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Original Research

Disentangling Twitter's Adoption and Use (Dis)Continuance: A Theoretical and Empirical Amalgamation of Uses and Gratifications and Diffusion of Innovations

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Abstract

Drawing on Uses and Gratifications (UG) Theory and Diffusion of Innovation Theory (DIT), this study aimed to augment an exploration of individual user needs based on UG constructs with an analysis of the material characteristics of the innovation based on DIT constructs to provide a comprehensive explanation of people's motivations underlying various Twitter usage levels and frequencies. Whereas previous literature on Social Network Sites (SNS) have explored individuals' motivations underlying initial adoption, the equally interesting and relevant question of use (dis-) continuance has so far been largely overlooked. To fill this void in the literature, this study compares active users that have continued to use Twitter and inactive users that initially adopted, yet discontinued usage of Twitter. This study provides insights into different usage levels and frequencies through an investigation of 1) users' perceptions of the medium, 2) users' expected outcomes associated with the medium's use, and 3) the role and effect of mobile access. An analysis of 130 surveys with Partial Least Squares (PLS) and R^2 partitioning revealed that an understanding of adoption and use (dis-) continuance of Twitter requires us to account for both user-related motivations (UG) and perceived characteristics of the medium (DIT), as combining UG and DIT increased explanatory power (R^2) for the overall sample. Furthermore, our findings showed that inactive users' initial adoption and subsequent discontinuance was solely impacted by user-related needs, (i.e. UG constructs), whereas active users' continued use was largely motivated by technology characteristics, (i.e. DIT constructs). Finally, our study revealed significant differences between active and inactive users in terms of the devices and platform used for accessing Twitter, with active users reporting a significantly higher use of mobile devices. Based on these findings, we discuss contributions and implications for future research and practice.

Keywords: Twitter, continuance, discontinuance, diffusion of innovation, uses and gratifications, DIT, UG, PLS

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INTRODUCTION

Social network sites (SNS) and social media have emerged as popular research topics in the area of computer-mediated communication (CMC) in recent years. Previous studies on Facebook and other SNS have focused largely on online identity and self-representation (Boyd and Heer, 2006), privacy issues (Gross and Acquisti, 2005; Hodge, 2006), and political participation (Gueorguieva, 2007; McClurg 2006). More recently, several studies have explored underlying motivations for using social media (Java, et al., 2007; Jung et al., 2007). However, as Hargittai (2008) pointed out, whereas people's motivations for using these new media have been explored, the equally interesting and relevant question about the underlying reasons for inactivity has been largely overlooked. Hence, there is a significant gap in the existing literature with respect to our understanding of the differences between SNS users and non-users (Hargittai, 2008), with the latter group comprising individuals who have either never used a SNS, used it only once, or used to use it but have since discontinued use. Consequently, a classification of three user types emerges: active users (i.e., currently using), inactive users (i.e., used it only once, or used to use it but have since discontinued use), and non-users (i.e., never registered). Insofar that these groups are systematically different, the predominance of research on active users may unintentionally risk excluding the other groups from discussion about SNS (Hargittai, 2008). This problematic focus on active users may be escalated by the growing proliferation and popularity of these SNS services and the consequent erroneous assumption that having an account represents active usage of these media (Archambault and Grudin, 2012; Liedtke, 2009).

Since the second half of 2009, a new social medium—Twitter—has received tremendous attention among practitioners and academics alike (Van Opstal, 2010; Rao, 2009; PRWeb, 2009). Twitter is a social networking and micro-blogging service that enables users to send, distribute and read short messages of up to 140 characters via mobile phones, email or the Web (Java et al., 2007). As of September 2011, the number of active Twitter users per month had reached 100 million (or 25%) of the reported 400 million registered user accounts worldwide (Messieh, 2012), compared to Facebook's 425 million monthly active users (or 53%) of its 800 million registered users worldwide by December 2011 (Facebook, 2012).

Although Facebook and Twitter have similar intended uses, including social activities such as daily chatting and social surveillance, as well as information purposes such as news reporting and information sharing (Java et al., 2007; PRWeb, 2009), Twitter has shown its superior potential for prompt news delivery and distribution by enabling concise real-time updates (Java et al., 2007; Lenhart and Fox, 2009). Examples of Twitter use for large-scale news delivery include the shooting at Virginia Tech in 2007 and more recently the 2011 Arab Spring. Therefore, the different nature of the medium—and its primary role in fulfilling information needs above and beyond social needs—may partially explain Twitter's lower popularity and user loyalty in comparison to other SNS, as evidenced by the fact that within one month of joining, 60 percent of new U.S.-based Twitter users become 'Twitter quitters' (Liedtke, 2009; HubSpot, 2009).

Twitter's lower popularity on a continuing basis affords a unique opportunity to explore what, if any, differences exist between individuals who are more or less likely to adopt (i.e. create an account) and subsequently continue their active usage of this social medium (Markus, 1987). Thus, Twitter is an ideal SNS with which to compare active and inactive users' reasons for initial adoption and subsequent use (dis-)continuance. Furthermore, few studies have examined why and how people use Twitter because of its relative infancy (Zhao et al., 2009; Johnson and Yang, 2009; Lee, 2009). With Twitter's high publicity and far-reaching impact, understanding people's motivations for adoption as well as use (dis-)continuance is necessary for effectively developing, implementing, and using these powerful tools in both an organizational context as well as society in general.

Twitter has potential for use beyond its social and microblogging functionalities to support various forms of organizational communication and collaboration (Honeycutt and Herring, 2009, Cha et al., 2010, Archambault and Grudin, 2012). Therefore, understanding the underlying factors that affect diverse usage frequencies (active and inactive) and behaviors (continuance and discontinuance) is important for obtaining a richer and more relevant image of SNS usage as well as for exploring ways to foster and enhance usage frequencies and behaviors regardless of the anticipated or desired purpose.

Moving beyond the recent literature on SNS, the general literature on technology adoption and diffusion of innovation has repeatedly emphasized that despite its real-life prominence, the nature of discontinuance (i.e., inactive engagement with novel technologies) is a topic that has been largely ignored and under-researched (Eysenbach, 2005; Haider and Kreps, 2004; Abraham and Hayward, 1984; Rogers and Shoemaker, 1971; Leuthold, 1967). Yet, in order to develop an adequate and holistic comprehension of the innovation and adoption process, understanding the reasons underlying discontinuance is crucial (Abraham and Hayward, 1984; Leuthold, 1967). In particular in the context of Twitter, a medium that has not yet reached a critical mass, reflects higher abandonment than adoption levels (13% versus 10% respectively) (Archambault and Grudin, 2012), and is characterized by high levels of inactive users (Liedtke, 2009; HubSpot, 2009) it is important to simultaneously explore factors that underlie both use continuance and discontinuance.

In this paper, we further propose that in order to understand Twitter's adoption and use (dis-) continuance, providing an explanation based on either user-related or technology-related characteristics alone is incomplete and myopic. Therefore, this study combines Blumler and Katz's (1974) Uses and Gratifications theory (UG) and Roger's (1962) Diffusion of Innovation theory (DIT) in order to provide a comprehensive explanation of people's active or inactive usage behaviors in relation to social media that attaches equal weight to explanations based on motivations of the user and characteristics of the medium. Hence, this study aims to answer two related research questions: 1) what motivations (i.e. perceived needs) and 2) what innovation constructs affect the adoption of Twitter, and are these consistent among active versus inactive users.

UG Theory as a theoretical framework identifies the needs that drive users to adopt Twitter, allowing us to determine if the initial motivating factors for active versus inactive Twitter users are significantly different. Additionally, DIT can help us understand the role that characteristics of the medium itself play in influencing initial adoption and subsequent use (dis-)continuance of Twitter. Therefore, in combining and comparing these two theoretical frameworks in their relative ability to explain the Twitter adoption phenomenon, this study offers a comprehensive theoretical model with high explanatory power that can also be applied beyond the context of Twitter to future innovations and other novel technologies.

Additionally, by paying attention to both social needs of users and material characteristics of the medium, we can reveal the relative weight of each in relation to active and inactive users respectively. In other words, we can answer the important question of whether user needs and medium characteristics are equally significant in predicting continued usage by active users as well as initial adoption and usage discontinuance by inactive users. Finally, by exploring users' mobile access of Twitter, this study aims to determine if the possibility for real-time communication and information exchanges from any location impacts usage behaviors for active versus inactive users differently. Consequently, this study will break new ground on research related to Twitter and offer insights into what drives its users to tweet or 'quit' (Liedtke, 2009; Hubspot, 2009) based on their perceptions of the medium, their expected outcomes from its use, and the role and influence of mobile devices in the use of Twitter and microblogging in general. To understand usage behaviors of active versus inactive Twitter users, we conducted a survey-based study among students, faculty and staff at a large Midwestern university and analyzed the data using partial least squares (PLS). Our findings show that understanding initial adoption as well as continued use of Twitter requires us to account for both user-related motivations and perceived characteristics of the medium. Furthermore, our findings show that although the combined model offers increased explanatory power, inactive users' initial adoption and subsequent use discontinuance is solely impacted by user-related needs (UG constructs), whereas active users continued use is largely motivated by technology characteristics related to the visibility, relative advantage, and perceived popularity of the medium (DIT constructs). Finally, our study reveals significant differences between active and inactive users in terms of the devices and platforms used for accessing Twitter, with active users reporting a significantly higher use of mobile devices.

In the next sections, following a brief summary of the relevant literature on Uses and Gratifications and Diffusion of Innovation theories, we provide a detailed description of the data collection and analysis procedures. Then, we outline the empirical evidence and discuss the findings in light of the aforementioned theories. Finally, we explore contributions and implications for further research and provide recommendations regarding the development, implementation and use of Twitter in organizations and society at large.

THEORETICAL BACKGROUND AND FRAMEWORK

Previous research into the factors underlying Twitter usage has identified three groups of Internet users as more likely to join (initially adopt) Twitter: SNS users, Mobile Internet users, and younger users under the age of 44 (Lenhart and Fox, 2009). Furthermore, existing studies have shown that initial motivation for adopting Twitter is related to both social and information motives (Johnson and Yang, 2009; Lee, 2009). Although this work has offered relevant insights about the significant factors underlying the motivations of Twitter users, these studies were characterized by two limitations.

First, the underlying motivations considered only included needs and characteristics of the user, while overlooking the equally important material characteristics of the medium. Second, the focus was restricted to those motivations that affect initial adoption, therefore myopically assuming consistent motivations across active and inactive users. That is, these studies have largely neglected the potential differences between motivations underlying active users' continued usage and inactive users' initial adoption and subsequent discontinued usage of Twitter. To fill this twofold void in the existing literature, this study investigates both user-related and technology-related characteristics by combining insights from Uses and Gratification Theory and Diffusion of Innovation Theory, while simultaneously comparing motivations of those who continue to use Twitter (active users) and those who discontinue their usage of the medium after initial adoption (inactive users) (Hargittai, 2008).

Uses and Gratifications Theory (UG)

For nearly three-quarters of a century, UG Theory has been applied in a wide range of media studies, including Herzog's (1944) study on quiz programs and the gratifications extracted from listening to radio broadcasted soap operas, Rubin and Bantz's (1987) research on the utility derived from Video Cassette Recorders (VCRs), and more recently on the user gratifications related to new media including the Web and online games (Chang et al., 2006). The central aim of UG has been to explain how social and psychological needs drive relatively active audiences to use different media for satisfying these needs (Rubin and Bantz, 1987). In this respect, the theory assumes that users purposely select the media they consume to satisfy their social and psychological needs, hence, it provides an explanation of individual media usage behaviors in terms of specific underlying motives and socio-psychological characteristics (Trammell et al., 2006).

Because of UG's focus on the motives for media use, the theory is particularly useful for understanding the initial adoption stage of new media usage (Li, 2005), making it an ideal theoretical lens for analyzing a relatively new medium like Twitter. In this comparatively early stage of Twitter, its communication brevity and interactivity have resulted in a significant and proliferating user base. Yet, its primary role in fulfilling information rather than social needs, when compared to other SNS such as Facebook, seem to result in lower popularity and user loyalty as evidenced by the large amount of 'Twitter quitters' (Liedtke, 2009; HubSpot, 2009), i.e., the high level of use discontinuance. Hence, studying Twitter at its current stage of adoption presents a unique opportunity for analyzing the potentially diverse motivations of both initial adoption and subsequent use discontinuance by inactive users as well as use continuance by active users. Hence, this study can generate relevant new insights for both theory and practice regarding changing motivations at different stages of the usage spectrum.

Perceived Motivation (Perceived Needs)

Since the popularization of the Internet in everyday life, extensive UG research has targeted the underlying motivations behind its use (Charney and Greenberg, 1996; Flanagin and Metzger, 2001; Papacharissi and Rubin, 2000; Stafford and Gonier, 2004) as well as the use of its constituent media, such as personal homepages (Jung et al., 2007; Noh, 1998; Papacharissi, 2002), electronic bulletin boards (James et al., 1995), ICQ instant messenger (Leung, 2001), and blogs (Li, 2005). One example of such a study specifically analyzed motivations underlying the use of Cyworld, a Korean-based SNS (Jung et al., 2007), and described Cyworld's users as "active gratification seekers." In a similar vein, we may perceive Twitter's users as "active gratification seekers," yet, the relevant motives, needs, desires, and/or pursued outcomes underlying their usage of this relatively new medium remain unknown. Hence, this study attempts to answer the following research question:

RQ1: What motivations (i.e. perceived needs) affect the adoption of Twitter, and are these consistent among active versus inactive users?

To organize the extensive UG Literature, Katz, Blumler, and Gurevitch (1974) offered the following theoretical definition: "…the social and psychological origins of (2) needs, which generate (3) expectations of (4) the mass media or other sources, which lead to (5) differential patterns of media exposure (or engagement in other activities), resulting in (6) need gratifications and (7) other consequences, perhaps most unintended ones" (p. 20).

Subsequent UG literature has offered a variety of categorizations of common social and psychological needs underlying media usage (McQuail, Blumler, and Brown, 1972; Katz, Gurevitch, and Haas, 1973; Papacharassi, 2002; Papacharassi and Mendelson, 2008). As becomes evident from our literature review, these various theories usually refer to the same underlying constructs while using different terminology. Therefore, in Table 1 we delineate a set of foundational constructs of social and psychological needs underlying media use that integrate the plethora of existing terms from the reviewed literature through defining a set of consistent and distinct concepts, which we further operationalize and test in this study. We model these eleven foundational (first-order) constructs as the second-order latent factor of perceived needs. Based on the core concepts and assumptions underlying UG, as heretofore discussed and summarized in Table 1, we hypothesize the following:

- H1: Perceived needs directly affect a tweeter's level of activity.

Furthermore, based on our research question and our aim of comparing the differences in motivations between active versus inactive users, we further determine whether any differences exist between the perceived needs of the two groups of users. However, given the lack of literature on this topic, the investigation of differences in perceived needs between active versus inactive users will be exploratory and will focus on the differences in the eleven underlying first-order constructs individually rather than the second-order latent factor of perceived needs.

Table 1: A classification for foundational constructs of social and psychological needs

		Existing concepts in the literature																					
		McQuail, Blumler and Brown (1972)				Katz, Gurevitch and Haas (1973)					Papacharassi (2002)						Papacharassi and Mendelson (2008)						
	Measured concepts (this study)	Diversion	Personal relations	Personal identity	Surveillance	Cognitive needs	Affective needs	Personal integrative needs	Social integrative needs	Tension release	Information	Passing time	Entertainment	Self-expression	Professional advancement	Communication	Social intraction	Entertainment	Information	Passing time	Coolness/Novelty	Self expression	Professional advancement
Diversion	Entertainment												x					x					
	Passing time											x								x			
	Escape	x								x													
	Relaxation	x																					
Personal Relationships	Social interaction		x						x							x	x						
	Companionship		x													x							
Utility	Information				x	x					x								x				
	Professional advancement							x							x								x
Identity Expression	Self expression			x			x	x						x								x	
	New/Cool trend																				x		
	Habit			x																			

Diffusion of Innovations Theory (or Innovation Diffusion Theory, DIT)

Diffusion of Innovations Theory (DIT) explains how an innovation or new idea propagates in a social system over time. The foci of the theory are on the knowledge, attitude change, and decision-making processes that affect the adoption of an innovation. Furthermore, in addition to adoption, the theory distinguishes two types of rejection that occur at the decision stage, namely: active rejection and passive rejection. In an active rejection situation, an individual tries an innovation, thinks about adopting it, but subsequently decides to reject the technology, that is, essentially to discontinue usage of the technology. In a passive rejection scenario, an individual, without explicit experimentation with the innovation, decides not to adopt the innovation (Rogers, 2003).

Existing literature on DIT has provided insights into several characteristics of the technology that affects a person's probability of adoption or rejection (Bennett and Bennett, 2003). Consideration of these predictive characteristics offers a relevant amalgamation and augmentation to the perceived needs and motivations underlying choice for media usage described in the previous paragraph. Yet, the existing DIT literature is characterized by a lack of attention to usage behaviors beyond the initial adoption of an innovation, while active rejection behaviors such as discontinuance or reinvention are overlooked (Rogers, 2003). As previous articles have emphasized, few studies have investigated the nature of discontinuance, despite its real-life prominence (Eysenbach, 2005; Haider and Kreps, 2004; Abraham and Hayward, 1984; Rogers and Shoemaker, 1971; Leuthold, 1967). Yet, disentangling the discontinuance phenomenon is crucial for obtaining an adequate comprehension of the innovation and technology adoption process. This is consistent with Hargittai's (2008) argument that the potential differences between who is and who is not an active SNS user have been largely ignored in the literature of SNS adoption to date; this knowledge gap consequently presents an important opportunity for further research.

Given the importance of the various DIT adoption processes, it is essential to briefly conceptualize these processes and position them in the context of this study. Within the world of Twitter, we define adoption as the creation of a user account on Twitter. Furthermore, use continuance is conceptualized as active engagement with the medium, as reflected in high usage frequencies as well as large network size (number of followers and following). Use discontinuance, on the other hand, is conceptualized as inactive engagement with the medium, as reflected in low usage frequencies as well as small network size (number of followers and following).

Previous DIT research on the individual level of adoption for Computer Mediated Communication has focused primarily on three factors affecting the adoption decision. The personal innovativeness of the adopter refers to how early an individual adopts an innovation compared to other members of a social system. Perceived characteristics of an innovation are ways in which an innovation and the services it provides are perceived by adopters and non-adopters respectively. The perceived popularity of an innovation refers to a future adopter or non-adopter's perception of how an innovation is adopted throughout social networking systems (Chang et al. 2006; Zhu and He, 2002).

In applying DIT to Twitter research, this study draws on these three constructs and additionally includes demographic variables and items regarding new media adoption to answer the second research question:

RQ2: What innovation constructs affect the adoption of Twitter, and are these consistent among active versus inactive users?

Personal Innovativeness

Rogers (2003) defined innovativeness as "the degree to which an individual or other unit of adoption is relatively earlier in adopting an innovation than other members of a social system" (p. 22). Thus, highly innovative individuals tend to be active information seekers that can handle high levels of uncertainty, and therefore are expected to develop more positive beliefs about the target technology at levels of media exposure equal to those of other less innovative individuals (Lu et al., 2009). Similarly, Hurt et al. (1977) have described personal innovativeness as an individual's willingness to change, and Joseph and Vyas (1984) have suggested that highly innovative individuals indeed display distinct intellectual, perceptual and attitudinal characteristics. Generally, innovativeness, or an individual's readiness to adopt an innovation, has been accepted as an extremely relevant construct for explaining the adoption of new products (Agarwal and Prasad, 1998; Robertson and Kennedy, 1968). Hence, we hypothesize that:

- H2: Personal innovativeness directly affects a tweeter's level of activity

Perceived Popularity of An Innovation

Rogers (2003) has suggested that perceived social norms and adoption may be caused not only by actual needs, but also by the pressure of an adopter's social network, referred to as perceived popularity. Perceived popularity is therefore related to network externalities—i.e. increased utility of a communication medium as a result of an increasing user base—that motivate users to adopt an innovation (Dickinger et al., 2008; Strader et al., 2007). In a similar vein, Katz and Shapiro (1985) have posited that network externalities occur when the utility that a user derives from consuming a good or medium increases with the number of other users consuming the same good or medium. Network externalities are particularly relevant in the context of SNSs, as their success largely depends on the number of people using them (Nysveen et al., 2005). Therefore, we argue that users may perceive increasing utility of Twitter as this novel medium continues to grow exponentially, hence:

- H3: Perceived popularity directly affects a tweeter's level of activity.

Perceived Characteristics of An Innovation

In addition to personal innovativeness and perceived popularity, Rogers (2003) proposed a set of generalized characteristics of an innovation that predict the rate of its adoption, five of which have been found to be the most reliable and strongest predictors of such adoption rates (Rogers, 2003), namely: relative advantage, compatibility, complexity, trialability, and observability, described as follows.

First, relative advantage refers to the degree to which an innovation is perceived as better than the idea it supersedes (Rogers, 2003). The degree of relative advantage is often described by economic profitability, low initial cost, social prestige, time and effort, satisfaction; that is, decreasing uneasiness or discomfort, as well as immediacy of reward. According to Pontin (2007), the relative ease of being connected through the use of a one-to-many application, an inherent characteristic of Twitter, is a key strength of this communication platform. Twitter users can easily send and distribute status updates to "Friends," "Followers," and even to others they may not be familiar with (Pontin, 2007), for instance through Twitter's "public timeline," which is an electronic pinup board constantly showcasing users' postings (Codel, 2006).

Second, compatibility refers to the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters (Rogers, 2003). According to Rogers (2003), the more compatible an innovation is, the lower the uncertainty associated with adoption. Hence, high compatibility with existing values—such as socio-cultural beliefs—can potentially accelerate the adoption process, whereas lack of such compatibility can lead potential adopters to reject an innovation. Because Twitter is available on both a web- and a mobile-based platform (e.g. Tweetdeck, Tweetie), it is possible for people to connect anytime and anywhere which enables them to easily exchange and spread their status and opinions. Furthermore, Twitter's use is as varied as the people who rely on it to stay 'connected.' Hence, it can be argued that Twitter is compatible with its users' existing values, beliefs, and their daily life.

Third, complexity refers to the degree to which an innovation is perceived as difficult to understand and use (Rogers, 2003). The greater the level of complexity—or inversely, the less intuitive its usage—the more negative the perception about the innovation, which subsequently impedes adoption. Twitter's major attraction appears to be the simple, clear user interface and short message length, which affords easy and instant communication. Therefore, the simple user interface and low complexity of use may positively affect the adoption of Twitter.

Fourth, trialability refers to the degree to which an innovation may be experimented on a limited basis (Rogers, 2003), thus allowing individuals to do a "try and buy." If trialing the innovative idea, practice, or product seems to satisfy individuals' needs, the individual is more likely to adopt the technology. Inversely, if the trialing experience is unsatisfactory, the individual will probably reject the innovation. When an innovation is designed to afford easy trialability by potential adopters, individuals can discover and experience the innovation's value proposition before making an investment, thereby decreasing uncertainty (Rogers, 2003). Anecdotally, it may be argued that Twitter has high trialability, as the sole requirement for use is a valid e-mail account.

Fifth and finally, observability refers to the degree to which the results of an innovation are visible to others (Rogers, 2003). When an adopter can easily observe the result of using an innovation, this perceptual experience is positively related with the innovation's adoption. Twitter has received extensive media coverage as a result of its adoption by many celebrities, athletes, and politicians, including then-Presidential candidate Barack Obama, who integrated Twitter in his 2008 election campaign (Diaz, 2007). Therefore, it can be anticipated that these public promotions and coverage of the medium have resulted in Twitter's high observability among potential adopters. Based on empirical research, Moore and Benbasat (1991) have suggested that the observability concept encompasses two distinct constructs, namely result demonstrability and visibility. Therefore, in this study, we augment the original operationalization of DIT by including these two composite constructs.

These six foundational (first-order) constructs have been modeled as the second-order latent factor of perceived characteristics. Based on the above discussion on the effects of an innovation's relative advantage, compatibility, complexity, trialability, result demonstrability, and visibility on adoption, we hypothesize the following:

- H4: Perceived characteristics of Twitter as an innovation directly affect a tweeter's level of activity.

As aforementioned, based on our research question and our aim of comparing the differences in motivations between active versus inactive users, we also explore if any differences exist between the personal innovativeness, perceived popularity, and perceived innovation characteristics reported by the two groups of users. However, given the lack of coverage of this topic in the literature, the investigation of differences between active versus inactive users with respect to these three sets of DIT constructs will be exploratory and will focus on the differences in personal innovativeness, perceived popularity, and the six underlying first-order constructs that comprise perceived characteristics.

The literature review of UG and DIT as well as the aforementioned hypotheses result in the following research model underlying this study (Figure 1).

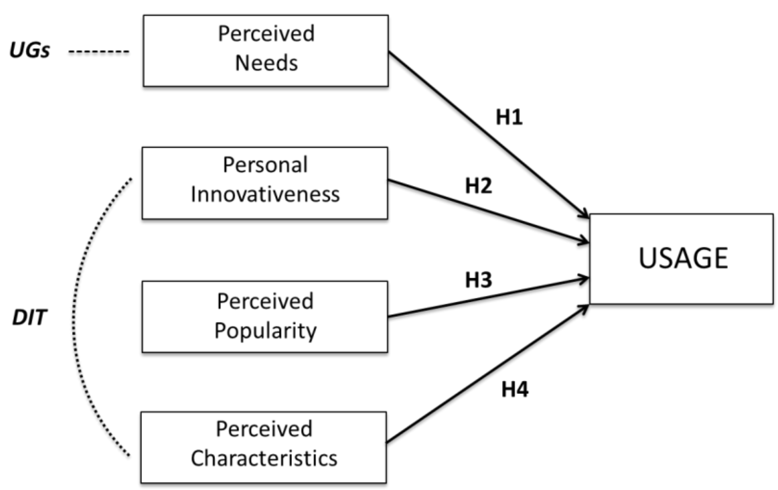


Figure 1: Research Model

METHODOLOGY

Research Design

We conducted an online survey at a US-based large mid-western university to gather data on Twitter users' motivations, innovation constructs, and actual Twitter usage. The data collection period lasted one week during August, 2010. To ensure the privacy of respondents, on completion of the study participants wishing to be considered for one of four $25 gift cards to be given out by means of a random draw included contact information (email addresses) by filling out a separate survey. We analyzed data using SPSS statistical software (SPSS 18) and Smart PLS (version 2.0.M3).

Participants

A random sample of 500 students and 500 faculty and staff received an email requesting their participation in this study. In total, 275 individuals responded; however, 143 (52%) of them indicated that they did not have a Twitter account and therefore were excluded from the study. We eliminated one outlier (with 900 minutes of usage in the past week per day). The remaining sample for analysis (N = 130), comprised 74 (56.9%) females and 56 (43.1%) males. There was no significant difference in the gender split between active and inactive Twitter groups. The average age was 28, ranging from 18 to 63 (*SD* = 11.732). Most respondents were Caucasian/White (72%) and African American (15.4%). Participants included undergraduate students (63.8%), graduate students (6.2%), staff (18.5%), faculty (8.5%) and others (3.1%) including postdocs and undergraduate staff (see Table 2).

Table 2: Participant Demographic Information (*N* = 130)

		All groups	Active	Inactive
Age	18 – 24	59.2%	70.0%	48.3%
	25 – 34	15.4%	11.4%	20.0%
	>= 35	25.4%	18.6%	31.7%
Gender	Male	43.1%	28.6%	60%
	Female	56.9%	71.4%	40%
Education	High school	2.3%	1.4%	3.3%
	Some college	49.2%	60.0%	36.7%
	College degree	24.5%	24.3%	25.0%
	Some graduate school	4.6%	1.4%	8.3%
	Graduate school	19.2%	12.9%	26.7%
Position	Undergraduate	63.8%	77.1%	48.3%
	Graduate	6.2%	2.9%	10.0%
	Staff	18.5%	12.9%	25.0%
	Faculty	8.5%	5.7%	11.7%
	Other	3.1%	1.4%	5.0%
Ethnicity	Caucasian/White	71.5%	64.3%	80.0%
	African American	15.4%	24.3%	5.0%
	Asian/Pacific Islander	6.9%	7.1%	6.7%
	Multiracial	2.3%	4.3%	0%
	Other	1.5%	0%	3.3%
	Would rather not say	2.3%	0%	5.0%

Single Source Bias

Single source bias, a potential hazard when using the survey methodology, can occur when independent and dependent variables are provided using the same method. Single source bias, a specific type of common method bias, represents an even higher risk that occurs when participants respond to items that measure both independent and dependent variables within the same survey instrument (Bagozzi et al., 1991; Campbell and Friske 1967; Podsakoff et al., 1984; Podsakoff et al., 2003). To help alleviate some of this risk, we collected and controlled for participant trait information. However, to statistically test for single source bias, we rearranged (i.e., paired) the data so that every participant would provide responses to either the independent or dependent variables only (Ostroff, Kinicki, and Clark, 2002). This way, no single participant would provide responses to items tapping into both independent and dependent variables. A within-treatment random assignment of binary numbers was used to pair (independent and dependent) data sets.

We then compared the factor score correlations to see if a significant difference existed between the two data sets (i.e. full sample versus half sample). The results in Table 3 show, through visual inspection, that there is minimal difference between correlations of factor scores using the total data set and the correlation of factor scores when participant data is paired. Thus, single source bias is not of concern in this study.

Table 3: Single Source Bias Test

	Correlation with Usage (n = 130)[1]	Correlation with Usage (n = 65)[2]	Absolute Difference
PerNeeds	0.485	0.436	0.049
PerInnovativeness	0.035	0.050	0.015
PerPopularity	0.106	0.155	0.049
PerCharacteristics	0.119	0.169	0.050

Note: [1] Correlation of factor scores between exogenous variables (independent and dependent variables: Needs, Innovat, Popular, Character) with the right-most endogenous variable (Usage) using total data.
[2] Correlation of factor scores using paired data.

Measurement Instrument

The questionnaire contained 5-point Likert-type scales ranging from "strongly disagree" to "strongly agree" that measured the four UG and DIT constructs shown in the research model through 71 items. In addition, there were five demographic items (age, gender, education, ethnicity, and employment category within the institution), and one item for the endogenous construct of usage (Minutes of Twitter use in the past week), along with two additional items relating to network information. Participants responded to the questionnaire after being prompted to reflect on their impressions of or experience with Twitter. The complete questionnaire, along with the sources of the scales, may be found in Appendix A.

Regarding the origin of the scales, the eleven most commonly applied constructs related to perceived needs were derived from two aforementioned UG studies of personal homepages and Facebook (Papacharissi and Rubin, 2000; Papacharissi, 2002; Papacharissi and Mendelson, 2008), which included scales for: information, passing time, entertainment, self-expression, professional advancement and companionship, interpersonal (social interaction), newer media (New and cool trend), professional advancement, habit, escape and relaxation (also see Table 1 in the previous section). These items were adapted in this study to fit the context, i.e., Twitter.

In addition to perceived needs, we adapted questionnaire items for personal innovativeness (Chang et al., 2006), perceived characteristics and perceived popularity (Moore and Benbasat, 1991) from previous studies leveraging DIT to fit the context of this study. Finally, we pilot tested the survey instrument before administration.

RESULTS

In line with the overall research questions underlying this study[1], we first analyzed the significance of the various UG and DIT constructs for the entire sample (N = 130), followed by an investigation of the significance of each of the UG and DIT constructs for active versus inactive users (n = 70 and n = 60 respectively). To ground the split-sample PLS analyses of active versus inactive users, we also conducted a one-way analysis of the differences of the means between active and inactive users for all UG and DIT constructs through SPSS ANOVA. Finally, to further verify and validate the PLS findings for both the full sample and the split sample analysis, we conducted an R2 partitioning to determine the unique variance contributed by the respective UG or DIT constructs to the overall model and the two separate structural models for active versus inactive users respectively.

Instrument Validity

In order to validate the survey instrument, we evaluated the measures and their corresponding constructs using various tests, starting with a review of factor loadings. The vast majority of the 71 items exhibited high reliabilities with loadings well above .50 (Carmines and Zeller, 1979; Hulland, 1999), except for seven items, which were consequently removed from further analysis (see Appendix A for the entire measurement instrument; removed items are marked with asterisks). Following the removal of these seven items, the item statistics were re-estimated for the remaining 64 items, as presented in Table 4.

Results of tests for convergent validity, discriminant validity, construct means, and Cronbach's α can be found in Table 5. All constructs had adequate reliability and internal consistency well above the 0.7 threshold. Cronbach's alphas were satisfactory for our constructs (ranging from α = 0.72 to α = 0.95) and constructs' average variance extracted (AVE) exceeded the 0.5 benchmark for convergent validity, except for Personal Innovativeness (AVE = 0.41), however item loadings for the scale strongly exceeded cross-loading values, offering adequate support for convergent validity. Similarly, item analysis confirmed the internal validity of the remaining constructs.

Table 4: Item Statistics

	COMP	ENT	ESC	HABIT	INFO	NEW	PASS	COMPATI	COMPLEX	DEMON	PI	PRO	RA	RELAX	SELF	SOCIAL	TRI	VISI	PP
COMP1	**0.873**	0.157	0.503	0.385	0.078	0.335	0.238	0.223	0.189	0.163	0.073	0.120	0.315	0.353	0.345	0.379	0.165	0.084	0.112
COMP2	**0.956**	0.261	0.554	0.519	0.060	0.386	0.432	0.206	0.216	0.256	0.185	0.046	0.272	0.426	0.421	0.448	0.219	0.195	0.039
COMP3	**0.914**	0.251	0.448	0.372	0.112	0.393	0.278	0.280	0.160	0.143	0.142	0.183	0.310	0.421	0.330	0.422	0.173	0.187	0.060
EN1	0.297	**0.963**	0.381	0.632	0.589	0.494	0.555	0.561	0.479	0.510	0.188	0.310	0.394	0.527	0.620	0.554	0.455	0.492	0.116
EN2	0.245	**0.946**	0.387	0.602	0.483	0.427	0.591	0.531	0.468	0.472	0.201	0.254	0.381	0.559	0.594	0.513	0.474	0.473	0.020
EN3	0.109	**0.789**	0.204	0.430	0.388	0.404	0.372	0.242	0.268	0.319	0.207	0.164	0.158	0.350	0.496	0.373	0.331	0.262	0.113
ESC1	0.535	0.320	**0.915**	0.497	0.065	0.359	0.373	0.240	0.228	0.267	0.123	0.140	0.291	0.469	0.330	0.323	0.168	0.107	0.093
ESC2	0.659	0.182	**0.780**	0.447	-0.032	0.352	0.413	0.092	0.117	0.152	0.235	-0.059	0.199	0.415	0.336	0.235	0.151	0.022	0.144
ESC3	0.363	0.403	**0.891**	0.441	-0.013	0.374	0.499	0.175	0.136	0.241	0.116	0.053	0.210	0.472	0.385	0.322	0.129	0.173	0.147
HABIT2	0.334	0.574	0.388	**0.775**	0.313	0.618	0.613	0.211	0.368	0.296	0.247	0.028	0.240	0.478	0.639	0.458	0.320	0.235	0.410
HABIT3	0.485	0.558	0.515	**0.957**	0.304	0.457	0.568	0.434	0.324	0.363	0.261	0.151	0.307	0.543	0.516	0.520	0.354	0.343	0.402
INFO1	0.103	0.511	0.015	0.311	**0.948**	0.259	0.166	0.522	0.436	0.369	-0.067	0.402	0.378	0.144	0.436	0.352	0.351	0.327	0.228
INFO2	0.057	0.546	0.066	0.361	**0.889**	0.285	0.215	0.487	0.390	0.294	-0.086	0.351	0.276	0.178	0.523	0.398	0.304	0.301	0.268
INFO3	0.065	0.456	-0.033	0.271	**0.910**	0.212	0.172	0.498	0.421	0.340	-0.019	0.429	0.352	0.141	0.406	0.385	0.311	0.366	0.325
NEW2	0.414	0.330	0.351	0.421	0.216	**0.787**	0.310	0.231	0.245	0.217	0.139	0.072	0.225	0.293	0.439	0.313	0.178	0.068	0.259
NEW3	0.395	0.494	0.418	0.569	0.240	**0.975**	0.381	0.297	0.183	0.203	0.201	0.076	0.279	0.418	0.395	0.338	0.212	0.155	0.267
PASS1	0.320	0.456	0.431	0.534	0.116	0.272	**0.916**	0.017	0.254	0.259	0.127	-0.156	0.099	0.378	0.516	0.393	0.256	0.234	0.273
PASS2	0.367	0.599	0.496	0.652	0.221	0.402	**0.975**	0.129	0.307	0.293	0.238	-0.063	0.176	0.501	0.686	0.528	0.262	0.286	0.324
PASS3	0.386	0.579	0.478	0.657	0.226	0.408	**0.963**	0.138	0.320	0.301	0.239	-0.018	0.205	0.483	0.689	0.554	0.272	0.341	0.332
COMPATI1	0.215	0.511	0.182	0.483	0.501	0.279	0.172	**0.915**	0.498	0.458	0.120	0.508	0.518	0.348	0.313	0.443	0.399	0.512	0.372
COMPATI2	0.289	0.479	0.204	0.362	0.468	0.308	0.133	**0.888**	0.438	0.414	0.198	0.432	0.542	0.365	0.335	0.451	0.385	0.447	0.352
COMPATI3	0.137	0.354	0.142	0.205	0.485	0.189	-0.079	**0.883**	0.460	0.379	0.094	0.637	0.657	0.209	0.136	0.241	0.371	0.423	0.110
COMPATI4	0.233	0.461	0.220	0.275	0.514	0.290	0.032	**0.895**	0.478	0.391	0.060	0.557	0.648	0.271	0.237	0.297	0.391	0.443	0.101

Note: COMP=Companionship; ENT=Entertainment; ESC=Escape; HABIT=Habit; INFO=Information; NEW=New/Cool Trend; PASS=Passing Time; COMPATI=Compatibility; COMPLEX=Complexity; DEMON=demonstrability; PI=Personal Innovativeness; PRO=Professional Advancement; RA=Relative Advantage; RELAX=Relaxation; SELF=Self Expression; SOCIAL=Social Interaction; TRI=Trialability; VISI=Visibility; PP=Perceived Popularity

Table 4: Item Statistics (Continued)

	COMP	ENT	ESC	HABIT	INFO	NEW	PASS	COMPATI	COMPLEX	DEMON	PI	PRO	RA	RELAX	SELF	SOCIAL	TRI	VISI	PP
COMPLEX1	0.269	0.396	0.205	0.363	0.397	0.209	0.237	0.547	**0.857**	0.404	0.060	0.415	0.438	0.317	0.290	0.346	0.320	0.447	0.101
COMPLEX2	0.126	0.413	0.153	0.333	0.422	0.198	0.296	0.451	**0.880**	0.486	0.106	0.346	0.404	0.221	0.377	0.368	0.383	0.401	0170
COMPLEX3	0.084	0.285	0.045	0.207	0.290	0.134	0.216	0.179	**0.627**	0.381	0.052	0.105	0.171	0.027	0.234	0.128	0.576	0.247	0.260
COMPLEX4	0.095	0.329	0.097	0.197	0.279	0.109	0.226	0.243	**0.714**	0.328	0.000	0.128	0.181	0.049	0.257	0.185	0.544	0.234	0.067
DEMO1	0.131	0.483	0.185	0.332	0.366	0.151	0.300	0.418	0.476	**0.869**	0.286	0.254	0.249	0.154	0.313	0.277	0.537	0.455	0.082
DEMO2	0.185	0.400	0.240	0.313	0.296	0.213	0.230	0.319	0.402	**0.872**	0.246	0.221	0.246	0.191	0.285	0.257	0.468	0.450	0.045
DEMO3	0.262	0.409	0.276	0.352	0.305	0.169	0.253	0.476	0.437	**0.893**	0.286	0.340	0.391	0.311	0.279	0.388	0.440	0.605	0.131
PI4	0.125	0.215	0.175	0.248	-0.067	0.187	0.253	0.054	0.096	0.236	**0.883**	-0.057	0.128	0.251	0.200	0.196	0.125	0.133	0.038
PI5	0.145	0.240	0.217	0.274	-0.031	0.156	0.247	0.138	0.131	0.330	**0.644**	-0.006	0.152	0.142	0.241	0.130	0.198	0.138	0.211
PI6	0.261	0.195	0.270	0.322	-0.125	0.157	0.220	0.110	-0.021	0.256	**0.848**	-0.067	0.133	0.342	0.184	0.219	0.159	0.174	0.146
PRO1	0.097	0.281	0.084	0.140	0.425	0.088	-0.109	0.594	0.342	0.314	-0.015	**0.934**	0.499	0.170	0.061	0.265	0.235	0.399	0.261
PRO2	0.080	0.172	0.101	0.105	0.291	0.099	-0.009	0.359	0.268	0.215	-0.126	**0.786**	0.327	0.172	0.067	0.262	0.087	0.281	0.152
PRO3	0.103	0.253	0.002	0.065	0.389	0.074	-0.070	0.519	0.401	0.272	0.024	**0.889**	0.423	0.172	0.103	0.317	0.194	0.384	0.251
ADV1	0.344	0.370	0.305	0.425	0.202	0.266	0.403	0.409	0.341	0.323	0.206	0.223	**0.795**	0.483	0.442	0.336	0.229	0.322	0.214
ADV2	0.219	0.260	0.170	0.154	0.362	0.215	0.034	0.609	0.374	0.318	0.010	0.521	**0.829**	0.088	0.108	0.145	0.289	0.314	0.143
ADV3	0.194	0.214	0.136	0.122	0.363	0.252	-0.007	0.536	0.305	0.198	-0.006	0.476	**0.813**	0.124	0.065	0.163	0.166	0.266	0.178
ADV4	0.264	0.259	0.241	0.217	0.357	0.229	-0.005	0.604	0.427	0.281	0.005	0.511	**0.860**	0.252	0.117	0.153	0.296	0.353	0.291
ADV5	0.197	0.307	0.216	0.194	0.339	0.254	0.011	0.584	0.328	0.206	0.041	0.467	**0.873**	0.301	0.136	0.102	0.216	0.272	0.121
ADV6	0.098	0.223	0.025	0.074	0.426	0.153	-0.205	0.645	0.401	0.274	-0.016	0.620	**0.753**	0.117	0.004	0.071	0.316	0.386	0.211
RELAX1	0.432	0.491	0.489	0.548	0.162	0.400	0.399	0.323	0.238	0.202	0.232	0.247	0.354	**0.952**	0.455	0.498	0.202	0.248	0.191
RELAX2	0.410	0.519	0.505	0.568	0.142	0.391	0.495	0.302	0.236	0.240	0.288	0.136	0.292	**0.970**	0.447	0.527	0.228	0.291	0.090
RELAX3	0.431	0.555	0.512	0.555	0.177	0.407	0.477	0.380	0.277	0.284	0.322	0.182	0.411	**0.956**	0.478	0.509	0.265	0.313	0.041
SELF1	0.336	0.432	0.211	0.400	0.427	0.342	0.360	0.273	0.302	0.164	0.081	0.189	0.201	0.393	**0.748**	0.535	0.178	0.121	0.130
SELF2	0.387	0.629	0.412	0.625	0.456	0.405	0.697	0.277	0.338	0.332	0.194	0.022	0.273	0.478	**0.951**	0.562	0.302	0.259	0.213
SELF3	0.364	0.562	0.376	0.532	0.435	0.333	0.574	0.269	0.378	0.335	0.148	0.107	0.229	0.370	**0.923**	0.557	0.280	0.201	0.114

Note: COMP=Companionship; ENT=Entertainment; ESC=Escape; HABIT=Habit; INFO=Information; NEW=New/Cool Trend; PASS=Passing Time; COMPATI=Compatibility; COMPLEX=Complexity; DEMON=demonstrability; PI=Personal Innovativeness; PRO=Professional Advancement; RA=Relative Advantage; RELAX=Relaxation; SELF=Self Expression; SOCIAL=Social Interaction; TRI=Trialability; VISI=Visibility; PP=Perceived Popularity

Table 4: Item Statistics (Continued)

	COMP	ENT	ESC	HABIT	INFO	NEW	PASS	COMPATI	COMPLEX	DEMON	PI	PRO	RA	RELAX	SELF	SOCIAL	TRI	VISI	PP
SOC1	0.454	0.514	0.358	0.568	0.374	0.363	0.507	0.400	0.382	0.340	0.227	0.210	0.220	0.579	0.575	**0.920**	0.208	0.405	0.410
SOC2	0.297	0.438	0.219	0.368	0.390	0.202	0.329	0.408	0.268	0.252	0.080	0.499	0.322	0.377	0.501	**0.756**	0.115	0.383	0.415
SOC3	0.427	0.472	0.310	0.492	0.336	0.318	0.489	0.328	0.327	0.326	0.293	0.222	0.172	0.422	0.539	**0.934**	0.215	0.374	0.313
TRI1	0.012	0.204	-0.047	0.180	0.180	0.015	0.146	0.220	0.302	0.337	0.086	0.059	0.035	0.040	0.096	0.019	**0.739**	0.392	0.130
TRI2	0.096	0.289	0.059	0.200	0.193	0.130	0.187	0.226	0.354	0.389	0.111	0.027	0.003	0.095	0.139	0.113	**0.779**	0.377	0.210
TRI3	0.217	0.406	0.212	0.347	0.242	0.094	0.264	0.316	0.361	0.463	0.210	0.147	0.250	0.205	0.258	0.186	**0.899**	0.421	0.140
TRI4	0.266	0.479	0.199	0.409	0.382	0.223	0.289	0.384	0.440	0.522	0.203	0.198	0.336	0.270	0.360	0.229	**0.903**	0.401	0.221
TRI5	0.190	0.479	0.174	0.360	0.375	0.178	0.235	0.528	0.502	0.526	0.207	0.306	0.390	0.272	0.290	0.243	**0.882**	0.454	0.311
VISI1	0.085	0.401	0.087	0.234	0.272	0.155	0.240	0.365	0.343	0.453	0.037	0.292	0.162	0.151	0.190	0.294	0.470	**0.701**	0.113
VISI2	0.177	0.394	0.089	0.285	0.279	0.113	0.219	0.456	0.388	0.523	0.192	0.403	0.338	0.284	0.175	0.389	0.396	**0.855**	0.218
VISI3	0.144	0.345	0.128	0.288	0.343	0.075	0.262	0.410	0.305	0.444	0.163	0.318	0.314	0.215	0.213	0.318	0.382	**0.841**	0.137
VISI5	0.171	0.412	0.137	0.314	0.304	0.129	0.279	0.461	0.444	0.478	0.202	0.330	0.421	0.286	0.220	0.410	0.379	**0.874**	0.126
PP1	0.037	0.292	0.162	0.151	0.164	0.081	0.189	0.201	0.145	0.310	0.292	0.336	0.318	0.289	0.189	0.310	0.098	0.119	**0.538**
PP2	0.102	0.014	0.289	0.384	0.440	0.522	0.203	0.037	0.292	0.162	0.151	0.141	0.298	0.313	0.216	0.241	0.217	0.214	**0.991**

Note: COMP=Companionship; ENT=Entertainment; ESC=Escape; HABIT=Habit; INFO=Information; NEW=New/Cool Trend; PASS=Passing Time; COMPATI=Compatibility; COMPLEX=Complexity; DEMON=demonstrability; PI=Personal Innovativeness; PRO=Professional Advancement; RA=Relative Advantage; RELAX=Relaxation; SELF=Self Expression; SOCIAL=Social Interaction; TRI=Trialability; VISI=Visibility; PP=Perceived Popularity.

Table 5: Construct Statistics

Construct	Mean (All Items)	Mean (Used Items)	Cronbach's Alpha	Composite Reliability (Internal Consistency)	Convergent Validity (AVE)	AVE
Entertainment	3.046	3.046	0.8865	0.9292	0.8150	0.9028
Information	2.808	2.808	0.9044	0.9398	0.8389	0.9159
Social interaction	1.990	1.990	0.8466	0.9056	0.7633	0.8737
Self-Expression	2.193	2.193	0.8675	0.9094	0.7717	0.8784
Pass time	2.603	2.603	0.9471	0.9661	0.9049	0.9513
Professional Advancement	2.213	2.213	0.8463	0.9043	0.7600	0.8718
New and cool trend	1.905	1.905	0.8573	0.8068	0.5996	0.7743
Habit*	2.054	2.027	0.7172	0.8613	0.7584	0.8709
Companionship	1.351	1.351	0.9109	0.9391	0.8373	0.9150
Escape	1.523	1.523	0.8378	0.8978	0.7462	0.8638
Relaxation	1.761	1.761	0.9568	0.9720	0.9204	0.9594
Personal innovativeness***	3.645	3.645	0.7905	0.7924	0.4125	0.6423
Perceived Popularity*	1.954	1.954	0.5404	0.7392	0.612	0.7823
Relative advantage	2.023	2.023	0.9209	0.9255	0.6748	0.8215
Compatibility	2.519	2.519	0.9222	0.9418	0.8018	0.8954
Complexity	3.477	3.477	0.8191	0.8564	0.6029	0.7765
Trialability	3.90	3.90	0.9039	0.9243	0.7109	0.8431
Result demonstrability*	3.379	3.564	0.8519	0.9097	0.7706	0.8778
Visibility*	3.465	3.635	0.8386	0.8909	0.6728	0.8202

Note: *Denotes one item removed from scale; ***Denotes three items removed from scale

Using the approach proposed by Fornell and Larcker (1981) and Hulland (1999), we also tested discriminant validity. Fornell and Larcker (1981) suggested that the correlation between any two constructs should be less than the square root of the variance extracted by the individual constructs separately. In other words, values along the diagonal of the correlation matrix in Table 6 must be greater than the corresponding values in each row or column. Since this is the case for all constructs, discriminant validity can be safely assumed.

Data Analysis

The first step in the data analysis process was to remove any outliers from the data collected. A good rule of thumb is to remove the outliers that are beyond (mean)+/-(2 × *SD*) (Hill and Lewicki, 2005). Our data included a self-reported mean of daily usage in minutes, which ranged from zero to 900 minutes (M = 32.98, SD = 89.158). Accordingly, we removed one data point that was well above the cutoff (900 minutes compared to 212 minutes), leaving a data set of 130 usable points (M = 26.31, SD = 46.245).

Second, we reviewed the histograms of these data and observed that nearly half of all data points had self-reported daily activity levels of 5 minutes or less. This 5 minute threshold was used as the cutoff point to classify active and inactive users into the two groups; inactive (N = 60) and active (N = 70) users (see Table 7).

The majority of inactive users (63%) reported no Twitter activity at all (i.e., 0 minutes per day), with an average of 1.23 minutes of use per day. The active users, on the other hand, reported an average daily usage of 47.80 minutes. A one-way ANOVA confirmed a significant difference between the two groups' Twitter usage (see Table 7), offering further support for the split between active and inactive users as reflected in the average usage frequency (in minutes). Furthermore, two additional ANOVAs confirmed significant differences between the number of followers and following for active versus inactive users (see Table 7). These findings are consistent with the definitions of use continuance and discontinuance in terms of usage levels and network size provided earlier.

Table 6: Correlation Matrix and Discriminant Validity Assessment

	ENT	INFO	SOC	SELF	PASS	PRO	NEW	HABIT	COMP	ESC	RELAX	PI	RA	COMPATI	COMPLEX	TRI	DEMO	VISI	PP
ENT	**.903***																		
INFO	.492**	**.916**																	
SOC	.520	.365	**.874**																
SELF	.587	.465	.626	**.878**															
PASS	.567	.178	.490	.603	**.951**														
PRO	.267	.440	.339	.089	-.107	**.872**													
NEW	.403	.198	.330	.448	.323	.062	**.774**												
HABIT	.618	.354	.567	.645	.658	.089	.512	**.871**											
COMP	.254	.103	.444	.393	.352	.132	.427	.403	**.915**										
ESC	.309	-.006	.298	.343	.486	.009	.364	.478	.542	**.864**									
RELAX	.544	.198	.525	.463	.497	.203	.325	.563	.437	.469	**.959**								
PI	.220	.009	.271	.233	.183	.001	.205	.297	.140	.202	.240	**.642**							
RA	.268	.406	.195	.139	.058	.552	.253	.209	.276	.214	.225	.066	**.822**						
COMPATI	.472	.541	.381	.287	.124	.537	.263	.349	.236	.162	.315	.192	.662	**.895**					
COMPLEX	.389	.400	.285	.331	.285	.286	.229	.384	.114	.173	.164	.158	.366	.424	**.777**				
TRI	.425	.330	.180	.264	.260	.163	.228	.361	.167	.133	.243	.253	.203	.357	.454	**.843**			
DEMO	.509	.370	.344	.371	.296	.283	.253	.385	.209	.282	.283	.377	.263	.427	.491	.516	**.878**		
VISI	.426	.338	.358	.202	.297	.383	.053	.300	.134	.034	.277	.116	.356	.458	.399	.487	.532	**.802**	
PP	.302	.362	.450	.355	.217	.160	.083	.124	-.008	.327	.064	.287	.285	.423	.463	.157	.307	.306	**.782**

Note 1: Fornell and Larcker's (1981) measure of discriminant validity which is the square root of the average variance extracted compared to the construct correlations. Bold values are supposed to be greater than those in corresponding rows and columns.
2: Off-diagonal values are correlations. All correlation values are significant at 0.01 level (2-tailed).
3: COMP=Companionship; ENT=Entertainment; ESC=Escape; HABIT=Habit; INFO=Information; NEW=New/Cool Trend; PASS=Passing Time; COMPATI=Compatibility; COMPLEX=Complexity; DEMON=demonstrability; PI=Personal Innovativeness; PRO=Professional Advancement; RA=Relative Advantage; RELAX=Relaxation; SELF=Self Expression; SOCIAL=Social Interaction; TRI=Trialability; VISI=Visibility; PP=Perceived Popularity

Table 7: Participant Self-Reported Weekly Twitter Usage and Network Size in Minutes

		N	Min	Max	Mean	SD	F-test
Usage	Active	70	10	360	47.80	54.585	15.234***
	Inactive	60	0	5	1.23	1.978	
Followers	Active	70	0	2700	120.24	329.391	5.366*
	Inactive	60	0	425	27.10	60.577	
Follow	Active	70	3	1000	116.01	163.277	13.795***
	Inactive	60	0	531	29.13	72.519	

Note: * significant at 0.05 level; ** significant at 0.01 level; *** significant at 0.001 leve

Using the variance-based PLS method, we then tested the research model shown in Figure 1. PLS allowed us to specify the relationships between the various endogenous and exogenous constructs in the model (structural model), as well as with their underlying items (measurement model). Thus, data analysis provided support for both how well the items measured each construct, and how well the hypothesized relationships between constructs supported the theory.

PLS features two additional advantages over other methodologies. First, PLS allows for multiple measures for each construct, so paths among constructs are more accurate estimates than those that would be obtained through multiple regression. The latter would display downward bias in these estimates due to measurement error (Chin and Gopal, 1995; Khalifa and Liu, 2002). Second, PLS can perform adequately with small to medium sample sizes (Chin, 1998; Compeau and Higgins, 1998). The minimum sample size for a PLS analysis should be the larger of (i) 10 times the number of items for the most complex construct; or (ii) 10 times the largest number of independent variables impacting a dependent variable (Barclay, Thompson, and Higgins, 1995). In our model, the most complex constructs have 6 items (personal innovativeness and relative advantage) and the largest number of independent variables estimated for a dependent variable is only 5. Thus, our sample size (*N* = 130) greatly exceeds the sample size of 60 needed for PLS in this case. However, recognizing the more recent debate over the "10 times" rule (Goodhue et al., 2006), we further performed a post-hoc power analysis to ensure that our sample size was satisfactory by computing the achieved power. Referring to the values reported as means and standard deviations for usage by the two user groups (active and inactive), Cohen's d and the effect-size correlation (r), were 1.206 and 0.516 respectively. Using the software G*Power (version 3.1), we performed a one-tailed t-test comparing our two means (Faul et al., 2009). Based on the calculated effect size (Cohen's *d* = 1.206), alpha error probability of 0.05, and sample sizes of 70 and 60 for the two groups respectively, the non-centrality parameter (delta) was found to be 6.86, with a critical t of 1.657, 128 degrees of freedom, and a power of 0.999, thus, providing further statistical support and bolstering our confidence in the adequacy of our sample size.

The first step in the data analysis was to validate the proposed research model shown earlier in Figure 1. We did so by first analyzing data for the entire sample, where all hypotheses were supported except for the effect of Personal Innovativeness on Usage (see Table 8).

Table 8: Hypothesis Testing for Entire Sample (Active and Inactive Users; *N* = 130)

Hypothesis	From	To	Path Coefficient	t-Value	Status
1	Perceived Needs	Usage	0.485	6.460***	Supported
2	Personal Innovativeness	Usage	0.035	0.400	Not Supported
3	Perceived Popularity	Usage	0.106	2.088*	Supported
4	Perceived Characteristics	Usage	0.119	2.013*	Supported

Note: * significant at 0.05 level; ** significant at 0.01 level; *** significant at 0.001 level

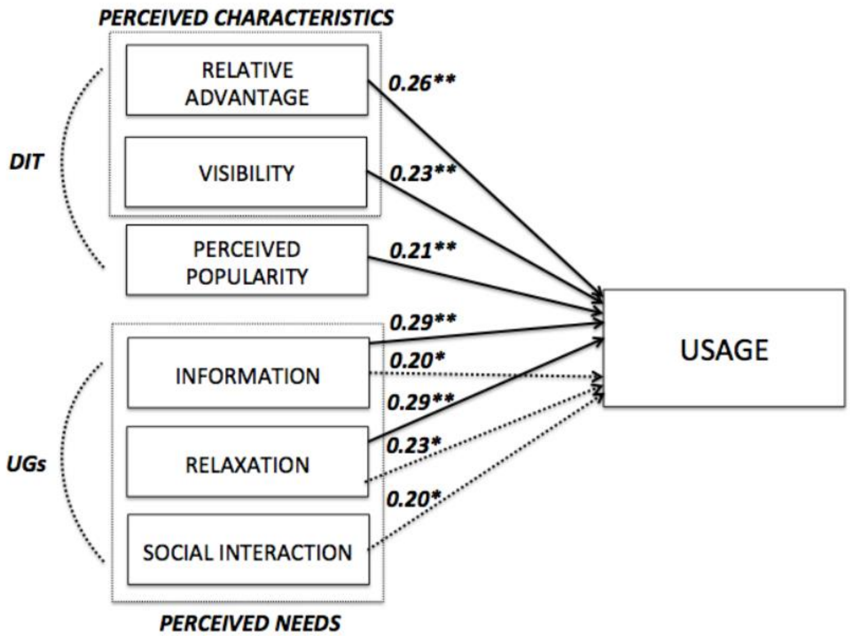
Next we sought to identify any differences between active and inactive users among all measures of perceived needs by means of ANOVA as a basis for our split-sample PLS analyses of active versus inactive users (n = 70 and n = 60) respectively. Results showed that there were significant differences between the two groups in all UG factors (see Appendix B). We conducted a similar analysis for the DIT constructs. ANOVA confirmed differences between the two users groups for every measurement; yet, no significant difference was found between the groups for Personal Innovativeness (see Appendix B).

To further examine the lack of a significant difference for the group means of Personal Innovativeness between active and inactive users (see ANOVA result in Appendix B), we computed the confidence interval between differences of means for the two groups. With mean Personal Innovativeness reported as 3.73 and 3.16 for active and inactive users respectively, at a confidence level of 95%, the effect size ranges from 0.23 to 0.90. Given that the difference in means between the two groups in our sample is .47, a larger sample size may be required to detect a significant difference in Personal Innovativeness at an alpha level of .05.

Given these significant differences between the two user groups, we proceeded to analyze the direct effects of the various motivations on usage for active and inactive users separately through split-sample PLS analyses. Based on the results from these two PLS analyses for active and inactive users respectively, as shown in Figure 2, we can conclude that active users' continued usage of Twitter was significantly affected by their personal need for information and relaxation (UG) coupled with the technology's relative advantage, visibility, and perceived popularity (DIT). In contrast, inactive users—who initially adopted Twitter, by means of creating an account, but completely or largely discontinued use of the medium—were significantly influenced by anticipated personal needs for information, relaxation and social interaction (UG) alone. Hence, none of the DIT constructs significantly predicted inactive users' initial adoption and subsequent discontinuance of Twitter.

Subsequently, through R^2 partitioning in SPSS, we contrasted the explanatory power of UG, DIT, and the multi-theoretical combined model proposed in this study. Results show that combining both theories offers the greatest explanatory power for Twitter usage (R^2 = 38.6%), compared to using UG alone (R^2 = 28.6%), or using DIT alone (R^2 = 10.0%) for the full sample (*N* = 130). More importantly, however, after testing the combined model for the active and inactive groups separately, it became evident that whereas the motives of inactive users can be more adequately explained by referencing perceived needs through UG constructs, the motives of active users for continued usage, beyond the initial motivation to adopt, are best explained by referencing characteristics of the medium and its perceived popularity through DIT constructs.

To ensure that the variance explained by the combined research model was significantly greater, we performed a series of F-tests, the results of which are shown in Tables 9 through 11 below. The stepwise regression models first included only UG constructs, augmented by the DIT constructs in the second step[2] . As Table 9 and 10 show, after adding DIT to the model, the combined model explained significantly more variance for the full dataset as well as for active users alone. Yet, adding the DIT constructs had no significant effect on increasing the explained variance for inactive users (Table 11), as can be expected from the aforementioned results reporting the sole significance of perceived needs as predictors of initial adoption and subsequent discontinuance by inactive users.



Note: * significant at 0.05 level; ** significant at 0.01 level; *** significant at 0.001 level
Solid: active users; Dashed: inactive users

Figure 2: Factors with Significant Direct Effects on Usage Reported for Active and Inactive Twitter Users

Table 9: Model Summary for All Users (*N* = 130)

Model	R^2	Adjusted R^2	Change R^2
Partial (UG)	.286	.249	.286***
Full (UG + DIT)	.386	.328	.100***

Note: * significant at 0.05 level; ** significant at 0.01 level; *** significant at 0.001 level

Table 10: Model Summary for Active Users (*n* = 70)

Model	R^2	Adjusted R^2	Change R^2
Partial (UG)	.203	.134	.203**
Full (UG + DIT)	.326	.218	.123**

Note: * significant at 0.05 level; ** significant at 0.01 level; *** significant at 0.001 level

Table 11: Model Summary for Inactive Users (*n* = 60)

Model	R^2	Adjusted R^2	Change R^2
Partial (UG)	.398	.309	.398***
Full (UG + DIT)	.476	.325	.077

Note: * significant at 0.05 level; ** significant at 0.01 level; *** significant at 0.001 level

Lastly, an interesting group difference emerged during a post-hoc analysis between the two user groups in terms of access. Active users reported significantly higher usage of mobile phones [$F(1, 129) = 29.04$, $p < .001$], mobile apps, [$F(1, 129) = 24.914$, $p < .001$], and web clients [$F(1, 129) = 4.871$, $p < .05$] than inactive Twitter users, suggesting that mobile access and third-party web clients may serve as further catalysts of Twitter usage and popularity.

DISCUSSION

With the proliferating use and far-reaching impact of SNS and social media, such as Twitter, understanding people's motivations for usage and use (dis-)continuance is necessary for effectively understanding, developing, and implementing these powerful tools in both an organizational context as well as society in general. Whereas existing research has examined people's motivations for the initial use or adoption of social media, the equally interesting and relevant question of discontinued usage has hitherto been largely overlooked, both in the social media literature specifically (Hargittai, 2008; Archambault and Grudin, 2012) and the diffusion of innovation literature more broadly (Eysenbach, 2005; Haider and Kreps, 2004; Abraham and Hayward, 1984; Rogers and Shoemaker, 1971; Leuthold, 1967). In particular, in the context of Twitter's low activity levels and high abandonment levels (Archambault and Grudin, 2012; Liedtke, 2009; HubSpot, 2009), exploring the topic of discontinuance is important for obtaining an accurate, rich, and more complete picture of tweeters' usage patterns and their underlying motives.

Furthermore, the literature on motivations for social media use to date is characterized by an artificial and myopic divide, focusing on either user-related explanations, based in Uses and Gratifications theory, or technology-related explanations of social media adoption, based in Diffusions of Innovation theory. In order to bridge this divide as well as to explore a wider spectrum of usage behaviors, including initial adoption, and subsequent use (dis-)continuance, this study combined Uses and Gratifications and Diffusion of Innovation theories in order to provide a comprehensive explanation of people's diverse usage frequencies (active or inactive) and behaviors (use continuance or discontinuance) in relation to social media in a way that attaches equal weight to explanations based on motivations of the user as well as characteristics of the medium.

Comparing both active users who continue to use Twitter on a daily basis and inactive users, who have fully or largely discontinued their use of Twitter, this study generated four sets of results. The first set of findings pertains to the second-order model of the full sample (N = 130). Here we showed that to reach a comprehensive understanding of the underlying reasons for initial adoption as well as (dis-)continued use of Twitter by explaining the usage patterns of both inactive and active users, both user-related motivations, i.e. perceived needs (Uses and Gratifications), as well as technology-related characteristics, namely perceived popularity and perceived characteristics of the medium, must be incorporated. Personal innovativeness was found to be insignificant, which may be caused by measurement error related to low convergent validity and insignificant factor loadings of half of the items, but also due to the narrow confidence interval between the means of active and inactive users. Thus, larger sample sizes may be required to detect significance at the .05 alpha level. Additionally, given the relative homogeneity of the sample drawn from a large Mid-western university, self-reports of personal innovativeness were of more modest ranges than what might have resulted from a larger, truly random sample. Hence, a broader scope during data collection could potentially result in a significant difference in Personal Innovativeness means for active versus inactive users that may in turn reveal a significant effect on usage. We conjecture that higher levels of Personal Innovativeness might have been reported by active users who voluntarily chose to adopt Twitter rather than active users who engaged with this medium due to contextual (e.g., work and classroom) needs, as may be the case in the analyzed academic context.

Second, if we zoom in on the first-order model and the differences between active versus inactive users, our results show that initial adoption and use (dis-)continuance were partially motivated by the same UG constructs, namely information—to produce or curate information—and relaxation. Interestingly, these two factors were the only two variables in our study that were significant for both active and inactive users; hence these factors cannot be used to account for the difference in their usage frequencies and behaviors. Furthermore, inactive users were additionally motivated by the initial anticipated benefit of social interaction, which was not a significant motivator for active users.
The only way to explain this finding is through an account of the characteristics of the technology, based on insights from Diffusion of Innovation theory, which shows that active users who continue to use Twitter do so because of its visibility, relative advantage, and perceived popularity in a workplace setting. Hence, leisurely use of Twitter alone does not sufficiently support long-term interest in the medium and therefore results in use discontinuance as social needs are likely better satisfied through the use of other social media, such as Facebook and similar social networking sites. Instead, Twitter does offer an advantage over other social media to users that are driven by work-related and information curating motivations as well as those aiming to support functional workplace interactions. Therefore, the visibility, relative advantage, and perceived popularity of Twitter in a workplace setting are the main technology characteristics that motivate continued use by active users.

Third, our results show that for a holistic understanding of adoption and use (dis-)continuance—i.e. active and inactive users—understanding both characteristics of the user as well as the medium through combining insights from Uses and Gratifications as well as Diffusion of Innovation theory indeed offers greater explanatory power, with the explained variance of both models (R^2 = .39) combined being significantly higher than the explained variance of the UG (R^2 = .29) or DIT (R^2 = .10) models separately for the full sample (N = 130) as well as for active users (UG R^2 = .20; DIT R^2 = .13; Combined R^2 = .33). The increase in explained variance for the combined model over the two separate models was not significant for the inactive users, which is consistent with the above mentioned result that discontinued Twitter usage by inactive users was solely affected by unfulfilled perceived needs, primarily the need for social interaction (UG R^2 = .40; DIT R^2 = .08; Combined R^2 = .48). These findings are in line with DIT research, which has anticipated that discontinuance is usually a result of dissatisfaction (Abraham and Hayward, 1984; Rogers and Shoemaker, 1971; Leuthold, 1967).

Although this finding is significant in and of itself, the real contribution here is in showing that user-related characteristics are primarily significant for inactive users (i.e., discontinued usage) while initial motivation to adopt Twitter and technology-related characteristics are highly significant for active users (i.e., continued usage) that continue active engagement with the medium. This can be explained by the fact that initial usage is largely impacted by users anticipated benefits, rather than the characteristics of the technology per se, due to limited exposure to and experience with the medium and its material characteristics. Rather, active users, only through their continued interaction with the medium, come to understand and appreciate characteristics of the technology—in particular its visibility and relative advantage—and therefore their motivation for continued usage is based to a larger extent on these material properties. Hence, beyond the greater explanatory power of the multi-theoretical combined model overall, our findings revealed that UG offers superior insights into the motivations underlying initial adoption and discontinued usage by inactive users, whereas DIT offers superior explanations of the motivations underlying continued usage by active users.

Finally, an interesting finding that emerged in this study is that mobile access was an important factor associated with continued usage of Twitter. Despite the relative homogeneity of the sample—young college students—a significant difference between active and inactive users emerged in terms of the devices and platforms they used to access Twitter. Active users reported accessing Twitter significantly more via mobile phones and mobile applications than inactive users. This might be in part due to the natural fit between the service's real-time update feed and mobile devices' portability that supports anytime, anywhere reachability and connectivity. Active users also appeared to use third-party web clients significantly more than inactive ones, highlighting their critical role at this early stage of Twitter adoption.

The above discussion of our findings points to several important implications and contributions for both theory and practice. First, by combining the relative strengths of UG and DIT, this study offers a more comprehensive model for explaining and testing technology adoption that disentangles adoption and use (dis-)continuance by appreciating and amalgamating characteristics of the user and the medium combined. Furthermore, it shows that whereas initial adoption might be more effectively explained through referencing user-related characteristics, understanding continued usage is strongly affected by material characteristics of the medium. Put differently, this may imply that initial adoption of Twitter is largely based on the need for satisfying hedonic and social needs, whereas continued adoption is affected to a larger extent by utilitarian needs, namely the medium's relative advantage. This contrasts previous studies, which have highlighted a combination of social and information motives as predictors of tweeting activity (Johnson and Yang, 2009; Lee, 2009). Rather, it appears from our findings that hedonic and social motives are more important among inactive users, yet, that these provide insufficient motivation for prolonged tweeting activity when no additional functional and informational benefits are experienced. Therefore, our results provide useful starting points for future research questions, both to those who wish to theoretically understand the interplay between hedonic and utilitarian motivations underlying various stages of technology adoption and usage as well as those who wish to design novel social media with a high probability of being adopted and embraced continuingly by users.

Second, our findings that the continued usage of Twitter is primarily motivated by the medium's relative advantage and strength for information curating are consistent with previous research that has emphasized the medium's strength for information sharing, knowledge management, and relationship management in organizational contexts (Archambault and Grudin, 2012). Hence, based on these insights, we may expect that people who are likely to use Twitter over a prolonged period of time represent knowledge brokers, i.e. individuals who are in charge of managing various information flows simultaneously and/or who are located at the juncture of various groups and organizations, including marketing and public relations professionals, academics and researchers, policy makers and government officials, as well as media and news agency practitioners. This is in line with previously identified Twitter influentials and continued users, such as content aggregation services, businessmen, politicians, public figures (e.g., celebrities), and news sources (Cha et al., 2010).

Third, given the medium's relative advantage for information curating, our results also provide a clear message to organizations and administrators. Organizations should educate employees, enforce policies, and empower employees with respect to Twitter usage in the workplace. Although organizations might be inclined to restrict or prohibit the use of social media in workplace settings (Brost, 2011), our results show that given that Twitter is not considered suitable for satisfying needs for entertainment and escapism, but highly useful for information curating, such restrictions might be counter-effective. Instead, given that tweets combine the ability to relax while supporting functional work-related interactions, allowing leniency in messaging and empowering employees will make Twitter an ideal medium in a workplace setting. However, to convince the relevant organizational users of the usefulness of Twitter and to guide relevant usage behaviors, organizations must educate and train their employees to showcase the potential of this medium.

To conclude, by providing a model that takes into account both personal and social needs as well as material characteristics of the medium, this paper offers a more holistic, and therefore realistic view of the motives underlying Twitter usage by both active and inactive users. Furthermore, by revealing that active Twitter users are primarily motivated by the perceived relative advantage of the medium in workplace settings, we hope managers can better see the potential role Twitter can play in the organizational processes of communication and information curation, and also better identify challenges and training opportunities associated with appropriate use of Twitter in the workplace. Therefore, we believe that the multi-theoretical model provided in this paper offers a comprehensive lens for understanding various Twitter usage behaviors and consequently takes a critical step towards enriching our understanding of fundamental differences between Twitter active and inactive users. We hope this model will motivate further research on Twitter adoption and use (dis-)continuance, for which we now present suggested directions.

Challenges and Future Research

The challenges from this study led to the identification of several relevant avenues for future research. First, college sampling and low response rates from staff and faculty may have affected the generalizability of findings. We attempted to draw upon the wider university population including students, faculty, and staff in order to collect data from a representative population in terms of age; however, in the end, the majority of responses came from respondents aged 18 to 63, with a mean of 28, and the largest proportion coming from those aged 18-24 and more broadly those aged 18-35. According to Pew Internet (2010) research, this is in line with general tweeting activity, as the greatest proportion of tweeters within any age bracket is found between the 18-29 range (18% of them tweet), followed by the 30-49 range (14% of them tweet). Thus, representativeness in terms of age can be assumed, however, the caveat lies within the context of the tweeting activity; the sample came from a higher education institution, so there may be biases in that regard. Future studies could be applied to the general population with a wider age range and geographic coverage.

Furthermore, the data for this study were self-reported, hence, may lack the sense of urgency or other contextual responses that a user may experience in a real-world setting. While this is a limitation in terms of the realism of the study, it is a means of controlling for additional variables that could not be otherwise measured during the survey. Future research can build on this study's findings by considering contextual factors and investigating the relative importance of the identified motivations and innovation characteristics influencing tweeting activity in those settings. For example, it is reasonable to expect public relations professionals to be not only more active users, but also to display different usage purposes, behaviors, and patterns from other professionals such as educators in higher education institutions.

Additionally, this study represents an attempt to analyze continuance and discontinuance following initial adoption of Twitter by means of cross-sectional data. Future research should attempt to analyze the full spectrum of adoption behaviors, including discontinuance, through longitudinal data collection to obtain a more accurate and dynamic understanding of the complexities and idiosyncrasies of the adoption process, e.g. through unraveling potential trigger events of discontinuance. Whereas the cross-sectional data in this study provided clear evidence of discontinuance—with 60% of inactive users reporting no activity at all—it does not provide insights into the amount of time that elapses after initial adoption (i.e., creating an account) until discontinuing usage. Hence, longitudinal data would be useful for disentangling the nature and timing of discontinuance and the overall evolution of the adoption process.

Finally, similar studies should attempt to replicate these findings internationally to explore the role of culture in Twitter's adoption, and therewith highlight any significant differences in the motivations of its use as consequents of cultural dimensions. Lastly, qualitative research is needed to explore the kinds of services that may stimulate activity among inactive users. In closing, as Twitter appears to be nearing (or recently having reached) critical mass, there are numerous questions that warrant investigation; answers to these questions which will help broaden the body of knowledge in new media adoption and use continuance.

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[1] The research questions were: what perceived needs and innovation constructs affect the adoption of Twitter, and are these consistent among active versus inactive users?

[2] Note that because UG—consistent with the presented theory and framework—is entered first into the model, all the covariance between UG and DIT is attributed to UG, therefore slightly amplifying its R^2 score.

APPENDIX A. MEASUREMENT INSTRUMENT

Do you have a Twitter account? *(Closed question: Yes/No)*
(Likert-scales follow ranging 1-5, from Strongly Disagree to Strongly Agree, unless otherwise noted)

UG (33) (Papacharissi, 2002) (Papacharissi and Rubin, 2000) (Papacharissi and Mendelson, 2008)	Entertainment	Because it's enjoyable
		Because it's entertaining
		Because it's fun to try out new things like this
	Information	To provide information
		To present information about a special interest of mine
		To share information that may be of use or interest to others
	Social Interaction	To keep in touch with friends and family
		To meet new people
		To communicate with distanced friends
	Self Expression	To provide personal information about myself
		Because I can express myself freely
		To tell others a little bit about myself
	Pass Time	When I have nothing better to do
		Because it passes the time away, particularly when I 'm bored
		Because it gives me something to do to occupy my time
	Professional Advancement	Because it is helpful for my professional future
		To post my resume and/or other work online
		To help me network with professional contacts
	New and cool trend	* Because everybody else is doing it
		Because it is the thing to do
		Because it is cool
	Habit	* Just because it's there
		Because I just like to play around on Twitter
		Because it is a habit, just something I do regularly
	Companionship	So I won't have to be alone
		When there's no one else to talk or be with
		Because it makes me feel less lonely
	Escape	So I can forget about school, work, or other things
		So I can get away from the rest of my family or others
		So I can get away from what I'm doing
	Relaxation	Because it relaxes me
		Because it allows me to unwind
		Because it is a pleasant rest
DIT (34)	PersonalInnovativeness (6) (Chang et al., 2006)	* I like to learn about new ideas
		* I am interested in news stories that deal with new inventions or discoveries
		* I am updating my computer to keep up with new technologies
		I like to change cellular phones to keep up with brand new designs or functions
		I like to try new things before they come into fashion
		I try brand new products in retail stores earlier than other people
	Relative advantage (6) (Moore and Benbasat, 1991)	Using Twitter would be better than doing anything else
		Using Twitter would make it easier to do my work
		Using Twitter would help me to accomplish tasks more quickly
		Using Twitter would improve the quality of the work I do
		Using Twitter would give me greater control over my work

		Using Twitter would enhance my effectiveness in my job
	Compatibility (4) (Moore and Benbasat, 1991)	Using Twitter is consistent with my daily lifestyle
		Using Twitter would be compatible with all aspects of my life
		Using Twitter would fit into my work style
		I think that using Twitter would fit well with the way I like to work
	Complexity (4) (Moore and Benbasat, 1991)	I believe it would be easy to use Twitter for whatever I want to do
		My interaction with Twitter is clear and understandable
		Learning to use Twitter would be easy for me
		Overall, I believe Twitter would be easy for me
	Trialability (5) (Moore and Benbasat, 1991)	Twitter is available for a trial whenever I would like to use it
		I can join Twitter as a free member and test its relevant functions
		Twitter provides enough freedom that lets me test its various functions
		When using Twitter, I can find its multiple functions
		To summarize, when using Twitter, I find it provides multiple and convenient functions
	Result demonstrability (4) (Moore and Benbasat, 1991)	I would have no difficulty telling others about the results of using Twitter
		I believe I could communicate to others the consequences of using Twitter
		The results of using Twitter are apparent to me
		*/** I would have difficulty explaining why using Twitter may or may not be beneficial
	Visibility (5) (Moore and Benbasat, 1991)	I have seen others using Twitter
		In my (personal/social or professional) circles, I can see Twitter on many computer screens (including mobile devices)
		I have seen people using Twitter outside my (personal/social or professional) circles
		*/** Using Twitter is not very visible in my (personal/social or professional) circles
		It is easy for me to observe others using Twitter in my (personal/social or professional) circles
Perceived Popularity (Zhu and He, 2002)		How many people in your family are using Twitter?
		In your estimate, about how many of your relatives, friends, and acquaintances are using Twitter?
		In your estimate, about how many people in your occupation are using Twitter?
Access		I use Twitter through …
Usage (duration) (Chang et al., 2006)		In the past week, on average, approximately how many minutes per day have you spent on Twitter?

Demographic (5)	What is your gender?
	What is your age?
	What is your ethnicity?
	What is your level of education?
	What is your position in (this academic institution)?

Note: * deleted items; ** reverse-scored items

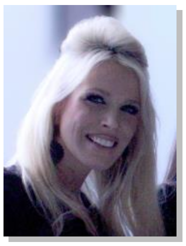
APPENDIX B. ANOVA OF NEEDS AND INNOVATION CONSTRUCTS BETWEEN ACTIVE AND INACTIVE TWEEERS

		Sum of Squares	df	Mean Square	F	Sig.
ENTERTAINMENT	Between Groups	54.319	1	54.319	60.789	.000
	Within Groups	115.270	129	.894		
	Total	169.589	130			
INFORMATION	Between Groups	23.306	1	23.306	16.777	.000
	Within Groups	179.204	129	1.389		
	Total	202.511	130			
SOCIAL INTERACTION	Between Groups	22.371	1	22.371	22.265	.000
	Within Groups	129.616	129	1.005		
	Total	151.986	130			
SELF-EXPRESSION	Between Groups	21.837	1	21.837	19.690	.000
	Within Groups	143.067	129	1.109		
	Total	164.904	130			
PASSTIME	Between Groups	42.136	1	42.136	29.464	.000
	Within Groups	184.478	129	1.430		
	Total	226.614	130			
PROFESSIONAL ADVANCEMENT	Between Groups	12.632	1	12.632	10.943	.001
	Within Groups	148.907	129	1.154		
	Total	161.539	130			
NEW and COOL TREND	Between Groups	5.855	1	5.855	6.980	.009
	Within Groups	108.206	129	.839		
	Total	114.061	130			
HABIT	Between Groups	34.561	1	34.561	45.746	.000
	Within Groups	97.458	129	.755		
	Total	132.019	130			
COMPANIONSHIP	Between Groups	6.264	1	6.264	10.287	.002
	Within Groups	78.545	129	.609		
	Total	84.809	130			
ESCAPISM	Between Groups	13.722	1	13.722	22.490	.000
	Within Groups	78.706	129	.610		
	Total	92.427	130			
RELAXATION	Between Groups	37.522	1	37.522	53.549	.000
	Within Groups	90.391	129	.701		
	Total	127.912	130			
PERSONAL INNOVATIVENESS	Between Groups	.597	1	.597	1.086	.299
	Within Groups	70.848	129	.549		
	Total	71.445	130			
PERCEIVED POPULARITY	Between Groups	6.846	1	6.846	11.556	.001
	Within Groups	75.824	129	.592		
	Total	82.670	130			
RELATIVE ADVANTAGE	Between Groups	16.022	1	16.022	26.892	.000
	Within Groups	76.857	129	.596		
	Total	92.879	130			

COMPATIBILITY	Between Groups	36.575	1	36.575	43.534	.000
	Within Groups	108.380	129	.840		
	Total	144.955	130			
COMPLEXITY	Between Groups	8.617	1	8.617	13.095	.000
	Within Groups	84.893	129	.658		
	Total	93.510	130			
TRIALABILITY	Between Groups	5.687	1	5.687	8.188	.005
	Within Groups	89.594	129	.695		
	Total	95.280	130			
RESULT DEMONSTRABILITY	Between Groups	15.582	1	15.582	21.871	.000
	Within Groups	91.906	129	.712		
	Total	107.488	130			
VISIBILITY	Between Groups	25.635	1	25.635	35.558	.000
	Within Groups	93.002	129	.721		
	Total	118.637	130			
USAGE	Between Groups	109081.618	1	109081.618	15.234	.000
	Within Groups	923671.664	129	7160.245		
	Total	1032753.282	130			
followers	Between Groups	390232.544	1	390232.544	5.366	.022
	Within Groups	9380889.303	129	72720.072		
	Total	9771121.847	130			
follow	Between Groups	302603.703	1	302603.703	13.795	.000
	Within Groups	2829715.213	129	21935.777		
	Total	3132318.916	130			
TWITTER ACCESS DEVICE						
Desktop	Between Groups	.205	1	.205	.850	.358
	Within Groups	31.153	129	.241		
	Total	31.359	130			
Laptop	Between Groups	.111	1	.111	.925	.338
	Within Groups	15.416	129	.120		
	Total	15.527	130			
Mobile	Between Groups	5.939	1	5.939	29.042	.000
	Within Groups	26.381	129	.205		
	Total	32.321	130			
TWITTER ACCESS PLATFORM						
Twitter Webpage	Between Groups	.023	1	.023	.249	.619
	Within Groups	11.687	129	.091		
	Total	11.710	130			
Web Client	Between Groups	.713	1	.713	4.871	.029
	Within Groups	18.890	129	.146		
	Total	19.603	130			
Mobile apps	Between Groups	5.108	1	5.108	24.914	.000
	Within Groups	26.449	129	.205		
	Total	31.557	130			
SMS	Between Groups	.261	1	.261	1.865	.174
	Within Groups	18.044	129	.140		
	Total	18.305	130			

ABOUT THE AUTHORS

Dr. Constantinos Coursaris studies user motivations, expectations, and experiences with new media and the consequent design implications with a focus on social systems. He supplements his research expertise with consulting on social media for governance and/or marketing, and has trained diverse organizations in North America, Europe, and the Middle East.



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