Organization's Adoption of User-Initiated Innovations in Online Brand Communities

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May 2011

Master of Science Thesis

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Abstract

Online brand communities for innovation have been launched by companies in order to collect innovation ideas from their customers in the past few years. This phenomenon could potentially transform the relationship between a company and its customers from the traditional producer-buyer relationship to that of co-creators of value. Adopting innovation ideas from its customers reduces the new product development cost and improves company's image and its customer relationship. However, until today, theoretical and empirical research investigating adoption of innovations in such brand communities for innovation is limited. This study examines the factors that influence an idea being adopted by a company. Drawing on Diffusion of Innovations (DOI) theory and Elaboration Likelihood Model (ELM), we have developed a theoretical model to explain the adoption decision of a company based on directly observable source and innovation characteristics. In particular, we examine the effects of contributor's prior participation, prior adoption rate, the innovation's popularity and supporting evidences. We also highlight the differences between B2C (Business-to-Consumer) and B2B (Business-to-Business) contexts in the effects of such factors in determining the adoption likelihood of an innovation idea. Our theoretical model is validated by analysis using logit regression on secondary data of 19,964 customer innovation ideas collected from Salesforce.com IdeaExchange and Dell IdeaStorm websites. The results show the significant impact of both sources and innovation characteristics on the adoption likelihood of customer innovation. Our finding suggests that brand community practitioners can attract more valuable innovation ideas by encouraging experienced users to make more contribution and facilitating the idea contributors to provide supporting evidences to elaborate on their ideas.

Keywords: Brand Community, User Innovation, Elaboration Likelihood Model, Diffusion of Innovations, Logit Model, Dell IdeaStorm, Salesforce.com IdeaExchange, B2B, B2C

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1. Introduction

Innovation is a crucial process to keep a company competitive in the market and maintain the popularity of its products among its customers. Many companies have invested immensely in their research and development of new products, services, and processes for incremental improvement or radical innovation. Managing innovation could be challenging and the cost of innovation can be considerable for each company. Every market player strives to create more valuable innovations. Industry practitioners are concerned about how to encourage more valuable innovations and reduce the innovation cost. The source of innovation may be internal, while innovation ideas can also be acquired external. Whether the innovation ideas are from internal knowledge or external source, successful innovators have to listen to the market and satisfy the immediate requirements of consumers.

Recent studies have shown that customers can also be involved as an important part of the innovation process (von Hippel 1976). For instance, innovations from users were bound to generate more sales potential than traditional market research techniques (Lilien et al. 2002). By including customers into the innovation process, companies not only benefit from lower product development cost, but also greater market acceptance of the innovations (von Hippel 2005). Recent years have witnessed the emergence of online brand communities for innovation. A brand community is “a specialized, non-geographically bound community based on a structured set of social relations among admirers of a brand” (Muniz et al. 2001). Many academic research papers on the brand communities have proven brand communities effective to improve marketing efficiency and increase brand loyalty (Fournier et al. 2009). The surfacing of brand community for innovation brings to focus the potential value of brand community in the innovation process of a company, as brand community can act as a valuable source of innovation ideas for the companies.

As the pioneers to do so, Salesforce.com and Dell have launched their online brand communities that encourage their customers to participate in the innovation process. By adopting ideas from its customers, Dell has introduced new options to its personal computer models, such as installing Linux as the primary operating system (Di Gangi et al. 2009) and being one of the first companies in the industry to include many recent computer components into its models. Salesforce.com has also ameliorated its products of Customer Relationship Management (CRM) software by building new features adopted from its brand community. Examples of such innovation idea are a mobile platform CRM and more customization option to generate site reports for its clients.

The managers are interested in understanding how to maximize the value of online brand community. Three essential questions we endeavor to answer in this research are: (1) What kinds of customers contribute more valuable innovation ideas to the companies? (2) Which characteristics of contributed ideas potentially influence a company's adoption decision? (3) What is the underlying difference in the effects of source and innovation characteristics between B2B (Business-to-Business) and B2C (Business-to-Consumer) online brand communities? By answering such questions, we intend to suggest a number of practical implications: should an online brand community focus its efforts in attracting new members or retaining experienced members? Are consumers with higher prior adoption rate more likely to contribute useful innovation ideas to the companies? Are ideas with higher popularity considered more useful by the company? What kinds of supplementary tools should a company provide on its brand community to help the members better describe their innovation ideas and enhance communication with the company? Should communities in the context of B2B and B2C be maintained under the same guiding principles?

Adoption of innovations by a company has been studied from various perspectives in prior research literature (Chwelos et al. 2001; Iacovou et al. 1995; Mehrtens et al. 2001; Rogers 1995). The context of online brand communities for innovation differs from previous research in the following two ways. Firstly, brand plays a central role in such an innovation community. Most members of online brand community are loyal customers enthusiastic about the brand. They voluntarily give away their innovation ideas to their favorite brand although there are no explicit rewards for their contributions to the brand. Interests, brand loyalty and reputation in the community constitute the main motivations of contribution in such online brand community (Füller et al. 2008; Li et al. 2010). Secondly, besides considerations of profitability and feasibility of adopting a particular innovation idea, companies also consider other commercial factors such as the impact of adoption on the activities in brand community itself, the brand image among its most loyal consumers and the acquisition of potential customers into its brand community. Most importantly, how an online brand community can be exploited to attract more valuable innovation ideas has been little studied in previous literature. While prior research on such online brand community mainly focuses on an individual customer's motivation of contributing innovation ideas (Füller et al. 2008; Li et al. 2010), there is a lack of study of the factors that influence the value of innovation contribution.

Our theoretical model is built on the Diffusion of Innovations (DOI) theory (Rogers 1995) and Elaboration Likelihood Model (ELM) (Petty et al. 1986). DOI proposes that an adoption decision can be influenced by the innovation characteristics, communication channels, time and organizational factors (Rogers 1995). In an online brand community, when the communication channels and organizational settings are constant among the consumers within the same company, innovation characteristics account for a major part of the variation in the likelihood of adoption. Nevertheless, DOI does not explain the influence of message characteristics on company's adoption decision. In this regard, ELM poses as a complimentary explanation on the adoption decision made by a company. ELM states that adoption decision is influenced by both central route and peripheral route processes (Petty et al. 1986). By integrating ELM into DOI, our theoretical model includes the considerations of source characteristics, such as individual contributor's prior participation and prior adoption rates, as well as innovation characteristics, including innovation idea popularity and the supporting evidences provided by the contributor. At the same time, contributors in B2B brand communities generally possess higher level of knowledge and longer experiences in using the products of this brand. Therefore the contributors in B2B brand communities are more generally considered credible to the potential adopter than contributors in B2C brand communities. Based on these observations, we believe differences exist between the effects of above factors on adoption likelihood.

This theoretical model is tested using data collected from Dell IdeaStorm and Salesforce.com IdeaExchange websites. A choice model (McFadden et al. 1977) is applied to the data from two popular online communities for innovation, Dell IdeaStorm and Salesforce.com IdeaExchange. We employ a choice model to study the adoption decision making of a company by assuming that the company receives an expected latent benefits in adopting an innovation idea from its customers. We have found significant effects of both source characteristics (prior participation and prior adoption rate of a contributor) and innovation characteristics (innovation idea popularity and supporting evidences) on the likelihood of a particular innovation idea being adopted. More interestingly, while the positive effect of prior participation of a contributor is greater in B2C (i.e., Dell IdeaStorm) than in B2B (i.e., Salesforce.com IdeaExchange), the positive effect of idea popularity is greater in B2B than in B2C brand communities. This could be explained by the different level of knowledge and capability to contribute, as well as the differences in the source credibility of these two types of communities.

Our findings suggest that practitioners can benefit from more valuable innovation suggestions from the brand community by adopting a strategy to retain its experienced members and those members with higher adoption rates. One practical way to do so is by providing the contributors who have a history of contributing valuable ideas with explicit rewards apart from implicit reputation rewards inside the community. Our result further suggests that such a strategy to retain active members may be more beneficial in a B2C context than in a B2B context. Practitioners should also encourage customers to provide more supporting evidences on the innovation idea, facilitating its customers to use more referenced pages and multimedia resources, such as image and video in the description of its innovation idea. Brand community can attract more useful innovation ideas for the company by providing supplementary interactive tools for the customers to contribute innovation ideas. Moreover, although idea popularity has been proved as a useful indicator of the potential value of an innovation idea, our results show that it will be more useful to consider idea popularity as a screening tool in a B2B brand community than in a B2C one.

The rest of the paper is organized as follows. We present the relevant literature in the next section, followed by hypotheses development in section 3. We then describe the data and methodology in Section 4. The results of our empirical analysis are presented in section 5. Section 6 discusses the theoretical contributions of the results, its implications and limitations of our findings, followed by the concluding remarks.

2. Conceptual Background

Innovation is described as an idea, material or artifact perceived to be new by the adopter (Zaltman et al. 1973). In the market competition, innovation is a key process to gain competitive advantage for the companies (Afuah 1998).Organizations that ignore new innovations run the risk of falling into uncompetitiveness (Fichman 1999). An innovation is commonly thought to originate from the manufacturer. However, users may also play a central role in the innovation process (von Hippel 1976). One of the first examples of user innovation has been described by early economist Adam Smith: a factory employee modified the working mechanism of the fire-engines (Smith 1776/1999). Several studies in the 1960s show examples of user innovations, including both minor improvements and radical innovations (Enos 1962; Freeman 1968; Hollander 1965). In von Hippel's research, it has been found that users play a central role in the innovation process (von Hippel 1976). Since von Hippel's investigation into this subject, a substantial amount of research has been conducted to study the phenomenon of making users the source of innovation.

Researchers of user innovation have been interested to study two central questions: (1) why do users innovate? (2) How can producers take advantage of users as innovators? For the first question, it has been shown that users are more likely to innovate if the innovation-related knowledge is "sticky", in other words, more expensive to transfer (Lüthje et al. 2005; Ogawa et al. 2006; von Hippel 1994). Based on unique knowledge, users sometimes innovate to solve their special needs (Franke et al. 2003; Lakhani et al. 2003; Slaughter 1993). On the other hand, user-innovators also expect themselves to benefit from their innovations (von Hippel 2005). Most of the user innovations come from the lead-users, those users who are early adopters of new products and whose needs portend the need of the general market (von Hippel 1986; von Hippel

2005). Some user-innovators benefit from selling their innovations (Foxall et al. 1984) or become entrepreneurs (Shah et al. 2007). Besides direct benefits from innovation, user innovator can also receive other implicit benefits from innovation, such as reputation (Lakhani et al. 2003) and social support (Li et al. 2010).

In response to the second question, studies have shown how producers can facilitate innovation and product improvement of the users (Douthwaite et al. 2001). There are various ways that companies can make customers the source of innovation, such as providing the customers with toolkits to create their own innovations (von Hipper et al. 2002), talking to lead users during the innovation process (Lilien et al. 2002), providing virtual customer environments (Nambisan et al. 2008), or using brand community as source of innovation (Füller et al. 2008). Customer can also use supplementary tools such as “customer-active paradigm” (CAP) to develop new ideas and transfer it to a producer (de Jong et al. 2009; von Hippel 1978).

A brand community is defined as “a specialized, non-geographically bound community based on a structured set of social relations among admirers of a brand” (Muniz et al. 2001). In a brand community, members practice in social networking, impression management, community engagement and brand use (Schau et al. 2009). Brand community practice brings benefits to both the company and its customers. For the company, brand community is helpful to achieve stronger customer loyalty, higher marketing efficiency and brand authenticity (Fournier et al. 2009). The customers also benefit from practices in brand community, while their perception and actions are influenced in brand community practices. Their knowledge can be increased and the customers are offered a network of relationships with other customers (Füller et al. 2008). Members of brand communities consist of a valuable source of innovation because of their passions, experience and cooperation in knowledge generation (Füller et al. 2008). Brand community provides cultural capital, produces a repertoire for insider sharing, generates consumption opportunities and reveals brand community vitality (Schau et al. 2009). Nonetheless, until now little research has been conducted to examine the factors that influence the value of innovation ideas from online brand community.

2.1. Diffusion of Innovation Theory

Adoption of innovation in an organization is an organizational decision to utilize a specific innovation. Diffusion is defined as “the process by which an innovation is communicated through certain channels over time” (Rogers 1995). Compared to individual’s technology adoption decision, organization’s decision making process takes longer time. It requires complex interactions among different roles in an organization (Fichman 1992; Rogers 1995). The study in innovation diffusion profits from contributions from multiple disciplines, such as sociology, education, marketing, organizational science, economics and many others.

In the most established model of diffusion of innovations (DOI) (Rogers 1995), the elements that influences adoption of an innovation include innovation characteristics, communication channels, time and social systems. The innovation characteristics have been investigated in several studies. In the classical model of diffusion, Rogers (1995) proposed five such characteristics, including relative advantage, compatibility, complexity, trialability and observability. These characteristics of innovation are believed to affect an individual’s decision on innovation. An individual’s decision on adopting an innovation goes through five stages: (1) knowledge, (2) persuasion, (3) decision, (4) implementation, and (5) confirmation (Rogers 1995). The innovation adoption decision in a company can be influenced by characteristics of user-community, organization, technology, task, environment (Kwon et al. 1987) and its industry (Robertson et al. 1986). At the same time, as companies obtain technology only when they possess sufficient technical know-how, knowledge and organization learning can act as potential barriers in an organization's adoption of innovations (Attewell 1992; Fichman et al. 1997). The factors that affect the diffusion and adoption of IT innovation can be innovation-specific characteristics, organization (context) characteristics, and those factors that pertain to a combination of innovation and organization (Fichman 1999; Meyer et al. 1988). In an online brand community for innovation, a company chooses to adopt the innovation ideas that are considered feasible and profitable for the company.

The usage of DOI can be found in various IS publications. Swanson (1994) applied DOI to the study on organizations' adoption of IS innovation by proposing a three-core model of innovation, which includes technical core, information systems core and administration core. Grover el al. (1997) has tested this three-core model in adoption of ten IS innovations. Iacovou et al. (1995) identified organizational readiness, external pressures to adopt and perceived benefits as main influences on the adoption of Electronic Data Interchange (EDI) in small companies. Forman (2005) applied DOI to study the variation in companies' decisions to adopt the Internet. Fichman (2001) developed aggregation measures to study the adoption of software process technologies of companies. Besides, DOI has also been adopted to study the assimilation of knowledge platforms in organizations (Purvis et al. 2003). Although institutional pressures may play a role in a company's innovation adoption decision, we conclude that the relative advantage of an innovation, which is comparable to the perceived usefulness of technology in an individual adoption decision context, is the single most important reason for adopting innovation for a company.

A research done by Di Gangi et al. (2008) has investigated the factors that influence a company's adoption decision in brand community. In this research, components of Roger's

Diffusion of Innovation Theory (Rogers 1995) have been utilized to study the variables that influences a company's adoption decision. The variables include perceived relative advantage and compatibility, as well as the extent of change agent's promotion efforts. Using ANOVA tests, the researchers have relied on data collected from Dell IdeaStorm and subjective assessments of the adopted ideas to investigate the research hypotheses. The result shows that adoption decision of a company is based on its ability to understand the innovation and to respond to community concerns. However, this research does not investigate the impact of other informational influences such as reference page, supplementary image as well as the distinction between B2B and B2C brand communities. Our research intends to investigate these unanswered questions using more objective measures.

2.2. Elaboration Likelihood Model (ELM)

While the DOI is a useful first step to understand the intentions of adoption, it does not completely address the question on the influence process itself. The influence process is particularly important in the context of online brand communities for innovation since innovation is described in the form of a message and webpage constitute the principle way of communication between the customers and the company in online brand communities. That is, while the same suggestion for innovation can be made by different community members, the likelihood of adoption by a company may differ since one's suggestion may appear to be more persuasive than others in a certain context but less so in other context. To fill this gap, we employ the Elaboration Likelihood Model (ELM). ELM has been widely used in understanding an individual's adoption behavior where the influence process plays an important role (Sussman et al. 2003).

ELM was firstly developed by Petty et al. (1986) to investigate the different levels of influence results across various individuals and contexts. The central idea of ELM is that different message recipients elaborate cognitively on a particular message to a different degree by allocating more or fewer cognitive resources.[1] The variations of elaboration likelihood influence the result of adoption in turn. In ELM, attitude changes might be caused by two routes of informational influence: the central route, in which a person makes decision after thoughtful consideration of a communicated message or argument, and the peripheral route, in which attitude change is a result of some simple cue without necessitating scrutiny (Petty et al. 1986). The influence process of information is a result of a complex mixture of both central and peripheral route processes (Petty et al. 1986). As elaboration likelihood increases, central route makes an increasingly significant impact on recipient's attitudes and beliefs. The central route is more stable, enduring and predictive compared to peripheral route. The peripheral route relies on cues regarding the behavior of target, such as source's attractiveness, likeability and credibility. Peripheral cues are informational indicators that are used to evaluate the content in the absence of substantial argument processing through central route. The prior research has found that elaboration likelihood of an individual can be increased in the workplace by changing the message, the source or the influence context (Bhattacherjee et al. 2006). The impact of peripheral cues in the persuasion context has been found to increase when a person as a receiver is less involved with an issue, or an issue is less relevant to a receiver as a result of low elaboration (Rhine and Severance 1970, Caiken 1980).

[1] Elaboration is a defined as "the extent to which a person thinks about the issue-relevant arguments contained in a message" while elaboration likelihood refers to the extent to which "conditions foster people's motivation and ability to engage in issue-relevant thinking" in a given persuasion context (Petty and Cacioppo 1986).

The study on ELM has been conducted in several different disciplines, including social psychology (Petty et al. 1981; Petty et al. 1986; Petty et al. 1995) and marketing (Lord et al. 1995). In the field of information systems, ELM has been employed to study the impact of users' participation in designing an expert system on the acceptance of system's recommendation (Mak et al. 1997). Dijkstra (1999) has adopted ELM to investigate why some users may have tendency to agree with incorrect advice given by others. ELM has also been used to study knowledge adoption via electronic mail-based communications (Sussman et al. 2003). Tam et al. (2005) have adopted ELM to study the persuasion effect of web personalization. Besides, Bhattacherjee et al. (2006) have studied the acceptance of information technology by using ELM. Cheung et al. (2008) leveraged ELM to study the extent to which opinion seekers are willing to accept online consumer review.

While most previous uses of ELM have been applied on the decision making process of individuals, ELM has also been adopted to study the decision made by organizations, such as companies (Eckert et al. 1997; Lohtia et al. 2003). Compared to an individual's decision making process, companies make their adoption decision through a more complex process. More people with professional expertises are also involved in the process. Nevertheless, ELM is also applicable to the decision making in the context of organization because the decision based on individual evaluators' judgment can be also affected by information process, including both central and peripheral routes of information. In an online brand community for innovation, since webpages serve as the the principle medium of communication between the company and its customers, the informational characterstics on a message, such as inclusion of hyperlinks to other sites, as well as images and other informational sources would have a significant impact on the company's decision making process. Eckert et al. (1997) claim that in the settings of companies as customers, high visioning companies process the selling companies' message more deeply while stagnant management is less likely to consider the core message of persuation. Lohitia et al. (2003) applied ELM to study the differences between business purchase decision and customer purchase decision.

3. Models and Hypotheses

Our research integrates the DOI theory with ELM to build a theoretical model of innovation adoption for a company. These two models complement each other in understanding the two channels of influences on a company's adoption decision. Prior use of ELM has mainly focused on the adoption decision of an individual by integrating ELM with individual-level technology adoption based on Technology Adoption Model (TAM).

We consider a customer-initiated innovation idea valuable and advantageous to a company if it has been adopted by the company, which is put forward by the DOI. As the adoption of the innovation idea usually requires the company's investment of resources and efforts, the adopted innovation ideas must be considered having potential commercial value for a company. Thus, the inherent value of innovation represented by innovation characteristics is a major determinant of adoption likelihood. However, the adoption decision of a company in an online community for innovation can also be shaped by the influence process at the same time. A few facilitators and moderators of innovation communities will do the first screening. These early facilitators are likely to be affected by the influence process. Even the later review of a particular innovation idea by a company's committee to decide its adoption is biased by the number of other community members who favored it as a signal of its potential value. Therefore, a better understanding of a company's innovation adoption can be achieved by consideration of the influence process as well as the characteristics of innovation.

In this study, we do not intend to provide an exhaustive list of the factors that affect the adoption likelihood of an innovation idea in online brand communities for innovation. Instead, we focus on the effects of two source-related characteristics (i.e., prior participation and prior adoption rate of members) and two innovation-related characteristics (i.e., idea popularity and supporting evidences) that are of practical implications due to their direct observability by community managers. In addition, we aim to study how a distinct context of such communities (i.e., B2B vs. B2C) may moderate the aforementioned effects.

Prior Participation In an online brand community for innovation, the members have distinct participation histories in the community. Previous research has attested the impact of prior experience on the adoption attitude of message recipients (Bhattacherjee et al. 2006; Petty et al. 1986). The practice of online brand community members can be seen as a process of informal learning. Informal learning is "the activity involving the pursuit of understanding, knowledge or skill which occurs without the presence of externally imposed curricular criteria" (Livingstone 2001). Customers informally learn about the brand and its products from their participation in the brand community. This informal learning process through participation in the brand community enables an individual member to better understand the innovation ideas contributed by other members in the community. Participation in brand community enhances individual's understanding of the company's values, market orientation and present needs. In addition, the participants' knowledge on the company's products and the industry trends expands by repetitive interactions with a community's moderator and other members. Such knowledge can be transformed into a greater level of relevance and practicability of their innovation idea contributions. Furthermore, by observing the adoption status of others' innovation ideas and comparing various ideas contributed in the brand community, members with higher prior participation are also expected to develop higher critical thinking skills and apply these skills in their product innovation. Consequently, an innovation idea contributed by a customer with higher prior participation tends to provide potentially higher relative advantage and compatibility to the company. According to the Diffusion of Innovation theory (Rogers 1995), higher perceived relative advantage and compatibility enhances the probability that a company adopts an innovation idea.

Besides an explanation in DOI, the impact of higher prior participation could also be explained in the theory of ELM (Petty et al. 1986). Apart from the above factors which are related to the central route in the ELM, it is notable that prior participation may also function as the peripheral cue to some adopting organizations. If a company's review committee of innovation ideas perceives that members' cumulative participation improves their ability to describe and propose more valuable innovation ideas, the company is more likely to use brand community members' prior participation as a peripheral cue. This case is more likely when a few review committee members have to examine a substantial number of ideas in a short period of time. Therefore, the effect of prior participation on the adoption likelihood will be reinforced by its possibility of being used as a peripheral cue.

Both DOI and ELM have confirmed the positive impact of higher prior participation on likelihood of adopting an innovation idea in an online brand community. With such observations, we propose our hypothesis.

H1: An innovation idea contributed by a customer with higher prior participation is more likely to be adopted by a company.

Prior Adoption Rate A company regularly selects among the candidate innovation ideas from brand community to implement. The prior adoption rate of each contributor varies across individuals and changes over time for each individual contributor. The prior adoption rate of an individual contributor discloses information on several aspects of the contributor of innovation idea. A contributor more knowledgeable on the brand and its products usually has higher prior adoption rate than others. Likewise, such a contributor with higher prior adoption rate is also likely to possess greater inherent capability to develop valuable and relevant innovation ideas for the company. These observations show that innovation ideas from a contributor with higher prior adoption rate are expected to be of higher relative value and relevance.

From another perspective, an innovation contributor considers it more worthwhile to contribute and her contribution is more likely to attract the attention of potential adopters when her previous adoption rate is higher. The self-efficacy of a contributor can also be enhanced if the company chooses to adopt her innovation idea. Self-efficacy positively affects an individual's motivation in contributing knowledge (Bock et al. 2002; Kankanhalli et al. 2005). Existing literature supports the view that self-efficacy improves individual's motivation (Bandura 1988) and work-related performance (Stajkovic et al. 1998; Taylor et al. 1984). Higher self-efficacy of idea contributor leads to higher quality of an idea contribution. As a result, the usefulness of an innovation idea is expected to increase with individual's prior adoption rate. In DOI, with higher perceived usefulness and compatibility, an innovation idea is more likely to be adopted by a firm.

The above arguments support the positive impact of prior adoption rate following DOI. This positive impact can also be explained in ELM alternatively. An individual's prior adoption rate can affect the adoption likelihood through a peripheral cue. As we have explained previously, a review committee member of a company may perceive that prior adoption rate of the innovation idea contributor is a useful signal to judge the attractiveness, credibility and potential value of an innovation idea under time constraints. This line of reasoning also reinforces the positive relationship between the prior adoption rate and the adoption likelihood of a proposed innovation idea. These observations lead to our second hypothesis.

H2: An innovation idea contributed by a customer with a higher prior adoption rate is more likely to be adopted by a company.

Idea Popularity A brand community consists of the group of customers enthusiastic about the brand (Fournier et al. 2009). Because of brand community members' identification to the brand and their fondness of its products, many brand community members are anticipated to be among the first adopters or users of a company's latest innovation products. With these observations, the popularity of a prospective product innovation idea in the online brand community can often be seen as a good indicator of its potential acceptance by the future customers as well as its potential popularity in the market. Therefore, the popularity in a brand community suggests to the company the potential market acceptance of a potential innovation idea.

In the online brand communities of this study, members are allowed to indicate their preferences on an innovation idea by "promoting" or "demoting" the idea on the website. As an innovation idea is only promoted when it is supported and considered favorable by another customer, an idea with high voting score can be seen as a popular innovation idea in the brand community. This feature of voting inside a brand community enables a company to gauge the potential acceptance and popularity of a particular innovation idea among its most loyal customers. This voting feature to some extent allows the market value of an innovation idea to be more observable by the company. According to DOI, an innovation idea that is perceived to be more useful and brings potential relative advantage over its competitors is more likely to be adopted by a company. So an innovation idea contribution which is supported by a larger number of brand community members has higher probability of adoption.

In addition to the explanation of the popularity in DOI, the theories in ELM can also be applied to interpret the role of popularity in a brand community. A company perceives the idea popularity as a signal for future popularity, which could become a screening measure for adoption. Therefore, the idea popularity can be seen as the peripheral cue in case of constraints due to time and resources. Using idea popularity as a peripheral cue, a company is more likely to adopt an innovation idea with higher popularity. With the above expectations, we propose the following hypothesis.

H3: A more popular innovation idea is more likely to be adopted by a company.

Supporting evidences When a brand community member makes a contribution of product innovation idea, the contributor may be enabled to add references to the innovation idea by inserting hyperlinks to other web pages on the Internet. Including reference pages in an innovation idea helps to ameliorate the quality of a message in the following ways. Firstly, since the information presented on a referenced webpage is often written in a more formal and professional way than the description produced by an amateur customer in online brand community, adding reference pages to an innovation idea improved the understandability and quality of the description. Secondly, web pages that referenced by other pages are very likely to be selected from credible information sources, in other words, well recognized organization or reputed websites. In this way, the credibility of an innovation idea is enhanced by including references pages.

Previous research has suggested that higher source credibility incurs significantly more opinion change than lower source credibility (Hovland 1951). Source credibility also has a positive effect on the perceived usefulness of technology (Bhattacherjee et al. 2006). On the other hand, enhanced elaboration on the innovation idea helps the adopting organization to better understand the innovation idea. For a positively considered innovation idea, better understandability leads to potentially higher perceived usefulness. In DOI, higher perceived usefulness of a technology leads to higher chance of the innovation idea being adopted.

In prior studies, source credibility has been sometimes regarded as a peripheral cue in ELM (Bhattacherjee et al. 2006; Sussman et al. 2003). When a potential technology adopter is under lower elaboration likelihood, the source credibility of an innovation idea could become an indicator influencing an individual's adoption decision. In an online brand community for innovation, the opinion change due to increased credibility also comes as a result of interpretation of the message after absorbing information from the reference pages. Following these lines of reasoning, including reference pages in an innovation idea is expected to have a direct positive effect on both central and peripheral cues of potential adopter. Thus it increases the innovation idea's likelihood to be adopted.

H4a: An innovation idea with a reference page is more likely to be adopted by a company.

In the online brand communities of our study, a contributor is permitted to add images inside her innovation idea description. An innovation idea, particular on designed products and web pages, could often be more clearly illustrated with images. For an innovation idea with potential market value for the companies, better description of an innovation idea helps to improve its perceived usefulness. DOI suggests that an innovation idea with higher perceived usefulness could have higher chance to be adopted by a company.

From another point, by including images into the description of an innovation idea, the contributor improves the media richness within the message. Media Richness Theory (MRT) suggests that richer media are generally more effective in communication (Draft et al. 1987). An innovation idea with higher media richness is likely to draw more attention from the brand community members as well as the company. Clearer illustration of the innovation idea leads to better understandability. With potentially more readerships, an innovation idea with images in its description is more observable by the company. In DOI, higher perceived observability brings higher chance of its being selected.

Additionally, ELM also lends support to the positive impact of image in the adoption of an innovation idea. It has been shown in prior literature that media richness moderates the effects of peripheral cues (Short et al. 1976). Higher media richness influences adoption decision by providing informational cues to potential adopters in assessing the innovation idea. Besides, sometimes higher media richness also improves the central route of information influence by improving the argument quality of the innovation idea and providing further details on this idea. Hence, we hypothesize the following.

H4b: An innovation idea with supplementary image is more likely to be adopted by a company.

Business-to-Business (B2B) vs. Business-to-Consumer Community (B2C) As shown in other contexts, the aforementioned relationship can be moderated by the characteristics of source or information providers. We highlight the difference in sources of innovation between business-to-business relationship and the one of business-to-consumer. Business-to-business (B2B) environments involve transactions between two companies, while business-to-consumer (B2C) relates to transactions between a company and an individual end consumer.

Several studies have been carried out to better understand the implications of these two different types of e-commerce communities. In the setting of online purchasing, corporate buyers are more concerned on specific information from B2B purchasers than the information from the

B2C consumers (Bridges et al. 2005; Gatticker et al. 2000). Another study has shown that a company's announcement of B2B e-commerce has a higher effect on the return than announcement of B2C e-commerce (Subramani et al. 1999).

An innovation contributor in a B2C community is normally an end user who is enthusiastic about the brand and its products. However, it is very likely that this end user is not a professional in developing and marketing these kinds of products. Providing innovations to her favorite brand is her pastime passion but not her profession. She may possess certain innovation skills and experiences but has not received professional training in this filed. In contrast, an innovation contributor in a B2B community is generally professional in working with the products of the brand. The products of the brand are often used to improve their work. She has professional experience in this field and might have experiences using the products provided by other companies. Generally, an innovation contributor in a B2B community is more capable of developing a useful innovation idea.

According to learning curve theory, the amount of knowledge that can be obtained from prior experiences is greater for novices than for experts (Adler et al. 1991). As a result, the effect of prior participation of members is expected to be greater in B2C than in B2B communities due to the differences in users' initial expertise in both communities. Since a contributor is generally less capable of developing innovation ideas in B2C, a company can expect a substantial improvement in their capability of contributing useful innovation ideas as they learn more through participation in brand communities. In an online brand community for innovation, greater capability of contributing useful innovation idea leads to a greater chance that her innovation idea is accepted by the company. This reasoning leads us into the following hypothesis.

H5a: The effect of prior participation is greater in an innovation idea for a B2C online brand community for innovation than in a B2B online brand community for innovation.

In a B2B brand community for innovation, a member is an employee or a company as a whole with professional backgrounds and knowledge about products and services to be purchased. Thus, B2B brand community members are more capable of describing their innovation ideas as well as judging innovation ideas from others. Evaluating other innovation ideas and their contributions are more likely to be considered relevant to a company as a potential adopter in a B2B community than B2C community as well. Therefore, with more knowledge on the products and brand, contributors and participants who vote in communities can be considered to possess higher credibility in B2B than in B2C. In a B2B brand community, catering to fragmented individual customers needs is more important since the volume of business with each customer is greater in B2B than in B2C community as well. Hence, a company engaged in a community benefits more by investing more resources in processing messages in B2B than in B2C communities if other conditions are equal.

The moderating effect of B2B community can also be explained by ELM (Petty et al. 1986). From an ELM perspective, the source credibility of each individual contribution and voting is higher in B2B brand community than B2C brand community. For instance, idea popularity that is judged by a set of other users can be more credible in this environment. The effect of idea popularity is expected to be greater in B2B as idea popularity can become a stronger indicator of more promising ideas. As noted earlier, members in B2B can better evaluate the value of ideas. Furthermore, the evaluation by members is more relevant and important to a company's business in B2B as a professional community than in B2C. B2B prescribes a high job relevance condition, which has been emphasized as a moderator in many ELM-related studies

(Lohtia et al. 2003). Under high relevance environments, source credibility and argument quality may play more important roles as shown in Bhattacherjee and Sanford (2006). Therefore, we expect that the effect of idea popularity positively moderated by presence in a B2B setting. This leads to our following hypothesis.

H5b: The effect of idea popularity is greater in an innovation idea for a B2B online brand community for innovation than in a B2C online brand community for innovation.

4. Research Method

4.1. Data Collection

We intend to explore the factors that influence a company's decision to adopt innovation ideas suggested by customers. For generalizability of our study, we chose multiple online brand communities for innovation. We have collected data from publicly available online source on the activities of posting, commenting, voting, and adopting innovation ideas in the online brand communities of Salesforce.com IdeaExchange and Dell IdeaStorm.

Salesforce.com is a San Francisco-based company that specializes in enterprise software solutions best known for its customer relationship management (CRM) products and cloud computing solutions. In September 2006, Salesforce.com IdeaExchange was launched to collect innovation ideas and improvement suggestions on its various products from its clients. Dallas-based Dell is one of the leading global producers of computer products and solutions. Dell IdeaStorm was launched "as a way to talk directly to customers" in February 2007.

In the two communities, IdeaExchange and IdeaStorm, users can contribute their innovation ideas after registration. They can also make comments on any posted ideas and participate in voting of the ideas on the website. Each idea can be placed into several categories by a contributor. Users can also view their submitted ideas by category or by their implementation status. Since the members of both online brand communities need to register to post and make comments on the website, there exists a clear boundary of brand community between users and non-users. Various features such as greeting to the members after logging in, the statistics of a customer's past activities, and their profile information available for others facilitate information sharing in the communities.

The two communities do not provide any monetary reward for members' participation or contribution of innovation ideas. The contributors of an adopted innovation idea do not receive any explicit rewards, either. Since most contributors of innovation ideas at Salesforce.com IdeaExchange are using its CRM products in their work for their company's business, the context of Salesforce.com IdeaExchange can be considered as a B2B brand community. In contrast, most innovation contributors on Dell IdeaStorm are consumers of Dell's personal computer products. Thus, Dell IdeaStorm is a B2C online brand community. These two communities are chosen for our study since they were launched around the same time and have adopted similar user interface and procedures for reviewing and implementing innovation ideas.

The data are compiled from publicly available information in the two online communities. We used a web-crawling software agent written in Python to download and analyze the pages written in HTML scripts on the two websites. The innovation ideas collected are contributed to the two brand communities from the launch of the websites to September 2010, across a period of 48 months for Salesforce.com IdeaExchange and 44 months for Dell IdeaStorm. Our dataset consists of 9,980 innovation ideas from Salesforce.com IdeaExchange and 9,984 innovation ideas from Dell IdeaStorm. Among these ideas, 221 ideas (2.21% of total) from Dell IdeaStorm and 381 ideas (3.82% of total) from Salesforce.com IdeaExchange have been adopted. In Appendix, Table 1 describes the detailed statistics of each variable in these two communities combined. Table 2 shows the description of independent variables among adopted ideas. The variable description of Salesforce.com IdeaExchange and Dell IdeaStorm are shown in Table 3 and Table 4, respectively. Table 5 illustrates the correlation between each pair of variables.

4.2. Variables

Dependent Variable The dependant variable in our model is the adoption status of a particular innovation idea. The two communities acknowledge the innovation ideas contributed by its brand community members on a regular basis. A status of the contributed idea is exhibited next to each idea. The communities regularly update the status of an idea when the idea is acknowledged, under review, partially implemented or fully implemented. Usually it may take several months for a company to review, consider and adopt an innovation idea after its publishing. Only the innovation ideas that are fully implemented are considered as an adoption in our analysis.

Independent Variables In both brand communities, a user can vote on an innovation idea by “promoting” or “demoting” an idea. The total voting score of a member is augmented (deducted) by 10 points if it is promoted (demoted) by a user. We transform the *popularity* variable to reduce the effect of extreme values. A contributor is enabled to insert hyperlinks or images into the description of her innovation idea. The *image* and *reference page* variables are two dummy variables to indicate whether an innovation idea contains any hyperlink or image. As shown in Table 3 and Table 4, 17% of innovation ideas on IdeaExchange contain at least one image, while only 3.7% on IdeaStorm include images. In contrast, 13.1% of innovation ideas on IdeaStorm contain hyperlinks to other websites, compared to 1.6% on IdeaExchange in our dataset.

Prior participation is measured by the number of comments a user has made before her contribution. Commenting is one of the most frequent activities made by online brand community members and is highly correlated with their contribution of ideas, which is as high as 0.88. *Prior adoption rate* is calculated by dividing the total number of adopted ideas before a member's current idea contribution by the total number of her contributed ideas before her current contribution. For a first time contributor, her prior adoption rate is evaluated as 0. As the customers of Saleforce.com are companies who use its CRM products to manage its customer relationship, Salesforce.com IdeaExchange can be considered as a B2B brand community. Dell IdeaStorm is a B2C brand community as its contributors are the end users of Dell products. The distinction between B2B and B2C communities are made by a dummy variable. A variable *B2B community* is coded as 1 if the idea is from the Salesforce.com and 0, otherwise.

It is important to account for the difference in the two websites. For example, it may be relatively easier to earn higher points per idea contribution in one community than in the other because of a varying level of voting activities in each community. In our dataset, the average number of points earned per idea is higher in Dell IdeaStorm (mean =427.2) than in Salesforce.com IdeaExchange (mean = 279.5). Without accounting for such difference, our estimation may be biased. Any moderating effect found later may actually reflect a scale effect as well. Therefore, we standardize three variables, including prior participation, prior adoption rate and idea popularity, to zero mean and unit standard deviation within each community for our analysis.

Control Variables We further control for the *length* of innovation idea, which is measured by the number of words contained in an innovation idea. The *length* of message has an effect on the quality of message (Johnson et al. 1989). Longer message in a brand community may complicate the description of an innovation idea and increase the difficulty in understanding. Under time constraints, reviewers are less likely to read a long innovation idea description in full than a short description. Moreover, more details contained in longer message also entail increasing possible difficulty in the implementation of an innovation idea.

Furthermore, an innovation idea may be influenced by sentiment expressed by a posted idea. For example, if a customer posted an idea on high end graphic card to her favorite PC brand, she may choose to write in a positive tone: “It will be the perfect notebook with such high end graphic card.” She can also suggest in a negative way: “I am not satisfied to buy any notebook without such high end graphic card.” These two messages could have drastically different impact on a company’s adoption decision. Politicians and marketers usually appeal to emotions as sources of leverage in persuasion. The impact of positive emotional state on persuasion has been examined in prior studies in psychology (Eagly et al. 1993; McGuire 1985; Petty et al. 2003). In an online brand community, the emotional state as a peripheral cue displayed by an innovation idea discloses the contributor’s sincerity, enthusiasm and credibility.

We use the term-counting method of sentiment classification technique (Kennedy et al. 2006; Turney 2002) to control for *emotional positivity* in innovation ideas. The accuracy of this classification technique ranges between 61% and 63.4% (Kennedy et al. 2006). We implemented this process by making use of a list of positive words and a list of negative words in the General Inquirer (GI) (Kennedy et al. 2006; Stone et al. 1966) publicly available on the website of the James Williams Hall of Harvard University. Following the term-counting method, an occurrence of positive word increases the *emotional positivity* by two, while an occurrence of negative word reduces it by 2. If a word with amplification effect appears before the sentimental word, the magnitude of change in *emotional positivity* will be increased to three. For example, the use of the word “very” in the sentence “the new feature is very enjoyable,” increases *emotional positivity* from two to three. If a word with diminishing sense is in front of a sentimental word, e.g. “this function is rather good”, the magnitude of change in *sentimental positivity* is reduced to one. If a sentimental word follows a word with negative sense, the change of *emotional positivity* will become the opposite. By this way, the sentimental value on the description of each innovation idea is calculated. In our model, *emotional positivity* was adjusted for the length of idea suggestion by dividing the positivity score by the number of words.

We also control for temporal characteristics such as *tenure* of a member in a community and *age* of a community. *Tenure* of a member is measured by the number of months elapsed since she made her first comments or contribution. *Age* of a community is the number of months elapsed since the launch of each community. In addition, we control for heterogeneity of adoption likelihood across different categories of innovation ideas. When a user contributes an innovation idea, she can opt to put the idea into several categories of her choice. There are 82 categories in Salesforce.com IdeaExchange and 42 categories in Dell IdeaStorm, covering different aspects of the companies’ products, operations, business strategy and the brand community. These categories can be further summarized into five general categories for IdeaExchange and three general categories for IdeaStorm, which are taken as dummy variables in our model. Besides capturing the differences of adoption rates between the two sites, *category dummy variables* also capture the disparity of difficulties in implementing an innovation idea across categories. For example, an innovation idea on the marketing strategy of the company is much harder to implement than one on its website design. The perceived value of innovation ideas in different categories could also diverge. It is worthwhile to note that these *category dummy variables* are not mutually exclusive and some contributors may not indicate any category of their contributions. Because the eight category variables represent three category variables of Dell IdeaStorm and five category variables of Salesforce.com IdeaExchange respectively, the variances caused by site are also controlled for by these *category dummy variables*.

Descriptive statistics of the variables used in our empirical model are given in Table 1. Table 2 shows the correlations between different variables in our empirical analysis. The correlations between each pair of variables are all below 0.2, we can consider that the correlations among independent variables do not significantly alter the estimation results.

4.3. Empirical Model

We use logistic regression to test our hypotheses. Logistic regression has been employed to explain a choice decision of individuals or companies in various contexts (McFadden 1974; McFadden et al. 1977). We assume that an underlying benefits by adopting innovation influences the choice made by a company. A company expects to receive unobserved benefits upon each adoption of innovation ideas from its customers. As we have discussed in the previous section, benefits of innovation adoption is the summation of the influences of source characteristics, innovation characteristics, the control variables and an unobserved constant. If a company adopts innovation idea i, its benefit function is

$$
\begin{aligned}
\mathrm{B}_i = {} & \alpha + \beta_1 \cdot (\text{Prior Participation}_i) + \beta_2 \cdot (\text{Prior Adoption Rate}_i) + \beta_3 \cdot (\text{Popularity}_i) \\
& + \beta_4 \cdot (\text{Reference}_i) + \beta_5 \cdot (\text{Image}_i) + \beta_6 \cdot (\text{Prior Participation}_i) \cdot (\text{B2}B\ \text{Community}_i) \\
& + \beta_7 \cdot (\text{Idea Popularity}_i) \cdot (\text{B2}B\ \text{Community}_i) + \beta_8 \cdot (\text{Message Length}_i) \\
& + \beta_9 \cdot (\text{Emotional Positivity}_i) + \beta_{10} \cdot (\text{Tenure in the Community}_i) \\
& + \beta_{11} \cdot (\text{Age of Community}_i) + \sum_{j=1}^{8} \gamma_j \cdot (\text{Category dummies}_{ji}) + \varepsilon_i
\end{aligned}
$$

Message length, *emotional positivity*, *tenure in the community*, *age of community* and *category dummies* are the control variables chosen in our study.

Except for the stochastic component ε_i of benefit, a company receives no additional benefit if it chooses not to adopt this idea. ε_i is assumed to be a random variable that is independently distributed and follows extreme value distribution. The above equation can be reduced to a probability function by integrating on the stochastic component (McFadden 1974). The probability function that a company chooses to adopt an innovation idea i is

$$
\Pr(\textit{idea } i \textit{ is adopted}) = \frac{1}{1 + \exp(-B_i)}
$$

Maximum likelihood estimation (MLE) method is adopted to estimate the coefficients of independent variables.

5. Results

5.1. Estimation Results

Table 6 shows the estimation results. The first column contains the coefficient estimates without using *category dummy variables*. The second column exhibits the coefficients of estimation including *category dummy variables*. The pseudo R-squared value, which explains the variance of adoption likelihood caused by the independent variables, is 9.09 % in the first model. The Pseudo R-squared value can be improved significantly to 15.63 % in the model with category variables. The third column includes moderating effects in H5a and H5b. The Pseudo R-squared value with moderating effects is evaluated to be 16.91 %. We have adopted robust standard errors in our analyses. Robust standard error is a more accurate measure than standard error (Efron 1981). In our results, except for H5a, all the above hypotheses were strongly supported with the coefficients significant at 1% level, while H5a was supported at 5 % level.

We refer to the third model in Table 6 as our main model for subsequent interpretations. It was predicted in Hypothesis 1 that an innovation idea from a contributor with higher *prior participation* is more likely to be adopted by the company. This hypothesis is supported by our empirical results (β = 0.126, *p-value* < 0.01). The coefficient for *prior participation* variable is positive. For every unit increase in historical comments made by a contributor, the odds that her innovation idea could be adopted increases by 13.4%.[2] This result demonstrates that contribution of innovation ideas by a community member involves substantial learning from their prior participation experiences. Alternatively, a company may perceive a contributor's prior participation as a peripheral cue to judge the value of her contributed idea.

Hypothesis 2 states that the *prior adoption rate* of a particular brand community member has a positive effect on the adoption likelihood of her idea. The estimation results confirmed this view (β = 1.518, *p-value* < 0.01). A unit percent in *prior adoption rate* leads to an increase of odds of adoption by 1.53 percentage point. This result reveals that prior adoption rate can be viewed as user's ability in contributing useful innovation ideas by an adopting company.

Hypothesis 3 on the effect of *idea popularity* has also been supported in our empirical results (β = 0.200, *p-value* < 0.01). The more popular the innovation idea is in the brand

[2] If the likelihood of adoption is *p*, the odds are defined as *p*/ (1 - *p*). That is, the odds ratio is defined as the ratio of the probability that an event would occur (i.e., adopted by a firm) to the probability that an event would fail to occur (i.e., not adopted by a firm).

community, the more likely that the idea is adopted by a company. This illustrates that popularity in the brand community is used as important indicator for a company in adopting customers' innovation ideas. As we have discussed above, the popularity of an idea in the brand community implies the market potential of an innovation idea.

The positive effects of *references page* and *image* in an innovation idea postulated as in Hypothesis 4a and 4b are validated in the results. By referring to another website, the odds of adoption increases dramatically by 434.95% (β = 1.677, *p-value* < 0.01). Referenced pages improve the explanation of an innovation idea and add further credibility on the information source. As a result, including referenced pages improves the quality of a message. Similarly, by including an image in an innovation idea, the odds of adoption increases dramatically by 37.85 % (β = 0.321, *p-value* < 0.01).

Both Hypothesis 5a and Hypothesis 5b are strongly supported. The results show that the positive effect of *prior participation* on the adoption likelihood is grater in a B2B context than in a B2C context (β = - 0.132, *p-value* < 0.05). The positive effect of *idea popularity* is greater in B2C than in B2B community (β = 0.326, *p-value* < 0.01). Thus, while a greater learning benefit is realized in B2C than in B2B, greater credibility can be given to members' ability to evaluate innovation ideas in B2B than in B2C community.

Although not hypothesized, it is interesting to note that the impact of *message length* on adoption likelihood is negative and significant. *Emotional positivity* is not significant, which shows that a company's adoption decision is not much influenced by sentiment expressed in suggested innovation ideas. The effect of a member's *tenure in community* is positive and marginally significant. Therefore, we believe that a member's learning accumulates by her participation in the brand community, not merely by her tenure in a community. *Age of* *community* is negatively associated with a company's likelihood of innovation adoption. It indicates that a community may suffer from a decrease in potentially valuable contribution by its members with age. *Emotional positivity* in the description of an idea did not increase the chance that the idea will be adopted.

The negative coefficient for *message length* in the estimation results shows that the longer an innovation idea is, the less likely it will be adopted by the company. Each word reduces the odds of adoption by 0.30%. This result reveals that negative effect of message length overrides its positive effect. Even though longer description of an innovation idea is likely to contain more arguments, it increases the difficulty in understanding this idea. Additionally, the complexity of innovation idea increases with its *message length*. The implementation of an idea described in long message could be more difficult. Because of these negative effects, companies are more likely to adopt an innovation idea with shorter length.

5.2. Robustness Checks

To add robustness to our estimation results, we have conducted three additional separate robustness checks to the data set. The data in our analysis are collected in September, 2010. Since a company spends some time to assess an innovation idea, usually from several days to several months, the recent innovation ideas might appear less likely to be adopted than older ones. This bias could cause potential inaccuracy in estimation. Considering this factor, we have applied the estimation method on the set of innovation ideas contributed at least six months before the data collection. The majority of adoptions have been decided within six months. By excluding those recent innovation ideas, the total number of innovation ideas in our data set decreases from 19,964 to 15,848. However, there is no essential difference between these two estimation results. The estimates suggest that our results are robust.

In our results, it is shown that *message length* has a negative effect on the adoption likelihood of an innovation idea, particularly in Dell IdeaStorm. Longer message leads to lower adoption likelihood. However, it is possible that the *message length* has a positive effect on likelihood when the total number of words is below a certain limit, while it exerts a negative effect when the total number of words is above it. To test for the robustness of our results, we added another variable, which is the square of *message length*. If this variable is significant, the effect of *message length* could have a quadratic impact. But in the estimation result, the square of *message length* is insignificant in the estimation either with or without category dummy control variables. This shows that *message length* has a negative effect on the adoption likelihood for any length.

Moreover, we have also tested estimation of the effects of each independent variable by using fixed effect panel logistic regression. Panel model takes into account the individual characteristics of each contributor. Table 7 illustrates the results of fixed effect panel logistic regression. In these results, most of the variables have similar coefficient as the results in logistic regression. However, past adoption rate in fixed effect panel logistic regression appears to be negative, which is contrary to our hypothesis. This result show that although past adoption rate has a significant positive impact on the likelihood of adoption, for each individual, adoption of their innovation is less likely when their past adoption rate increases. This phenomenon can be explained by the fact that the total number of an individual contributor's useful ideas has certain limitation. When some of her best innovation ideas have been adopted by the firm, the innovation contributor's capability to contribute additional useful innovation idea diminishes. Hence, the adoption likelihood of an individual could decrease with her prior adoption rate. Although panel logistic model offers us a different view on a firm's adoption decision based on the variance within each individual, it could not be used as the principle model of this paper because in this panel logistic model, the data is strongly unbalanced and a majority of contributors (76.45%) contribute less than two innovation ideas in the dataset.

6. Discussion

Despite the rapid adoption of online brand community as a source of innovation these years, a theory explaining the heterogeneity in an innovation idea's adoption likelihood is lacking. This study builds upon the literature of user innovation in brand community (Bogers et al. 2010; Füller et al. 2008; von Hippel 1976) as well as on adoption of innovations within a company (Kwon et al. 1987; Robertson et al. 1986; Rogers 1995). The central research questions that this study intends to address are (1) What kinds of customers contribute more valuable innovation ideas to the companies? (2) Which characteristics of innovation ideas potentially influence a company's adoption decision? (3) What is the underlying difference in the effects of the studied factors between B2B and B2C online brand communities? To answer these three questions, we started with a thorough literature review on user innovation and recent development of using online brand community as source of innovation.

The central contribution to information systems research is the usage of a theory merging two well-developed theories: Diffusion of Innovation (DOI) theory (Rogers 1995) and Elaboration Likelihood Model (ELM) (Petty et al. 1986) to the context of brand community for innovation. The findings of this theoretical approach lead to better understanding on the value of innovation ideas from the customers and the innovation adoption likelihood of companies, as well as the impact of B2C and B2B community on adoption likelihood. The empirical validation of our model uses logit regression on publicly available secondary data collected from two online brand communities for innovation, Dell IdeaStorm and Salesforce.com IdeaExchange.

In the study, it is found that both source characteristics, such as one's prior participation and her prior adoption rate, and characteristics of an innovation idea, including its popularity and supporting evidences, have significant effects on the likelihood of a particular innovation idea to be adopted by the company. Previous research on brand community for innovation has mainly focused on individual's motivation to contribute (Füller et al. 2008; Li et al. 2010), while the question on the value of a customer's innovation to the company has yet to be answered. How to leverage its brand community and utilize the ample knowledge resource from its brand community is an important question for a company. A successful brand community not only helps the company to improve its brand loyalty and marketing efficiency, but also reduces cost in new product development and increases the market share of its products. This research has filled in the gap of knowledge on value of innovation from the customers. Although adoption of an innovation idea does not necessarily imply its commercial value, the implementation of a customer innovation into its final products often indicates the innovation idea's potential commercial value perceived by the company.

6.1. Theoretical Contribution

This research makes important contribution to the diffusion of innovations (DOI) literature (Rogers 1995) by integrating DOI with ELM. The innovation characteristics, including relative advantage, compatibility, complexity, trialability and observability (Rogers 1995) explains a large part of the variances in likelihood of adoption. However, these characteristics fail to explain the impact of influence process in adoption decision. A valuable innovation idea might not be adopted because its description does not convey sufficient relevant information on this innovation idea. The adopter's decision can also be affected to a large extent by the message itself (Sussman et al. 2003). ELM provides useful explanations to understand how the message characteristics influence an adoption decision. By combining these two theories, we have derived seven hypotheses related to our research question and tested these hypotheses in our empirical model. The empirical estimation results support our hypotheses on the two streams of influences in an adoption decision.

While some existing literature attempts to apply ELM to the settings of companies (Eckert et al. 1997; Lohtia et al. 2003), most previous IS literature using ELM has mainly focused on how an individual's knowledge adoption is formed (Bhattacherjee et al. 2006; Sussman et al. 2003; Tam et al. 2005). This research intends to extend the usage of ELM to the setting of a company. ELM states that depending on the cognitive efforts involved, the influential factors on a message recipient's decision are different. Compared to an individual, the decision making process in an organization takes a longer period of time and involves interactions of different roles in the organization (Fichman 1992; Rogers 1995). An adoption of innovation idea from its customers induces substantial financial cost in implementation as well as unforeseeable market risk on the company. The adoption decision maker in such an organization is usually a team of experienced professionals in this market. They evaluate the commercial value of an innovation idea based on their past experiences and knowledge on the products and the market. At the time of decision making, the influence process engenders an impact on the adoption decision of each individual as well. Our empirical results have verified the impact of both central and peripheral routes on adoption decision.

Choice model (McFadden et al. 1977) has been widely adopted in marketing and economics literatures to explain consumer's choice on products, by assuming that consumers make rational decision in order to optimize their underlying utility in choosing products. While facing a list of innovation idea suggestions from its brand community, a company also has an underlying benefit function in adoption, which signifies the advantages the company expects to gain from the adoption of innovation ideas. This latent expected benefits is determined by the innovation idea's perceived relative advantage, compatibility and complexity by the company, while the perceived value can be moderated by the characteristics in a message, such as idea popularity, supporting evidences, message length and emotional positivity. With this observation, we applied logistic regression in our empirical analysis to study the adoption behavior of a company in its brand community. The result indicates that 19.85% of variations can be explained by our hypothesis in the logistic regression.

The most important result of our study is perhaps the finding that innovation ideas from the customers with greater prior participation in the brand community have higher chance of being accepted. This confirmed with our assumption that experience in participating in online brand community increased a consumer's knowledge of the brand, its products and its market. Füller et al. (2008) states that through brand community practices, a consumer's perception is influenced, her knowledge is enhanced. Learning theory also lends us theoretical support in the way that informal learning of brand community members in brand community practices increases consumer's ability to contribute. With more experiences and knowledge, contributions from experienced users tend to be more useful for the company. Consequently, the likelihood that an idea will be accepted increases with a contributor's prior participation in the brand community.

Besides, our findings also suggest the positive impact of contributor's prior adoption rate and the popularity of an idea on the likelihood of adoption. It is understandable that a consumer with higher historical adoption rate tends to be more capable to innovate and deliver the innovation idea to its potential adopters. At the same time, as stated in ELM, higher adoption rate could presents as a peripheral cue for the adoption company. Accordingly, the innovation ideas contributed by such customers are often perceived to be of higher value by the company. On the other hand, a popular innovation idea is supported by the members of an online brand community. Such popularity in a brand community predicts its potential commercial value for the company. Higher perceived relative advantage leads to higher adoption likelihood of an innovation idea by the company.

This study also lends support to the positive impact of supporting evidences on adoption likelihood. References to other websites add more explicit explanations to the message recipients. Details of an innovation idea could usually be better depicted in a referenced website. By including references in an innovation idea, the description of innovation idea is made more easily understandable. Moreover, referencing to a more cited web page also increased the source credibility of a message. Source credibility is an important factor on an individual's adoption decision (Bhattacherjee et al. 2006; Mak et al. 1997; Sussman et al. 2003). Besides referenced pages, inserting images in an innovation idea also adds to the media richness of message. Richer media in the description attracts more readerships and also draws more attention from the potential adopter, which leads to higher possibility to consider this idea into the list of potential implementations. In this view, with increased argument details and source credibility, supporting evidences have a positive effect on a company's adoption decisions as well.

Moreover, our results have proved the moderating effects of B2B/B2C community on the effects of the prior participation of contributors and innovation idea popularity. A key difference between B2B and B2C communities is that contributors in B2B community are more professional and knowledgeable in the products and the market of brand. Their contributions and ratings are therefore of higher credibility than B2B community members. This impact is reflected on higher effect of popularity on adoption likelihood in a B2B community. At the same time, according to learning curve theory, inexperienced contributors are likely to gain more knowledge from their participation in brand community practices (Adler et al. 1991). This has led to higher effect of prior participation on adoption likelihood in B2C community than B2B community.

6.2. Practical Implication

Previously, brand community strategy is mainly administered by the marketers as a way to increase customer loyalty and market share. The advent of brand community as source of innovation shows that customers can be involved in more organizational processes such as new product development. By understanding the adoption likelihood of innovation ideas from its customers, our research has several implications to the practitioners.

Firstly, it has been shown that customers with higher prior participation and prior adoption rate are likely to contribute innovation ideas that are perceived to be more useful by the company. Brand community can profit from retaining such experienced members. In addition to the brand knowledge, the participation in the brand community has increased their knowledge on the products and the market of a company. This knowledge source is potentially a precious source of innovation for the companies, yet it is a source difficult to leverage for many companies. Neither Dell IdeaStorm nor Salesforce.com IdeaExchange offers explicit rewards to its customers for contributing useful innovation idea. Aspirant practitioners might profit largely from offering to contributors explicit incentives, such as monetary rewards in order to retain those valuable customers in the brand community and leverage on their knowledge and creativity by encouraging more contributions of innovation ideas from them. Moreover, this study has shown that such rewards are more beneficial in B2C community than B2B communities. On the other hand, our previous study has found that the tenure in the community has a negative effect on individual’s likelihood of contribution (Li et al. 2010). In this view, despite of greater difficulty, it is beneficial for brand community practitioners to encourage those experienced users to contribute more innovation ideas.

Secondly, by providing supporting evidences to the description of an innovation idea, the likelihood of adoption increases. Providing more details of an innovation idea will certainly facilitate understanding of the innovation idea and improve its argument quality. Therefore from the results of our research, it is suggested that brand community practitioners encourage the innovation contributors to provide more details on their innovation ideas. To achieve this, practitioners can either leverage on information technology to make use of online applications, such as inserting hyperlinks, attaching documents, images and other media files more easily accessible. Another possible measure to encourage more sharing of supporting evidences is to grant higher reputation points to the consumers who include reference pages and images in their contribution descriptions. As reputation is proved to be an important encouragement in a brand community, it could increase the customers’ motivation in sharing supporting evidences.

Thirdly, though not hypnotized, by adding control variables, it is shown in this research that the length of message has a negative effect on the likelihood of adoption. The longer the description of an innovation idea is, the less likely it could be adopted by a company. This finding gives important advice to the brand community practitioners that using text message input may not be the best approach to attract innovation ideas from the brand community. Current development in the information technologies allows companies to provide more animated tools to its brand community members to develop innovation ideas. It will be a worthy investment for the practitioners to provide alternative methods for customers to make a contribution. For example, virtual customer environments (VCE) is proved to be a very useful tool in the value co-creation process between a company and its customers (Nambisan et al. 2008). By providing toolkits, the efficiency of an innovation is improved and cost of innovation could be reduced (von Hipper et al. 2002). An online brand community with such features to provide its customers with different options to contribute their innovation ideas will help the company to make better use of its customers as source of innovation.

6.3. Limitation

Although brand community for innovation is a relatively new concept in industry, it has been increasingly adopted by the practitioners to increase the brand loyalty as well as marketing efficiency. As customer relationship and innovations are becoming progressively more important determinant factors in the market competition, brand community for innovation provides companies a practical channel to connect with its customers and also to receive helpful innovation suggestions from the customers. So far, this new area has received relatively less attention from the academic community. Our research attempts to indirectly address the question on the factors influencing the value of customer innovation contribution. The adoption of an innovation idea by a company indicates its perceived potential value for the company, though it does not necessarily suggest its commercial value in the market, as the value of an innovation idea could be influenced by many other factors, such as the marketing campaign, the industry's trends, the competitors' strategies and the macro-economic environment. Further research can be fruitfully conducted with other more direct measures on the values of users' contribution, such as the increased sales volume and increased customer satisfaction rates due to adopting innovation ideas from its brand community.

The data we have used in the empirical analysis is publicly available secondary data obtained from the Internet. The data provides us relevant information on a customer's participation characteristics, such as the historical idea contribution, commenting activities and adoption rate, as well as idea specific variables, including the message length, its referenced pages and images. We also used sentimental classification technique to measure the emotional positivity in a message. However, some other information on a consumer remains unobserved in our data. Including more customer-specific variables in the analysis could help to explain a larger part of the variance in adoption likelihood. We will be allowed to better understand the dynamics in a brand community if more information can be obtained, such as each contributor's purchase history, demographic data and attitudes on the brand are provided. Additional work is needed to study such communities with direct measure on the customer's characteristics. With more complete dataset and different measures on other characteristics of the innovation or the customers, a better econometric model could be constructed to study the value of innovation idea from brand community.

It is also worthwhile to point out that both Dell and Salesforce.com are US-based companies in IT industry. Customers of those companies tend to be young and more IT-savvy. In other more traditional industries, customers might be less accustomed to use online channel to voice their innovation ideas. In many cases, an innovation idea could be of potential economic value for the customer (Mansfield 1985). It is important to note that, by revealing such innovation idea to the company without receiving any explicit compensation, an opportunity cost is induced on the customer because her innovation could be alternatively used by herself in other more profitable ways. In some industries, such innovation is easier to realize than computer industry. Therefore it is possible that customers in other industries or cultures could develop different attitudes towards contributing innovation ideas. Because of this, the factors studied in this paper could have different impacts on a company's adoption decision. Such restriction in our research provides opportunities for further research under different industry and cultural contexts.

7. Conclusion

Our results validate and provide support for a theoretical relationship between adoption of customer's innovation and the identified independent variables in online brand communities for innovation. In order to address the question on what kinds of customer innovation ideas are more likely to be adopted by a company, we applied DOI and ELM to the context of a company. The customer's prior participation, prior adoption rate, the innovation idea's popularity and supporting evidences are identified as key factors and B2B/ B2C communities as moderating factors. Using dataset collected from Dell IdeaStorm and Salesforce.com IdeaExchange, we investigated the effects of those variables. Our hypotheses are validated in the empirical analysis. This paper sheds light on what kinds of customers are more important for such brand communities and how a contributor's characteristic and an idea's characteristics influence its perceived usefulness. Our finding suggests companies to retain users with more experiences and higher adoption rate in order to derive more valuable innovation contributions from its online brand community. Companies can also improve the quality of innovation ideas by facilitating customers to give supporting evidences and providing tools of to facilitate more dynamic contribution.

APPENDIX

Table 1. Description of Variables

	N	Mean	Std. Dev.	Min	Max
Adoption of Innovation	19,964	0.03	0.17	0.00	1.00
Prior Participation	19,964	63.4	285.9	0.0	2,966.0
Idea Popularity	19,964	353.4	2,166.2	-1,460.0	118,080.0
Prior Adoption Rate	19,964	0.01	0.08	0.00	1.00
Reference Page	19,964	0.07	0.26	0.00	1.00
Image	19,964	0.10	0.30	0.00	1.00
Message Length	19,964	93.2	94.2	1.0	2,502.0
Emotional Positivity	19,964	0.08	0.08	-0.67	1.22
Tenure in Community	19,964	5.61	8.76	1.00	48.00
Age of Community	19,964	21.87	16.13	0.00	48.00
Salesforce.com Category 1	19,964	0.09	0.19	0.00	1.00
Salesforce.com Category 2	19,964	0.10	0.18	0.00	1.00
Salesforce.com Category 3	19,964	0.27	0.34	0.00	1.00
Salesforce.com Category 4	19,964	0.01	0.06	0.00	1.00
Salesforce.com Category 5	19,964	0.01	0.08	0.00	1.00
Dell Category 1	19,964	0.31	0.44	0.00	1.00
Dell Category 2	19,964	0.17	0.35	0.00	1.00
Dell Category 3	19,964	0.02	0.12	0.00	1.00

Table 2. description of adopted ideas

	N	Mean	Std. Dev.	Min	Max
Adoption of Innovation	602	1.00	0.00	1.00	1.00
Prior Participation	602	136.18	463.38	0.00	2922.00
Idea Popularity	602	1508.64	3254.93	-180.00	34650.00
Prior Adoption Rate	602	0.04	0.15	0.00	1.00
Reference Page	602	80.95	67.80	1.00	548.00
Image	602	0.22	0.41	0.00	1.00
Message Length	602	0.22	0.41	0.00	1.00
Emotional Positivity	602	6.54	8.45	1.00	43.00
Tenure in Community	602	15.70	12.83	0.00	47.00
Age of Community	602	0.08	0.08	-0.20	0.60
Salesforce.com Category 1	602	0.50	0.50	0.00	1.00
Salesforce.com Category 2	602	0.49	0.50	0.00	1.00
Salesforce.com Category 3	602	0.53	0.50	0.00	1.00
Salesforce.com Category 4	602	0.02	0.16	0.00	1.00
Salesforce.com Category 5	602	0.05	0.22	0.00	1.00
Dell Category 1	602	0.22	0.42	0.00	1.00
Dell Category 2	602	0.19	0.39	0.00	1.00
Dell Category 3	602	0.03	0.18	0.00	1.00

Table 3. Description of Variables in Salesforce.com IdeaExchange

	N	Mean	Std. Dev.	Min	Max
Adoption of Innovation	9980	0.04	0.19	0.00	1.00
Prior Participation	9980	8.40	30.68	0.00	580.00
Idea Popularity	9980	279.54	1070.86	-120.00	37110.00
Prior Adoption Rate	9980	0.02	0.10	0.00	1.00
Reference Page	9980	0.02	0.12	0.00	1.00
Image	9980	0.17	0.38	0.00	1.00
Message Length	9980	74.17	57.32	1.00	1542.00
Emotional Positivity	9980	0.09	0.08	-0.67	1.08
Tenure in Community	9980	7.36	10.20	1.00	48.00
Age of Community	9980	29.76	14.93	0.00	48.00

Table 4. Description of Variables in Dell IdeaStorm

	N	Mean	Std. Dev.	Min	Max
Adoption of Innovation	9984	0.02	0.15	0.00	1.00
Prior Participation	9984	118.32	395.53	0.00	2966.00
Idea Popularity	9984	427.23	2868.10	-1460.00	118080.00
Prior Adoption Rate	9984	0.01	0.05	0.00	1.00
Reference Page	9984	0.13	0.34	0.00	1.00
Image	9984	0.04	0.19	0.00	1.00
Message Length	9984	112.17	117.22	1.00	2502.00
Emotional Positivity	9984	0.07	0.08	-0.67	1.22
Tenure in Community	9984	3.87	6.58	1.00	45.00
Age of Community	9984	14.00	13.18	0.00	44.00

Table 5. Correlations of Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Adoption of Innovation									
(2) Prior Participation	0.04								
(3) Idea Popularity	0.09	0.00							
(4) Prior Adoption Rate	0.07	0.07	0.01						
(5) Length of Innovation Idea	-0.02	0.03	0.02	-0.01					
(6) Reference Page	0.10	0.22	0.09	0.01	0.17				
(7) Image	0.07	0.04	0.03	0.12	-0.01	0.05			
(8) Tenure in Community	0.02	0.29	-0.03	0.22	-0.03	0.05	0.20		
(9) Age of Community	-0.07	-0.05	-0.11	0.02	-0.08	-0.14	0.07	0.31	
(10) Emotional Positivity	0.00	-0.05	0.01	0.02	-0.09	-0.05	-0.02	-0.01	0.02

Table 6 Estimation Results

	Variables	Without Category Dummy Variables	With Category Dummy Variables	With Moderate Effects
	Intercept	-3.082 *** (0.101)	-3.930 *** (0.583)	-3.972 *** (0.582)
H1	Prior Participation	0.114 *** (0.032)	0.113 *** (0.038)	0.126 *** (0.037)
H2	Prior Adoption Rate	1.964 *** (0.261)	1.493 *** (0.284)	1.518 *** (0.287)
H3	Idea Popularity	0.221 *** (0.055)	0.190 *** (0.049)	0.200 *** (0.037)
H4a	Reference Page	1.134 *** (0.125)	1.662 *** (0.143)	1.677 *** (0.146)
H4b	Image	0.725 *** (0.113)	0.389 *** (0.117)	0.321 *** (0.122)
H5a	Prior Participation * B2B Community			-0.132 ** (0.064)
H5b	Idea Popularity * B2B Community			0.326 *** (0.073)
	Message Length	-0.004 *** (0.001)	-0.003 *** (0.001)	-0.003 *** (0.001)
	Emotional Positivity	0.171 (0.490)	-0.717 (0.517)	-0.661 (0.529)
	Tenure in Community	0.008 (0.006)	0.012 ** (0.006)	0.011 * (0.006)
	Age of Community	-0.027 *** (0.003)	-0.044 *** (0.004)	-0.041 *** (0.004)
	Category Dummies	No	Yes	Yes
	Pseudo R-Squared	9.09%	15.63%	16.91%

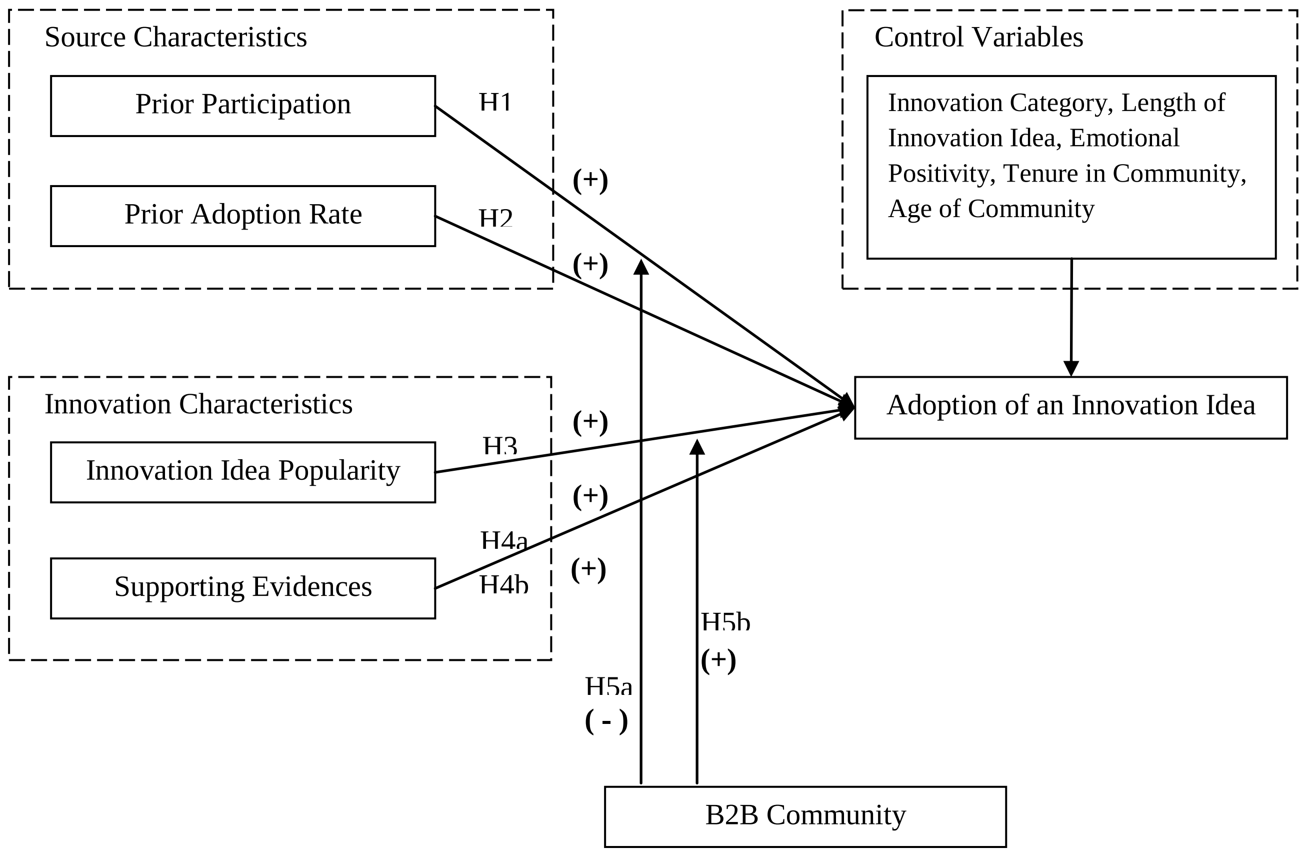
*Significant at 1 % ***, 5 % **, and 10% *. Standard errors in parentheses.*

Table 7 Panel Logit Regression Estimation Results

	Variables	Without Moderate Effects	With Moderate Effects
H1	Prior Participation	0.0538 (0.0522)	0.1371 (0.0875)
H2	Prior Adoption Rate	-0.5396 (0.0698)***	-0.549 (0.0708)***
H3	Idea Popularity	0.1872 (0.0377)***	0.1647 (0.0863)*
H4a	Reference Page	1.1552 (0.1846)***	1.1591 (0.1848)***
H4b	Image	0.4299 (0.1728)**	0.4379 (0.1731)***
H5a	Prior Participation * B2B Community		-0.0042(0.0035)
H5b	Idea Popularity * B2B Community		0(0.0001)
	Pseudo R-Squared	14.00%	14.09%

*Significant at 1 % ***, 5 % **, and 10% *. Standard errors in parentheses.*

Figure 1 Research Model



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