Jack of All, Master of Some:

The Contingent Effect of Knowledge Breadth on Innovation

Completed Research Paper

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Abstract

This study investigates how individuals' knowledge structure affects their new product ideation outcome. Because individuals who possess diverse knowledge can potentially create more novel recombination, broad knowledge has been touted as the key driver of innovation. Yet, a shallow grasp of a wide array of knowledge might be sufficient to generate novel ideas but are insufficient to produce innovative ideas that should also be useful and economically feasible. Deep knowledge complements broad knowledge by aiding individuals to effectively combine diverse set of knowledge and to identify constraints of potential solutions. Consequently, individuals with both broad and deep knowledge are expected to outperform those who only possess broad knowledge in innovation tasks. Our findings in a new product idea crowdsourcing community are consistent with our predictions: knowledge breadth feeds into novelty of ideas, but its effect on usefulness and innovativeness of ideas is contingent on the presence of deep knowledge.

Keywords: innovation, knowledge breadth, knowledge depth, crowdsourcing

Introduction

The ability to innovate is critical for an organization's success. Innovative organizations make higher profit, market value, and are more likely to survive (Banbury and Mitchell 1995, Cefis and Marsili 2006). Due to the important role of innovation in organizations, scholars have been intrigued to examine what contributes to innovation performance of organizations. Mostly focused on innovation efforts by internal research and development (R&D) departments, scholars have identified various factors that contributes to organizations' innovation performance: to name a few, prior related knowledge (Cohen and Levinthal 1990), network positions (Hansen 1999, 2002), and the type of alliances (Sampson 2007).

So far innovation efforts have been mostly concentrated on organizations' internal R&D departments. However, research has found that users are an important source of innovation because users can tap into valuable market needs information. For instance, in some industrial goods markets, users are the actual developers of commercially successful new products: e.g., 82% of all commercialized scientific instruments are developed by actual users (von Hippel 1976, 1988). Further, most successful user-driven innovation is done by "lead users" of products. First introduced by von Hippel (1986), the term lead users describes the users who face needs that are still unknown to the public and who also benefit greatly if they obtain a solution to these needs (von Hippel 1986). Examples of lead users of flashlight are policemen and home inspectors. The effectiveness of user-driven innovation is documented by several studies (Henkel and von Hippel 2005, Laursen and Salter 2006, Rosenberg 1982, Urban and von Hippel 1988, von Hippel 1976).

With advancement of information technology, organizations can now engage users in their R&D efforts in an unprecedentedly larger scale through crowdsourcing approach. Crowdsourcing is the practice of outsourcing a function once performed by employees from an undefined large network of people through an open call (Howe 2008). In contrast to most previous user innovation that occur in industrial goods market (e.g., medical instruments), recent movement of innovation crowdsourcing occurs in customer products markets such as personal computer, beverages, and mobile services. Since the last decade, several pioneering organizations such as Dell, Starbucks, BMW, Nike, and BestBuy have set up ongoing online innovation crowdsourcing communities where customers can propose new product or service ideas.

Despite the growing popularity and potential of large scale user-driven innovation phenomenon, we have relatively limited understanding on what leads to successful new product ideation efforts. Although there exist extensive research on innovation, most of them were conducted at organizational level, probably because so far innovation activities occur within organizations. A few recent studies have documented valuable findings in the setting of innovation crowdsourcing: it has been found that users who have proposed multiple ideas (Bayus 2013), who possess occupation outside of the innovation area (Jeppesen and Frederiksen 2006), and who are at technically and socially marginal position (Jeppesen and Lakhani 2010) are more likely to generate innovative ideas. In addition, users who are positioned at the core of user community but also spanning boundaries to other communities are found to be more innovative (Dahlander and Frederiksen 2012). Further, Huang et al. (2014) examined participation dynamics of crowdsourcing community. They find that the observed decreasing trend of participation is because low-ability participants are dropping out after learning that they lack ability to come up with high-quality ideas.

Although the previous findings are valuable, more attention should be given to how idea generator's pre-existing knowledge affects innovation outcome. Preexisting knowledge of an idea generator plays a crucial role in innovation process because innovation process involves substantial amount of recombining or rearranging pre-existing knowledge (Fleming 2001). We often see that scientists borrow solutions outside of one's field. In IDEO, a design and innovation-consulting firm located in Palo Alto, new product development teams purposely invite experts from unrelated fields to encourage adopting a fresher perspective on a problem (Hargadon and Sutton 1997). As adding extra knowledge components to the pre-existing knowledge pool exponentially increases the number of new combinations, scholars have contended that individuals who are knowledgeable on diverse topics (i.e. individuals who possess broad knowledge) have higher potential to generate innovative ideas (Taylor and Greve 2006).

In this study, we examine how idea generators' preexisting knowledge affects their innovation efforts. We argue that broad knowledge by itself is not a satisfactory condition that contributes to innovation performance. Innovation is a commercial application of an invention (Schumpeter 1939, Sternberg and Lubart 1995): an idea should be novel but also be useful and economically feasible in order to be innovative. Despite the multifaceted nature of innovation, with exception of Franke et al. (2013), so far the focus of most studies was on the novelty dimension of ideas (e.g., Taylor and Greve 2006). What diverse knowledge enhances is the novelty of an idea because a large number of pre-existing knowledge allows more novel recombination. Consequently, our understanding on the factors that influence the other important aspects of innovation (usefulness and feasibility) is limited.

We argue that broad knowledge positively contributes to innovation performance only when an individual is able to effectively utilize diverse knowledge. Further, we propose that such ability is a function of whether an individual possess deep knowledge in any of his or her knowledgeable domain areas. Here, deep knowledge is equivalent to expertise, so we will use the two terms interchangeably in this paper. While broad knowledge may help to generate novel ideas through providing rich ingredients to recombine, it may harm an idea generator's ability to create ideas that are useful and economically viable because individuals are less likely to process knowledge correctly as the number of knowledge components grows (Martin and Mitchell 1998). We propose that possessing deep knowledge in any of the knowledgeable areas enables individuals to reap the benefit of diverse knowledge while not suffering from such adverse effect because individuals gain ability to connect seemingly unrelated information across divers knowledge and to identify constraints from potential solutions through deep knowledge. Despite the important complementary role of deep knowledge to broad knowledge, with exception of Boh et al. (2014) and Katila and Ahuja (2002), studies have not considered both dimensions simutaeneously.

In the context of online new product idea crowdsourcing community, we investigate our research question of how deep knowledge complements broad knowledge in innovation tasks. A crowdsourcing community is the ideal setting because it allows us to observe large number of innovation projects at individual level. Further, the crowdsourcing community provides richer data compared to U.S. Patents dataset, the conventional setting of innovation studies, in that all innovation efforts including both failed and successful efforts can be observed: U.S. Patents data only reflect successful innovation efforts.

To examine how knowledge breadth and depth affect individuals' innovation efforts and performance, we classified individuals based on their knowledge breadth and depth and examine how each group is different in terms of the quality and quantity of their new product ideation activities. First, based on the number of domains that each individual is knowledgeable on, we identified generalists and non-generalists. Generalists are individuals who are knowledgeable on relatively larger number of domain areas (e.g., more than one standard deviation above the mean) regardless of whether they are experts in any of the areas. On the other hand, non-generalists are individuals who are knowledgeable on a smaller number of areas (e.g., less than one standard deviation below the mean), again regardless of whether they are experts in any of the areas. The group of individuals we are interested in is generalist. While Taylor and Greve (2006) have compared performance of generalists and non-generalists, in this study, we further differentiate generalists based on whether they possess expertise: the ones who possess expertise in any of the knowledgeable areas and the others who do not have expert knowledge on any of the knowledgeable areas. For ease of reference, we call the former group as deep generalists and the latter group as shallow generalists.

After identifying the three groups (i.e., deep generalists, shallow generalists, non-generalists), we investigate how deep and shallow generalists are different from non-generalists in terms of quantity and quality of their proposed new product ideas. We suggest that it is only deep generalists who are more likely than non-generalists to create higher quality new product ideas because deep knowledge helps individuals to better connect relevant information across diverse knowledge as well as to better identify constraints of potential solutions.

Further, we examine how deep and shallow generalists are different from non-generalists in terms of the quantity of new product ideation efforts. Given that generalists possess richer pool of knowledge to recombine, we may assume that generalists are more likely to create greater number of ideas compared to non-generalists. However, we expect that deep generalists and shallow generalists are again different in terms of the quantity of ideas generated. We expect that shallow generalists will propose greater number of new product ideas compared to non-generalists. Paradoxically, we expect that deep generalists will propose fewer number of ideas compared to non-generalists because deep generalists tend to filter out low quality ideas. Consequently, we expect that only deep generalists have higher idea acceptance ratio compared to non-generalists.

At an online community by a British telecommunication company that crowdsource new product/service ideas, we empirically tested our theory by evaluating 8,110 individual innovation "projects" in a real world setting. The results are consistent with our predictions: it is only the ideas by deep generalists that are more likely to have higher quality than those by non-generalists. Additionally, we find that deep generalists tend to propose less new product ideas than non-generalists while shallow generalists tend to propose more ideas than non-generalists. Our findings theoretically contribute to innovation literature by identifying boundary conditions of broad knowledge on innovation performance.

Theory and Hypotheses

In this section, we theorize how individuals' knowledge structure (i.e. the level of knowledge breadth and depth) affects the quality as well as the quantity of their new product ideation efforts. Here, knowledge breadth refers to the scope of domains individuals are knowledgeable on and deep knowledge is equivalent to expertise.

Broad Knowledge As a Source of Novelty

"Creativity is just connecting things. When you ask creative people how they did something, they feel a little guilty because they didn't really do it, they just saw something."

Steve Jobs in *Wired*, February 1995

Rather than breaking out of the old to produce the new, creative thinking builds on existing knowledge (Hayes 1989, Kulkarni and Simon 1988, Weisberg 1999). Most novel solutions are generated through the process of recombining or rearranging the knowledge in a new way (Fleming 2001, Gilfillan 1935, Nelson and Winter 1982, Schumpeter 1939, Usher 1954). For example, an established solution in a certain field might be used as a novel way to solve a problem in a different field. We often see that scientists borrow solutions across industries or knowledge domains. Also, a novel solution might be an integration of multiple solutions in other fields. For example, new product development teams at IDEO purposely invite experts from unrelated fields to encourage adopting a fresher perspective on a problem (Hargadon and Sutton 1997).

Based on the knowledge-based view of innovation (Hayes 1989, Kulkarni and Simon 1988, Weisberg 1999), the extant literature suggests that broad knowledge is the key driver of innovations. With larger pool of pre-existing knowledge, innovators can generate more novel solutions because combinatorial possibilities increase exponentially with additional knowledge component added to the pool (Gilfillan 1935, Gilson and Shalley 2004). For example, let us assume that a film producer has participated in producing diverse genre movies. She would be capable of and motivated to combine genres. The resulting cross-genre film (e.g., horror/comedy/musical/fantasy) would certainly be more novel one than a film, which could be clearly categorized under one genre (e.g., romance).

However, novelty alone does not guarantee innovation. Innovation is defined as commercially applicable invention (Schumpeter 1939). In other words, an idea should be novel, useful, and practical in order to qualify as innovation (Sternberg and Lubart 1995). A novel solution that does not meet current market needs or is not economically feasible cannot be considered as an innovation. This distinction is important because it implies that broad knowledge may not be the satisfactory condition to generate an innovative idea.

Although broad knowledge may ensure novel idea generation, it may hurt usefulness and feasibility of ideas because individuals are less likely to process knowledge correctly as the number of knowledge components increases (Martin and Mitchell 1988). Consequently, the quality of an idea cannot be determined only by the level of knowledge breadth. Instead, broad knowledge are found to increase the upside potential of innovation performance; thereby increases the variance, rather than the average level, of individuals' innovation performance. For example, Taylor and Greve (2006) have shown that the collector market value of comic books become highly variable as the number of genre experience of comic writers increases.

The Role of Deep Knowledge

We propose that innovators who have a wide range of knowledge can create high quality innovation only if they were able to effectively combine the diverse set of knowledge. For instance, in the cross-genre film producer example, the quality of the new film will depend on how effectively the film producer integrates the diverse genres rather than how many genres are combined. We argue that it is deep knowledge that enhances innovators' ability to utilize diverse knowledge effectively.

Scholars occasionally mentioned the important role of deep knowledge on innovation. Cohen and Levinthal (1990) emphasized the importance of deep knowledge in developing absorptive capacity. They contend that brief exposure to the knowledge is insufficient to develop absorptive capacity. Also, it has been consistently found that extensive domain-specific knowledge is required for creativity (Weisberg 1999). A set of studies have documented that creative individuals have spent extensive amounts of time to acquire master level of knowledge in one's field before innovation is produced (Csikszentmihalyi 1996, Ericsson et al. 1993, Gardner 1993).

Despite its importance on innovation process, our understanding of the role of deep knowledge in the innovation process is limited. In this study, we propose that deep knowledge complements broad knowledge in generating high quality ideas for the following reasons. First, deep knowledge boosts innovators' ability to utilize diverse information. Through in-depth understanding of a matter, individuals develop more abstract representation of knowledge, which help them to pay attention to more relevant, and structural features (Glaser 1989, Newell and Simon 1972). On contrary, individuals without deep knowledge (non-experts) tend to pay more attention to less relevant and superficial features, which usually reside on surface level.

Analogical reasoning, an important psychological process of creative cognition, involves comparing two components in different domains in order to infer or borrow solutions from one to the other (Dunbar 1995). The level of expertise has been found to influence the effective use of analogy (Casakin 2004, Collins and Burstein 1989, Vosniadou 1989). When attempting to use analogical reasoning, individuals who have deep knowledge in any of the knowledge domains were more likely to establish successful analogies (Novick 1988) because the deep understanding enable them to map relevant features across different knowledge domains. Conversely, novices tend to retrieve irrelevant, surface features. Consequently, experts are able to map relevant features across knowledge domains more effectively than novices, which lead to higher likelihood of experts to establish successful analogies (Novick 1988).

Similarly, deep generalists are expected to excel in identifying and retrieving relevant information out of diverse knowledge. As a result, deep generalists are expected to integrate diverse knowledge in a more meaningful way. On the other hand, shallow generalists are expected to make less useful ideas because they tend to miss meaningful linkages across diverse knowledge domains. Therefore, we hypothesize that:

> *Hypothesis 1. Only deep generalists are more likely to propose new product ideas that are of higher quality than non-generalists.*

Further, given that generalists possess richer pool of knowledge to recombine, we may assume that generalists are more likely to create greater number of ideas compared to non-generalists. However, we expect that shallow generalists will propose greater number of new product ideas compared to non-generalists. Paradoxically, we expect that deep generalists will propose fewer number of ideas compared to non-generalists because deep knowledge aids innovators to identify constraints of potential ideas.

Thorough understanding of a problem is a crucial part of problem solving (Simon 1981). It has been found that experts dedicate a substantially greater effort than novices to elaborate their understanding of a problem, add ill-defined and implicit constraints to the problem (Eckert et al. 1999). For example, in an experiment of architectural design, Casakin (2004) observed that experts added more constraints to the design problem, which decreased the total number of alternative design solutions of experts. On the other hand, novices generated more solutions but most of them were not feasible solutions because they failed to consider potential constraints each design problem has. In a chess game setting, Chase and Simon (1973) also found that novice players are more likely to conduct an exhaustive search through relevant and irrelevant knowledge in order to find an appropriate solution. Conversely, master players successfully limit their solutions to those that would potentially lead to promising outcomes based on their assessment of current constraints. Likewise, due to the self-filtering ability, we expect that deep generalists are more likely to propose fewer ideas. Therefore, we hypothesize that:

Hypothesis 2a. Deep generalists are more likely to propose fewer new product ideas than non-generalists.

Hypothesis 2b. Shallow generalists are more likely to propose more new product ideas than non-generalists.

Given that deep generalists are more likely to create fewer number of higher quality new product ideas, we expect that deep generalists would be more efficient than non-generalists in generating high-quality ideas. Therefore, we hypothesize that:

Hypothesis 3. Only deep generalists are more likely to have higher idea acceptance ratio than non-generalists.

Method

Research Context

Our empirical context is an innovation crowdsourcing community hosted by Giffgaff, a British telecommunication company. Giffgaff sells SIM cards and related telecommunication services. Unlike conventional mobile telephone operators, Giffgaff crowdsource many of its operations from customers. For example, Giffgaff crowdsource call centers. Instead of setting up huge call centers as other mobile operators do, Giffgaff let its customer crowds handle customer support. Other than confidential billing questions, crowds handle all questions. Also, Giffgaff crowdsource marketing, sales, and innovation efforts from customer crowds. According to Vincent, Head of Community, the average response time for questions is just three minutes, day or night, with 95% of questions being answered within an hour (Williams 2011). In return for the services, customers are rewarded with monetary compensation called 'Payback'. Payback points can be cashed out, credited against monthly bills, or donated to charity. The top earning GiffGaff customer earned over £13,000, who used it to pay his college tuition (Williams 2011).

Giffgaff's two main crowdsourcing communities are customer support and innovation communities. In order to participate in the communities, individuals must register with an anonymous user name. Anyone can join the Giffgaff's communities but one should be a customer with active Giffgaff SIM card in order to be compensated. At Giffgaff's innovation crowdsourcing community, customers can propose new product or service ideas. During the first two years after inception, about 7,000 ideas were posted and one idea was implemented every three days on average (Williams 2011). After an idea is submitted, its status remains as proposed until it receives 20 customer votes. Any community member can cast one vote for an idea they would like to be implemented. Once a proposed idea receives 20 votes, it can be taken to ideas meeting, where Giffgaff management team discusses and selects ideas to implement. Each month, selected ideas are publicly announced through Giffgaff's *IdeaBroadcast* blog. Innovators of implemented ideas are rewarded with Payback points.

Data

Our research question is to examine how knowledge breadth and depth affect various innovation outcomes. In order to test our hypotheses, we need individual-level data of all innovation efforts including both successful and failed ones. Also, for each idea, we need to know how useful it is and whether it is chosen by the company to implement. Further, we need to know knowledge breath and depth of each innovator at each time period. The Giffgaff crowdsourcing communities provide unique data opportunities that satisfy the above-mentioned empirical requirements.

In order to construct our variables, we collected data from Giffgaff innovation and customer support crowdsourcing communities. Data span three years from the company's inception on November 2009 to October 2012. Data from the innovation crowdsourcing community were used to evaluate individuals' innovation performance. For our empirical test, we dropped ideas that were still under review at the end of our empirical test window. Further, we excluded innovators who have not contributed to customer support community. About 90% of all innovators participated in both innovation and customer support communities. The 10% of innovators who have only participated in innovation community were not significantly different from the other 90% innovators in their innovation activities. The exclusion leads to our final dataset of 8,110 ideas by 2,705 innovators. Among 8,110 ideas, 426 ideas (≈ 5%) were implemented.

Data from the customer support community were used to measure innovator's knowledge breadth and depth. Because behavior of providing an answer to solve others' problems indicates that the helper is knowledgeable on the question domain (Zhang et al. 2007), we use the traces of individual's helping behavior in customer support crowdsourcing community to gauge how broadly and deeply each innovator is knowledgeable. On average, innovators posted 37 questions and 206 answers during the period. The distribution of posts is skewed to the right, as it is typical in online communities that few users contribute many messages.

We measured knowledge depth and breadth of innovators based on the following procedures. First, we code contents of all messages posted to both of the communities into 115 distinct topics. We used Latent Dirichlet Allocation (LDA), a natural language processing topic classification technique, to automatically discover clusters of messages with similar topics. LDA is a bag-of-words model, which treats each document as a mixture of topics. LDA attempts to learn the topics of each document by backtracking from the words that appear in messages to find a set of topics that are likely to have generated the words. We used software Mallet (McCallum 2002) to run LDA.

The 115 topics that are identified are narrowly defined topics, hence the topics are interrelated. For example, we find that the LDA identified five topics that are about a "goody bag", which is a bundle of calling minutes, number of texts, or data plan. Table 1 lists the five topics related to goody bag.

Topic number	Topic description
2	Goody bag discount buy
10	Goody bag cancellation
49	Goody bag initial purchase
77	Setting up goody bag automatic top up
96	Rolling over unused good bag minutes

Table 1. Sample LDA-classified topics

The topic classification enriched our dataset because now we can observe the contents of information that flow through user interactions. Specifically, with topics labeled to each message, we can track on which topics each innovator is knowledgeable. After we obtained topics of all messages, we constructed a knowledge profile for each innovator for each time period. Each innovator's knowledge profile is captured by a time-evolving vector of 115 elements, $\mathrm{K_{it}} = (\mathrm{K_{it}^{1}} \cdots \mathrm{K_{it}^{s}})$, where $\mathrm{K_{it}^{s}}$ represents the number of answers in topic area S by innovator i up to time t. Innovators' knowledge profiles are used as a base matrix to construct knowledge breadth and depth measures for each innovator.

Measures

We constructed a pooled panel dataset, which consists of different individuals over time. Because participants propose approximately two new product ideas per three month on average, we set our time interval as three months. All variables are constructed at an individual level and independent and control variables are lagged by one period in order to avoid reverse causality issue. Our final data contain 3,697 observations. Definitions of all variables are summarized in Table 2.

Dependent variables	
Quantity $_{it+1}$	Total number of ideas produced by an innovator i at time t+1
Usefulness $_{it+1}$	Average customer votes received for ideas submitted by an innovator i at time t+1
Acceptance Ratio $_{it+1}$	$\frac{\boldsymbol{Number\ of\ implemented\ ideas\ by\ innovator\ i\ at\ time\ t+1}}{\boldsymbol{Total\ number\ of\ submitted\ ideas\ by\ innovator\ i\ at\ time\ t+1}}$
Independent variables	
Deep generalist $_{it}$	1 if innovator i was deep generalist at time t, 0 otherwise
Shallow generalist $_{it}$	1 if innovator i was shallow generalist at time t, 0 otherwise
Control variables	
Experience $_{it}$	Total number of ideas submitted by innovator i up to time t
All Answers $_{it}$	Total number of answers offered by innovator i up to time t
Time $_{it}$	Time index

Table 2. Summary of Variables

Dependent variables

As noted earlier, we employed multiple outcome variables in order to investigate how an innovator's knowledge breadth and depth affect various aspects of innovation outcomes. In order to test whether deep generalists tend to produce fewer ideas (H1), we constructed $\mathrm{Quantity}_{it+1}$. The variable represents the total number of ideas produced by an innovator i at time t+1. On average, innovators generated 2.12 ideas per period.

The variable $\mathrm{Usefulness}_{it+1}$ represents the average usefulness of ideas submitted by an innovator i at time t+1. Members vote for an idea when they like it and want the idea to be implemented. Because member votes represent the potential usefulness of an idea by Giffgaff customers, Giffgaff uses the member votes as an initial filter to sort out quality ideas. Only the ideas that have received 20 or more customer votes are eligible for management review. Hence, we used the number of customer votes as a proxy of idea usefulness. We constructed $\mathrm{Usefulness}_{it+1}$ by calculating the average number of customer votes received for the ideas submitted by an innovator i at time t+1. On average, ideas received about 5 customer votes and the most popular idea received 518 customer votes.

$\mathrm{Acceptance\ Ratio}_{it+1}$ is calculated by dividing the number of implemented ideas by the total number of ideas submitted by innovator i at time t+1. Only the ideas that are novel, useful, and feasible are selected by Giffgaff for implementation. Hence, the portion of ideas that are implemented represent the true measure of an individual's innovativeness.

Independent variables

Independent variables of this study are two dummy variables that indicate whether innovator i was a deep generalist or a shallow generalist at time t. Deep generalist$_{it}$ is coded as 1 if an innovator i is a deep generalist at time t, 0 otherwise. Shallow generalist$_{it}$ is coded in the same manner. In order to classify innovators, we measured knowledge breadth and depth for each innovator and for each time.

Knowledge breadth, which captures the scope of an innovator (i)'s knowledge up to time t, is measured by counting the number of distinct topics on which an innovator (i) has provided at least five answers up to time t. Although an innovator who offered one answer on a certain topic might be knowledgeable on the topic, we raised the bar to five answers in order to be conservative. As a robustness check, we calculated knowledge breadth based on various thresholds (5 answers ± 2). The directions and significant of our results remain consistent. In our panel dataset, innovators are knowledgeable on about 11 topics on average.

In order to measure knowledge depth, we identified experts for each topic area, for each period. We used the total number of answers offered to each topic as a proxy to the degree of knowledge depth on the topic. Among innovators who have offered at least one answer to a certain topic, we consider only those who fall in top 10% as an expert on the topic domain. As a robustness check, we employed various thresholds (10% ± 5%) to determine deep knowledge. The directions and significance of our results remain consistent. The threshold to be an expert varies across domains but on average an innovator had to offer 63 answers in order to be classified as an expert in a domain.

Based on the knowledge breadth and depth measure, we created indicator variables that distinguish two groups of innovators who have high level of knowledge breadth but different levels of knowledge depth. Based on knowledge breadth measure, we first segregated innovators into generalists and non-generalists. Generalists are the ones who are knowledgeable on diverse topics. In our data, we considered innovators who are knowledgeable on the number of topics that are more than one standard deviation above the mean as generalists. Innovators who are knowledgeable on more than 40 topic areas are classified as generalists. Among them, deep generalists are the ones who possess deep knowledge in at least one topic area while shallow generalists are the ones who are not expert in any of the topic areas. In other words, deep generalists are the innovators who possess both broad and deep knowledge while shallow generalists are the ones who only have breadth but no depth.

Control variables

Individuals' innovation outcomes may also be influenced by other factors. In order to tease out the effect of knowledge depth and breadth on innovation outcome, we incorporated several control variables. First, innovators may learn to produce high quality ideas in the course of generating multiple ideas. To control for the learning-by-doing effect (Argote 2012), we included $Experience_{it}$ variable, measured by the cumulative number of ideas generated by each innovator up to time t. Second, we incorporated $All\ answers_{it}$ in order to tease out the effect of knowledge structure (breadth and depth) from the total amount of knowledge. $All\ answers_{it}$ is calculated by summing up all answers contributed by innovator i up to time t. Third, our dataset spans over three years. In order to control for any unobserved effects caused by time differences (e.g. competition level), our model includes the variable $Time_t$, which is an index for time period. Lastly, we included random effect for each innovator in order to control for any unobserved individual-specific heterogeneity.

Model specification

Observations of our panel dataset are not independent with each other because an innovator may appear multiple times in different time periods. A common solution to the matter is to incorporate fixed or random effects for each innovator. Hausman test is conducted to determine which model should be used (Greene 2011). Based on the test result, we incorporated individual random effects into our estimation model in order to control for any unobserved heterogeneity of innovators.

Different estimation models are employed according to the distribution of dependent variables. To estimate the effect of knowledge breadth and depth on usefulness and innovativeness of ideas (Hypotheses 2 and 3), we employed panel ordinary least-squares regression because the dependent measures are continuous variables. However, to test Hypotheses 1 and 4, we employed panel negative binomial regression because the outcome measures (total ideas and breakthrough) are count variables.

Results

Preliminary Analysis: Generalists vs. Non-Generalists

Before we test our hypotheses regarding the difference among deep generalists, shallow generalists, and non-generalists of their innovation outcomes, we conducted preliminary analysis examining the difference between generalists and non-generalists. Specifically, we examined the differences of ideas generated by generalists and non-generalists in their idea quantity, novelty, usefulness, and acceptance ratio. We will use the results as a baseline to interpret our hypothesized relationships. As novel ideas tend to be either extremely useful or useless (Fleming 2001, March 1991), previous studies have operationalized the level of idea novelty as the variance of its collector market value (Taylor and Greve 2006). Similarly, we operationalized the level of idea novelty as the variance of usefulness of ideas submitted by innovator *i* at time *t+1*.

The results are summarized in Table 3. Compared to non-generalists, generalists tend to create more ideas (Model 1). Consistent with Taylor and Greve (2006), ideas by generalists tend to be highly variable in its usefulness (Model 2) because some ideas are extremely popular useful ideas while others are useless ideas. Also, ideas by generalists are more useful and are more likely to be accepted on average (Model 3 and 4). The findings of preliminary analysis suggest that broad knowledge is the key driver for successful innovation outcomes.

	Model 1	Model 2	Model 3	Model 4
Dependent variable	Quantity $_{it+1}$	Usefulness Variance $_{it+1}$	Usefulness Average$_{it+1}$	Acceptance Ratio $_{it+1}$
Generalist $_{it}$	0.3183 ***	3.4094 ***	2.6642 ***	0.0203 ***
	(0.047)	(0.842)	(0.557)	(0.009)
Experience $_{it}$	-0.0077 ***	-0.0303	0.0154	0.0002
	(0.002)	(0.036)	(0.029)	(0.000)
All answers $_{it}$	0.0000	0.0017 ***	0.0025 **	0.0000 **
	(0.000)	(0.000)	(0.000)	(0.000)
Time $_{it}$	-0.0298 ***	-0.0803	-0.3819 ***	-0.0115 ***
	(0.008)	(0.148)	(0.080)	(0.001)
Number of observations	3,697	3,697	3,697	3,697
Number of individuals	2,643	2,643	2,643	2,643
Estimation method	*Negative Binomial*	*OLS*	*OLS*	*OLS*

******* *Significant at 0.001 level (two-tailed)*
** *Significant at 0.05 level (two-tailed)*
* *Significant at 0.1 level (two-tailed)*

Table 3. New Product Ideation Outcomes: Generalists vs. Non-Generalists

Main Analysis: Deep Generalists vs. Shallow Generalists vs. Non-Generalists

The results of preliminary analysis confirm claims of extant literature: knowledge breadth is the key to the innovation. However, once we further segregate generalists based on whether they possess deep knowledge or not, the story becomes clearer. The descriptive statistics of variables are reported in Table 4 and Table 5 presents the results of panel regression analyses that predict various innovation outcomes of deep and shallow generalists.

		mean	std.dev.	min	max	1	2	3	4	5
1	Deep generalist	0.08	0.26	0	1	1.00				
2	Shallow generalist	0.05	0.23	0	1	-0.03	1.00			
3	Experience	2.22	7.08	0	101	0.41	0.11	1.00		
4	All answers	119.06	612.48	1	60	0.59	0.02	0.46	1.00	
5	Time	5.95	2.11	2	9	0.11	0.06	0.13	0.12	1.00
	n = 3,697									

Table 4. Descriptive Statistics and Correlation

	Model 5	Model 6	Model 7
Dependent variable	Quantity $_{it+1}$	Usefulness Average$_{it+1}$	Acceptance Ratio $_{it+1}$
Deep generalist $_{it}$	-0.0477 **	8.0899 ***	0.0582 ***
	(0.020)	(0.786)	(0.001)
Shallow generalist$_{it}$	0.0244 ***	1.7130	0.0463
	(0.006)	(1.580)	(0.025)
Experience $_{it}$	0.0063	0.0152	0.0002
	(0.034)	(0.027)	(0.000)
All answers $_{it}$	0.0011 **	0.0012 **	0.0000 **
	(0.000)	(0.000)	(0.000)
Time $_{it}$	-0.1130	-0.4170 ***	-0.0118 ***
	(0.149)	(0.079)	(0.001)
Number of observations	3,697	3,697	3,697
Number of individuals	2,643	2,643	2,643
Estimation method	*Negative Binomial*	*OLS*	*OLS*

**** Significant at 0.001 level (two-tailed)*
*** Significant at 0.05 level (two-tailed)*
** Significant at 0.1 level (two-tailed)*

Table 5. New Product Ideation Outcomes:

Deep Generalists vs. Shallow Generalists vs. Non-Generalists

In Hypothesis 1, we expect that only deep generalists would generate new product ideas that are more useful that those proposed by non-generalists. The result supports our prediction: the coefficient of deep generalist $_{it}$ in model 6 is positive and significant. On contrary, the coefficient of shallow generalist $_{it}$ is not significant, meaning that the average usefulness of ideas generated by shallow generalists are not different from the average usefulness of ideas generated by non-generalists.

Our second set of hypotheses about the effect of individuals' knowledge structure on the quantity of new product ideas are also supported. In Model 5, the coefficient of Deep generalist $_{it}$ is negative and statistically significant (Model 5), indicating that deep generalists generate fewer ideas. On the other hand, the results indicate that shallow generalists propose more ideas.

The results of hypotheses 1 and 2 implies that deep generalists are more efficient than non-generalists in creating high quality new product ideas because they tend to propose small number of more useful ideas. Hypothesis 3 tests the efficiency. As predicted, only deep generalists are more efficient in creating in high-quality ideas (i.e. in model 7, their idea acceptance ratio is higher than that of non-generalists). Interestingly, the results indicate that there is no learning-by-doing effect for innovation tasks. The coefficient of Experience $_{it}$ is not significant across all the models.

Figure 1 illustrates how ideas by distinctive groups of innovators are different in various dimensions: Novelty (variance of idea usefulness), Usefulness, and Acceptance Ratio. We compared three groups of innovators: deep generalists, shallow generalists, and non-generalists. As it is knowledge breadth that drives novelty of ideas, we don't see dramatic difference in terms of the level of novelty between the ideas produced by deep generalists and shallow generalists (Figure 1(A)). However, in terms of both usefulness and innovativeness of ideas, deep generalists outperform shallow generalists. And the performance of shallow generalists is not much better than that of non-generalists.

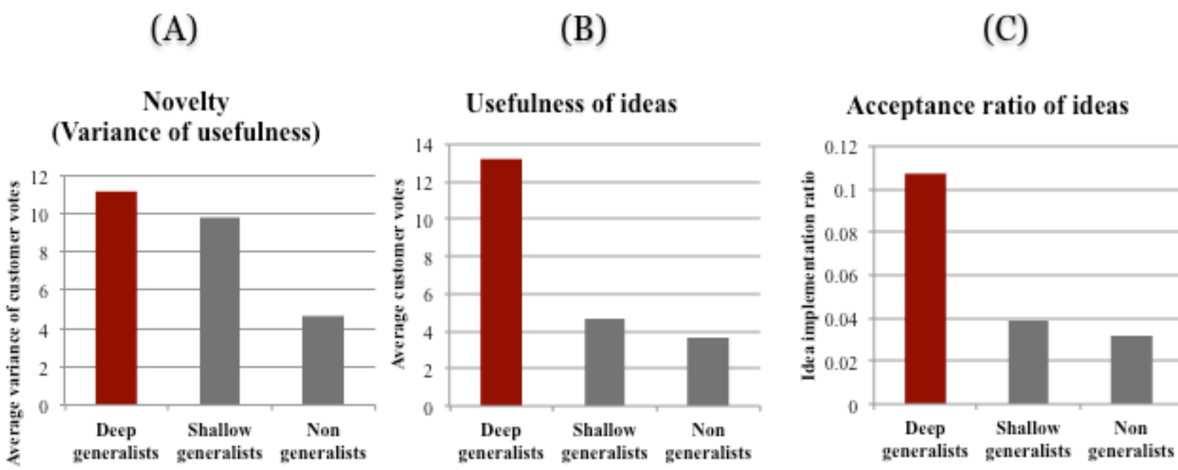

Figure 1. Comparison of New Product Ideation Outcomes

Discussion and Conclusion

For the last decade, formal organizations have increasingly started to crowdsource new product ideas from their customers. Sourcing innovation efforts from customers have great promises because customers can instill important market needs information. Although its growing popularity and great promises, we know only a little about the nature of innovation efforts in innovation crowdsourcing online communities.

Creative thinking builds on existing knowledge. Most innovative ideas are formulated by recombining or rearranging pre-existing knowledge components. Based on this knowledge view of innovation, scholars have argued that broad knowledge is the key driver for innovative ideas: richer set of ingredients allows more novel recombination through increasing potential combinatorial possibilities.

However, innovation is multi-faceted. In order to be qualified as innovation, ideas should be novel, useful, and feasible enough to be commercially applicable. Even though broad knowledge may guarantee novelty aspect of an idea, it's effect on usefulness, feasibility of ideas, and consequently on innovativeness of ideas is unknown. Previous research suggests that broad knowledge may hurt usefulness or feasibility of ideas (Martin and Mitchell 1998, Taylor and Greve 2006). Instead of enhancing average quality, broad knowledge tends to increase the variance of idea quality because with more knowledge components to deal with, innovators are less likely to process them correctly.

In this study, we proposed and empirically tested that innovators should be knowledgeable both broadly and deeply in order to be able to create high quality ideas. Innovators who have wide range of knowledge can create high quality innovation only if they were able to effectively combine the diverse set of knowledge. We argue that it is deep knowledge that enhances innovators' ability to utilize diverse knowledge effectively. Deep knowledge helps innovators to make more meaningful recombination by enabling them to see more meaningful linkages across diverse knowledge. Further, deep knowledge help innovators to generate practical ideas by helping them to identify constraints of potential solutions.

Consistent with our predictions, the results show that knowledge depth and breadth are complementary factors that positively predict innovation performance. The positive effect of knowledge breadth on innovation is contingent on whether an innovator possesses deep knowledge. Specifically, it is only innovators with both broad and deep knowledge who can generate more useful ideas than non-generalists. Although it was diverse knowledge that helped innovators to come up with more number of novel ideas, without deep knowledge, innovators were not able to create useful and practical ideas. Further, we find that deep generalists are likely to be more efficient in that they propose smaller number of higher quality ideas. As a result, their acceptance ratio is higher than that of non-generalists.

This research makes several contributions to innovation literature. Based on our analysis of longitudinal data spanning over three years of individual new product ideation activities in crowdsourcing community, we were able to estimate the effects of individuals' knowledge breadth and depth on various outcomes of their new product ideation efforts. While it has been hypothesized that broad knowledge is the main source of innovation, this research adds boundary conditions of positive effects of broad knowledge on innovation. Only when accompanied by deep knowledge, broad knowledge positively influences innovation outcome.

The results also advance our understanding on lead users. Lead users are defined as the users who face needs that are still unknown to the public and who also benefit greatly if they obtain a solution of these needs (von Hippel 1986). Our findings suggest that effective lead users are the ones who are knowledgeable on diverse areas and at the same time an expert in some of the areas. Firms that are attempting to use lead-user method to design a new product may use the results of this study in identifying lead users who are more likely to be a high performer.

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