamiliar, ingroup/outgroup), and *hypothetical* (e.g., high versus low probability, real versus hypothetical). Beyond these four dimensions, related research (e.g., Fiedler 2007; Freling et al. 2014) has identified additional distance dimen-

[3]We systematically went through the independent variables (IVs) of the prior studies in Tables A1 and A2 and extracted those that were benefits. We then grouped the similar benefits together in Table A3 to derive the expected benefit constructs for our model.

[4]The IVs that did not fall under our user innovation theoretical lens (i.e., either trend leadership or expected benefits) were used as controls. Further, since innovativeness, locus of control, betweenness centrality, and divergent thinking affect lead userness (whose dimensions are already proposed as antecedents in our model), we do not include them as controls in our model.

sions that also affect construal level, such as *experiential* distance (e.g., experience versus no experience). They also note that the various dimensions have a common meaning in terms of psychological distance and are often correlated.

CLT posits that an object or activity is psychologically distant whenever it is not part of one's direct experience (Fiedler 2007; Trope et al 2007). On that basis, potential user innovators in our study context should have a more distal perspective and thus a higher-level construal about MDS innovation as compared to actual user innovators who have had a direct experience of the activity. Further, as per the dimensions of psychological distance, we could classify the difference between potential and actual user innovators as primarily experiential—that is, the MDS innovation activity has been experienced by actual user innovators and not by potential user innovators. As construal levels will affect the framing and salience of the perceptions of events, which influence people's choice of actions (White et al. 2011), we expect that the antecedents of MDS innovation would be weighted differently by potential and actual user innovators in our model as described next.

Research Model and Hypotheses Development

User service innovation has been defined as the new services or changes in services, production, or delivery created by users (Magnusson et al. 2003; Miles 2005), which can range from incremental to radical. In the context of our study, this refers to the new MDS applications created by users. In order to compare potential and actual user innovators, we adopt future intention to innovate MDS as the dependent variable (DV).[5] Our research model is shown in Figure 1 (the constructs are defined in Table A6). As a baseline, we hypothesize effects of trend leadership, the expected benefit constructs, toolkit support, and the interaction of anticipated enjoyment and toolkit support on the DV for both potential and actual user innovators. We also formulate several comparison hypotheses (i.e., differential effects of the antecedents, for the two groups).

Trend Leadership

Trend leadership refers to the extent to which users experience unique needs that cannot be satisfied in the current market and may later be experienced by others. User innovation theory argues that trend leadership is a key reason for users to engage in innovation activities (Von Hippel 2005). Trend leadership can become a motivation for users to innovate if the investment on the unsatisfied needs is justified (Franke et al. 2006). This is because users' needs information is often tacit and sticky to transfer to firms (Von Hippel 1994). Consequently, Lüthje et al. (2005) observed that when user innovators experience high trend leadership, it is more efficient and effective for them to create their own solutions for their needs. With instances of such needs seen in MDS innovation contexts (Kim et al. 2012), we expect that the extent to which both potential and actual users experience unique needs for MDS that are unavailable in the current market will be related to their innovation intention.

H1a, p: Trend leadership is positively related to intention to innovate.

With trend leadership being the identifying characteristic of user innovators (Franke et al. 2006), we expect it to be similarly important in influencing both potential and actual user innovators. While actual user innovators' current degree of unique needs would be likely to motivate their future intention to innovate (Lüthje et al. 2005), we expect a similar effect for potential user innovators (i.e., the extent to which they experience unique needs should also drive their future intention to innovate). As mentioned earlier, the difference between the two groups is only likely in terms of the level of trend leadership, with actual user innovators having higher levels than potential user innovators. Therefore, we do not hypothesize a differential effect of trend leadership for the two groups.

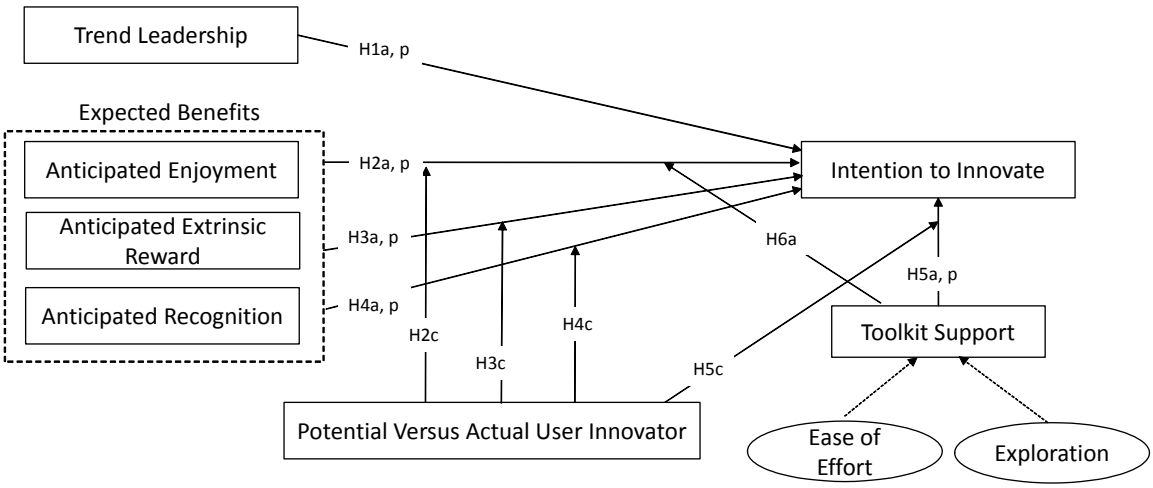
Expected Benefits

Anticipated Enjoyment

Innovation tasks can provide value in the form of enjoyment to user innovators (Lüthje 2004). For example, intellectual satisfaction and enjoyment experienced during the activity are suggested to be key intrinsic drivers for participation in open innovation (Boudreau and Lakhani 2009). For new product development, enjoyment was seen to motivate online community members to contribute to joint innovation tasks (Füller et al. 2009). In the context of our study, we expect that both potential and actual user innovators who anticipate greater enjoyment from innovation will have a higher intention to innovate MDS applications. Therefore, we hypothesize

H2a, p: Anticipated enjoyment is positively related to intention to innovate.

[5]We ran *post hoc* analyses with number of MDS innovations and MDS popularity as DVs for actual user innovators as reported later.



Note: p = potential user innovator; a = actual user innovator; c = comparison

Figure 1. Proposed Research Model

However, we expect that the strength of the above effect will differ for potential and actual user innovators as a distal versus proximal perspective toward an activity (in this case, MDS innovation) leads to differences in the importance of *desirability* and *feasibility* concerns as per CLT literature (Trope et al. 2007). A distal, high-level construal has been found to emphasize *desirability* (e.g., interest, enjoyment) concerns of an individual, while a proximal, low-level construal focuses on *feasibility* (e.g., convenience and ease) concerns toward performing the activity. For example, Agrawal et al. (2006) found that individuals considered desirability (e.g., would they really enjoy the concert?) more important when the event (e.g., deciding to attend a concert) was distant, while considering feasibility (e.g., cost of the ticket) more salient when it was proximal. Similarly, potential user innovators (with a greater psychological distance from the innovation activity) should place higher importance on desirability considerations (e.g., enjoyment during MDS innovation) when deciding on their future intention to innovate as compared to actual innovators (with a more proximal perspective). Thus we hypothesize,

H2c: Anticipated enjoyment is a stronger driver for potential user innovators' intention to innovate than for actual user innovators.

Anticipated Extrinsic Reward

By designing their own products, user innovators may be able to derive profits from selling their innovations (Shah and Tripsas 2007). In the context of our study, user innovators may be paid according to the downloads of their MDS applications or may obtain job opportunities through their innovation activities (Kim 2010; Turel et al. 2010). Extrinsic rewards can attract users to create new products when they perceive that the incentives exceed the costs of innovating (Jawecki 2008). With such rewards seen in new MDS creation (Hughes 2011), we expect that anticipated extrinsic reward will motivate the intention to innovate for both potential and actual user innovators. Therefore,

H3a, p: Anticipated extrinsic reward is positively related to intention to innovate.

Nevertheless, we expect that the strength of the above effect will differ for potential and actual user innovators. CLT related studies have found that psychological distance from an event or activity (in this case, MDS innovation) is related to *idealistic* versus *pragmatic* concerns with respect to the activity (Trope et al. 2007). A distal perspective (such as for potential user innovators) has been found to shift attention inward toward the core values that define a person, activating the *idealistic self* with respect to the target object or activity. In contrast, proximity to the target (such as for actual user innovators) is found to highlight extrinsic inducements (e.g., financial benefits) by activating the *pragmatic self* (Kivetz and Tyler, 2007). The pragmatic versus idealistic distinction has been validated in a number of studies on different behaviors and choices (Tenbrunsel et al. 2010). Based on the above arguments, we expect that actual user innovators' greater proximity to the innovation activity will activate their

pragmatic self, whereby extrinsic rewards will more strongly drive their innovation intention as compared to the idealistic self that is activated for potential user innovators, which makes external rewards less salient for them. Thus, we hypothesize

H3c: Anticipated extrinsic reward is a stronger driver for actual user innovators' intention to innovate than for potential user innovators.

Anticipated Recognition

Another benefit for users to engage in innovation could be recognition (Jeppesen and Frederiksen 2006). Creating innovative services can enhance one's reputation or status in the eyes of others (e.g., peers). Recognition acknowledges the contribution and capabilities of users, satisfies their internal needs of confirmation, and hence motivates them toward the behavior (Cissna and Sieburg 1981)—in this case, innovation. In the context of MDS, recognition could be a driver for user innovation on mobile phone platforms (Boudreau and Lakhani 2009). Thus, we expect that anticipated recognition will drive the intention to innovate MDS for both potential and actual user innovators.

H4a, p: Anticipated recognition is positively related to intention to innovate.

However, we expect that the strength of the above effect will differ for potential and actual user innovators. As per CLT, a distal perspective activates the *idealistic s*elf while a proximal perspective invokes the *pragmatic* self with respect to the target (Kivetz and Tyler 2007). For instance, students who considered an academic course to start the next academic year (distant future outcome) focused more on idealistic, *identity-oriented benefits* of the course (e.g., whether the professor treated students with respect) as compared to instrumental benefits. In contrast, when considering a course to start a few days later, participants concentrated more on *instrumental benefits* of the course (e.g., the professor's tendency to give high grades). In line with this logic, the distal perspective of potential user innovators is likely to invoke their idealistic self with respect to the innovation activity, which places less emphasis on instrumental benefits. On the other hand, the proximal perspective of actual user innovators would invoke the pragmatic self, which emphasizes instrumental or extrinsic benefits such as image, status, or recognition (Amabile et al. 1994; Niemiec et al. 2009). Thus, recognition is expected to be more influential for actual than potential user innovators for their intention to innovate.

H4c: Anticipated recognition is a stronger driver for actual user innovators' intention to innovate than for potential user innovators.

Toolkit Support

By synthesizing past literature in the context of our study we identified that innovation toolkits can support user innovation by enabling exploration of innovations and easing the effort in creating them. For instance, these tools can provide information about the market needs as well as other users' innovations (Harker and Taheri 2011). This should help users identify if their ideas are worth pursuing for service innovation. Further, these tools can reduce the implementation barriers for user innovation (e.g., by providing module libraries) (Franke and Shah 2003; Piller et al. 2004). In the context of our study, we expect that the perception of greater toolkit support can enhance both potential and actual user innovators' intention to create MDS applications in the future. Thus,

H5a, p: Toolkit support is positively related to intention to innovate.

Nevertheless, the strength of the above effect should differ for potential and actual user innovators. A number of CLT studies have found that distal versus proximal perspectives toward an activity or event lead to differences in the importance of *desirability* and *feasibility* concerns (Trope et al. 2007). Specifically, a distal, high-level construal is found to emphasize desirability (e.g., interest, enjoyment) concerns of an individual, while a proximal, low-level construal emphasizes feasibility (e.g., convenience, ease) concerns toward performing the activity. For example, Liberman and Trope (1998) found that desirability (e.g., how interesting the lecture was), was more important when psychological distance from the event (e.g., deciding whether to attend a guest lecture) increased, while feasibility (e.g., how convenient the timing of the lecture was) was more important when distance decreased. Thus, we expect potential user innovators to place less importance on feasibility considerations (e.g., toolkit support to ease innovation effort), as compared to actual user innovators with a greater proximity to the innovation activity. In other words, potential user innovators should be less concerned about the feasibility aspects (e.g., toolkit support), when deciding about their intention to innovate.

H5c: Toolkit support is a stronger driver for actual user innovators' intention to innovate than for potential user innovators.

As we had earlier argued for H2c, the effect of anticipated enjoyment should be less salient for actual user innovators since they are likely to value desirability (in this case, anticipated enjoyment) less as compared to potential user innovators, based on CLT (Trope et al. 2007). Yet, the effect of toolkit support should be more salient for actual user innovators (H5c) since they are likely to value feasibility (in this case, toolkit support) more than potential user innovators, as argued above. We, thus, posit that the interplay between these two effects determines an interaction between anticipated enjoyment and toolkit support for actual user innovators. Specifically, when toolkit support is low, anticipated enjoyment may matter little for actual user innovators since the effect of enjoyment is marred by the difficulty of carrying out MDS innovation. However, when toolkit support is high, these difficulties are reduced (Shneiderman 2007), and anticipated enjoyment is expected to become more important for their innovation intention.

H6a: The relationship between anticipated enjoyment and actual user innovator's intention to innovate is strengthened when toolkit support is perceived as high.

As mentioned previously as per CLT (Trope et al. 2007), the distal view of MDS innovation for potential user innovators may result in lesser concern for feasibility considerations. Therefore, the provision of toolkit support may not be important for them in their anticipated enjoyment of MDS innovation in contrast to actual user innovators. Thus, we do not hypothesize an interaction of toolkit support and anticipated enjoyment on MDS innovation intention for potential user innovators.

Research Methodology

A survey methodology was employed to test our research model. Before conducting the survey, interviews with five potential and two actual user innovators were conducted to validate the instrument and enrich our understanding of the study context. For the *actual user innovators*, the survey was conducted for two platforms (iOS and Android) through the Phoenix iOS Developer Group[6] and the Code Android Group.[7] We searched for application creation sites and these two were selected as they were openly accessible (we could email the members) and the administrators allowed us to post our survey link on their site. For the *potential user innovators*, the survey questionnaire was sent to computer science and engineering students who are iPhone or Android phone users in a large public university.

Survey Instrument

The constructs of *trend leadership* (TLS), *anticipated enjoyment* (AEJ), *anticipated extrinsic reward* (AER), *anticipated recognition* (REG), and *intention to innovate* (ITI) were operationalized as reflective constructs by adapting items from previously validated instruments (see Table A7). *Toolkit support* (TKS) has two dimensions—*ease of effort* (EOE) and *exploration* (EXP)—as discussed earlier (see Table A5). The subdimensions can be viewed as causing the focal construct and are not interchangeable (Petter et al. 2007). Accordingly, we operationalize toolkit support as a formative, second-order construct composed of two, first-order reflective constructs with three items each (see Table A7). All of the survey items were measured using seven-point Likert scales anchored from "strongly disagree" to "strongly agree." Following prior user innovation studies (e.g., Schreier and Prugl 2008), we included age, gender, and educational level as control variables. For instance, previous literature (e.g., von Hippel et al. 2012) noted that younger males with higher education showed greater likelihood of participating in technical innovation. We also included tenure, programming skill, and platform (iOS versus Android) as contextual control variables. These controls are included to account for alternative explanations of the variance in the dependent variable.

Survey Administration

For the *actual user innovator*s, an online survey link was created and posted to the two sites mentioned above. We posted the link for two weeks with forum administrators helping to highlight the survey invitation. In appreciation of the respondents' effort, we offered a token $10 for each response. First, to verify that the respondents were actually *users* of iPhone or Android applications, they were asked to answer specific questions related to iPhone or Android applications, such as the default icon of "iOS or Android market," default web browser used, and default applications for reading PDF files with iPhone or Android phones. Second, to ensure that the respondents were *actual innovators*, we verified their account name and the applications they created.[8] Third, we asked the respondents about their occupation and employer

[6]http://phoenixios.wordpress.com/.

[7]http://www.codeandroid.org/ (this site is now on Facebook).

[8]This was done for 98 respondents for which data in the iOS or Android platforms were available (a few respondents did not publish their applications on these platforms). We also checked that they had developed fairly radical innovations (measured inversely by the number of similar apps available in the market). The median radicalness for these innovators was three or four similar applications for their most radical MDS created.

(self-report questions) and used this information to filter out professional developers (i.e., those who design applications for a living or work in application development companies). The remaining respondents proceeded to fill out the rest of the survey. Overall, a total of 101 valid responses from actual user innovators remained after removing incomplete data.

For the *potential user innovators*, the questionnaire was administered to junior and senior computer science and engineering students who are iPhone or Android phone users in a public university. The pool of students was screened and survey invitations sent to those who (1) had at least basic programming knowledge, and (2) were interested in MDS application creation (asked through self-report questions) but had not done so yet (as per our definition in the "Introduction"). Respondents were invited to fill out paper-based questionnaires for which 111 valid responses were received from the potential user innovators. The demographic information about both groups of respondents is reported in Table B1 (Appendix B).

Data Analysis and Results

The survey data was analyzed using partial least squares (PLS). PLS is a suitable choice for analyzing our model with a formative construct (i.e., toolkit support) and its interactions (Gefen et al. 2011; Wetzels et al. 2009). For toolkit support, we created the superordinate second-order construct using factor scores for the first-order constructs (Wold 1989). The interaction term (AEJ × TKS) was computed by cross-multiplying the standardized items of the relevant constructs (Chin et al. 2003). We first tested for measurement validity of the survey instrument followed by hypotheses testing.

Measurement Validity

To validate our measurement model, three types of validity were assessed: content validity, convergent validity, and discriminant validity (Hair et al. 2006). *Content validity* was established by refining the items based on the potential and actual user innovators feedback and adapting items used in previous literature. Further, item sorting was carried out as per the procedure outlined in DeVellis (2003), with satisfactory results. We assessed *convergent validity* by examining the composite reliability (> 0.7), Cronbach's Alpha (> 0.7) and average extracted variance (> 0.5) of all reflective constructs (Straub et al. 2004). Table 1 shows the mean, standard deviation (SD), correlations, Cronbach's Alpha (CA), composite reliability (CR), and average extracted variance (AVE) for the constructs for potential and actual user innovators. These values satisfy the criteria for adequate convergent validity.

Discriminant validity is demonstrated when (1) indicators load higher on their intended factor than on other factors and (2) the square root of each factor's AVE is higher than its correlations with other factors (Straub et al. 2004). As observed from Table 1 and the factor analysis results (see Table B2), both sets of conditions are met, thus demonstrating discriminant validity (Hair et al. 2006). In addition to validity assessment, we also checked for multicollinearity. The variance inflation factor (VIF) values for all constructs were found acceptable (i.e., between 1.16 and 1.85). For the second-order formative construct (TKS), significance of dimension weights was examined to determine the relative contribution of items to the construct (Chin et al. 2003). All dimensions were significant at $p < 0.001$, indicating satisfactory validity (see Table B3). We conducted tests for common method bias (see Table B4) and measurement invariance (reported in Appendix C). The tests indicate lack of common method bias and measurement invariance across potential and actual user innovator groups that allows us to compare the two groups with the same survey instrument.

Results of Hypotheses Testing

The results of hypotheses testing are shown in Table 2. The results indicate that for *actual user innovators*, effects of trend leadership (H1a), anticipated extrinsic reward (H3a), anticipated recognition (H4a), toolkit support (H5a), and interaction of toolkit support with anticipated enjoyment (H6a) are significant, while anticipated enjoyment (H2a) is not. For *potential user innovators*, effects of trend leadership (H1p), anticipated enjoyment (H2p), and anticipated extrinsic reward (H3p) are significant, while anticipated recognition (H4p) and toolkit support (H5p) are not. The model explained 57 percent of the variance in intention to innovate for actual user innovators and 52 percent for potential user innovators. Also, programming skill affects intention to innovate in the controls-only results (models 1 and 4). The rest of the control variables were not found to be significant.

Comparison Between Actual and Potential Innovators

With the measurement invariance largely established (see Table C1), we tested the hypotheses involving the differences between potential and actual user innovators. Following Keil et al. (2000), we statistically compared the corresponding path coefficients and computed the T-values shown in Table 3.

Table 1. Mean, SD, Correlations, CA, CR and AVE (Actual | Potential)

	Mean	SD	CA	CR	TLS	AEJ	AER	REG	EOE	EXP	ITI
TLS	5.15|4.77	1.01|1.36	0.80|0.87	0.86|0.91	0.82|0.89						
AEJ	5.20|4.87	0.83|1.10	0.77|0.84	0.86|0.90	0.20|0.45	0.83|0.87					
AER	5.34|4.83	1.60|1.27	0.76|0.78	0.84|0.82	-.05|0.13	0.02|0.09	0.86|0.80				
REG	4.73|4.53	1.04|1.22	0.73|0.75	0.84|0.80	0.45|0.28	-.04|0.16	0.30|0.05	0.77|0.786			
EOE	4.98|4.33	0.84|1.22	0.80|0.75	0.88|0.87	0.16|0.21	-.03|0.26	0.18|0.22	0.31|0.21	0.91|0.90		
EXP	4.87|4.35	0.91|1.12	0.71|0.83	0.84|0.89	0.17|0.19	-.07|0.14	0.21|0.17	0.20|0.14	0.39|0.42	0.85|0.90	
ITI	4.84|4.86	1.55|1.46	0.83|0.94	0.90|0.96	0.17|0.35	0.25|0.51	0.36|0.25	0.45|0.22	0.40|0.34	0.33|0.29	0.86|0.94

Notes:

1. Each pair of values represent actual | potential user innovator samples.
2. Diagonal elements are the square root of average variance extracted (AVE)
3. Trend Leadership (TLS), Anticipated Enjoyment (AEJ), Anticipated Extrinsic Reward (AER), Anticipated Recognition (REG), Ease of Effort (EOE), Exploration (EXP), Intention to Innovate (ITI).

Table 2. Hypotheses Testing Results (DV =Intention to Innovate)

Variables Entered	Actual User Innovator				Potential User Innovator			
Controls	**1**	**2**	**3**	**Result**	**4**	**5**	**6**	**Result**
Age	0.19	0.09	0.10	N.S.	0.09	0.10	0.10	N.S.
Gender	0.03	0.08	0.08	N.S.	0.02	0.07	0.07	N.S.
Programming Skill	0.15*	0.10	0.09	Partially significant	0.10*	0.10	0.10	Partially significant
Educational level	-0.16	-0.01	-0.01	N.S.	0.04	0.11	0.11	N.S.
Platform	-0.14	0.01	0.01	N.S.	0.01	0.01	0.01	N.S.
Tenure	-0.03	-0.03	-0.02	N.S.	N.A.	N.A.	N.A.	N.A.
Main Effects								
TLS		0.13*	0.12*	**H1a supported**		0.11*	0.12*	**H1p supported**
AEJ		0.08	0.07	H2a not supported		0.54**	0.47*	**H2p supported**
AER		0.29**	0.25**	**H3a supported**		0.18**	0.17**	**H3p supported**
REG		0.27*	0.26*	**H4a supported**		-0.12	-0.13	H4p not supported
TKS		0.31***	0.29**	**H5a supported**		0.06	0.05	H5p not supported
Interaction Effect								
AEJ × TKS			0.30*	**H6a supported**			-0.21*	
R^2	0.10	0.54	0.57		0.05	0.45	0.52	

*p < 0.05, **p < 0.01, ***p < 0.001

Notes:

1. Models 1 and 4 are controls only; models 2 and 5 are with main effects added; models 3 and 6 include interaction effect as well.
2. Trend Leadership (TLS), Anticipated Enjoyment (AEJ), Anticipated Extrinsic Reward (AER), Anticipated Recognition (REG), Toolkit Support (TKS).

Table 3. Results for Comparison Hypotheses

Comparison Hypotheses		TLS	H2c (AEJ)	H3c (AER)	H4c (REG)	H5c (TKS)
Path coefficient (Standard error)	**Actual**	0.130(0.064)*	0.080(0.064)	0.293(0.086)**	0.273 (0.057)**	0.310(0.097)***
	Potential	0.110(0.077)*	0.542(0.069)**	0.176(0.062)**	-0.118(0.060)	0.058 (0.063)
S_{pooled}		0.0711	0.0667	0.0744	0.0586	0.0809
T-test across groups		2.04	-50.40****	11.43****	48.52****	22.62****
Results			**H2c Supported**	**H3c Supported**	**H4c Supported**	**H5c Supported**

***p < 0.001, ***p < 0.0001

Notes: Trend Leadership (TLS), Anticipated Enjoyment (AEJ), Anticipated Extrinsic Reward (AER), Anticipated Recognition (REG), Toolkit Support (TKS)

From the T-values, it can be seen that all the comparison hypotheses (H2c, H3c, H4c, and H5c) are supported and the difference is not significant for trend leadership as expected.

We *post hoc* tested the influence of the independent variables on the number of MDS applications created and the average popularity of these MDS applications for the actual user innovator group. As shown in Table C2, the results are largely similar to the findings in Table 2. The moderation plots for hypotheses H2c, H3c, H4c, H5c, and H6a are shown in Appendix D.

Discussion and Implications

By and large, our model was validated with 12 out of 15 hypotheses supported. In order to find out the reasons behind the unsupported hypotheses we *post hoc* interviewed five actual and three potential user innovators from our respondents.[9] While the remaining five hypotheses are supported for actual user innovators, anticipated enjoyment has no effect on their intention to innovate (H2a not supported). The actual user innovator interviewees reported several difficulties with MDS innovation including the challenges of design, slow approval process, frequent changes of platform software, and lack of time that could hamper their anticipated enjoyment. A user innovator for the Android platform observed, *"Android was very immature and kept changing, certainly between v0.9 and v1.5. Now it is more mature, but faces fragmentation.*"

Another reason appearing from the interviews was that anticipated extrinsic rewards could dilute the impact of expected enjoyment as a motivational force for actual user innovators. However, the effect of anticipated enjoyment depends on level of toolkit support (H6a is supported). For the actual user innovators, the positive effect of anticipated enjoyment becomes significant at high levels of perceived toolkit support, when the difficulties of MDS innovation may be sufficiently mitigated. In other words, there is a level of toolkit support above which the effect of anticipated enjoyment becomes significant (threshold analysis for this point is provided in Appendix D).

For the potential user innovators, anticipated recognition and toolkit support have no impact on intention to innovate (H4p and H5p not supported). This could be because of the lack of direct experience of potential user innovators such that they place little emphasis on the toolkit support and the recognition through creating MDS applications, consistent with CLT. Interestingly, our empirical results show a negative moderating effect of toolkit support on the relationship between anticipated enjoyment and intention to innovate for potential user innovators, which we did not hypothesize. When we asked the potential innovators about this finding, an interviewee said, *"the tool could compete for our attention and just distract from the process of creating new apps*" when expected enjoyment from MDS innovation is high. Thus, in the case of potential user innovators, the reverse (as compared to actual user innovators) interplay between anticipated enjoyment and toolkit support is seen. When anticipated enjoyment is high, these users value anticipated enjoyment anyway and toolkit support does not seem to matter; TKS just serves as a distraction (as mentioned in the *post hoc* interview comments). However, as anticipated enjoyment becomes lower, the effect of toolkit support is seen to gain importance (i.e., starts to matter). In this case, there is a level of anticipated enjoyment below which the effect of toolkit support becomes significant for potential user innovators (threshold analysis for this point is also provided in Appendix D).

[9]The *post hoc* interviewees for both potential and actual user innovator groups were those who were willing to provide feedback to us when asked whether they could be contacted for further information in the survey. Further, we selected those who were not likely to agree with H2a (e.g., relatively high ITI but low AEJ), H4p, and H5p, so that they could inform us on the reasons for these unsupported hypotheses.

Limitations and Future Research

The results of this study should be interpreted in light of its limitations. First, the current findings are based on cross-sectional survey data. Thus, we did not examine the change of motivations when users transition from potential innovators to actual innovators. While this study reveals significant differences between the two groups, future research could capture longitudinal data to measure the transition of user innovators' motivations and the feedback effects of innovation on user innovators' perceptions. Second, we have examined the antecedents of service innovation intention from a variance perspective. Future work can explore the process of user service innovation, such as how knowledge acquisition and transfer take place for user innovation (Bogers et al. 2010). For example, researchers can apply a learning perspective (Wang and Ramiller 2009) to explore how user innovators acquire knowledge on such service innovation platforms. Third, this study was carried out in the context of MDS innovation, which has certain unique characteristics as discussed in the "Introduction." Future work could examine if the findings apply to other user service innovation contexts such as OSS, social media application creation, and crowdsourcing contexts such as Netflix competitions or Dell Ideastorm. Fourth, we could not robustly assess the differences between the two MDS platforms in our study due to sample limitations. Future research could explore the differences between MDS innovation platforms in terms of toolkit support and other antecedents to examine how this influences user innovation. Last, while this study does not differentiate between different kinds of MDS innovations (e.g., games, news, etc.), it could be a fruitful avenue for future research to examine if the antecedents vary for the different types of MDS apps.

Theoretical Contributions

This study contributes to existing literature in several important ways. First, it is an initial attempt to theoretically model and empirically test the antecedents of the user's service innovation intention in the unique context of MDS innovation, which is an emerging area with a lack of extant theory. In this manner, this paper extends both the user and service innovation literatures, which have seen limited studies on the antecedents of user service innovation, little coverage of the expected benefits, and lack of research on potential user innovators (as seen in our review in the "Introduction"). Specifically, this study identifies user attributes (trend leadership), expected benefits (anticipated extrinsic reward, enjoyment, and recognition), and artifacts (toolkit support) that are salient for potential and actual user innovators in the context of user MDS innovation.

Second, this study is novel in developing a comparative theoretical model to understand the differences in the antecedents of intention to innovate for potential and actual user service innovators. Relying on CLT, this work extends previous research that has tended to focus on actual user innovators (see Tables A1 and A2). Our findings contribute to research using CLT by showing that the theory is useful to explain the differences in the antecedents of actual and potential user innovators' intention to innovate based on their experiential distance from the innovation activity. It also adds to the body of literature on CLT where much of the work has examined the effects and implications of temporal, spatial, social, and hypothetical distance dimensions (e.g., Trope and Liberman 2010), rather than the experiential distance dimension as is done in this study.

Third, this paper adds to prior research (e.g., Franke and von Hippel 2003) through the conceptualization and measurement of toolkit support. Although previous studies have viewed the support from toolkits in terms of different features (e.g., Franke and von Hippel 2003; von Hippel and Katz 2002), here we conceptualized toolkit support in a comprehensive way by synthesizing the prior work. We operationalized it as a second-order construct consisting of two dimensions (i.e., exploration and ease of effort). Further, previous research (e.g., von Hippel and Katz 2002) suggests that users can participate in the innovation process by completing need-related tasks (e.g., obtaining information about users' unique needs) while leaving the solution-related tasks (e.g., implementing the innovation) to companies. This paper contributes by clarifying that toolkit support enables user innovators of MDS to undertake both the need- and solution-related tasks of innovation.

Fourth, this paper extends prior work (e.g., Franke and Piller 2004) on the effects of innovation toolkits in supporting innovation. While previous studies have tested if the presence of toolkit support affects users' satisfaction and willingness to pay for user innovations (e.g., Franke and von Hippel 2003), there is a lack of research that theorizes and tests the effect of toolkit support on innovation itself. Our study theoretically models and empirically validates both the direct effect of toolkit support and its moderating effect on the relationship between anticipated enjoyment and intention to innovate. We find that for actual user innovators, it positively impacts their innovation intention and enhances the effect of anticipated enjoyment on innovation intention. In contrast, for potential user innovators, toolkit support reduces the effect of anticipated enjoyment on innovation intention.

Practical Implications

Practically, our results offer suggestions to host firms and administrators on how to encourage users to participate in MDS innovation. Instead of treating all user innovators identically, this study distinguishes the antecedents of two groups (i.e., potential and actual user innovators). The findings suggest that firms should differentiate their strategies in attracting potential user innovators to participate and in encouraging actual user innovators to design MDS applications again. Specifically, we found that potential user innovators value anticipated enjoyment and place less importance on anticipated extrinsic reward, anticipated recognition, and toolkit support than actual user innovators for MDS innovation. These differences could be used by firms to influence potential user innovators to carry out MDS innovation. A possible approach could be through facilitating their interaction with actual user innovators that can revise their perceptions with reality. Potential user innovators could be identified as those users with interest in MDS innovation and at least basic programming knowledge, as was done in our sample. Also, firms could provide try-out sessions for potential user innovators to understand their needs better and educate them on the toolkit support available.

For actual user innovators, strengthening perceptions of anticipated extrinsic rewards, anticipated recognition, and toolkit support is likely to encourage them to innovate MDS again. Expectation of extrinsic rewards could be heightened by guiding previous user innovators on how best to leverage the commercialization mechanisms available and highlighting success stories of monetary rewards and career opportunities obtained by other user innovators. Recognition expectations can be enhanced by providing visibility of user innovators' success to peers, other users, and professional developers on the platform. Further, the host firm can enhance the functionality of innovation toolkits for actual user innovators both for innovation exploration and easing development effort. This can the have additional benefit of activating the anticipated enjoyment motivation for actual user innovators when toolkit support is perceived as high. Last, trend leadership can be enhanced for this group to increase their likelihood of innovating again (e.g., through increasing the customer knowledge of the user innovators) (Faullant et al. 2012; Schreier and Prugl 2008).

Conclusion

This study is motivated by the unique context of user MDS innovation, the practical challenges regarding the attrition of actual user innovators, as well as the theoretical gaps in the user innovation literature. Thus, we developed and tested a model to explain the antecedents of users' MDS innovation intention in terms of individual drivers and toolkit support and the differences in the effects of the antecedents for potential and actual user innovators. In sum, this study offers theoretical and practical contributions with respect to an emerging phenomenon (i.e., MDS innovation) that is gaining interest among researchers and practitioners.

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RESEARCH ARTICLE

COMPARING POTENTIAL AND ACTUAL INNOVATORS: AN EMPIRICAL STUDY OF MOBILE DATA SERVICES INNOVATION

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Appendix A

Literature Summary and Model Constructs

Table A1. Previous Empirical Research Related to User Product Innovation (Studies arranged by date within each category)

DV	Study	Constructs	Method	Key Findings
DV is aspects of User Innovation	Lüthje (2004)	Independent variables • Innovation related core benefits • Product knowledge • Fun by dealing with innovation • Expected financial compensation Dependent variable • Innovation effort	Survey of 153 consumers of two outdoor product manufacturers. Outdoor consumers are end users who buy and/or use these products **Unit of analysis**: User level	Innovation related core benefits (facing new needs, dissatisfaction with existing products) and expertise in product use (product knowledge, use experience, and fun by dealing with innovation) positively affect user innovation effort, while financial related benefits does not affect the DV.
	Jeppesen and Frederiksen (2006)	Independent variables • Lead userness • Firm and peer recognition • Enhance career opportunities Dependent variable • User innovation	Survey of 345 users in a computer controlled music instrument innovation community **Unit of analysis**: User level	Lead userness and firm recognition positively affect user innovation behaviors in the community.

Table A1. Previous Empirical Research Related to User Product Innovation (Continued) (Studies arranged by date within each category)

DV	Study	Constructs	Method	Key Findings
DV is aspects of User Innovation (continued)	Franke et al. (2006)	Independent variables • Ahead of trend • High benefit expected • Technical Expertise Dependent variables • User innovation probability • Innovation attractiveness	Survey of 456 users in kite surfing communities **Unit of analysis**: User level	High benefit expected positively affects the probability of user innovation while ahead of trend positively affects the probability of user innovation and the attractiveness of user innovation.
	Franke et al. (2008)	Independent variable • User toolkit feature: Having access to other users' designs versus no access Dependent variables • Integration of existing solution chunks • Quality of self-designed skis	Experiment with 191 subjects on use of toolkits to develop personal skis **Unit of analysis**: User level	Having access to other users' designs stimulates the integration of existing solution chunks into the problem-solving process, which enhance the quality of self-designed skis.
DV is Lead Userness or Lead Userness is a mediator	Schreier and Prugl (2008)	Independent variables • Consumer knowledge • Use experience • Locus of control • Innovativeness personality • Mediators • Lead userness: Trend position; Expected benefits from innovation Dependent variables • New product adoption • Replacement rate	Examine the antecedences and consequence of lead userness for extreme sports, e.g., sail planning, technical diving, kite surfers Survey of 461 users in 3 samples on sport-related product innovation **Unit of analysis**: User level	Consumer knowledge, use experience, locus of control, and innovativeness personality significantly enhance lead userness, which positively affects the number of new products adopted, yearly spending on kite surfing equipment, and the replacement rate for major equipment.
	Kratzer and Lettl (2009)	Independent variable • Betweenness centrality Dependent variable • Lead userness	Survey of 537 children in 23 school classes on toy design **Unit of analysis**: User level	Betweenness centrality positively affects the lead userness of children.
	Faullant et al. (2012)	Independent variables • Divergent thinking • Use experience • Product knowledge Dependent variables • Ahead of trend • Expected benefits	Survey of 146 product testers for small kitchen appliances **Unit of analysis**: User level	Divergent thinking, product knowledge, and use experience positively affect the ahead of trend and expected benefit dimensions of lead userness.

Table A2. Previous Empirical Research Related to User Service Innovation (Studies arranged by date within each category)

Unit of Analysis	Study	Constructs	Method	Key Findings
Organization Level	Chen et al. (2009)	Independent variables • Innovation orientation • IT capability • External partner collaboration Dependent variable • Service delivery innovation	Survey of 420 Taiwanese financial firms **Unit of analysis**: Organizational level	Innovation orientation and IT capability positively affect service delivery innovation while external partner collaboration does not.
	Carbonell et al. (2009)	Independent variables • Technical novelty • Technical turbulence • Mediator • Customer involvement Dependent variables • Innovation speed • Technical quality of innovation • Competitive advantage • Sales performance	Survey of 102 Spanish service firms **Unit of analysis**: Organizational level	Customer involvement positively affects technical quality of innovation, and innovation speed but does not affect sales and competitive advantage. Technical novelty and technical turbulence positively affect customer involvement.
	Ordanini and Parasuraman (2011)	Independent variables • Customer collaboration • Employee collaboration • Business partner collaboration • Knowledge integration mechanisms • Customer orientation Dependent variables • Innovation radicalness • Innovation volume	Survey of 91 five star hotels in Italy **Unit of analysis**: Organizational level	Customer collaboration and employee collaboration positively affect the volume of service innovation while business partner collaboration, employee collaboration, knowledge integration mechanisms, and customer orientation positively affect the radicalness of service innovation.
User Level	Morrison et al. (2000)	Independent variables • Leading-edge status • In-house technical capabilities Dependent variable • Probability of user innovation behavior	Survey of 122 users of library information systems OPAC **Unit of analysis**: User level	Leading-edge status and in-house technical capabilities positively affect user innovation behavior.
	Magnusson et al. (2003)	• Comparing ordinary users, consulting users versus professionals Dependent variables • Originality • Reproducible • User value of ideas for service innovation	Experiment on 12 professional employees in a Swedish mobile telephony operator, 19 ordinary users, and 20 consulting users **Unit of analysis**: User level	Ordinary users and consulting users can generate ideas of higher originality and user value but of less producibility than professional employees.
	Matthing et al. (2004)	• Comparing consumers versus professionals Dependent variables • Originality • User value of service innovation idea	Experiment on 86 Sweden end-users to generate ideas for mobile phone services **Unit of analysis**: User level	Consumer generated service ideas are found to be more innovative, in terms of originality and user value, than those of professionals.

Table A2. Previous Empirical Research Related to User Service Innovation (Continued) (Studies arranged by date within each category)

Unit of Analysis	Study	Constructs	Method	Key Findings
User Level	Matthing et al. (2006)	Independent variable • Technology readiness Dependent variables • Propensity to adopt new tech-based services • Seek new tech and solve related problems • Willingness to participate in new tech-based service development • Originality • User value of service innovation idea	Survey of 1004 Swedish users of telecom services, followed by experiment with 52 users **Unit of analysis**: User level	Technology readiness is positively related to propensity to adopt new tech-based services, actively seek new technologies and solve problems related to them, and be willing to participate in new technology-based service development. Potential "lead users," are capable of actually generating a large, diverse and original set of new service ideas.
	Kratzer and Lettl (2008)	Independent variable • Betweenness centrality Dependent variables • Lead userness • Creativity	Experiment with 366 children in 16 school-groups to develop ideas on improving an online application, 'CineKidStudio', for their personal use **Unit of analysis**: User level	Betweenness centrality positively affects the lead userness and creativity of children.
	Franke and von Hippel (2003)	Independent variables • Heterogeneity of user needs • Innovation toolkits Dependent variables • User innovation • User satisfaction	Survey of 131 individual users for open source Apache security software (no regression) **Unit of analysis**: User level	Innovation toolkits can better serve heterogeneous needs. Heterogeneous needs lead users to customize their software. User who customize their software with the help of innovation toolkits are more satisfied than those who did not customize.

Table A3. Antecedents and Controls for our Model mapped from Previous Literature

Variables	Constructs in Our Model			Constructs Previously Studied	Studies
Antecedents	**Lead Userness**			Lead user	Jeppesen and Frederiksen (2006)
				Lead userness	Franke et al. (2006)
		Trend Leadership		Leading-edge status	Morrison et al. (2000)
				Technology readiness	Matthing et al. (2006)
				Innovation related core benefits (facing new needs, dissatisfaction with existing products)	Lüthje (2004)
		Expected Benefit (Franke et al 2006)	**Anticipated Extrinsic Reward**	Expected financial compensation	Lüthje (2004)
				Enhance career opportunities	Jeppesen and Frederiksen (2006)
			Anticipated Enjoyment	Fun by dealing with innovation	Lüthje (2004)
			Anticipated Recognition	Peer recognition and firm recognition	Jeppesen and Frederiksen (2006)
Controls	**Tenure**			Product knowledge	Lüthje (2004)
	Programming Skill			In-house technical capabilities	Morrison et al. (2000)
				Technical expertise	Franke et al. (2006)
Not included	Antecedents of **lead userness**, which is already included in our model			Consumer knowledge	Schreier and Prugl (2008)
				Locus of control	Schreier and Prugl (2008)
				Innovativeness	Schreier and Prugl (2008)
				Use experience	Schreier and Prugl (2008) Faullant et al. (2012)
				Divergent thinking	Faullant et al. (2012)
				Betweenness centrality	Kratzer and Lettl (2009)

Table A4. Previous Research Related to Toolkit Support (Studies arranged by date)

Study	Constructs	Method	Key Findings
Von Hippel and Katz (2002)		**Conceptual**	Effective toolkits for user innovation should include the following features • Offer users a "solution space" • User friendly, easy for novices to use • Contain libraries of commonly used modules • Facilitate trial and error learning • Translate user design for production
Franke and von Hippel (2003)	Independent variables • Heterogeneity of user needs • Innovation toolkits Dependent variables • User innovation • User satisfaction	**Survey** of 131 individual users for open source Apache security software (no regression) **Unit of analysis**: User level	Innovation toolkits can better serve heterogeneous needs. Heterogeneous needs lead users to customize their software. User who customize their software with the help of innovation toolkits are more satisfied than those who did not customize.
Franke and Piller (2004)	• Toolkit use: module library, solution spaces Dependent variables • Heterogeneity of design result • Willingness to pay for the watch designed	**Four Experiments** on user innovation in watch design using the toolkit of Idtown **Unit of analysis**: User level	Users who use toolkits to self-design watches are significantly more willing to buy the watches. The self-designed watches vary quite widely. Toolkits can support users for trial and error learning, experimentation.
Piller et al. (2004)	• Toolkit function	**Case Study** of user tool *Game Creator* for mobile game	As a module of *Game Creator*, the *Component Creator* has functions enabling users to save components in the library and search for and build upon existing components in the library.
Jeppesen (2005)	• Toolkit support for peer/user-to-user communication • The costs of consumer involvement	**Case study** of user innovation in computer games by Westwood Studios Use toolkits (Final Alert 2—a 2D graphics editor) for game innovation	Toolkit use extends the product lifetime -computer games can stay popular longer when additional product content that adds to the consumption experience is produced on a continuing basis. Toolkits can reduce the costs (time and effort) of involvement through peer support.
Shneiderman (2007)	• Tool features to support creative activities	**Conceptual**	Tool features that can accelerate innovation: • support exploratory search • enable collaboration • provide rich history-keeping • easy for novices to get started with
Franke et al. (2008)	Independent variable • User toolkit feature: Having access to other users' designs versus no access Dependent variables • Integration of existing solution chunks • Quality of self-designed skis	**Experiment** with 191 subjects on use of toolkits to develop personal skis **Unit of analysis**: User level	Having access to other users' designs stimulates the integration of existing solution chunks into the problem-solving process, which enhance the quality of self-designed skis.

Table A5. Toolkit Support Dimensions Mapped to Previous Literature

Dimensions in Our Model	Features Previously Studied	Studies
Exploration	Experimentation Trial and error learning	Franke and Piller (2004), Von Hippel and Katz (2002)
	Having access to other users' designs	Franke et al. (2008)
	Support exploratory search	Shneiderman (2007)
	Appropriate solution space	Von Hippel and Katz (2002)
Ease of effort	Module library	Franke and Piller (2004) Von Hippel and Katz (2002)
	Component library save and search	Piller et al. (2004)
	Provide rich history-keeping	Shneiderman (2007)
	Reduce the costs of consumer involvement Increase ease of use User friendly	Jeppesen (2005) Shneiderman (2007) Von Hippel and Katz (2002)
Not applicable in study context	Enable user communication and collaboration	Jeppesen (2005) Shneiderman (2007)
	Translate user design for production	Von Hippel and Katz (2002)

Table A6. Definitions of Constructs in the Model

Constructs	Definition	Source
Anticipated Extrinsic Reward	The degree to which users believe that they will receive monetary incentives if they create new MDS applications	Adapted from Bock et al. (2005)
Anticipated Recognition	The degree to which users believe that their recognition will increase if they create new MDS applications	Adapted from Jeppesen and Frederiksen (2006)
Anticipated Enjoyment	The degree to which users believe they will obtain pleasure if they create new MDS applications	Adapted from Lakhani and Wolf (2005)
Trend Leadership	The degree to which users have ahead of trend needs	Adapted from Franke et al.(2006); Lüthje (2004)
Toolkit Support	The expected extent to which users believe that toolkits will support their MDS innovation by reducing effort and facilitating exploration	Adapted from Shneiderman (2007); Franke et al. (2008)
Intention to Innovate	The degree to which users believe that they will engage in creating new MDS application in future	Adapted from Agarwal and Karahanna (2000)
Mobile data services	Digital data services available on or accessible via mobile devices	Lee et al. (2009)

Table A7. Operationalization of Constructs

Construct		Items	Sources
Trend Leadership	**TLS1**	I need to create service applications that better facilitate my daily work or entertainment *(unique need)*	Adapted from Franke et al. (2006); Kratzer and Lettl (2009)
	TLS2	I always need new service applications *(unique need)*	
	TLS3	I am always the first one to adopt new service applications *(leadership)*	
Anticipated Enjoyment	**AEJ1**	I will have fun creating a new service application	Adapted from Agarwal and Karahanna (2000); Fuller et al. (2009)
	AEJ2	Creating a service application will provide me with a lot of enjoyment	
	AEJ3	I will enjoy the process of materializing my ideas into service applications	
Anticipated Extrinsic Reward	**AER1**	I expect to receive monetary rewards in return for my service application created	Adapted from Bock et al. (2005)
	AER2	It is important for me to get monetary rewards in return for creating new service applications	
	AER3	I expect to gain enhanced career prospects in return for creating new service applications	
	AER4	It is important for me to improve career prospects through participating in new service application creation activities	
Anticipated Recognition	**REG1**	Recognition from others is a great reward for creating new service applications	Adapted from Jeppesen and Frederiksen (2006); Wasko and Faraj (2005)
	REG2	Creating new service applications in the platform enhances my status	
	REG3	Creating new service applications improves my image	
Ease of Effort	**EOE1**	The development tools help me save a lot of effort for collecting information and designing new service applications for the market	Self-developed
	EOE2	With the help of the development tools, it is easy to collect information and design applications for the market	
	EOE3	With the help of the development tools, it is easy to use component library for service application design	
Exploration	**EXP1**	The development tools enable me to extensively explore service applications in the market	
	EXP2	The development tools help me explore my peers' latest developed applications	
	EXP3	With the help of the development tools, I can experiment with (ideas of) creating service applications	
Intention to Innovate	**ITI1**	I will create service applications in the next 6 months	Developed from Agarwal and Karahanna (2000)
	ITI2	I am likely to develop service applications in the next 6 months	
	ITI3	I am contemplating to create service applications in the next 6 months	

Appendix B

Supporting Data Analyses

Table B1. Demographics of Respondents

Demographic Variables		Actual Innovators' Frequency and Percentage (N = 101)		Potential Innovators' Frequency and Percentage (N = 111)	
Gender	Male	72	71.3%	86	77.5%
	Female	29	28.7%	25	22.5%
Age	≤20	24	23.7%	3	2.7%
	21–25	30	29.7%	75	67.6%
	26–30	30	29.7%	30	27.0%
	31–35	12	11.9%	2	1.8%
	36–40	2	2.0%	0	0.0%
	> 40	3	3.0%	1	0.9%
Educational Level	High School	0	0.0%	42	37.8%
	Diploma	6	5.9%	42	37.8%
	Bachelors	34	33.6%	24	21.7%
	Masters	53	52.5%	3	2.7%
	Doctorate	8	8.0%	0	0.0%
Platform	iOS	66	65.3%	62	55.9%
	Android	35	34.7 %	49	44.1%
Programming Skill	1 (Low)	0	0.0%	1	0.9%
	2	1	1.0%	3	2.7%
	3	5	4.9%	10	9.0%
	4 (Medium)	11	10.9%	36	32.5%
	5	29	28.7%	33	29.7%
	6	35	34.7%	18	16.2%
	7 (High)	20	19.8%	10	9.0%
Tenure (Months)	< 6	7	6.93%	-	-
	6–12	32	31.68%	-	-
	13–24	38	37.62%	-	-
	>24	24	23.76%	-	-

Table B2. Results of Factor Analysis (Actual | Potential)

	1	2	3	4	5	6	7
AER1	**0.71|0.75**	-0.14|0.00	0.20|0.12	0.12|0.17	-0.09|0.12	-0.01|0.21	0.31|0.23
AER2	**0.82|0.84**	0.04|0.13	0.19|0.17	0.33|0.26	0.11|0.15	0.22|0.31	0.25|0.32
AER3	**0.77|0.78**	-0.02|-0.08	0.24|0.27	0.32|0.20	-0.05|-0.05	0.03|0.42	0.33|0.24
AER4	**0.74|0.84**	-0.14|0.09	0.21|0.32	0.24|0.28	0.03|0.07	0.29|0.22	0.30|0.35
AEJ1	0.08|0.03	0.18|0.32	0.31|0.23	0.11|0.35	**0.76|0.79**	0.05|0.10	0.01|0.02
AEJ2	-0.03|0.14	0.18|0.41	0.21|0.32	0.25|0.54	**0.90|0.93**	0.15|0.08	0.05|0.04
AEJ3	0.05|0.06	0.18|0.39	0.36|0.33	0.22|0.52	**0.89|0.92**	0.18|0.07	0.08|0.10
TLS1	-0.07|0.07	**0.93|0.94**	0.40|0.43	0.19|0.34	0.20|0.40	0.10|0.05	0.07|0.15
TLS2	0.00|0.06	**0.79|0.93**	0.41|0.12	0.10|0.32	-0.13|0.37	-0.01|0.01	0.10|0.13
TLS3	-0.09|0.02	**0.73|0.78**	0.42|0.23	0.03|0.24	-0.27|0.36	0.11|0.03	0.01|0.02
EOE1	0.28|0.17	0.03|0.11	**0.91|0.87**	0.42|0.33	0.24|0.11	0.37|0.02	0.27|0.12
EOE2	0.22|0.23	-0.08|0.23	**0.87|0.78**	0.35|0.33	0.28|0.01	0.41|0.02	0.11|0.12
EOE3	0.12|0.20	0.02|0.10	**0.66|0.68**	0.21|0.25	0.11|0.15	0.32|0.09	0.09|0.10
EXP1	0.14|0.37	0.05|0.33	0.25|0.27	0.32|0.43	0.16|0.01	**0.86|0.76**	0.16|0.11
EXP2	0.20|0.17	0.08|0.05	0.27|0.34	0.35|0.43	0.13|0.21	**0.88|0.87**	0.15|0.20
EXP3	0.19|0.08	0.01|0.02	0.30|0.24	0.26|0.21	0.29|0.18	**0.67|0.69**	0.17|0.09
REG1	-0.06|0.34	0.05|0.06	0.05|0.31	0.28|0.23	0.14|0.21	0.10|0.27	**0.80|0.87**
REG2	-0.02|0.02	0.00|0.07	0.17|0.21	0.26|0.24	0.16|0.17	0.13|0.34	**0.75|0.81**
REG3	-0.04|0.03	0.14|0.05	0.18|0.27	0.27|0.34	0.14|0.11	0.27|0.33	**0.77|0.81**
ITI1	0.34|0.34	0.17|0.33	-0.01|0.02	**0.88|0.95**	0.22|0.55	0.28|0.33	0.38|0.30
ITI2	0.26|0.24	0.16|0.35	-0.05|0.04	**0.87|0.96**	0.26|0.49	0.35|0.23	0.25|0.18
ITI3	0.35|0.24	0.12|0.29	0.02|0.04	**0.86|0.94**	0.26|0.47	0.39|0.27	0.18|0.25
Eigen value	5.54|6.76	4.01|4.31	2.80|3.01	2.52|2.63	1.83|1.95	1.38|1.87	1.20|1.08
Variance explained (%)	22.12|23.06	16.06|16.91	11.01|11.89	9.21|9.56	7.89|8.23	7.01|7.20	6.21|5.70
Cumulative variance (%)	22.12|23.06	38.18|39.97	49.19|51.86	58.40|61.42	66.29|69.65	73.03|76.85	79.51|82.55

Table B3. Weights of Formative Dimensions

Construct	Group	Dimension	Weights	T-Value
Toolkit Support (TKS)	Actual User Innovator	Ease of Effort (EOE)	0.59	13.21
		Exploration (EXP)	0.54	12.98
	Potential User Innovator	Ease of Effort (EOE)	0.56	27.34
		Exploration (EXP)	0.57	27.10

Common Method Bias Test

Harman's single factor test was conducted by running an exploratory factor analysis with all variables included. The factor analysis produced neither a single factor nor one general factor that accounted for the majority of the variance (< 50%) as desired, suggesting no common method bias. We have also followed Liang et al. (2007) to test the common method bias (see Table B4). The analysis results show that only 4 of the 20 paths for actual innovators and 3 of 20 for potential innovators from the common method factor were significant, providing evidence that the study results were not affected by common method bias (Podsakoff et al. 2003).

Table B4. Common Method Bias Analysis

Construct	Items	Substantive Factor Loading (R1)		$R1^2$		T-value		Method Factor Loading (R2)		$R2^2$		T-value	
Trend Leadership	TLS1	0.88	0.93	0.77	0.86	**56.47**	**92.02**	0.01	0.04	0.00	0.00	1.52	1.89
	TLS2	0.86	0.92	0.74	0.85	**43.24**	**66.50**	0.01	0.02	0.00	0.00	0.95	1.11
	TLS3	0.61	0.82	0.37	0.67	**7.18**	**28.68**	0.02	-0.00	0.00	0.00	0.97	0.00
Anticipated Extrinsic Reward	AER1	0.78	0.78	0.61	0.61	**17.58**	**18.23**	0.02	0.06	0.00	0.00	1.05	1.50
	AER2	0.78	0.78	0.61	0.61	**15.63**	**17.64**	-0.01	0.11	0.00	0.01	0.03	**3.02**
	AER3	0.76	0.75	0.58	0.56	**16.89**	**23.42**	0.04	0.09	0.00	0.01	1.50	1.09
	AER4	0.76	0.77	0.58	0.59	**19.02**	**24.72**	0.04	0.10	0.00	0.01	1.31	1.20
Anticipated Enjoyment	AEJ1	0.77	0.77	0.59	0.59	**16.07**	**23.45**	0.10	0.08	0.01	0.01	**2.31**	1.28
	AEJ2	0.89	0.89	0.79	0.79	**49.82**	**30.61**	0.10	0.10	0.01	0.01	**2.58**	1.02
	AEJ3	0.90	0.90	0.81	0.81	**44.59**	**30.31**	0.04	0.10	0.00	0.01	1.64	1.64
Anticipated Recognition	REG1	0.85	0.85	0.72	0.72	**29.87**	**31.06**	0.07	0.05	0.00	0.00	1.36	1.36
	REG2	0.84	0.88	0.71	0.77	**26.27**	**35.10**	0.06	0.06	0.00	0.00	1.22	1.07
	REG3	0.83	0.88	0.69	0.77	**31.61**	**36.28**	0.07	0.07	0.00	0.00	1.34	1.16
Ease of Effort	EOE1	0.91	0.91	0.83	0.83	**34.91**	**61.38**	0.08	0.15	0.01	0.02	**1.99**	**2.99**
	EOE2	0.90	0.90	0.81	0.81	**56.17**	**47.43**	0.07	0.14	0.00	0.02	**1.94**	**2.71**
	EOE3	0.89	0.88	0.79	0.77	**45.32**	**44.01**	0.06	0.07	0.00	0.00	0.87	0.10
Exploration	EXP1	0.90	0.93	0.81	0.86	**53.28**	**90.47**	0.05	0.12	0.00	0.01	1.06	1.06
	EXP2	0.90	0.93	0.81	0.86	**58.78**	**96.97**	0.06	0.12	0.00	0.01	1.36	0.96
	EXP3	0.88	0.90	0.77	0.81	**54.10**	**70.26**	0.10	0.09	0.01	0.01	1.10	0.97
Intention to Innovate	ITI1	0.91	0.95	0.83	0.90	**72.86**	**127.63**	0.03	0.06	0.00	0.00	1.33	0.88
	ITI2	0.92	0.96	0.85	0.92	**73.47**	**154.86**	0.05	0.07	0.00	0.00	1.40	1.32
	ITI3	0.90	0.94	0.81	0.88	**69.46**	**84.06**	0.06	0.06	0.00	0.00	1.39	1.51

Note: Each pair of values represent actual | potential user innovator samples.

Appendix C

Measurement Invariance Test and *Post Hoc* Test

In order to compare the responses from potential and actual user innovators, we tested the measurement model and evaluated the measurement invariance (Cheung and Rensvold 2002). This test is performed to validate that any differences observed between the different samples of respondents (actual versus potential innovators) can be attributed to true attitudinal differences. Following previous literature using such analysis (e.g., Phang et al. 2009), we used LISREL 8.8 to conduct the invariance test. As per the previous literature (e.g., Milfont and Fischer 2010; Phang et al. 2009), we tested three required hierarchical levels of invariance: configural, metric, and scalar invariance test (Steenkamp and Baumgartner 1998). For the configural invariance, we found that the values of IFI, NNFI, and CFI of the combined model of two groups are above 0.90 and RMSEA below 0.08. Therefore, the configural invariance between the groups of potential innovators and actual innovators is established. Further, the difference between CFI in the configural model and the metric model (Δ CFI = 0.9211 – 0.9132 = 0.0079) is well below 0.01. According to the criteria in Cheung and Rensvold (2002), metric invariance is satisfied in our study. Moreover, the difference between CFI in the metric model and the scalar model (Δ CFI = 0.9132 – 0.9026 = 0.0106) marginally exceeds the 0.01 threshold. As per Hong et al. (2003), scalar invariance is largely satisfied in our model.

Table C1. Results of Measurement Invariance Tests

Models	X^2	df	IFI	NNFI	CFI	RMSEA
Actual	122.3	80	0.93	0.91	0.92	0.072
Potential	169.8	80	0.92	0.94	0.92	0.079
Baseline (Configural)	**292.2**	**160**	**0.92**	**0.92**	**0.9231**	**0.062**
Metric	**376.8**	**175**	**0.91**	**0.92**	**0.9168**	**0.070**
Scalar	**485.7**	**190**	**0.91**	**0.91**	**0.9066**	**0.081**

We *post hoc* tested the influence of the independent variables on the number of MDS applications created and the average popularity of these MDS applications.

Table C2. *Post Hoc* Test

DV	DV = Number of Innovations[†]		DV = Log (MDS Popularity)	
Variables	**1**	**2**	**3**	**4**
TLS	0.17*	0.16*	0.13*	0.17**
AEJ	0.07	0.06	-0.11	-0.18
AER	0.32**	0.32**	0.25***	0.26***
REG	0.13*	0.12*	0.11*	0.10*
TKS	0.35***	0.33**	0.16*	0.14*
AEJ * TKS	-	0.14*	-	0.22*
R^2	0.52	0.58	0.32	0.38

*p < 0.05, **p < 0.01, ***p < 0.001

[†]We verified the accuracy of the number of applications reported by actual user innovators by checking the agreement of the reported values against the actual data listed in the two platforms. The correlations were high (r = 0.90, p < 0.001) and none of the means differences were significant (t = 1.06, p < 0.30).

Appendix D

Moderation Plots and Threshold Analysis

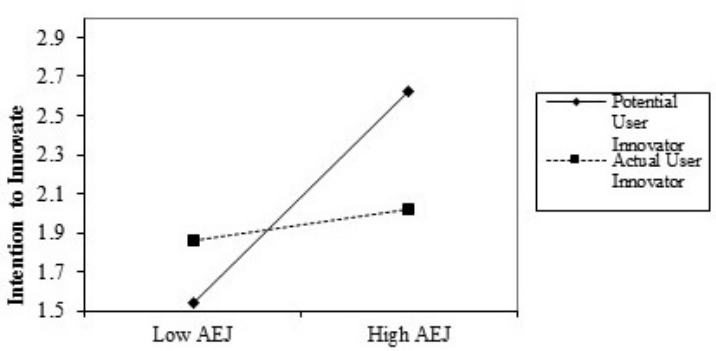

Figure D1. Plot for H2c

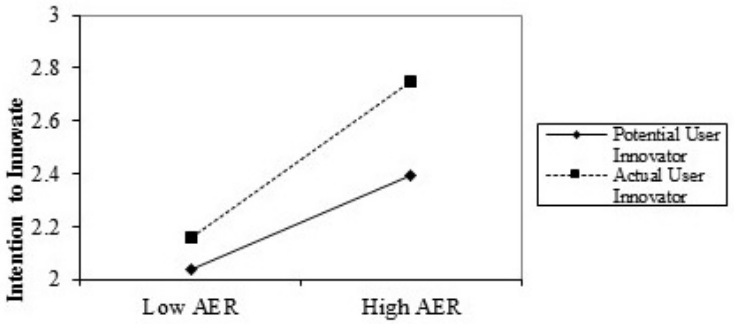

Figure D2. Plot for H3c

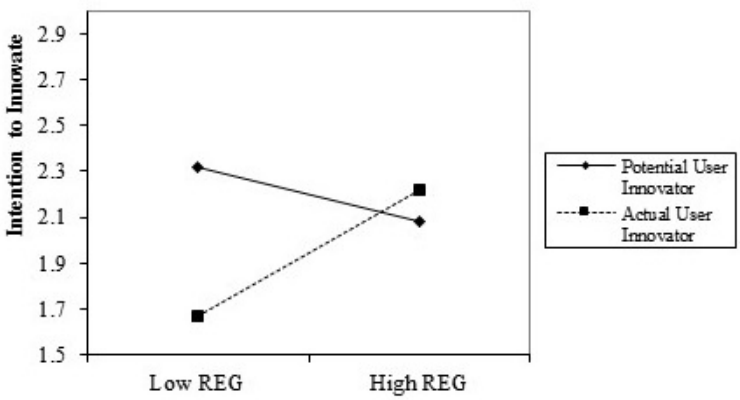

Figure D3. Plot for H4c

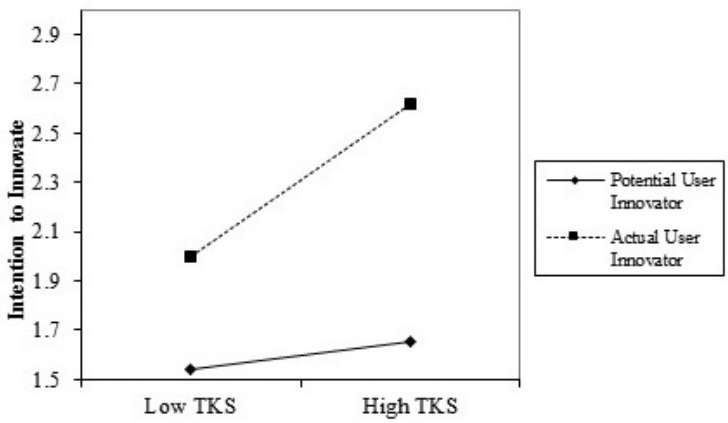

Figure D4. Plot for H5c

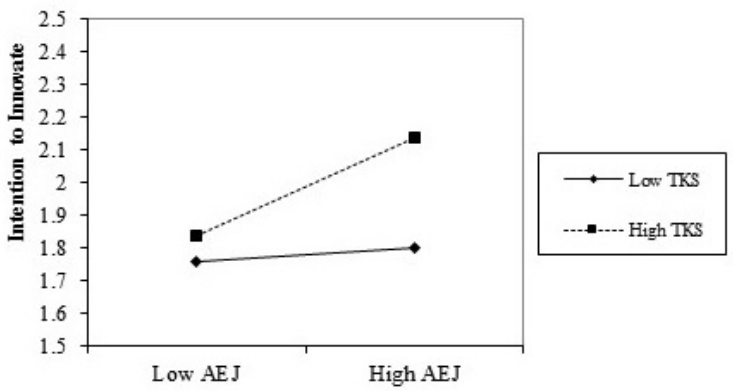

Figure D5. Plot for H6a

The plots in Figures D1-D4 show the differences between potential and actual user innovators as indicated in Table 3.

From the results in Table 2, we also see a moderation effect between AEJ and TKS on ITI for actual user innovators (H6a) but no direct effect of AEJ on ITI for this group (H2a). We could explain these two results in terms of the level of TKS. Specifically, when the level of TKS is low, we do not see an effect of AEJ on ITI. However, as TKS increases, there is a threshold beyond which the effect of AEJ on ITI becomes significant (see Figure D5). This is consistent with Baron and Kenny (1986), who noted one of the specifications of a moderator as a threshold beyond which the effect of the IV on the DV becomes significant. To obtain a rough estimate of the threshold, we split the actual user innovators sample into four quartiles based on the values of TKS and estimated the coefficient of AEJ on ITI for each quartile (see Table D1). As the coefficient is significant only in the fourth (highest) quartile, we further split this quartile into two to more precisely estimate the threshold. We found that the coefficient changes from insignificant to significant at the TKS value of 5.67. We could not split the sample further to more precisely determine the threshold since the sample size becomes too small to estimate the effects robustly. Baron and Kenny also state that theories in social psychology are usually not precise enough to specify the exact threshold at which the change occurs. However, our empirical analysis shows such a threshold.

We did a similar threshold analysis for potential user innovators as our results showed a negative interaction between AEJ and TKS for this group, but no main effect of TKS. Here, we split the sample by AEJ and observed that the effect TKS on ITI is significant for lower levels of AEJ but becomes insignificant for higher levels of AEJ (see Table D2). We found that the coefficient changes from significant to insignificant at the AEJ value of 5.57 (i.e., between the second and third quartiles).

Table D1. Threshold Analysis for Actual User Innovators AEJ*TKS

TKS	First Quartile	Second Quartile	Third Quartile	Fourth Quartile	
Coefficient of AEJ on ITI	0.01	0.04	0.10	0.24**	
Split by two				0.11	0.20*

Table D2. Threshold Analysis for Potential User Innovators AEJ * TKS

AEJ	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
Coefficient of TKS on ITI	0.34*	0.12*	-0.01	-0.10

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