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RESEARCH ARTICLE

USER SERVICE INNOVATION ON MOBILE PHONE PLATFORMS: INVESTIGATING IMPACTS OF LEAD USERNESS, TOOLKIT SUPPORT, AND DESIGN AUTONOMY[1]

Hua (Jonathan) Ye
Department of Information Systems and Operations Management, The University of Auckland Business School,
12 Grafton Road, Auckland 1142, NEW ZEALAND {hua.ye.nus@gmail.com}

Atreyi Kankanhalli
Department of Information Systems and Analytics, National University of Singapore, 13 Computing Drive,
SINGAPORE 117417 {atreyi@comp.nus.edu.sg}

User participation is increasingly being seen as a way to mitigate the challenges that firms face in innovation, such as high costs and uncertainty of customer acceptance of their innovations. Thus, firms are establishing online platforms to support users in innovating services, such as iOS and Android platforms for mobile data service (MDS) innovation. Mobile phone platforms are characterized by technology (toolkits) and policy (rules) components that could influence user's innovation. Additionally, attributes of user innovators (lead userness) are expected to drive their innovation behavior. Yet it is unclear how these characteristics jointly impact users' service innovation outcomes. To address this knowledge gap, we propose a model that builds on user innovation theory and the work design literature to explain the influences of lead userness, design autonomy, toolkit support, and their interactions on user's innovation outcomes (innovation quantity) on these platforms. We conceptualize toolkit support in terms of two constructs (i.e., ease of effort and exploration), and design autonomy in terms of three constructs (i.e., decision-making autonomy, scheduling autonomy, and work-method autonomy). The model was tested using survey and archival data from two dominant mobile phone platforms (i.e., iOS and Android). As hypothesized, lead userness, exploration through toolkits, and ease of effort through toolkits positively affect users' innovation quantity. Additionally, decision-making autonomy and work-method autonomy influence innovation quantity, but scheduling autonomy does not. Further, the proposed three-way interactions between lead userness, toolkit support, and design autonomy constructs on users' quantity of MDS innovation are largely supported. The findings enhance our understanding of user innovation on mobile phone platforms.

Keywords: User innovation, mobile phone platform, design autonomy, toolkit support, lead userness, three-way interaction

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Introduction

Engaging customers or users in the process of service innovation is increasingly seen as an approach to sustain firms' competitive advantage (Lusch et al. 2007; Magnusson et al. 2003). *Service innovation* refers to service offerings not previously available to the firm's customers, including an addition to the current service mix or a change in existing services (Menor and Roth 2007). User innovators can offer several benefits, such as contributing diverse and commercially attractive ideas, and even creating the innovation at a relatively low cost (Carbonell et al. 2009). Prior research has reported that anywhere from 19% to 76% of innovations in various fields could be attributed to user innovators (Shah et al. 2012). To enable user innovation, firms are establishing online platforms (Boudreau and Lakhani 2009; Ebner et al. 2009). For example, Apple iOS and Google Android are two dominant platforms where users can create new mobile data service (MDS) applications. Adapting from previous definitions (Boudreau 2012; Tiwana et al. 2010), we define *mobile phone platforms* as software-based systems that provide functionality to support the development of mobile applications and transactions among multiple sets of actors. Indeed, MDS are among the most popular form of IT-enabled services in current customer markets (Leimeister et al. 2014). *MDS* refers to digital data services available on or accessible via mobile devices (Hong and Tam 2006; Lee et al. 2009). It includes services such as mobile banking, gaming, news, shopping, location-based information, and internet surfing. The market for mobile services is growing rapidly with revenues of U.S. $41.1 billion in 2015 and expected to hit U.S. $101 billion by 2020 (Statista 2016), of which MDS has exceeded voice revenues (Lopes 2014).

As the market for MDS applications is highly competitive (Gupta 2013), MDS innovation becomes vital for phone and carrier companies. Yet, while the participation of external innovators (user innovators and professional developers) is essential for MDS innovation, the rate of innovator attrition on such platforms is high (Burrows 2010; Kim 2010). Particularly, user innovators of MDS face barriers, such as lack of necessary knowledge and uncertainty about the process of applications development (Moon and Bui 2010). These challenges prevent host firms and customers from availing the benefits of user innovation (Boudreau 2012). Indeed, several studies observed that user innovators produce more original and higher user value ideas than professionals (Magnusson et al. 2003; Matthing et al. 2004). With these barriers and benefits, it is important to understand how to encourage user innovation of MDS (Boudreau and Hagiu 2009). We are further motivated to explore this phenomenon as user MDS innovation differs from IT innovation contexts previously studied.

First, *user innovators* of MDS can be characterized by their *lead-userness*, that is, the extent to which they are ahead of other users (pure users or consumers) in experiencing market needs, and expect to benefit significantly from obtaining solutions to these needs (von Hippel 2005). This differs from *professional developers* who create MDS applications as their career. Second, users typically may not have the complete knowledge needed to create and publish new MDS applications (Hughes 2011). Yet, host firms want to encourage broad-based participation in these innovation platforms (Boudreau 2010, 2012) for which they provide innovation toolkits. Innovation *toolkits* refer to coordinated sets of design tools that aim to enable users to take part in innovation (Franke and von Hippel 2003). Toolkits become particularly relevant for them as MDS user innovators both generate ideas and develop new MDS applications (Ye et al. 2011), as opposed to users in other innovation communities such as Dell Ideastorm, who propose and evaluate innovation ideas but do not implement them (Di Gangi and Wasko 2009). Although innovation toolkits constitute a key technology component of mobile phone platforms, there is little study of how they work in conjunction with other user and platform factors to stimulate user innovation, as per our literature review on mobile phone platforms in the following section.

Third, user's participation in MDS innovation differs from user participation in more structured innovation contexts, such as crowdsourcing competitions where the innovation task, reward, and time period are typically specified (Ye and Kankanhalli 2013). While users' development of MDS innovations is not structured in this way, it is still likely to be influenced by the platform's policy (rules) component. Mobile phone platforms typically set a number of policies to regulate innovators' behaviors, which determine the design autonomy afforded to user innovators (Boudreau 2012; Boudreau and Hagiu 2009). We define *design autonomy* as the extent to which individuals perceive that the platform allows them freedom and discretion to schedule work, make decisions, and choose methods for design and innovation (adapted from Breaugh 1999). Indeed, prior studies have highlighted the need to examine how platform owners' control can be balanced against the autonomy of independent innovators on such platforms (Boudreau 2012; Tiwana et al. 2010).

The above differences coupled with the lack of prior research highlight the need to examine the effects of key user characteristics (lead userness), and platform technology (toolkit support) and policy (design autonomy) components on user's MDS innovation. Motivated thus, we develop a theoretical model to answer the following research question: *How do their lead userness, perceptions of design autonomy, and toolkit support in mobile phone platforms jointly affect user*

MDS innovation outcomes? To develop the model, we draw on *user innovation theory* to explain the effects of lead userness and toolkit support, and the *work design literature* to understand how design autonomy impacts user innovation. Broadly speaking, user innovation theory (von Hippel 2005) describes the motivations, processes, and outcomes of user innovation. It posits that user innovators are characterized by their lead userness. It also proposes that knowledge of both needs and solutions are required for innovation, from which the dimensions of toolkit support are inferred that can help gain such knowledge. The work design literature (e.g., Grant and Parker 2009) suggests that autonomy is a key enabler for complex and nonroutine work, such as innovation. We use this literature to conceptualize the dimensions of design autonomy for our model. Further, user innovation theory suggests that user, tool, and design characteristics could interact in influencing creativity and innovation (von Hippel 2005). Also, the work design literature shows mixed findings[2] on the relationship between design autonomy and creativity, suggesting that contingent factors may influence the relationship. This leads us to propose three-way interaction effects between lead userness, toolkit support, and design autonomy dimensions on user innovation.

Our model was tested using survey and archival data of user MDS innovators from both Google Android and Apple iOS platforms, and was found to be largely supported. Our study thus contributes to the user innovation and IT platform literatures by developing a theoretical model to explain the impacts of user and platform characteristics on MDS user innovation. It theorizes, operationalizes, and tests the direct and interaction effects of the focal constructs on user's MDS innovation. It also provides insights to practitioners on how lead-userness and perceptions of design autonomy and toolkit support can be managed for enhancing users' MDS innovation outcomes.

Conceptual Background

In this section, we start off by introducing the research context (mobile phone platforms) for our model and then summarize prior research on user innovation to position our study. Subsequently, we describe the theoretical foundations, that is user innovation theory and the work design literature, from which the dimensions of lead userness, toolkit support, and platform design autonomy are conceptualized respectively. Last, we describe the literature on innovation phases which we use to theorize interactions between the user and platform characteristics for MDS innovation.

[2]Some studies reported positive impacts (e.g., Zhou 1998) of design autonomy on creativity, while others observed no impact (De Jong et al. 2011).

Mobile Phone Platforms and Related Literature

Software-based platforms such as the Apple iOS are emerging as a salient model for application development and software-based services (Tiwana et al. 2010). Unlike traditional software development, they leverage the expertise of a diverse developer community to create new applications. With increasing interest in these platforms, various conceptualizations of IT platforms have been proposed (see Table A1 in Appendix A). Of these, Tiwana et al. (2010) describe how IT platforms have been defined in various ways, for example, as software families (Eisenmann et al. 2006) and infrastructural investments (Fichman 2004). From the commonalities of these conceptualizations, Tiwana et al. define a software-based platform as the extensible codebase of a software-based system that provides core functionality shared by the modules that interoperate with it, and the interfaces through which they interoperate (e.g., Apple iOS), where modules are the add-on software that connect to the platform to add functionalities (e.g., iOS apps). They then define the collection of the platform and its modules as a platform-based ecosystem.

Viewing IT platforms in economic terms as compared to the technical perspective above, previous research (e.g., Boudreau 2012) has defined platforms as multisided networks where they support the interactions and transactions of multiple sets of actors and facilitate technical development. Boudreau (2012) gave the example of the Google Android platform where network effects result from a large number of external software producers creating new applications. Synthesizing the literature above, we define *mobile phone platforms* (e.g., Apple iOS and Google Android) as software-based systems that provide functionality to support the development of mobile applications and transactions among multiple sets of actors.

The platform actors include consumers/users, external (third-party) application creators, and the platform owner. The application creators can be professional developers or user innovators, the latter being the focus of our study. Indeed, user innovation is crucial to the success of mobile phone platforms, where innovation success is typically measured through its quantity (Boudreau 2010; Ordanini and Parasuraman 2011). In our study, too, the *quantity* of user innovations is important as it can increase the diversity of MDS applications and enhance the sustainability of the platform (Boudreau 2010). At the same time, the quality of apps on mobile phone platforms determines customer acceptance and platform sustainability (Boudreau and Hagiu 2009). Further, while attitudinal outcomes, such as satisfaction (Franke and von Hippel 2003) and behavioral outcomes, such as innovation willingness (Matthing et al. 2006) may be useful, they are not as objective indicators of user innovation performance like the quantity of MDS created. Thus, we adopt innovation quantity as our main outcome variable (so as to maintain model parsimony), but also test the model with *quality* measures in our *post hoc* analyses shown in Appendix B. Measuring the outcome variable objectively from the MDS platforms is an advantage of this study as compared to subjective measures of the intention to innovate in prior research.

In mobile phone platforms, typically individual users or small teams of them participate in application creation (Boudreau 2012). User innovators are particularly important to study as they have been found to generate more valuable ideas than professionals in other innovation contexts (Magnusson et al. 2003; Matthing et al. 2004), which may be attributed to their *lead userness* (von Hippel 2005). However, as user innovators face technical barriers (Kim 2010) and policy controls (Tiwana et al. 2010) on these platforms, it is vital to understand how user and platform (technical and policy) characteristics together play a role in shaping user MDS innovation.

As per the definition and discussion above, we characterize mobile phone platforms by two salient components (i.e., the technical component to enable application development, and the policy component to provide the rules under which the development and transactions take place). The technical component of the platform includes the operating system (OS), tools, and libraries to support application creation. Of these, *innovation toolkits* are a key and relevant component for our study since they provide access to the OS and libraries, and can support MDS innovation by users who may not have the required IT knowledge to innovate (Boudreau 2010, 2012). Specifically, Apple provides the Xcode development environment with the iOS software development kit (SDK), while Google provides the Android Studio and SDK. Along with API libraries, these tools can support all stages of MDS application development (i.e., design, development, debugging, testing, and publishing). The tools also provide analytics for each MDS application in the market, including reviews and ratings, which allows user innovators to gain information about the market needs as well as others' innovations (Harker and Taheri 2011).

The policies and rules constitute the other important component of mobile phone platforms. The policies for registering, developing, and publishing applications govern the transactions among the associated actors. For example, Apple Store provides guidelines on the criteria by which new applications are evaluated, rewarded, or penalized (Apple 2015). These rules are likely to influence the *design autonomy* of user innovators, which is an important but understudied characteristic of mobile phone platforms (Boudreau 2012; Boudreau and Hagiu 2009). Previous studies have highlighted the need to examine how platform owners' control can be balanced against the autonomy of independent innovators on such platforms (Tiwana et al. 2010).

While the above discussion suggests the need to understand the effects of lead userness, toolkit support, and design autonomy on user innovation in such platforms, there are limited prior studies in this area. This can be seen from our review of past research related to IT platform level innovation in Table A2 in Appendix A. We classified the past research in terms of the nature of innovation antecedents studied (i.e., pool of producers/innovators), the contest task (i.e., for innovation contests), and platform features. With respect to innovators, these studies mainly examined characteristics of the whole pool (e.g., Boudreau 2012; Boudreau et al. 2011), rather than that of individual innovators as we do. With respect to platform features, prior research has studied the effect of platform regulation on profits and other organizational outcomes (Boudreau and Hagiu 2009) as well as the impacts of the level of access and giving up control in handheld computing platforms on the number of new handheld devices developed (Boudreau 2010). Thus, there is a lack of research in this stream that examines the impacts of technical and policy-related platform features on user innovation.

We also reviewed another stream of related literature: past empirical studies on service innovation at the user level (see Table A3 in Appendix A). From the table it can be seen that several studies investigated the influence of user characteristics such as technology readiness (Matthing et al. 2006), leading edge status (Morisson et al. 2000), and trend leadership (Kankanhalli et al. 2015), which are related to the ahead of trend dimension of lead userness. However, we did not find studies examining the impact of lead userness (which includes ahead of trend and unmet needs dimensions, as discussed in the next section) on user innovation behavior, as we do. Regarding toolkits, prior research has studied the impact of toolkit support in an aggregated manner. For example, Franke and von Hippel (2003) noted that innovation toolkits can serve heterogeneous needs of users designing security software. Kankanhalli et al (2015) measured toolkit support as a single construct and found direct and moderating (with anticipated enjoyment) effects on innovation intention. Thus, research studying the impacts of the various dimensions of toolkit support is lacking, that too, on user innovation behavior. Further, past literature suggested (von Hippel 2005), but did not model and test, that user, tool, and design characteristics could interact in influencing creativity and innovation.

Overall, our reviews identified gaps related to the constructs of interest (i.e., lead userness, design autonomy, and innovation toolkits) and their interactions that help to theoretically motivate our study. As a result, we draw on the user innovation theory, work design, and innovation phases literatures to study the impacts of lead userness, innovation toolkit, design autonomy, and their interactions on user MDS innovation, which will be introduced in the following sections.

User Innovation Theory

The motivation for user innovation theory derives from the shift to user-centered innovation from the traditional firm-centered innovation (von Hippel 2005). Von Hippel and his colleagues observed that users rather than firms are often the initial developers of commercially significant products and services (Lilien at al. 2002; Urban and von Hippel 1988). The theory posits that innovation among users tends to be concentrated on lead users (people with high lead userness) of those products or services (Morrison et al. 2000; von Hippel 1986). Lead userness (Franke et al. 2006, von Hippel 1986) refers to the degree to which people possess two key characteristics: (1) they are at the leading edge of important trends in a market and so are currently experiencing needs that will later be experienced by many others (ahead of trend dimension), and (2) they expect to benefit significantly by obtaining solutions to those needs (high expected benefits, or strong unmet needs dimension). Those who have strong unmet needs expect significant benefits from innovating to fulfil them (Faullant et al. 2012; Schreier and Prugl 2008). Some studies (e.g., Schuhmacher and Kuester 2012) also label this dimension as “dissatisfaction” with existing services.

Prior studies found both knowledge and personality related antecedents of lead userness, that is, consumer knowledge, use experience, locus of control, innovativeness (Schreier and Prugl 2008), creativity, betweenness centrality (Kratzer and Lettl 2008) and divergent thinking (Faullant et al. 2012). Particularly, lead userness should be distinguished from its antecedents such as innovativeness (a personality trait that refers to a person’s generalized predisposition toward innovations; Im et al. 2003) and creativity (the ability to produce novel and useful ideas; Amabile 1988). Further, lead userness has been linked to various outcomes, such as coming up with new product concepts (Herstatt and von Hippel 1992), innovative behavior, innovation attractiveness (Franke et al. 2006), idea quality (Schuhmacher and Kuester 2012), and propensity of knowledge sharing (Jeppesen and Laursen 2009). In sum, people with high lead userness are usually the first to try out new applications related to the service domain (ahead of trend dimension), which allows them to be leaders in identifying problems/ unmet needs with existing services (Faullant et al. 2012). Thus, they are able to anticipate customer needs ahead of others in the market. Also, their unmet needs are strong (unmet needs dimension) whereby they expect great benefits from creating solutions that would satisfy those needs. As a key characteristic of user innovators, we include *lead userness* as an antecedent of user’s MDS innovation in our model. Building on prior studies (e.g., Faullant et al. 2012; Schuhmacher and Kuester 2012) we consider lead userness as composed of two dimensions: ahead of trend and unmet needs. This is also supported by Franke et al. (2006) who find that the dimensions of lead userness are “conceptually independent dimensions rather than reflective” (p. 311) and suggest that the two dimensions “do have an independent meaning, are not inter-changeable, and cannot be merged into an index variable without loss of information” (p. 303).

Other than explaining the characteristics of user innovators, user innovation theory also suggests how firms can help users participate in innovation activities. Specifically, innovation requires two types of knowledge, *need-related* and *solution-related* (von Hippel 2005). The first type refers to the knowledge of a need, problem, or opportunity for change that lead users possess. The second type refers to the knowledge of a solution or technique for satisfying the need, solving the problem, or capitalizing on the opportunity that innovating firms possess. Von Hippel and Katz (2002) noted that it could be sticky to transfer need-related knowledge from users to the firm, whereas it could be sticky to transfer solution-related knowledge from the firm to users. They suggested that the time and cost of innovation will be reduced if need-related design tasks are assigned to users and solution-related tasks are assigned to the firm/manufacturer. Thus, they proposed toolkits as an effective way to assign need-related design tasks to users such that they can create a custom product or service design according to their unmet needs. Subsequently, the firm will take the design (e.g., for a semiconductor chip) and perform the solution-related tasks (e.g., manufacture the chip).

However, in our study context, we note that user innovators developing MDS applications complete the entire innovation development by themselves (i.e., both need and solution related tasks). Accordingly, toolkits for MDS innovation should support both aspects of innovation requirements (i.e., exploring needs’ knowledge and providing solution knowledge). Borrowing from prior literature (Kankanhalli et al. 2015) we consider two dimensions of toolkit support: (1) exploring innovation ideas (*exploration*) and (2) reducing innovation effort (*ease of effort*). Innovation toolkits can support exploration by allowing user innovators to search for existing innovations and trends in the market to enhance their own ideas and to experiment with them (e.g., Apple iOS provides analytics, ratings, and popularity of existing applications in the market). Thus, exploration support through toolkits should help to fulfill the need-related knowledge requirement for innovation. Such support should be particularly important during idea generation, when need-related knowledge is usually collected for deciding what innovation should be created.

Innovation toolkits can also reduce users' effort for innovation through providing module libraries and development tools (e.g., Google Android provides SDK and APIs). Ease of effort support through toolkits should, thus, help fulfil the solution-related knowledge requirement for innovation. Solution-related knowledge includes the specific details of how innovations should be implemented and deployed. Thus, such support should be particularly important during idea implementation, when solution-related knowledge is required. To summarize, *toolkit support* is defined as the extent to which the user innovator perceives that the platform tools will facilitate exploration and ease of effort for MDS creation. Thus, deriving from user innovation theory, we include exploration and ease of effort as antecedents reflecting the technical component of platforms in our model.

As discussed earlier, other than toolkits that characterize the technical component, a relevant characteristic related to the policy component of platforms for MDS user innovators is design autonomy, which we conceptualize using the work design literature.

Work Design Literature and Autonomy

For several decades, work design studies (e.g., Hackman and Oldham 1980) have attempted to describe and explain how jobs and roles are structured and enacted. This, in turn, informs how work design affects a multitude of outcomes including attitudinal (e.g., satisfaction) and behavioral (e.g., performance and productivity) outcomes (Fuller et al. 2006). Among various job characteristics, this literature suggests that job autonomy is a key enabler for complex and nonroutine work (Grant and Parker 2009), such as innovation. In work environments, job autonomy is determined by factors such as benevolent leadership (Wang and Cheng 2010) and has been linked to various positive outcomes such as job ownership, satisfaction, well-being, and performance (e.g., Chung-Yan 2010). In the IS literature as well, job autonomy has been related to positive outcomes such as low turnover intention (e.g., Shih et al. 2011), job satisfaction (Morris and Venkatesh 2010), and employees' trying out new IT (Ahuja and Thatcher 2005).

The concept of autonomy comprises three dimensions (Morgeson and Humphrey 2006), *scheduling autonomy* (i.e., the degree of freedom people have regarding the scheduling, sequencing, or timing of their task), *decision making autoanomy* (i.e., the extent of freedom people have regarding the choice of task type and task goals), and *work-method autonomy* (i.e., the degree of choice people have regarding the procedures or methods for performing tasks) (Breaugh 1999). People may perceive high autonomy when there are limited instructions and requirements imposed on them (Grant and Parker 2009). In contrast, if there are many rules, norms, and restrictions, users may perceive low autonomy during the process of new service design.

On mobile phone platforms, user MDS innovators can experience different degrees of autonomy. *Decision-making autonomy* may be impacted by platform rules about what kind of applications can be created, which matters when innovation ideas are being generated. These rules could be administratively enforced through standard-form licensing contracts or documentation (Manner et al. 2013). For example, Apple Store prespecifies the criteria by which applications are evaluated, rewarded, or penalized (Apple 2015). The App Store Review Guidelines say "if your app doesn't do something useful, unique or provide some form of lasting entertainment … it may not be accepted." Other guidelines also restrict the kind of applications that can be created on the platform. These rules and their enforcement are likely to affect individual's perception of decision-making autonomy.

Additionally, rules about how applications may be developed are enforced through contracts and policy documents (Manner et al. 2013), for example, through the Program License Agreement (PLA) or Human Interface Guidelines (HIG) in Apple Store. For example, App Store rejects apps that do not notify and obtain user consent before collecting, transmitting, or using location data. This could affect the individual's perception of *work-method autonomy* (e.g., the need to conform to prescribed methods for collecting customer information as per PLA and HIG), which would, thus, matter during innovation implementation. Google Play also has a few administrative rules about app design methods, although these are considered less onerous than App Store.[3]

Further, the *sequencing* of application development and launch is to some extent controlled by the platform owner (Apple 2015; Tiwana et al. 2010). For example, App Store Review Guidelines suggest that the sequencing or scheduling of application development and launch will be controlled or monitored. Hence, user innovators' perception of scheduling autonomy may be affected, which will be particularly important during innovation implementation and launch. Additionally, Tiwana et al. (2010) note that on such platforms, shared beliefs or norms could affect developers' behaviors (e.g., how to schedule their development activities). Overall, as per the work design literature, we expect that the dimensions of design autonomy will impact user's MDS innovation outcomes.

However, when reviewing the literature relating design autonomy to innovation we found few studies (e.g., Lewis et al.

[3] http://www.cultofmac.com/329381/app-store-vs-google-play-is-it-time-apple-stopped-being-a-control-freak/

2002) that have empirically examined the relationship, although several other studies have suggested so (e.g., Grant and Parker 2009). Specifically, Lewis et al. (2002) reported that directive control possessed by project teams in the form of scheduling autonomy led to greater project innovation in a chemical company, while participative control in the form of decision-making autonomy showed no effect on such innovation. Other related studies mainly focused on examining the effects of design autonomy on individual creativity, but here, too, the findings have been mixed with some studies observing positive impacts for certain autonomy dimensions (e.g., Greenberg 1994; Zhou 1998) while others found no impacts (e.g., Greenberg 1994; De Jong et al. 2011). Such mixed findings highlight the possibility of contingency factors determining the impacts of design autonomy on innovation, which could be modeled as interaction effects (Chin et al. 2003). Additionally, past literature has suggested that the impacts of lead userness could be affected by contextual factors (Wellner 2015) and the effects of innovation toolkits could depend on the degree of design freedom afforded to user innovators and the innovation needs of these users (von Hippel 2005). Thus, we expect interactions between lead userness, the dimensions of toolkit support, and those of design autonomy on user MDS innovation, which can be explained based on the innovation phases literature described next.

Innovation Phases Literature and Interaction Effects

Other than the theory of user innovation discussed earlier, the literature on innovation phases has offered theoretical explanations of how innovation takes place. Innovation has been defined as a process that involves the generation and implementation of new ideas, practices, or artefacts (Axtell et al. 2000). Although innovation is recognized as a complex, iterative process, and several classifications of innovation phases exist, most approaches identify two key innovation phases (Axtell et al. 2000; Wolfe 1994). The first is an "awareness" of the innovation, or idea suggestion/generation phase, while the second is an implementation phase. This categorization of phases allows us to explain the interaction effects between lead userness, design autonomy, and toolkits on innovation outcomes.

Particularly, prior literature suggests that the antecedents for idea generation and idea implementation differ (Axtell et al. 2000; Axtell et al. 2006). In terms of toolkit support, *exploration* of existing applications through toolkits is more likely to be salient for idea generation, when user innovators are seeking new ideas (see Table A4 in Appendix A). On the other hand, *ease of effort* through using module libraries and APIs would be important for idea implementation, as these can reduce the implementation effort. Among the three dimensions of autonomy, *decision-making autonomy* is more relevant for the idea generation stage. For example, Axtell et al. (2000) found that idea production ownership (related to decision-making autonomy) is positively correlated to idea generation. Further, during the idea generation stage, toolkit exploration support can enhance user innovators' exploration for new ideas while decision-making autonomy will enable user innovators to freely choose among various new ideas for innovation. As a result, the effects of lead userness on user innovation will be affected by exploration support and decision-making autonomy. Thus, a joint moderation effect of decision autonomy and exploration on the relationship between lead userness and innovation is expected.

On the other hand, *method and scheduling autonomy* are more relevant for the idea implementation stage. Axtell et al. (2000) observed that individual method control (akin to work method and scheduling autonomy) is positively correlated to idea implementation. During the idea implementation stage, toolkit ease of effort support can provide user innovators relevant modules and components for creating MDS applications, while method and scheduling autonomy provide the freedom to choose methods and scheduling in implementing ideas to create innovations. Thus, these two dimensions of autonomy are expected to complement ease of effort in influencing the effect of lead userness on user innovation. Our model encompassing the variables discussed above is presented next.

Research Model and Hypotheses

User service innovation has been defined as the new services, or changes in services' production or delivery created by users (Magnusson et al. 2003), which can range from incremental to radical changes. As discussed in the "User Innovation Theory" subsection above, our dependent variable captures the success of user service (here, MDS) innovation through its quantity. We utilize user innovation theory to identify and conceptualize *lead userness* and *toolkit support* constructs (i.e., exploration and ease of effort) and their relationship to the quantity of user's service innovation. Further, based on the work design literature, we conceptualize and relate *design autonomy* constructs (i.e., decision-making autonomy, scheduling autonomy, and work-method autonomy) to the quantity of user's service innovation. Last, drawing from the innovation phases literature, we hypothesize that lead userness and certain dimensions of design autonomy and toolkit support would interact to impact the quantity of user service innovation. The proposed model is shown in Figure 1.

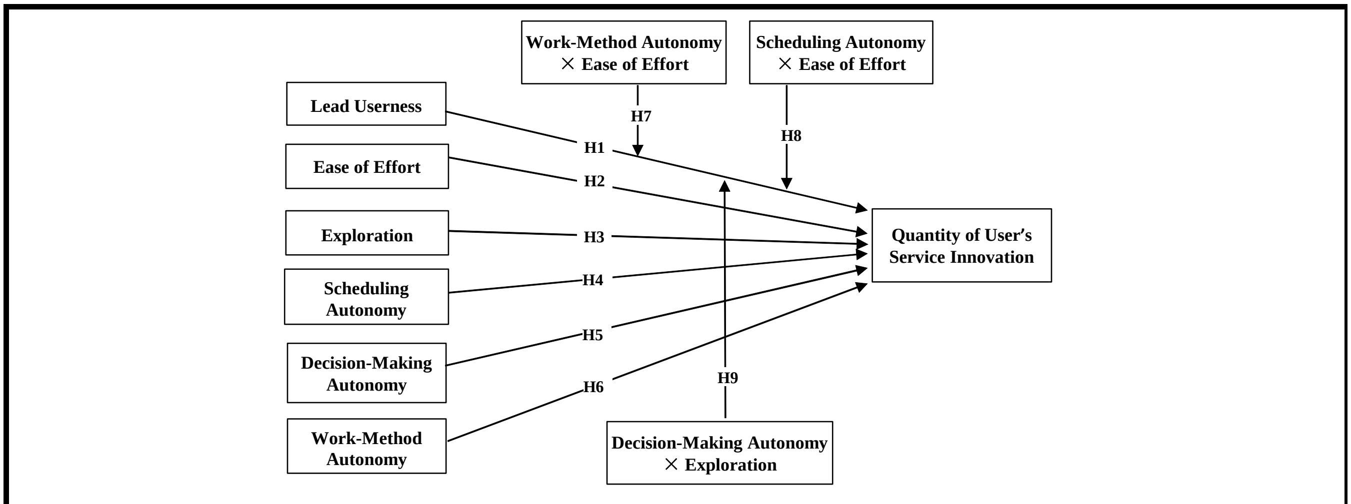

Figure 1. Proposed Theoretical Model

Lead Userness

As discussed in the "User Innovation Theory" subsection, lead userness is composed of two dimensions: ahead of trend and unmet needs. People with high lead userness are usually the first to try out new applications related to the service domain (ahead of trend dimension), which allows them to be leaders in identifying problems/unmet needs with existing services (Faullant et al. 2012). Thus, they are able to anticipate customer needs ahead of others in the market (von Hippel 2005). Also, their unmet needs are strong (unmet needs dimension) whereby they expect great benefits from creating solutions that would satisfy those needs. This should drive them to innovate to satisfy their needs (Franke et al. 2006). For MDS innovation, too, user innovators are seen to have strong ahead of trend unmet needs (Kim et al. 2012) that can motivate them to create new MDS applications. For example, a classic car enthusiast created one of the first apps to collect and display classic car model pictures. Together, the lead userness dimensions should increase individual's likelihood of carrying out MDS innovation. Indeed, prior studies have reported lead users' higher probability to innovate (Morrison et al. 2000) and create a greater number of ideas (Matthing et al. 2006). Thus,

> *H1*: *Lead userness is positively related to the quantity of user's service innovation.*

Toolkit Support

As a dimension of toolkit support, ease of effort refers to the perceived extent of support provided by innovation toolkits to reduce time and effort for users to innovate. Through providing module libraries and development aids, toolkits can save time and effort of user innovators for design and implementation activities during MDS creation. As per user innovation theory (von Hippel 2005), the knowledge provided to user innovators about the means of MDS innovation through such tools will reduce development effort and result in more innovations being created. With the support of innovation toolkits to ease the effort of collecting information and designing new applications, users may be more productive in innovation development and hence produce a higher quantity of MDS applications in a time period.

> *H2*: *Ease of effort through toolkits is positively related to the quantity of user's service innovation.*

As a second dimension of toolkit support, exploration refers to the perceived extent of support that innovation toolkits provide in terms of exploring information about published innovations, customer preferences, and market trends, to develop innovation ideas and experiment with them. This allows user innovators starting with their initial ideas to search for and collect relevant market information (Franke and Piller 2004) and enables them to shape their ideas accordingly. Prior IS literature has also argued that through exploration, users can modify how features of a system are used (Sun 2012) and the resultant performance outcomes (Hsieh et al. 2011). With exploration support, users may readily align their ideas with external market information and experiment with them to create more MDS innovations. In contrast, with a low level of exploration support through innovation toolkits, users may be overwhelmed by the challenges of exploring the market in order to develop and experiment with their innovation ideas (Randall et al. 2005). Thus,

> *H3*: *Exploration through toolkits is positively related to the quantity of user's service innovation.*

Design Autonomy

As a dimension of design autonomy, scheduling autonomy refers to the degree of freedom individuals have regarding the scheduling, sequencing, and timing of their tasks (Breaugh 1999). For MDS innovation, scheduling autonomy is reflected in individual's perception of the platform regulations and policies on the prescribed sequencing and scheduling of new MDS creation. With high scheduling autonomy, users feel that they can self-govern the sequence and schedule of the innovation process. In contrast, with a low level of scheduling autonomy, users are unable to control the timing of the design activity and may be hampered in their innovation efforts. For example the rigorous app review process at Apple Store could introduce uncertainty about when their new MDS would be published (Apple 2015). Building on the work design literature, scheduling autonomy provides users better control of their time (Parker et al. 2001) for innovation and thereby should enable them to be more productive in MDS innovation. Therefore,

> *H4*: *Scheduling autonomy is positively related to the quantity of user's service innovation.*

Decision-making autonomy refers to the degree of freedom that individuals have regarding the choice of the type and goals of their tasks (Morgeson and Humphrey 2006). For MDS innovation, individual perception of decision-making autonomy could be affected by platform regulations on the content and type of MDS applications that can be created (Apple 2015). For example, Google Play Store places restrictions on violent content of apps, although the restrictions vary for different maturity levels.[4] With high decision-making autonomy, users have the freedom to materialize their ideas through self-design. In contrast, with a low level of decision-making autonomy, individuals may feel that they cannot freely decide what they want to do (Gagne and Deci 2005). With the feeling of being constrained in their choices (Silver 1991), users may be less motivated to participate in self-design. Thus, the perception of decision-making autonomy allows users to create the MDS innovations of their choice, leading to a greater number of innovations. Hence we expect

> *H5*: *Decision-making autonomy is positively related to the quantity of user's service innovation.*

Work-method autonomy refers to the degree of choice people have regarding the procedures and methods for completing tasks (Breaugh 1999). With high work-method autonomy, users can choose the method for their design and may feel that they can control the process. In contrast, with low work-method autonomy, users may feel that they have to conduct the activity using a particular method and perceive a lack of freedom. For MDS innovation, user's perception of work-method autonomy could be affected by platform rules on the prescribed procedures or methods for new MDS application creation. For example, Apple Store applications are restricted to be developed only on iOS. With high work-method autonomy perception, users can use the methods that they find most appropriate which could allow them to be more productive in new MDS development. These conditions can result in a greater number of innovations being created. Thus,

> *H6*: *Work-method autonomy is positively related to the quantity of user's service innovation.*

Interaction Effects

The user innovation literature suggests that innovation outcomes would be determined by satisfaction of user needs using toolkits depending on the degree of design freedom afforded to user innovators (von Hippel 2005). This suggests three-way interactions between lead userness, and different dimensions of toolkit support and design autonomy in influencing user's service innovation outcomes. Three-way interactions are suggested when the relationship between an independent variable and a dependent variable (in this case quantity of user MDS innovation) is contingent on two other independent variables (Dawson and Richter 2006). Specifically, as discussed in the earlier subsection on innovaton phases and interaction effects and elaborated below, we expect three-way interactions between (1) lead userness, work-method autonomy, and ease of effort, (2) lead userness, scheduling autonomy, and ease of effort, and (3) lead userness, decision-making autonomy, and exploration, in impacting the dependent variable (DV). While we argue for these effects, we also take note of observations from the previous literature that proposing specific hypotheses related to three-way interactions is complex, and they are best interpreted from empirical findings (Angst and Agarwal 2009; Dawson and Richter 2006; Jaccard and Turrisi 2003).

As discussed in our arguments for H1, user innovation will primarily be driven by lead userness, which leads to a greater number of innovations being produced. However, this effect

[4] https://support.google.com/googleplay/androiddeveloper/answer/188189?hl=en

is likely to depend on the perceived toolkit support available. Specifically, the ease of effort facilitated through toolkits can reduce the implementation barriers for innovation (e.g., through providing module libraries and development aids; Franke and von Hippel 2003; Kankanhalli et al. 2015). As a result, such support should allow users' innovation ideas to be materialized more rapidly leading to a greater number of innovations generated (i.e., a positive two-way interaction between lead userness and ease of effort). In contrast, with low or without ease of effort support, users may encounter difficulties and barriers in implementing their ideas. Thus, the effect of lead userness on innovation may be lower than for the high ease of effort support condition.

Further, work-method autonomy is likely to enhance the supportive effect of ease of effort on lead userness' impact on quantity of innovations. When the degree of work-method autonomy is high (Morgeson and Humphrey 2006), ease of effort can enable user innovators (depending on their lead userness) to create more MDS innovations, since they have greater freedom to choose the procedures and work methods most suitable for them (Manner et al. 2013) to develop the new applications (e.g., the programming language with which they are most familiar and comfortable). In contrast, when work-method autonomy is low, it may be less possible for user innovators (again depending on their lead userness) to readily implement their innovation ideas even with easing of effort, as their use of methods to develop the ideas into MDS innovations may be restricted. For example, if a user innovator wants to develop various mHealth applications on the Android platform, greater ease of effort from API libraries and reusable UI elements can increase the number of applications created for the same level of lead userness. Further, this interaction effect of lead userness and ease of effort on quantity of MDS innovation can be increased if there is greater choice of work method (e.g., the freedom to develop the applications using various programming languages). In other words, work-method autonomy will compound the effect of ease of effort on the relationship between lead userness and quantity of MDS innovation. Hence,

> *H7: Lead userness will have the strongest, most positive relationship with the quantity of user's service innovation if work-method autonomy and toolkit ease of effort are high.*

As discussed in our arguments for the previous hypothesis, we expect a positive two-way interaction between lead userness and ease of effort on the quantity of innovations produced. However, this effect is also likely to depend on scheduling autonomy. When scheduling autonomy is high, user innovators would be able to control their timing and scheduling (Breaugh 1999) of carrying out the innovation implementation and launch (e.g., there would not be uncertainty about how long their application review will take). With the help of innovation toolkits that ease their effort, user innovators with high scheduling autonomy will be able to make better use of the time saved for their innovation activities (Kossek and Michel 2010). Hence, with the effort reduction or time savings through ease of use and the freedom to use the time as they wish for innovation activities, user innovators would be able to design more applications in a period of time depending on their lead userness. In contrast, with low scheduling autonomy (Morgeson and Humphrey 2006), the freedom to plan and schedule innovation activities is restricted, which may hinder user innovators and dampen their innovation momentum even with the easing of effort by innovation toolkits. In other words even if they can save time due to ease of effort, this time may not be used as efficiently for MDS innovation when there is low scheduling autonomy. Taking the previous example of a user innovator who wants to develop various mHealth applications on the Android platform, greater ease of effort from API libraries and reusable UI elements can increase the number of applications created for the same level of lead userness. This interaction effect of lead userness and ease of effort on quantity of MDS innovation can be increased if there is greater control of schedule (e.g., there is no uncertainty in the review duration for publishing new MDS on the platform). In other words, scheduling autonomy will compound the effect of ease of effort on the relationship between lead userness and quantity of MDS innovation.

> *H8: Lead userness will have the strongest, most positive relationship with the quantity of user's service innovation if scheduling autonomy and toolkit ease of effort are high.*

Last, we also expect a positive two-way interaction between lead userness and exploration with toolkits. High exploration support through toolkits enables user innovators to better compare their ideas with other applications in the market and collect information about customer preferences (Kankanhalli et al. 2015) than low exploration support. Greater toolkit exploration, hence, will enable more of user innovators' innovation ideas (that depend on their lead userness) to be honed and materialized, leading to a greater quantity of innovations produced.

However, this effect is likely to depend on the level of decision-making autonomy. With high decision-making autonomy, individuals can determine their choice of tasks and set their own goals for task completion (Morgeson and Humphrey 2006). With the help of exploration tools, user innovators (depending on their lead userness) with high decision-making autonomy can explore more possibilities for

MDS innovation in the market and have the freedom to implement them. In contrast, with low decision-making autonomy, even if their innovation ideas can be explored through the tools, the individual may be restricted in which ideas they can implement (e.g., due to content restrictions) as MDS innovations. Under these conditions, even with the support of exploration tools, user innovators may not be able to implement all the desired MDS innovations (resulting from their lead userness) due to the lack of decision-making autonomy. For example, if an user innovator wishes to create more cartoon applications (based on their lead userness) and the exploration capability helps them hone their ideas of topics based on market preferences, the number of applications can still be restricted if some of the content is not allowed due to the defamation policy of App Store. Therefore,

> *H9: Lead userness will have the strongest, most positive relationship with the quantity of user's service innovation if decision-making autonomy and toolkit exploration are high.*

In addition to the above interactions, we do not hypothesize other moderating effects for the following reasons. First, we do not expect decision-making autonomy to moderate the effect of ease of effort on the quantity of user's MDS innovation. This is because decision-making autonomy is more related to the idea generation phase (Axtell et al. 2000) while ease of effort is more salient during idea implementation. Second, we do not expect work-method autonomy and scheduling autonomy to moderate the effect of exploration on the quantity of user's MDS innovation. This is because these two dimensions are more related to the idea implementation phase (Axtell et al. 2000) while exploration is more salient during idea generation. Thus, we do not hypothesize three-way interactions between lead userness and these combinations of design autonomy and toolkit support dimensions on our DV.

Research Methodology

Survey methodology was employed to test the research model. Interviews with user innovators were conducted to validate the instrument and enrich our understanding of the study context.

Data Collection

The survey was conducted on the Apple developer forum[5] and Code Android Group,[6] which are based on the iOS and Android platforms respectively, that have the highest market share and support users to design MDS applications (Boudreau and Lakhani 2009). The two platforms are appropriate to test our model for several reasons. First, as the rules, policies, and innovation toolkits differ for the two platforms, there would be variances in design autonomy and toolkit support perceptions that allow us to test our model (see Table A5 in Appendix A). Further, even within a platform, there could be variance due to individual perceptions. As the technology adoption literature observes that individuals have different perceptions toward the same technology (e.g., Brown et al. 2010; Davis et al. 1989), in this context, too, individual users could have different perceptions toward design autonomy and toolkit support on one platform. Second, it was possible for us to mine the archival data from these two platforms to assess our dependent variable (i.e., the quantity of user service innovation). We were also able to collect data on innovation quality outcomes (the number of downloads and radicalness) for our *post hoc* analysis. The use of such objective measures can help reduce the risk of common method variance and hence increase the validity (Podsakoff et al. 2003) of our findings.

In order to reach users who have participated in MDS innovation, online survey links were created and posted on the iOS user group and Android group to recruit those who had already created an MDS application. We posted the links in the two platforms for two weeks with the help of the administrators to highlight the survey invitation. In appreciation of the respondents' effort, we offered a token amount of $10 for each response. To verify that the respondents were users of iOS or Android applications, they were asked to answer specific questions related to iOS or Android applications, such as the default icon of "iOS or Android market," default web browser used, and default applications for reading PDF files in iOS or Android phone. After this we checked if the person was an actual innovator (based on the apps created), and last we checked if the person was a professional developer (by asking about their occupation and employer) and if they develop apps for a living. At this point we filtered out those who worked as developers in a company or rely on app development for a living. A total of 156 responses were received of which 146[7] valid responses remained after removing

[5]http://developer.apple.com/devforums/

[6]http://www.codeandroid.org/

[7]An *a priori* power analysis using G*Power indicated that a sample size of 126 is needed to detect a medium effect (size 0.15) for our main model, with a desired power of 0.80 at alpha level of 0.05 (as per Cohen 1988). However, a sample size of 961 is needed to detect a small effect (size 0.02) with the desired power and alpha level. Thus, our sample size of 146 is able to detect medium or large effects for the model with sufficient power, but not small effects.

Table 1. Operationalization of Constructs

Construct		Items		Sources
		In this platform…		
Design Autonomy	Scheduling Autonomy	SAU1	I can choose any time to develop the application	Adapted from Breaugh (1999); Morgeson and Humphrey (2006)
		SAU2	I can set my own schedule for completing the application development	
		SAU3	I have control over the sequencing of application development activities	
	Work-method autonomy	WAU1	I have a lot of freedom to choose any method to design applications	Adapted from Morgeson and Humphrey (2006))
		WAU2	I am allowed to use any method to design applications	
		WAU3	I can choose my own method to develop applications	
	Decision-making autonomy	DAU1	I can choose to develop any application I like	
		DAU2	I have control over which type of applications I design	
		DAU3	I can decide what application should be designed on my own	
Toolkit Support	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	Kankanhalli et al. (2015)
		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	
Lead Userness (Formative)	Ahead of Trend	LUSA1	I usually find out about new applications earlier than others	Faullant et al. (2012)
		LUSA2	I am always the first one to adopt new service applications	Kratzer and Lettl (2008)
	Unmet Needs	LUSB1	The current applications cannot fulfil my particular needs	Schuhmacher and Kuester (2012) Franke et al (2006)
		LUSB2	I have new needs that are not satisfied by current applications	Faullant et al. (2012) Franke et al (2006)

Note: The definition and meaning of the term platform was clarified in the questionnaire introduction

incomplete and duplicate data. Of these, 78 responses were from the iOS platform and 68 from the Android platform. Since a web-based survey design may suffer from non-response bias (Roztocki 2001), we tested for such bias by comparing the early and late respondents as recommended in Armstrong and Overton (1977). T-tests of the differences between the earliest 10% of respondents and the last 10% of respondents in terms of demographics, the number of applications developed, and average downloads, revealed no systematic differences. Thus, nonresponse bias is not expected here.

Operationalization of Model Variables

We operationalized the independent variables (*two dimensions of lead userness, two dimensions of toolkit support,* and *three dimensions of design autonomy*) as reflective constructs. Lead userness was modeled as a multidimensional formative construct (Petter et al. 2007) with its two reflective dimensions (ahead of trend and unmet needs). The dimensions of toolkit support and design autonomy were separate constructs as per our model in Figure 1. These variables were measured with items adapted from previously validated instruments (see Table 1). All items for the independent variables were measured using seven-point Likert scales anchored from "strongly disagree" to "strongly agree."

The dependent variable, *quantity* of user's service innovation (QNT), was assessed by the number of MDS applications the user created in the 3 month period after the rest of the model variables data were collected through the survey. We included *age, gender, programming skill, tenure, education,* and *platform* (iOS versus Android) as control variables in our model. Of these, individual ability was controlled for by programming skill and education level. Further, differences in the platform popularity and other unobserved platform characteristics were controlled for by the platform dummy variable.

Data Analysis and Results

We pooled the data across the two platforms for better generalizability. As required, we checked for sample homogeneity prior to that based on Chow's test (Chow 1960). Our results show support for pooling the samples, $F(6, 134) = 1.17$, $p > 0.05$. Further, our platform dummy variable allowed us to account for unobserved differences across the two platforms. The demographic information about the respondents is listed in Table 2.

Instrument Validation

To validate our instrument, convergent validity and discriminant validity were tested (Hair et al. 2006). We assessed convergent validity by examining the Cronbach's α (CA > 0.7), composite reliability (CR > 0.7), average extracted variance (AVE > 0.5), and factor analysis results (Straub et al. 2004). Table 3 shows that the CA, CR, and AVE for each reflective construct in the model satisfy the thresholds. Also, convergent validity was demonstrated since the factor loading (see Table 4) of each item on its intended construct was larger than 0.6 (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 1.32 and 2.01).

Discriminant validity was assessed by examining the indicator-factor loadings and comparing AVEs with inter-construct correlations as suggested in Straub et al. (2004). The results in Table 4 show that all indicators load more strongly on their corresponding constructs than on other constructs. The results in Table 3 show that the AVEs are larger than the inter-construct correlations. Thus, the constructs demonstrate discriminant validity. For the formative construct, lead userness, we assessed the construct validity by examining the weights of the two dimensions (LUSA and LUSB) in contributing to the construct (Petter et al. 2007). These weights were found to be significant, thus demonstrating acceptable construct validity (see Table A6 in Appendix A). Also, the VIF value for LUSA and LUSB to LUS is 1.88, which is acceptable. Since we collected data for our independent variables and dependent variable from two independent sources, common method variance (CMV) should not be an issue in our study (Podsakoff et al. 2003).

Results of Hypothesis Testing

Moderated multiple regression (MMR) analysis is the method of choice to detect moderator effects in field research and is superior to strategies such as comparison of subgroup-based correlation coefficients (Dawson and Richter 2006; Jaccard and Turrisi 2003). Other than linear regression, the data was also analyzed using Poisson regression since the DV (the quantity of MDS innovations) is a count variable, for robustness. Interaction terms for moderating hypotheses were computed by cross-multiplying the mean-centered items of the relevant constructs.[8] Further, the terms were entered in hierarchical steps of controls first, then main effects, followed by all corresponding second-order and the three-way interaction terms, as suggested in prior research (Dawson and Richter 2006; Jaccard and Turrisi 2003).

The path coefficients and explained variances for the regression model (Model 3) are shown in Table 5. The model explains 61% of the variance in the quantity of user's service innovation. We also conducted incremental F test of the R^2 change. The results in Table 5 suggest that the independent variables and interactions offer unique contributions to the explanation of the variance in the quantity of users' service innovation ($F1 = 9.50$, $p < 0.001$; $F2 = 6.82$, $p < 0.001$).

As hypothesized (H1), lead userness is found to affect the dependent variable. Consistent with our predictions, both exploration and ease of effort dimensions of toolkit support are positively related to the quantity of user's service innovation, thereby supporting H2 and H3. Further, decision making and work-method autonomy dimensions of design autonomy are found to positively affect the quantity of user's service innovation (H5 and H6 are supported). However, scheduling autonomy does not impact the quantity of user's service innovation (H4 is not supported).

[8]Since lead userness is a formative second order construct, we used a two-stage PLS approach for estimating its interaction effects. We used PLS to estimate the latent variable scores and then used those scores in multiple linear regression analysis (Henseler and Fassott 2010, p. 724).

Table 2. Demographic Statistics of Respondents							
Demographic Variables		Frequency (N = 146)	Percentage	Demographic Variables		Frequency (N = 146)	Percentage
Gender	Male	114	78.0%	**Programming Skill**	1 (Low)	9	6.2%
	Female	32	22.0%		2	12	8.2%
Age	≤ 20	24	16.4%		3	27	18.5%
	21–25	41	28.0%		4 (Medium)	30	20.5%
	26–30	43	29.4%		5	32	21.9%
	31–35	22	15.0%		6	20	13.7%
	36–40	7	4.8%		7 (High)	16	11.0%
	> 40	9	6.4%	**Tenure**	≤ 6 months	23	15.8%
Education	High School	3	2.1%		7–12 months	30	20.5%
	Diploma	10	6.8%		13–18 months	55	37.7%
	Bachelors	54	37.0%		>18 months	38	26.0%
	Masters	71	48.6%	**Platform**	iOS	78	53.4%
	Doctorate	8	5.5%		Android	68	46.6%

Table 3. Descriptive Statistics, Correlations, AVE

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age	1.00												
2. Gender	0.17	1.00											
3. P. Skill	0.44**	0.01	1.00										
4. Educ.	0.24*	-0.03	0.49***	1.00									
5. Tenure	0.44**	-0.13	0.61***	0.54	1.00								
6. LUSA	0.20*	0.12	0.06	-0.02	-0.04	1.00							
7. LUSB	0.12	0.20	0.02	0.01	-0.08	0.40***	1.00						
8. EOE	0.29	-0.03	0.23***	0.08	0.26	0.20	0.12	1.00					
9. EXP	0.26	0.03	0.14**	0.17	0.15	0.22*	0.32*	0.39*	1.00				
10. SAU	0.21	-0.14	0.11	0.05	0.27	0.07*	0.10*	0.05	-0.03	1.00			
11. DAU	0.05*	0.12	-0.11	0.02	0.03	0.15**	0.22*	-0.11	-0.02	0.29**	1.00		
12. WAU	0.25*	-0.06	0.06	0.07	0.19	0.11	0.01	0.11	0.10	0.31*	0.11*	1.00	
13. QNT	0.22*	0.13	-0.02	-0.08	-0.05	0.21**	0.23*	0.47*	0.36*	0.08	0.21*	0.15*	1.00
Mean	21.95	0.73	4.71	2.45	10.9	4.35	4.52	4.95	5.22	5.33	5.30	5.17	3.20
SD	5.35	0.44	1.31	0.68	4.14	0.73	0.68	0.86	0.72	1.06	1.04	1.16	1.95
CA	–	–	–	–	–	0.70	0.73	0.74	0.74	0.73	0.70	0.83	–
CR	–	–	–	–	–	0.82	0.83	0.88	0.89	0.83	0.80	0.89	–
AVE	–	–	–	–	–	0.62	0.65	0.77	0.80	0.63	0.60	0.75	–

Notes:
1. – Indicates that the value is not applicable for single indicator variable
2. Ease of Effort (EOE), Exploration (EXP), Scheduling Autonomy (SAU), Decision-Making Autonomy (DAU), Work-Method Autonomy (WAU), Quantity of User Service Innovation (QNT), Lead Userness (LUS)
3. Significance at *p < 0.05, **p < 0.01, ***p < 0.001

Table 4. Factor Analysis Results

		1	2	3	4	5	6	7
Ease of Effort	**EOE1**	0.33	**0.90**	-0.11	0.31	0.06	0.02	0.06
	EOE2	0.37	**0.91**	0.02	0.27	0.05	0.05	0.15
	EOE3	0.14	**0.68**	0.01	0.13	0.14	0.13	0.15
Exploration	**EXP1**	**0.91**	0.41	0.05	0.15	0.08	0.05	0.04
	EXP2	**0.86**	0.26	0.06	0.20	0.00	0.04	0.04
	EXP3	**0.69**	0.20	0.12	0.14	0.01	0.05	0.11
Scheduling Autonomy	**SAU1**	0.11	0.22	-0.03	**0.86**	0.13	0.02	0.02
	SAU2	0.28	0.35	0.13	**0.86**	-0.04	0.04	0.01
	SAU3	0.04	0.23	-0.01	**0.80**	0.04	0.01	0.02
Decision-making autonomy	**DAU1**	0.06	-0.06	**0.96**	0.08	0.26	0.22	-0.02
	DAU2	0.03	-0.03	**0.70**	-0.08	0.11	0.10	0.12
	DAU3	0.04	0.01	**0.75**	-0.04	0.15	0.14	0.21
Work-method autonomy	**WAU1**	0.01	0.10	0.13	0.07	**0.88**	0.21	0.25
	WAU2	0.00	0.00	0.09	0.00	**0.84**	0.20	0.21
	WAU3	0.12	0.06	0.44	0.07	**0.91**	0.31	0.24
Lead Userness	**LUSA1**	0.02	0.01	0.10	0.28	0.11	0.50	**0.85**
	LUSA2	0.14	0.02	0.25	0.14	0.11	0.49	**0.80**
	LUSB1	0.11	0.28	0.19	0.02	0.24	**0.79**	0.43
	LUSB2	0.22	0.10	0.34	0.14	0.21	**0.86**	0.46
Eigenvalue		3.32	2.94	2.50	2.36	1.92	1.34	1.15
Variance explained (%)		18.01	15.91	12.12	10.01	8.65	6.86	6.19
Cumulative Variance (%)		18.01	33.92	46.04	56.05	64.70	71.56	77.75

Table 5. Results of Hypotheses Testing

	DV= QNT				
	1	**2**	**3 (OLS)**		**4 (Poisson)**
Age	0.14 (0.011)	0.10 (0.009)	0.06 (0.003)		0.05 (0.010)
Gender	-0.02 (0.042)	-0.08 (0.001)	-0.10 (0.002)		-0.15 (0.002)
Prog. Skill	0.01 (0.009)	0.09 (0.006)	-0.12 (0.002)		-0.02 (0.008)
Education	-0.05 (0.010)	-0.05 (0.005)	-0.05 (0.003)		-0.08 (0.007)
Tenure	0.13 (0.092)	0.09 (0.006)	0.02 (0.002)		0.06 (0.005)
Platform	-0.01 (0.008)	-0.01 (0.005)	-0.07 (0.003)		-0.10 (0.012)
LUS		0.24** (0.008)	0.25** (0.005)	H1supported	0.13* (0.004)
EOE		0.22* (0.007)	0.22** (0.004)	H2 supported	0.12** (0.002)
EXP		0.37** (0.001)	0.34* (0.005)	H3 supported	0.14* (0.004)
SAU		-0.09 (0.080)	-0.03 (0.028)	H4 not supp.	-0.05 (0.026)
DAU		0.20** (0.005)	0.21* (0.002)	H5 supported	0.11* (0.003)
WAU		0.17* (0.003)	0.22* (0.003)	H6 supported	0.12* (0.002)
EOE*SAU			-0.08 (0.052)		-0.03 (0.000)
LUS*EOE			-0.05 (0.012)		-0.03 (0.014)
LUS*SAU			-0.04 (0.013)		-0.03 (0.011)
EOE*WAU			0.17* (0.003)		0.10* (0.001)
LUS*EXP			0.02 (0.011)		0.01 (0.003)
LUS*WAU			0.01 (0.010)		0.01 (0.004)
EXP*DAU			0.08 (0.010)		0.03 (0.011)
LUS*DAU			0.03 (0.001)		0.01 (0.012)
LUS*EOE*WAU			0.09 (0.022)	H7 not supp.	0.02 (0.009)
LUS*EOE*SAU			0.26* (0.003)	H8 supported	0.14* (0.002)
LUS*EXP*DAU			0.20* (0.005)	H9 supported	0.12* (0.002)
R^2	0.10	0.37	0.61	Pseudo R^2	0.14
R^2 (F Value)	–	9.50***	6.82***	Log likelihood	-219.41

1. EXP– Exploration, EOE– Ease of Effort, SAU–Scheduling Autonomy, DAU–Decision-Making Autonomy, WAU– Work-Method Autonomy, LUS– Lead Userness
2. Unstandardized regression coefficients are shown. Robust standard errors are shown in the bracket.
3. Significance at *$p \leq 0.05$, **$p \leq 0.01$ ***$p \leq 0.001$
4. The number of observations is 146 for all the models

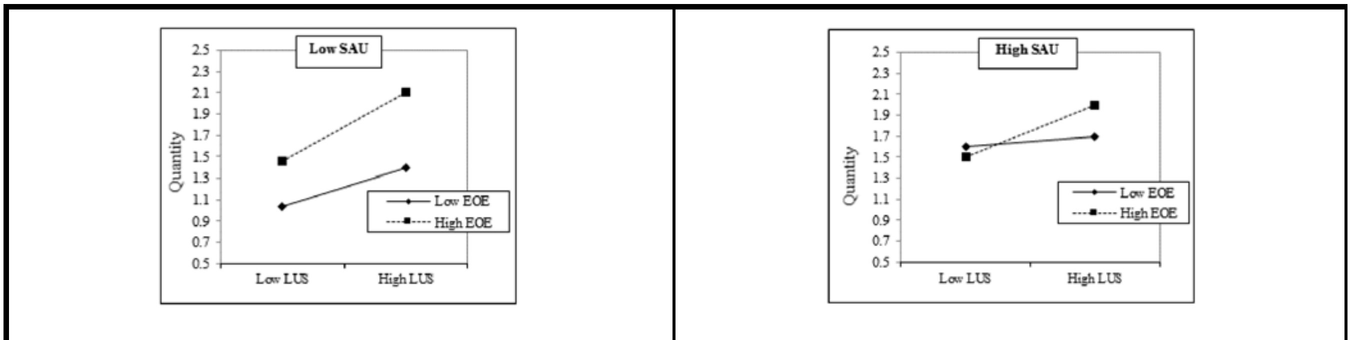

Figure 2. Interaction Plots for LUS*EOE*SAU

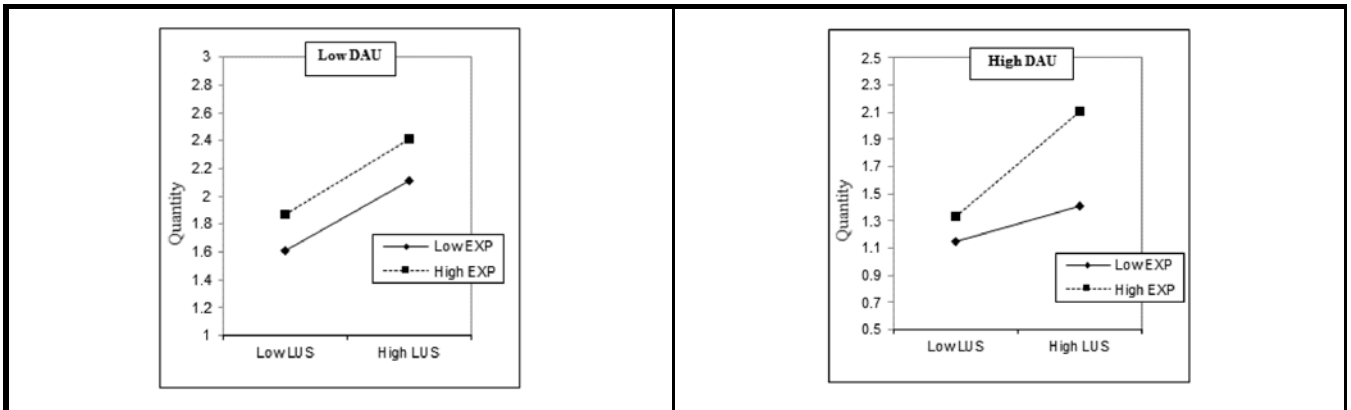

Figure 3. Interaction Plots for LUS*EXP*DAU

In addition, significant interaction effects are found as per the analysis (see Table 5). Specifically, scheduling autonomy is found to positively moderate the relationship between the ease of effort and lead userness interaction and the quantity of user's service innovation (H8 is supported). Also, decision-making autonomy positively moderates the relationship between the exploration and lead userness interaction and our DV (H9 is supported). However, work-method autonomy does not moderate the relationship between the ease of effort and lead userness interaction and the quantity of user's service innovation (H7 is not supported). The results of the Poisson regression (Model 4 in Table 5) are similar to the OLS results in terms of the hypotheses supported.

To further interpret a three-way interaction, the relation between one independent variable and the dependent variable at high and low levels of one of the moderators may be plotted in two separate graphs at high and low levels of the other moderator (Aiken and West 1991; Jaccard and Turrisi 2003). Such a plot allows a quick, visual indication of the nature of an interaction effect, and the direction of the slopes can be interpreted on the basis of face validity. The 2 three-way interaction hypotheses that were supported in Table 5 are interpreted below.

For H8, Figure 2 shows the interaction between LUS and EOE on QNT for low and high levels of SAU. Our test results also showed that the two-way interaction effect (LUS*EOE) changes from 0.05 to 0.11 ($T = 3.35$, $p < 0.01$) when going from the low SAU to the high SAU group. The positive change is seen in the positive sign of the three-way interaction of LUS*EOE*SAU in Table 5. As can be seen from the figure, the difference in the slopes of the two lines for low SAU increases for high SAU. In other words, scheduling autonomy accentuates the interaction effect between lead userness and ease of effort on the quantity of user's MDS innovation. Furthermore, we conducted Dawson and Richter's (2006) slope difference test to accurately test this hypothesis. The results in Table A7 in Appendix A show that slopes at high levels of ease of effort and scheduling autonomy differed significantly from any other pair of slopes. Thus, H8 was supported.

For H9, Figure 3 shows the interaction between LUS and EXP on QNT for low and high levels of DAU. Our test results also showed that the two-way interaction effect (LUS*EXP) changes from -0.02 to 0.12 ($T = 7.45$, $p < 0.001$) when going from the low DAU to the high DAU group. The positive change is seen in the positive sign of the three-way interaction of LUS*EXP*DAU in Table 5. As can be seen from the figure, the difference in the slopes of the two lines for low DAU increases for high DAU. In other words, decision-making autonomy enhances the interaction effect between exploration and lead userness on the quantity of user's MDS innovation. Furthermore, slope difference test results in Table A7 in Appendix A show that slopes at high levels of exploration and decision-making autonomy differed significantly from any other pair of slopes. Thus, H9 was supported.

Further, we conducted *post hoc* tests with innovation quality outcome variables (popularity and radicalness) as shown in Models 1 and 2 of Table B3 in Appendix B. The results using popularity as the DV are similar to the original results except for one of the three-way interactions, whereas the results for radicalness differ on two of the three-way interactions, requiring further investigation in future research. We also conducted a *post hoc* test analyzing the two samples from the iOS and Android groups separately. Prior to that, we checked for measurement invariance across the two samples following Cheung and Rensvold (2002). The results are materially similar on the two platforms although, as we expected, the mean values of the two IVs (i.e., EXP and DAU) are significantly different across the two platforms (see Table A5 in Appendix A). As a last *post hoc* test, we examined the three remaining interactions between toolkit support and design autonomy dimensions (i.e., EXP*SAU, EOE*DAU, and EXP*WAU), for which we did not hypothesize three-way interactions with LUS. As expected, they were not significant.

Discussion and Implications

Through this study, we sought to explain how user (lead userness) and platform (design autonomy and innovation toolkits) characteristics on innovation platforms can jointly promote user service innovation. Specifically, we examined user's MDS innovation, which is a major source of innovation on mobile phone platforms. Our findings show that lead userness and both dimensions of toolkit support (i.e., ease of effort and exploration) positively influence the quantity of new services created by users. Additionally, two dimensions of design autonomy (i.e., decision-making autonomy and work-method autonomy) impact the quantity of new services, but scheduling autonomy does not. Further, there exists a positive three-way interaction of scheduling autonomy, ease of effort, and lead userness on the quantity of new services. We also see a significant interaction of lead userness, exploration, and decision-making autonomy on the DV. However, work-method autonomy does not moderate the relationship between the ease of effort and lead userness interaction and the DV. In all, seven out nine model hypotheses are supported.

Contrary to our initial hypothesis, scheduling autonomy does not impact the quantity of user's MDS innovation (H4 is not supported). While certain platform practices or rules (e.g., uncertainty in the time taken to review new MDS on Apple Store) could impair scheduling autonomy, it appears that this may not reduce the number of MDS produced, since user innovators can adopt strategies to counteract them. We note that user innovators could have a few MDS projects at different stages running concurrently, by which they can mitigate the impact of such scheduling issues. However, under specific conditions of the other variables (e.g., ease of effort saving time and enhancing the effect of lead userness), scheduling autonomy still matters in order to utilize the time saved productively (H8 is supported).

Further, the three-way interaction between lead userness, ease of effort, and work-method autonomy is insignificant (H7 is not supported). This could be understood from the result that the interaction effect of ease of effort and work-method autonomy is positive (Table 5), but with the moderation of lead userness, the overall three-way effect becomes insignificant. When the degree of work-method autonomy is high, ease of effort can enable user innovators to create more MDS innovations, as they have greater freedom to choose the procedures most suitable for them (e.g., the programming language with which they are most familiar), but the strength of this two-way relationship does not depend on lead userness. In other words, lead userness does not increase the synergy between work-method autonomy and ease of effort; rather, it increases the opportunities for user innovation.

Theoretical Contributions

Our study offers significant theoretical contributions. Most importantly, it theoretically models and empirically tests the impacts of key user (lead userness), and platform (toolkit support and design autonomy) characteristics, on the quantity of user service innovation. Specifically, we are able to model the influences of two salient aspects of innovation platforms—toolkits representing the technology component and design autonomy representing the policy component—on user innovation behavior. This is particularly valuable in the context of MDS innovation on mobile phone platforms, which is an emerging area with limited extant theory, and which is differentiated from previously studied user innovation contexts (see the "Introduction"). As we hypothesized, the user, technology, and policy characteristics exhibit complex three-way interaction effects on user innovation outcomes.

Second, our work adds to user innovation research, where individual characteristics have mainly been compared among user innovators, professionals, and non-users (e.g., Magnusson et al. 2003, Matthing et al. 2004, Morrison et al. 2000) and potential versus actual innovators (Kankanhalli et al. 2015), rather than studying the impact of lead userness within user innovators as this research does. This allows us to robustly examine the relationship between a continuous measure of lead userness and objective innovation outcomes (quantity, popularity, and radicalness) for this target group. We also extend research on user innovator characteristics in another way. While prior work has mainly explored the antecedents and consequences of lead userness (e.g., Morrison et al. 2000, Schreier and Prugl 2008) and suggested that the impacts of lead userness could be affected by contextual factors (e.g., Wellner 2015), the precise nature of these contingencies is unclear. Here, we explicate the consequences of leader userness by uncovering its interaction effects with specific toolkit support and design autonomy dimensions on key innovation outcomes.

Third, we contribute significantly to innovation research on design autonomy, which has received little research interest until now in online and extra-organizational contexts as compared to offline and organizational contexts (e.g., Guntert 2015). This is a salient problem for online innovation platforms as they embed rules or policies to control user innovation (Boudreau 2012), yet obtaining a balance between platform control and users' design autonomy is critical for the sustainability of such platforms (Tiwana et al. 2010). Also, there has been a lack of empirical study of how perceptions of autonomy influence user innovation behavior, which we remedy here through a natural comparison between two major innovation platforms that vary on rules and policies (see Table A5 in Appendix A). Additionally, prior IS research has mainly examined the aggregated effect of autonomy (e.g., on turnover intention of IT personnel; Shih et al. 2011). Our results here show that the three dimensions of design autonomy act in different ways to facilitate user innovation, supporting our position that it is valuable to model their effects separately for a better understanding of their impact.

Fourth, we add to research (e.g., Franke and Piller 2004) regarding the effects of innovation toolkits on user innovation. While prior studies have examined if toolkit support in aggregate enhances users' satisfaction, willingness to pay for user innovations (e.g., Franke and von Hippel 2003), and intention to innovate (Kankanhalli et al. 2015), there is a lack of understanding of the effect of toolkit support dimensions (ease of effort and exploration) on actual innovation outcomes. Here, we uncover that toolkit support dimensions both separately and jointly (with lead userness and specific design autonomy dimensions) impact user innovation in terms of quantity, popularity, and radicalness. This also illustrates the interdependencies among the three sets of characteristics in influencing key innovation outcomes on mobile phone platforms.

Practical Implications

From a pragmatic perspective, this study offers insights to practitioners regarding the characteristics of user innovators and the perceptions of design autonomy and innovation toolkits in platform environments that can enhance user's service innovation. First, as our findings show, identifying and encouraging lead users (individuals with high lead userness) in the user community is a valuable strategy for firms to pursue in fostering user innovation. While methodologies for the lead user approach have been developed for company teams,[9] these techniques would need to be extended to online user innovation communities. Other than engaging individuals with high lead userness to participate in MDS innovation, our work suggests that it is also important that the user innovators feel autonomous along various dimensions and obtain toolkit support in order to produce a larger number of MDS (and more radical or popular MDS as per our *post hoc* tests in Appendix B).

Thus, second, platforms may relax the monitoring of what kind of MDS can be created so that innovators can have more leeway in creating the MDS apps in which they are interested. While regulating quality, platforms may empower user innovators to decide the content an MDS application intends to deliver. Such decision-making autonomy allows user innovators to include their heterogeneous knowledge in the MDS innovation, hence increasing the innovation quantity, radicalness (novelty), and popularity of MDS on these platforms. In this regard, Google Android's lighter control approach of allowing users to create mature content apps as long as they rate the maturity appropriately seems to be preferable to Apple iOS platform's tight controls on app content (see Table A5 in Appendix A).

Third, such platforms could allow user innovators to use their own methods (e.g., using different programming languages) for development and publishing of the MDS they are creating. Since such empowerment may cause some degree of technological incompatibility, platforms could provide conversion tools to provide interoperability. At the same time, platforms like Apple iOS may still want to enforce certain (e.g., user interface) guidelines to maintain the desired attributes of the app (e.g., the look and feel) as per the firm's strategy. In this

[9] http://evhippel.mit.edu/teaching/

way, platforms may be able to maintain a mix of providing autonomy on some aspects of the innovation methods but not others.

Fourth, this study finds that providing scheduling autonomy together with ease of effort support for lead users is beneficial to their productivity of creating MDS innovations. Facilitating exploration along with decision-making autonomy is also useful for enhancing productivity of lead users. In this regard, Apple iOS platform's exploration tools are noteworthy in providing customer information about downloads, in-app purchases, and other analytics to support user innovation. On the other hand, providing both exploration capability along with work-method autonomy may be counterproductive for lead users as they may be overloaded by too many choice options from both.

Limitations and Future Work

The findings of this study should be interpreted in light of its limitations. First, our study is restricted in its ability to make broad generalizations by examining specific (although major) mobile phone platforms (i.e., iOS and Android platforms), in which users participate in all aspects of innovation. Future research could examine user innovation in other online settings (e.g., brand communities for idea generation such as Ideastorm, and crowdsourcing contests) by extending the theoretical model. Further, the robustness of the findings is to some extent constrained by the sample size, which could be expanded in future research.

Second, while this paper studied the influence of mobile phone platform features on the outcome of user service innovation, future work can explore the process of service innovation. For instance, researchers can investigate what platform attributes influence ideation and implementation phases in user service innovation and cause different outcomes. Another avenue is to apply a learning perspective to explore the process and consequences of learning on user service innovation behaviors.

Third, this study explores the influences of three salient sets of antecedents (i.e., lead userness, design autonomy, and innovation toolkits) on use service innovation. Future research can examine other IT features, such as the IT artefacts suggested by Yoo (2010), in the context of service innovation and empirically test their influences on service innovation. Other avenues could be to examine the influences of these platform features on innovation of professional MDS developers. Fourth, other indicators of innovation quality (e.g., expert ratings) and user value (e.g., customer satisfaction) could be used as DVs in future research, although the employment of an objective measure for the DV in this study offers various advantages. Here, it would also be useful to compare the differences in antecedents of innovation quality and quantity to understand how both outcomes could be balanced.

Conclusion

Considering the importance of MDS innovations to the profitability of the mobile industry, practitioners have expressed substantial concerns about encouraging innovation behaviors for MDS (Hong and Tam 2006). At the same time, research and understanding has been lacking on how firms can promote user's MDS innovation through tools, the design environment, and identifying characteristics of user innovators. To this end, we developed a theoretical model based on user innovation theory and work design literature to examine the influence of lead userness and key platform features (i.e., design autonomy and innovation toolkits) on the quantity of user's service innovation. Our findings indicate that in addition to the direct effects of lead userness, toolkit support, and design autonomy dimensions, these antecedents interact in complex ways to influence user's service innovation. These findings not only contribute to research on user service innovation, but also inform practitioners on the characteristics of user innovators and the design of platform tools and policies to promote user's service innovation.

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About the Authors

Hua (Jonathan) Ye is a senior lecturer in the Department of Information Systems and Operations Management at the University of Auckland. He obtained his Ph.D. from the National University of Singapore. His research interests are in IT-enabled open innovation, service innovation, and crowdsourcing. His research has been published in *MIS Quarterly, Journal of Strategic Information Systems, Information and Management, Electronic Commerce and Research Applications, Computers in Human Behavior,* and *Communications of the AIS*. His research has also appeared in the proceedings of premium IS conferences such as the International Conference on Information Systems, the European Conference on Information Systems, the Pacific Asia Conference in Information Systems, and the Hawaii International Conference on System Sciences. Jonathan is currently serving as an associate editor for *Electronic Commerce and Research Applications* and on the Editorial Review Board of *IEEE Transactions on Engineering Management*. He serves or has served on several information systems conference committees.

Atreyi Kankanhalli is a professor in the Department of Information Systems and Analytics at the National University of Singapore. She obtained her B. Tech. from IIT Delhi, M.S. from Rensselaer Polytechnic Institute, and Ph.D. from the National University of Singapore. She has been a visiting scholar at the University of California Berkeley, and the London School of Economics. She has considerable work experience in industrial R&D and has consulted for organizations including World Bank and Bosch. Her research interests pertain to online communities and collaboration, IT innovation, and adoption (particularly in e-government and healthcare). Her work has appeared in *MIS Quarterly, Information Systems Research, Journal of Management Information Systems, Journal of the American Society for Information Science and Technology, IEEE Transactions on Engineering Management, Communications of the ACM, International Journal of Human–Computer Studies,* and the proceedings of the International Conference on Information Systems, among others. She serves or has served on several information systems conference committees and on the editorial boards of journals including *MIS Quarterly, Information Systems Research* and *Journalof the Association for Information Systems*. She has received the ACM SIGMIS Best Doctoral Dissertation Award and the IBM Faculty Award among other honors.

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RESEARCH ARTICLE

USER SERVICE INNOVATION ON MOBILE PHONE PLATFORMS: INVESTIGATING IMPACTS OF LEAD USERNESS, TOOLKIT SUPPORT, AND DESIGN AUTONOMY

Hua (Jonathan) Ye
Department of Information Systems and Operations Management, The University of Auckland Business School, 12 Grafton Road, Auckland 1142, NEW ZEALAND {hua.ye.nus@gmail.com}

Atreyi Kankanhalli
Department of Information Systems and Analytics, National University of Singapore, 13 Computing Drive, SINGAPORE 117417 {atreyi@comp.nus.edu.sg}

Appendix A

Additional Tables

Table A1. Definitions of Platforms Related to IT in Previous Literature

Study	Term	Definition
Boudreau and Hagiu (2009)	Multisided platform, e.g. App store	**Platforms** are products, services, or technologies that serve as foundations upon which other parties can build complementary products, services, or technologies A multisided platform is both a platform and a market intermediary. Distinct groups of consumers and "complementors" interact through multisided platforms.
Boudreau (2012)	Handheld computer platforms	**Computer platforms** are a particular type of multisided platforms, which support interactions across multiple sets of actors and can facilitate technical development. Network effects result from a large number of independent software producers creating applications.
Ceccagnoli et al. (2012)	Platform	A **platform** refers to the components used in common across a product family whose functionality can be extended by applications
Fichman (2004)	IT platform	An **IT platform** is broadly defined as a general-purpose technology that enables a family of applications and related business opportunities. This includes computing platforms (e.g., Palm OS), infrastructure platforms (e.g., wireless networking), software development platforms (e.g., Java), and enterprise application platforms (e.g., ERP).
Tiwana et al. (2010)	Software based platform	**Software based platform** is the extensible codebase of a software-based system that provides core functionality shared by the modules that interoperate with it and the interfaces through which they interoperate. Module is an add-on software subsystem that connects to the platform to add functionality to it (e.g., iOS apps, modular innovation). the collection of the platform and the modules specific to that platform as that platform's ecosystem .

Table A2. Previous Research Related to IT Platform Level Innovation				
Focus	**Study**	**Constructs**	**Method**	**Key Findings**
Producer/ Innovator and Task Features	Boudreau et al. (2011)	Independent variables • Number of competitors • Problem uncertainty Dependent variable: • Innovation performance	Field data from 645 software innovation contests in Topcoder from 2001 to 2007 **Unit of Analysis:** • Software contest	• More competitors will improve the average innovation performance of the contest • More competitors enhance contest innovation performance for highly uncertain problems
Producer/ Innovator Features	Boudreau (2012)	Independent variables • Number of producers • Producer diversity and heterogeneity Dependent variables • Application variety on the platform • Individual producers' scope • Time to new version	Field data from application producers on leading handheld computer platforms from 1999 to 2004 **Unit of Analysis:** • Producer level (5994 producers) • Platform level (393 platform-months)	• Number of producers will increase variety of application titles on the platform • Heterogeneity and diversity of producers and the number of producers on the platform enhance the scope of individual producers • The number of producers who produce the same type of applications increases the time for producers to develop a new version
Platform Features	Boudreau and Hagiu (2009)	• Platform regulation on multisided platforms	Case studies of digital (Facebook, Topcoder) and non-digital (Roppongi Hills, Harvard Business School) platforms	• Platform regulation involved using strategic instruments, i.e., legal, technological, informational and others (along with price setting) to implement desired outcomes. The outcomes were to minimize costs associated with a range of externalities, complexity, uncertainty, asymmetric information and coordination problems • The regulatory role played in these cases by multisided platforms was pervasive and at the core of their business models
	Boudreau (2010)	Independent variables • Granting access vs. devolving control Dependent variable • Number of new devices developed	Using data on 21 handheld computing systems from 1990 to 2004 **Unit of Analysis:** • Platform level	• Granting greater levels of access to independent hardware developer firms accelerated the development of new handheld devices by up to five times • Where operating system platform owners went further to give up control (beyond just granting access to their platforms) the incremental effect on new device development was still positive but an order of magnitude smaller
	Tiwana et al. (2010)	• Platform architecture • Platform governance • Environmental dynamics	**Conceptual**	• Platform architecture, governance, and environmental dynamics affect innovation on platforms and platform evolution

Table A3. Previous Empirical Service Innovation Research at User Level (Studies arranged by date within each category)

Focus	Study	Constructs	Method	Key Findings
User characteristics	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	Leading-edge status and in-house technical capabilities positively affect user innovation behavior
	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 dev. • Fluency (# of ideas) • Flexibility (# of distinct categories of ideas) • Originality	Survey of 1,004 Swedish users of telecom services, followed by experiment with 52 users	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 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	Betweenness centrality positively affects the lead userness and creativity of children
Innovation Toolkit Features	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)	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 do not customize

Table A3. Previous Empirical Service Innovation Research at User Level (Continued) (Studies arranged by date within each category)

Focus	Study	Constructs	Method	Key Findings
User Characteristics and Innovation Toolkit Features	Kankanhalli et al (2015)	Independent variables • Trend leadership • Anticipated enjoyment • Anticipated extrinsic reward • Anticipated recognition • Toolkit support • Potential vs. Actual innovator Dependent variable • Intention to innovate	Survey of 111 potential and 101 actual users for MDS applications	Trend leadership and anticipated extrinsic reward influence both potential and actual user innovators' intentions to innovate Anticipated recognition and toolkit support affect only actual user innovators Anticipated enjoyment affects only potential user innovators Toolkit support strengthens the influence of anticipated enjoyment for actual user innovators but weakens its influence for potential user innovators Potential user innovators value anticipated extrinsic rewards less than actual innovators do

Table A4. Mapping Toolkit Support and Design Autonomy into Innovation Phases

	Innovation Phases	
	Idea Generation	**Idea Implementation**
Toolkit Support	Exploration	Ease of Effort
Design Autonomy	Decision-making autonomy	Work-method autonomy Scheduling Autonomy

Table A5. Comparison between Android and IOS Platforms

	iOS	Android	Mean (Android: iOS)	p-value
Decision-making autonomy	• Need to pay $99 per year for the base developer program that allows access to iOS SDK and the right to publish in Apple's app store • App Store Review Guidelines have many restrictions on type/ content of apps that can be created (e.g., violent or adult content) (https://developer.apple.com/app-store/review/guidelines/)	• There is a one-time fee of $25 for Google Play developers • Apps that contain certain objection-able content are not permitted in Google Play at lower maturity rating but are allowed if the maturity rating is high (https://support.google.com/googleplay/androiddeveloper/answer/188189?hl=en)	5.21: 4.13	0.001
Scheduling autonomy	• Scheduling of app release is con-strained by how long the review process by Apple takes and revisions if the app is rejected	• Quick and mainly automated app review process, but app may be removed and developer account may be terminated for policy viola-tions (https://play.google.com/about/ enforcement.html#enforcement-process)	5.41: 4.88	0.23
Work-method autonomy	• Development environment on Mac • Programming language: C, C++, Objective C, Swift • Apple has design and interface guidelines that apps must use the same basic UI elements • Must publish and download the apps via App Store • More tablets, more commercial infrastructure (e.g., payment processing)	• Can develop apps anywhere since Android SDK available for Windows, Linux, Mac • Programming language: C, C++, Java • No enforced UI guidelines • Can distribute apps openly (http://developer.android.com/distribute/tools/open-distribution.html) • Less tablets, slower in introducing payment processing, etc.	5.27: 5.31	0.75
Ease of effort	• Xcode with iOS SDK is relatively easy to use • App configuration is complex • Simulator is fast and responsive • Relatively mature SDK, stable API • Difficult to publish app	• Eclipse IDE with SDK is unwieldy, Android Studio (in Beta) is better • Easier app permissions • Emulator is slower and can fail • Changes in environment • Different hardware manufacturers use different OS versions • Easy to publish app	5.10: 4.95	0.37
Exploration	• Provides app creators tools to explore existing applications in the market • Provides analytics, i.e., downloads for free and paid apps, in-app purchases, updates, information available per country	• Provides app creators tools to explore existing applications in the market • Provides information of current and total installs	4.97: 5.75	0.01

Table A6. Item Weights for LUS		
LUS	LUSA (Ahead of Trend)	0.58***
	LUSB (Unmet Needs)	0.52***

***p < 0.001

Table A7. Slope Difference Test Results		
Pairs of Slopes	t-value	df
$\Delta EOE_{high}, SAU_{high} / EOE_{high}, SAU_{low}$	2.14*	122
$\Delta EOE_{high}, SAU_{high} / EOE_{low}, SAU_{high}$	2.85**	122
$\Delta EOE_{high}, SAU_{high} / EOE_{low}, SAU_{low}$	3.01***	122
$\Delta EXP_{high}, DAU_{high} / EXP_{high}, DAU_{low}$	3.45***	122
$\Delta EXP_{high}, DAU_{high} / EXP_{low}, DAU_{high}$	2.88**	122
$\Delta EXP_{high}, DAU_{high} / EXP_{low}, DAU_{low}$	8.12***	122

Significance at $*p \leq 0.05$, $**p \leq 0.01$ $***p \leq 0.001$

Appendix B

Post Hoc Tests for Alternate DVs

Various definitions and indicators of innovation *quality* have been proposed in the literature. Typical indicators include the novelty, feasibility (producibility), and user value of the innovation[1] (e.g., Magnusson et al. 2003; Matthing et al. 2004). In our study context, the feasibility indicator is less relevant since we are considering MDS applications that have already been created by user innovators. Rather, *novelty* and *user value* are considered relevant to MDS innovation *quality* here. Novelty or *radicalness* of the innovation has been noted as an important quality indicator in several studies (Magnusson et al. 2003; Matthing et al. 2004) and will be included in our *post hoc* analysis. Additionally, customer downloads (*popularity*) as an indicator of potential user value and quality of the MDS application, especially for the paid apps (Liu et al. 2012), is evaluated in our *post hoc* analysis. This also aligns with previous work in OSS where downloads are often used as measures of user value (Crowston et al. 2006).

Table B1. Coding Schemes for Popularity and Radicalness			
Number of Downloads Shown in Websites	Popularity	Related Apps Available in the Market	Radicalness
<50	1	>10	1
50-100	2	9-10	2
100-500	3	7-8	3
500-1000	4	5-6	4
1000-5000	5	3-4	5
5000-10000	6	1-2	6
10000-50000	7	0	7
50000-250000	8		
>250000	9		

[1]Other indicators of innovation quality are based on expert evaluations or user outcomes such as user satisfaction. However these data were not available in this study.

For MDS applications innovation quality, *popularity* was measured by the number of downloads (Ye et al. 2011). Since a user innovator is the unit of analysis, we computed the popularity of their service innovation by the average score of $\frac{1}{n}\left[\sum_{i=1}^{n}\left(\frac{D_i}{T_i}\right)\right]$, where n is the total number of applications a respondent has developed, D_i is the number of downloads of i application, T_i is the number of months since i application has been published. To obtain the number of downloads D_i for each MDS application developed by a respondent, we mined archival data from the platforms. This was done by searching for the "publishers" name provided by the respondent and averaging the number of downloads from their applications created as per the formula given above. Since the Android and iOS platforms in our study indicate the downloads of each application in an ordinal way (see column 1 of Table B1), we followed established data coding principles (De Vaus 2002) to code the number of downloads using the scheme shown in Table B1. Such nonlinear coding schemes have been found useful for assessing number of downloads in previous studies (Fershtman and Gandal 2011). The platforms also indicate the number of related apps available in the market for each MDS app. We used this information to measure *radicalness* (see Table B1), that was averaged for each user innovator. Both popularity and radicalness variables were collated 3 months after the survey and used for our *post hoc* analysis, as indicators of innovation quality.

Table B2. Descriptive Statistics and Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Age	1.00														
2. Gender	0.17	1.00													
3. P. Skill	0.44**	0.01	1.00												
4. Educ.	0.24*	-0.03	0.49***	1.00											
5. Tenure	0.44**	-0.13	0.61***	0.54	1.00										
6. LUSA	0.20*	0.12	0.06	-0.02	-0.04	1.00									
7. LUSB	0.12	0.20	0.02	0.01	-0.08	0.40***	1.00								
8. EOE	0.29	-0.03	0.23***	0.08	0.26	0.20	0.12	1.00							
9. EXP	0.26	0.03	0.14**	0.17	0.15	0.22*	0.32*	0.39*	1.00						
10. SAU	0.21	-0.14	0.11	0.05	0.27	0.07*	0.10*	0.05	-0.03	1.00					
11. DAU	0.05*	0.12	-0.11	0.02	0.03	0.15**	0.22*	-0.11	-0.02	0.29**	1.00				
12. WAU	0.25*	-0.06	0.06	0.07	0.19	0.11	0.01	0.11	0.10	0.31*	0.11*	1.00			
13. QNT	0.22*	0.13	-0.02	-0.08	-0.05	0.21**	0.23*	0.47*	0.36*	0.08	0.21*	0.15*	1.00		
14. Popu.	0.24*	0.04	0.18	0.01	0.25*	0.23*	0.18*	0.45*	0.38*	0.10	0.25**	0.35**	0.35***	1.00	
15. Rad.	0.05	-0.03	-0.11	-0.05	-0.16	0.21*	0.30*	0.07	0.30*	0.07	0.16*	0.17*	0.06	0.16*	1.00
Mean	21.95	0.73	4.71	2.45	10.9	4.35	4.52	4.95	5.22	5.33	5.30	5.17	3.20	2.91	3.91
SD	5.35	0.44	1.31	0.68	4.14	0.73	0.68	0.86	0.72	1.06	1.04	1.16	1.95	0.67	1.22

Notes: 1. Indicates that the value is not applicable for single indicator variable
2. Significance at *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

We *post hoc* test innovation quality outcome variables (popularity and radicalness). Correlations and descriptive statistics are shown in Table B2 and the regression results are shown in Models 1 and 2 of Table B3. The results using popularity as DV are similar to the original results except for one of the three-way interactions, whereas the results for radicalness differ on two of the three-way interactions, requiring further investigation in future research.

Table B3. *Post Hoc* Test Results for Alternate DVs

	Model 1 (DV = Popularity)	Model 2 (DV = Radicalness)
Age	0.05 (0.004)	0.05 (0.008)
Gender	-0.14 (0.005)	-0.08 (0.008)
Prog. Skill	-0.02 (0.02)	0.03 (0.000)
Education	-0.01 (0.001)	-0.13 (0.001)
Tenure	-0.30 (0.11)	0.08 (0.010)
Platform	0.10 (0.009)	0.10 (0.011)
LUS	0.23* (0.003)	0.15* (0.009)
EOE	0.20* (0.011)	0.17** (0.005)
EXP	0.27** (0.008)	0.25** (0.004)
SAU	0.07 (0.007)	-0.09 (0.011)
DAU	0.23** (0.005)	0.25** (0.001)
WAU	0.18* (0.001)	0.16* (0.005)
EOE*SAU	0.01 (0.002)	0.02 (0.004)
LUS*EOE	0.05 (0.004)	0.03 (0.010)
LUS*SAU	-0.04 (0.005)	0.11 (0.003)
EOE*WAU	0.23* (0.002)	0.16* (0.002)
LUS*EXP	-0.02 (0.11)	0.03 (0.005)
LUS*WAU	0.11 (0.12)	0.09 (0.005)
EXP*DAU	0.15 (0.004)	0.07 (0.008)
LUS*DAU	0.01 (0.004)	-0.11 (0.000)
LUS*EOE*WAU	0.04 (0.005)	0.04 (0.001)
LUS*EOE*SAU	0.19** (0.010)	0.06 (0.001)
LUS*EXP*DAU	-0.13 (0.012)	0.22* (0.008)
R^2	0.32	0.23** (0.005)

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