The Dissertation Committee for Yee Man Ng Certifies that this is the approved version of the following Dissertation:

Building an Innovation Discontinuance Model: The Case of Twitter

Committee:

Hsiang Iris Chyi, Supervisor

Gina Chen

Thomas Johnson

Hai Liang

Dhiraj Murthy

Building an Innovation Discontinuance Model: The Case of Twitter

by

Yee Man Ng

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May 2018

Dedication

To my Heavenly Father.

Your grace is enough for me.

Acknowledgements

I have depended upon the counsel, support, and love of many people in the preparation of this dissertation. These spare words of thanks seem insufficient, but I am deeply indebted to them.

First and foremost, I would like to thank my dissertation supervisor, Dr. Iris Chyi, who offered insightful, wise, and careful—not to mention rapid—readings of the several drafts of this dissertation. She is the best teacher, guide, mentor, and friend I ever could have ever anticipated. Her support and encouragement helped me traverse through the tough PhD life. I cannot thank her enough. Second, I want to express my gratitude to my committee members, Dr. Gina Chen, Dr. Tom Johnson, and Dr. Dhiraj Murthy. They provided insightful suggestions for my graduate work and dissertation. They set up the best examples for me to follow as a productive scholar. I also thank my external committee member, Dr. Hai Liang. He is overseas but is always just a text away. His advice and support provided me with the impetus for finishing this dissertation.

Further, I want to thank my dear friend, Alexandre Gonçalves, who always spends time talking with me. His comfort replaces my irrational fears with power, courage and strength. His origami crafts were the cheering team which got me through those sleepless nights of writing. I also thank Leonardo Luís for his prayers. The jokes we shared are precious memories that I will recall whenever I need to cheer up myself. My gratitude also goes to my ladies, Yiji Kim and Yalin Sun, who have prayed with me through ups and downs.

My sincere appreciation goes to Saif Shahin, Krishnan Vasudevan, and Vickie Chen. They are the best resources when I was doing my dissertation and job search. Thanks to my friends and my PhD cohort, especially Joseph Yoo, Ryan Wang, Shuning Lu, Lourdes Cueva Chacón, and Heloisa Sturm. Life as a PhD student has been a roller coaster of emotions, but we will all make it. I am also grateful to my childhood friends in Hong Kong, particularly Jenny Chun and Yan Lee, whose friendships have been the greatest joys of my life. I owe special thanks to my fellowship FBCC and my church mentors Kunhua Chen and Grace Chen for spending tremendous time and love to nurture me.

Finally, I want to thank my family, who have always been there for me: I am grateful in more ways than I can express to my parents' and my brother's support over the years. I am falling short of words when it comes to my sister Crystal. Who would have thought we would end up studying at the same institution for a PhD? Life is a lot easier because of her (and Shakespe, the crazy naughty corgi) during my PhD final year. I will always remember those days she took care of me and stayed up late at midnight to read my dissertation. I am so lucky to have her as my sister. Thanks also to Kun, who always reminds me to work harder, dream bigger, and stand stronger.

I thank my Heavenly Father. Thank you for your goodness and faithfulness in my life. You do miracles in my life. It is with reverence for your love and blessings that I dedicate my dissertation to you.

Abstract

Building an Innovation Discontinuance Model: The Case of Twitter

Yee Man Ng, PhD

The University of Texas at Austin, 2018

Supervisor: Hsiang Iris Chyi

This dissertation seeks to extend Everett Rogers's Diffusion of Innovations theory by examining social media users' post-adoption behavior.

Despite the rapid growth of social networking sites (SNSs), the rate of user discontinuance is staggering. Keeping users active and engaged has always been a crucial issue for SNSs. Prior diffusion research has largely focused on innovation adoption, whereas innovation discontinuance is overlooked. However, innovation discontinuance is a vital facet of the diffusion process. In the real world, only a few innovations become institutionalized while most end up being fads that most users discontinue quickly.

While early studies approached discontinuance as a one-time, complete abandonment of an innovation, this study extends the concept by examining two types of discontinuance: intermittent and permanent. Intermittent discontinuers are users who leave an innovation for a break but resume the use at a later time; permanent discontinuers are those who have no intentions to return. This study takes a mixed-methods approach—combining a user survey with computational analyses of "big data"

drawn from Twitter—to explore the differences between intermittent and permanent discontinuers in three dimensions: (1) their distinctive characteristics (demographic, behavioral, and psychographic), (2) reasons for discontinuance, and (3) decision processes. The concept of intermittent discontinuance leads to the development of a new post-adoption decision-making model, which accounts for discontinuers' planned and unplanned readoption behavior. This cyclical, multi-stage model also provides a systematic framework to compare the behavior and cognitive reasoning between intermittent and permanent discontinuers at each phase of the post-adoption cycle.

While prior studies employed both qualitative and quantitative research methods to examine discontinuance, few came up with clear and reliable ways to measure the timeframe of discontinuance and users' reasons for discontinuance. To address the arbitrariness of determining what length of inactivity constitutes intermittent and permanent discontinuance, this study introduces a mathematical approach based on an innovation's life cycle and its user base. To examine users' reasons for discontinuance, this study refines and expands Rogers and Shoemaker's replacement-disenchantment typology—by factors and by discontinuance typologies.

While Rogers conceptualized the innovation-diffusion process as an uncertainty reduction process, this study suggests that post-adoption decision-making process is a disturbance-coping mechanism—a temporal settlement of the constant interplay between an innovation's utilitarian performance and social media exhaustion. Intermittent discontinuance usually occurs due to information overloads. Permanent discontinuance tends to occur due to perceived innovation shortcomings and innovation replacement.

This dissertation provides theoretical insights into the temporal instability of an innovation, and why and how an innovation is discarded or discredited. The findings contribute to an adequate comprehension of the entire innovation diffusion process, which also helps SNS providers develop tailor-made retention solutions to re-engage SNS users.

Table of Contents

List of Tables

List of Figures

INTRODUCTION

Chapter 1: Social Media Use Discontinuance

In recent years, there has been a proliferation of social networking sites (SNSs) that allow people to interact in online space. However, not all SNS providers have managed to retain the interest of their users for long. For example, once-successful platforms like Friendster and Myspace lost members after a relatively short period of time. Even the SNS giant Facebook is not immune to the threat of membership loss, as it is facing a decline in teenage users (Olson, 2013). A survey conducted by the Pew Research Center revealed that 61% of Facebook users in the United States took extended, weeks-long breaks from Facebook, and about 20% quit permanently (Rainie, Smith, & Duggan, 2013). Social media fatigue and privacy concerns have garnered substantial attention as some of the reasons leading to SNS discontinuance (e.g., Maier, Laumer, Eckhardt, & Weitzel, 2015; York & Turcotte, 2015; Zhang, Zhao, Lu, & Yang, 2015), also known as churning (Kim, Choi, Lee, & Rhee, 2017). Those fatigue and concerns have prompted some opinion leaders to advocate taking a social media vacation or “cleanse”—time away from SNSs (e.g., Aiisha, 2016; Bievens, 2017).

The sustainability of a SNS depends not only on people joining, but also on people staying and contributing. Even if a SNS rapidly gains its user base, it has a retention problem if it cannot keep its acquired users active (e.g., Ahn, Han, & Lee, 2006; Kim, & Yoon, 2004). SNS discontinuance is not uncommon. For instance, while Twitter has reported membership growth every year, a considerable number of user accounts have shown prolonged inactivity. Liu, Kliman-Silver, and Mislove (2014) observed that up to one-third of all Twitter accounts were inactive at the end of 2013. Similarly, Fu and Chau (2013) found that 57.4% of accounts at Sina Weibo, a popular Chinese microblogging site, had no content on their timelines. Such staggering statistics call for more research on what SNS users do after the adoption (i.e., post-adoption behavior).

Theoretical Argument

Everett Rogers's diffusion of innovations theory (1962) has been employed frequently in previous research on adoption behavior. The theory seeks to explain how, why, and at what rate people adopt innovations (i.e., new ideas and technologies). However, innovation adoption is not necessarily the end of the process: An innovation may be discarded at any time after adoption. With the growing number of SNSs, it is not uncommon that users opt out of a digital platform or switch from one platform to another. Rogers (2003) used the term *discontinuance* to refer to the decision to drop an innovation after it has been adopted. Nevertheless, the diffusion of innovations theory focuses on the adoption process, while examination on the innovation post-adoption behavior is lacking. The emphasis on adoption research is not surprising as the theory was developed during a time of economic and technological growth and reflected an interest in new practices and ideas (Newell, Genschel, & Zhang, 2014). In the real world, however, only a few innovations actually become institutionalized while most end up being fads (Strang & Macy, 2001). If researchers understand discontinuance and its relation to diffusion, they may be able to develop theoretical insights into the temporal instability of an innovation, and why and how an innovation is discarded or discredited. Subsequently, researchers may gain an adequate comprehension of the entire innovation diffusion process (Abraham & Hayward, 1984; Leuthold, 1967).

Applying the diffusion of innovations theory, this dissertation aims to enrich the literature on SNS discontinuance and users' post-adoption behavior. Given the prevalent practice of taking short-term breaks from SNSs, this study attempts to extend the concept of discontinuance to intermittent and permanent discontinuance. Subsequently, this study explores and compares the differences between intermittent and permanent discontinuers in three dimensions— (1) their distinctive characteristics (demographic, behavioral, and psychographic), (2) reasons for discontinuance, and (3) post-adoption decision processes. The innovation-decision process itself generally has been presented as a sequence of stages; this study aims to develop a similar stage-by-stage post-adoption decision-making model, but in cyclic structure that involves six phrases: pre-evaluation, evaluation, preparation, action, post-action, and relapse over time. Also, Rogers and Shoemaker's (1971) replacement-disenchantment typology is critically evaluated. The typology generalizes the reasons for innovation discontinuance to replacement discontinuance (i.e., an innovation is rejected because a better innovation replaces it) and disenchantment discontinuance (i.e., an innovation is abandoned because the adopter is dissatisfied with its performance). This study suggests a more comprehensive and rigorous categorization of reasons for discontinuance, by factors (i.e., user-, context-, relationship-, function-, and content-related factors) as well as by discontinuance typologies (i.e., disenchantment, replacement, completion, and indifferent discontinuance).

REASONS FOR STUDYING SOCIAL MEDIA DISCONTINUANCE

One interesting aspect of SNSs is that users can have multiple accounts on different platforms at the same time. A survey conducted by the Pew Research Center in 2018 estimated that, in general, the average American uses three SNS platforms. For instance, roughly three-quarter of Twitter (73%) and Snapchat (77%) users indicate that they also use Instagram (Smith & Anderson, 2018). Yet, while users may have multiple SNS options, they have limited time and cognitive energy to engage with all these accounts (Arrese & Albarran, 2003). Therefore, they have to decide how much time to spend and how active they get involved in one site over another. This becomes an issue for an incumbent SNS as the rise of alternative sites may shift focus on the alternatives. Parthasarathy (1995) believed that people may abandon innovations that can easily be substituted by another innovation because they become obsolete. As SNSs do not require financial switching costs that often incurs as a result of changing brands or products (Park, 2014), discontinuance is more likely to happen when the incumbent SNS is not as good as the alternative sites.

Following this further, when users leave or limit their use of a SNS, they not only affect themselves but also those who connect with them on the platform. Research has suggested that social factors play a key role in technology adoption as they help reduce uncertainties toward innovations (Rice, 2009; Rogers, 2003). These social factors could also apply to the discontinuance behavior. Parthasarathy (1995) found that individuals who stop using an innovation due to dissatisfaction are more likely to disparage the product to other adopters. Negative interpersonal influence of discontinuers is generally stronger than their positive influence (Oliver, 1997). Therefore, once users discontinue their use of a SNS, other users may be aware of the decision and follow suit, creating a cascade effect.

THE IMPORTANCE IN PREDICTING SOCIAL MEDIA DISCONTINUANCE

Even if a SNS has attracted a huge number of users, only active users make major contributions to the sustainability of the site. The proportion of active users in the user base is an important measure of healthy SNS development (Valenzuela, Park, & Kee, 2009). Jarvenpaa, Knoll, and Leidner (1998) argued that if an online community experiences low participation, poor content, unorganized contributions, and transient memberships, the community would not be able to sustain for long. Hence, it is important for SNS providers to monitor users' activities and engagement levels.

While SNSs can easily identify an inactive user, it is hard for them to define which users are discontinuers. In telecommunication or newspaper industries, their businesses are usually based on subscription models. A discontinuer can be clearly defined when the subscriber terminates the service (Kim et al., 2017). In contrast, SNSs are widely based on freemium models (Owyang, 2012). Users could leave platforms for a few months or even years without notifying anyone. As such, SNS providers can only rely on users' activity levels to determine whether a user account is dormant or not (Fader & Hardie, 2007). However, by the time a user is confirmed as a definite discontinuer, the SNS may have already lost that user. This fact motivates researchers and SNS providers to explore factors that could predict user discontinuance and, subsequently, identify potential discontinuers in advance. Discontinuance prediction allows businesses to plan for timely retention strategies to keep their users, and thus, maintain a profitable business.

Early discontinuance prediction research has been conducted in a variety of commercial fields such as banking (e.g., Anil Kumar & Ravi, 2008; Xie, Li, Ngai, & Ying, 2009), mobile telecommunicatios (e.g., Ahn et al., 2006; Kim & Yoon, 2004), gaming (e.g., Kawale, Pal, & Srivastava, 2009; Kim et al., 2017), and online communities, such as Yahoo! Answers (Dror, Pelleg, Rokhlenko, & Szpektor, 2012). In each field, discontinuance prediction has evolved in accordance with the industry development. Specifically, the cost of acquiring new users is five to seven times higher than the cost of keeping existing customers. Therefore, SNS providers are also advised to focus on user retention and user engagement (Khalifa & Liu, 2007). Identifying

SNS discontinuers at an early stage helps ensure timely delivery of retention solutions and recapture users' attention. Likewise, knowing why users abandon certain SNSs can provide insights into platforms' technological shortcomings, and ultimately, leading to the creation of higher-quality digital platforms (York & Turcotte, 2015).

Besides these managerial implications, user discontinuance prediction is also of great theoretical importance. Existing studies on SNSs mainly focus on static descriptions and explanations of what has already happened, such as user motivation and intention to use SNSs (e.g., Chen, 2015; Java, Song, Finin, & Tseng, 2007; Raacke & Bonds-Raacke, 2008). To complement existing literature on SNSs, this study seeks to explore factors (also known as features in the field of data science) that predict Twitter users' future behavior and the possibility of discontinuance.

TWITTER AS THE CASE OF STUDY

This dissertation focuses on Twitter as the innovation to study.

Established in 2006, Twitter has received tremendous attention among media practitioners and scholars. According to the Pew Research Center, 24% of online adults in the United States use Twitter (Smith & Anderson, 2016). While its user base is considerably smaller than Facebook's (68% of online adults in the United States), Twitter arguably has a disproportionate influence because many politicians, journalists, and celebrities utilize this platform. On Twitter, users can publicly post messages (*tweets*) up to a limit of 280 characters[1] to respond in real time to events happening around the world (Kwak, Lee, Park, & Moon, 2010).

[1] In the hope that it will encourage more people to post, Twitter has doubled the number of characters to 280 characters per tweet since September 2017. Before the time, each tweet only allowed up to a limit of 140 characters.

Unlike the Facebook's invitation-only format, Twitter users can follow other users and read their tweets without the need for approval (Park & Kaye, 2017), thereby, constructing a directed network among them. Moreover, a user can propagate tweets of others to his or her followers using a function called *retweet*, which results in information diffusion (Kawamoto, 2013). Therefore, in addition to interpersonal communication, Twitter is increasingly used as a strong medium for opinion expression and rapidly changes the way how audience gathers information (Newman, 2009). Televised sporting events such as the Olympic Games, or entertainment events such as the Academy Awards ceremony, cause massive real-time spikes in global Twitter activity; disasters such as Hurricane Harvey, and tragedies such as the Las Vegas shooting, show instantaneous aftereffects on the platform, as users search for information and report their experiences, often as the incidents are unfolding. This dynamic makes Twitter seemingly irresistible to the mass media. As such, Bruns and Burgess (2012) claimed that Twitter is the most prominent example of a recent shift in SNSs, saying "Twitter is both a social networking site and an information stream" (p. 803). Similarly, Highfield, Harrington, and Bruns (2013) observed that Twitter has deeply embedded in the media ecology and served as an "unofficial extension" of traditional media (p. 381).

Since its early years, however, Twitter has been struggling to re-engage inactive users. In 2009, research analyst firm Nielsen Online (2009) reported that the number of Twitter quitters outnumbered those who stayed, claiming that approximately 60% of Twitter users quit the platform within the first month of joining in. Likewise, Page (2014) found that there are more than a billion dormant Twitter accounts. Also, a report from Survey Monkey Intelligence showed that Twitter's discontinuance rate is almost 10 times higher than Facebook's (Allan, 2016). Verto Analytics, an American media analytics company, also reported similar results—Twitter suffered from a churn rate of about 25%, losing nearly a quarter of its user base between quarter 3 and quarter 4 in 2016 (Hwong, 2017). In 2017, Twitter officially reported a decline in its monthly user base in the United States from 70 million in Q1 to 68 million in Q2 2017. Its global user base stayed stagnant at 328 million users (Trefis, 2017). Therefore, keeping users active and engaged has always been a crucial issue for Twitter.

Given its high publicity, far-reaching impact, but low retention rate, Twitter as a platform affords researchers a unique opportunity to explore its users' post-adoption behavior. Therefore, this study examines the characteristics of Twitter discontinuers, the reasons for their discontinuance, and their decision-making processes of discontinuance.

An Interdisciplinary, Mixed-Methods Approach—Survey and Machine Learning

This study examines and compares discontinuers' characteristics, their post-adoption decision-making processes as well as their reasons for dropping an innovation. To gain a comprehensive understanding of Twitter use discontinuance, this study utilizes a mixed-methods approach combining a computational analysis of the "big data" drawn from Twitter (Study 1, N = 28,404 Twitter accounts) with a Twitter user survey (Study 2, N = 419 respondents). The complementary analytic approach affords a thorough understanding—with explanation, interpretation, and prediction—of Twitter use discontinuance behavior. Specifically, this study used computational analysis to determine a timeframe that defines whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer. The benchmark was then used to draft questionnaire questions about Twitter use in the user survey. To investigate distinctive characteristics between intermittent discontinuers and permanent discontinuers, both computational analysis and user survey were employed.

ORGANIZATION

To summarize, this dissertation adopts an interdisciplinary, mixed-methods approach—combining survey and computational methods—to generate a holistic portrayal of Twitter use discontinuance. The purpose of this dissertation is four-fold: (1) To understand different types of discontinuance (intermittent discontinuance and permanent discontinuance) observed among Twitter users; (2) to investigate differences between intermittent discontinuers and permanent discontinuers, in terms of their distinctive characteristics (demographic, behavioral, and psychographic), reasons for discontinuance, and discontinuance processes; (3) to propose a new theoretical post-adoption decision-making model; and (4) to build a Twitter use discontinuance prediction model.

Chapter 2 provides theoretical foundation of this study: The diffusion of innovations theory. It summarizes existing scholarship concerning the characteristics of adopters and discontinuers and discusses the conceptual differences between intermittent and permanent discontinuance. Chapter 3 reviews the reasons for discontinuance. Rogers and Shoemaker's replacement-disenchantment typology and other discontinuance typologies, such as indifferent discontinuance and completion discontinuance, are evaluated. Chapter 4 presents a new theoretical post-adoption decision-making model. Chapter 5 discusses the strengths and weaknesses of studying innovation discontinuance with a user survey and how to complement it with the emerging "big data" analysis. This chapter also provides a methodological overview of prior discontinuance studies. Chapter 6 describes the complementary analytic approach and the procedures. It outlines the process of data collection and introduces the constructs and measurements. Chapter 7 and Chapter 8 present the results from the computational analysis and the user survey analysis, respectively. Chapter 9 discusses the findings and summarizes the major contributions of this work. This chapter also suggests future directions that could build on the methods proposed in this dissertation.

THEORETICAL BACKGROUND

Chapter 2: Aspects of Adoption and Discontinuance

This chapter summarizes the existing scholarship concerning the characteristics of adopters and discontinuers. It further discusses the conceptual differences between intermittent and permanent discontinuance and criticizes the arbitrariness of determining what length of inactivity constitutes intermittent and permanent discontinuance in the prior literature. Finally, this chapter proposes a mathematical approach, based on an innovation's own life cycle and its user base, to generate the benchmark (i.e., the duration *D* of a break),

DEFINITION OF INNOVATION ADOPTION

In 1962, Everett Rogers began his groundbreaking work on the process of innovation diffusion. Since then, Rogers's diffusion of innovations theory has served as the framework for thousands of studies on the adoption of technologies; specifically, how innovations spread within and between communities. The theory has been applied in almost every discipline, from anthropology to marketing, to general sociology (e.g., Dearing, 2009; Harting, Rutten, Rutten, & Kremers, 2009).

Rogers (1983) defined an innovation as "an idea, practice, or object, that is perceived as new by an individual or other unit of adoption" (p. 11). Further, he considered adoption to be an individual decision "to make full use of an innovation as the best course of action available" (p.21), and the phrase *full use* was interpreted by Parthasarathy (1995) as the conscious decision to use an innovation; therefore, adopters are individuals who follow this conscious decision to use an innovation.

Five Stages of the Innovation-decision Process

According to Rogers (2003), the innovation-decision process refers to “an information-seeking and information-processing activity, where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation” (p. 172). This process occurs in a time-ordered sequence of five stages: knowledge, persuasion, decision, implementation, and confirmation (Figure 1). During the **knowledge** stage, potential adopters become aware of the existence of an innovation through mass media messages and attempt to determine “what the innovation is and how and why it works” (Rogers, 2003, p. 21). The second stage, **persuasion**, occurs when individuals form positive or negative attitudes and beliefs regarding the innovation, in reaction to knowledge gained in the previous stage. At the **decision** stage, individuals choose to adopt or reject the innovation, which reflects the development of behavioral intentions to implement the innovation. The **implementation** stage refers to the initial trial period for the new technology, which references overt behavior. Finally, in the **confirmation** stage, adopters seek reinforcement for the adoption decisions already made and may revoke their adoption if they are exposed to conflicting messages regarding the innovation. Thus, those same stages that end in continued adoption (retention) can also end in discontinuance (rejection after initial adoption) (Ratts & Wood, 2011).

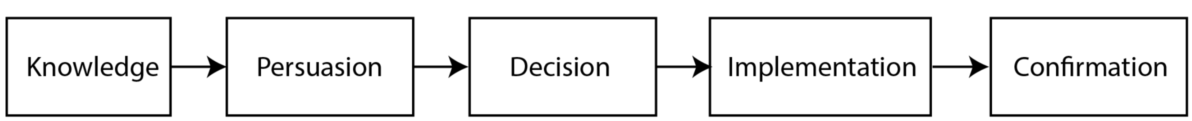

Figure 1: Five Stages of the Innovation Decision Process. Adopted from Rogers (2003).

DEFINITION OF INNOVATION DISCONTINUANCE

The term *discontinuance* was first introduced by Rogers (1995), referring to the action of rejecting an innovation after adoption. Rogers emphasized that for discontinuance to occur, a discontinuer must have previously adopted and used an innovation, so that, could later make a conscious decision to stop using an innovation (Parthasarathy, 1995). Discontinuance is perceived as an indication that an innovation has not been fully adopted as a standard practice for an individual or organization. It is also perceived as a failure to reduce uncertainty about the expected consequences of the innovation at the implementation stage (Rogers, 2003).

Although innovation diffusion has attracted voluminous attention from different disciplines, innovation discontinuance has, thus far, received relatively little systematic research. Rogers (1995) observed: "Perhaps owing to the pro-innovation bias that pervades much diffusion inquiry…, investigation of rejection behavior of all kinds has not received much scientific attention." (p.172). This imbalanced concentration on adoption does not demonstrate an adequate comprehension of the entire innovation diffusion process. While an innovation may appear to have a continuous growth in new adopters, unnoticed user discontinuance may also happen.

Some scholars have acknowledged the importance of studying discontinuance. They have argued that an understanding of the conceptual meaning of discontinuance and its relation to diffusion is pivotal to the development of the entire innovation diffusion process (Abraham & Hayward, 1984; Leuthold, 1967). For instance, in Leuthold's study (1967) of farm innovations among Wisconsin farmers, he found that the number of innovation discontinuers was roughly approximate to the number of new adopters in any given year. He concluded that the success of a technology depends on both of its rate of adoption and its degree to which current users continue or stop using the technology. Thus, Leuthold argued that absence of both continuance and discontinuance measures of an innovation obscures the portrayal of the overall impact of an innovation. Likewise, Black (1983) postulated that diffusion is dynamic in nature, with users who “are continually entering and leaving the [diffusion] process” (p.358). Hence, neglecting the discontinuance process of adopters would create an incomplete picture for innovation diffusion.

Several early studies presented a general approach for studying how a practice is discontinued. In 1965, DeFleur studied the discontinuance of four mass media (i.e., newspapers, films, radio, and TV), calling for a “curve of abandonment” for “once-institutionalized behavior forms that are dropped from a social or cultural system by a given group or society” (p. 318). Rogers (1995) proposed the theoretical path of discontinuance as a reverse S-curve, which is opposite to the typical S-shaped curve illustrating innovation adoption (Terlaak, Gong, & Kim, 2008). While both S-shaped curves illustrate the cumulative number of adopters of an innovation over time within a social system, a typical diffusion curve shows a slow adoption by only a few users, followed by a steep increase in uptake before the curve flattens again as the few remaining individuals finally adopt. In contrast, the reverse S-curve illustrates the decline in usage—starts out slowly, picks up speed, then slows as the continued usage approaches the point of extinction (Figure 2). Rogers, Chapman, and Giotsas (2012) further explained that the decline phase (discontinuance) begins “when continuous investment is no longer sensible as there has been a failure to progress to the natural growth phase” (p. 122).

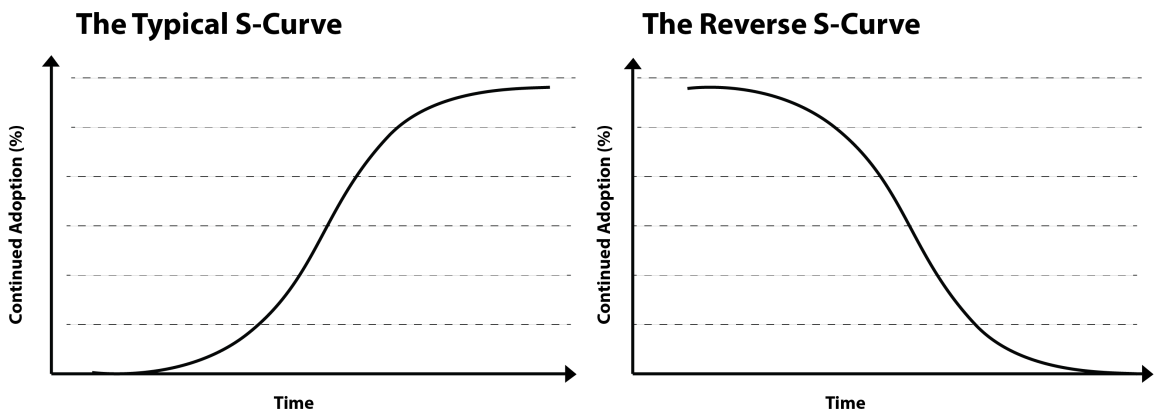

Figure 2: Traditional S-Curve for the Diffusion of Innovations theory (Left) & Theoretical Discontinuance Curve (Right). Adopted from Rogers (2003).

Although diffusion curves tend to be S-shaped, variance lies in the slope of the S-curves. While new innovations that diffuse rapidly create steeper S-curves, some innovations have a more gradual slope for their slower rate of adoption or discontinuance (Peshin & Dhawan, 2009). The rate of innovation diffusion is largely affected by adopters' and innovations' characteristics. This study, specifically, examines how users' characteristics affect the rate of innovation diffusion.

ADOPTER CATEGORIES

The diffusion rate has been an important research area to sociologists and advertisers. According to the diffusion of innovations theory, individuals in a society system do not adopt an innovation at the same time. Rather, they adopt an innovation at different time points during the innovation diffusion process. Rogers (1983) identified five distinct categories of adopters (i.e., innovators, early adopters, early majority, late majority, and laggards) according to the development of a typical S-shaped curve (Figure 3). Within the "lag" time between introduction and saturation, the S-shaped curve predicts a slow period of growth (i.e., introduction), then a fast rate of progression (i.e., adoption), followed by a plateauing (i.e., saturation) (Dearing, 2009).

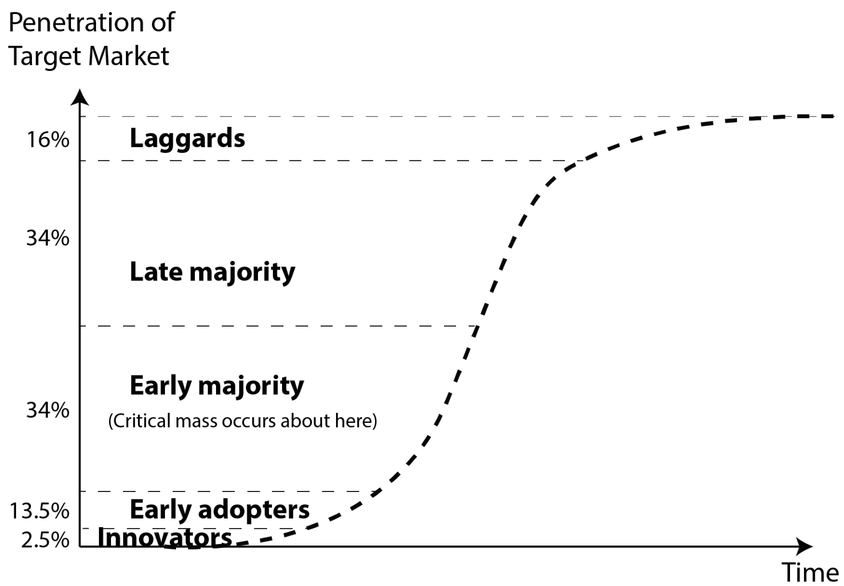

Figure 3: S-curve for the Diffusion of Innovations Theory and the Adopter Categorization.

Innovators constitute the first 2.5% of the adoption groups and rarely face immediate mimicking because of how far ahead this group is in relation to others (Abrahamson & Rosenkopf, 1993; Rogers & Shoemaker, 1971). **Early adopters** (13.5%) use significant interpersonal communication with members in similar organizations (i.e., a social system) to find out about new ideas. Typically, early adopters are opinion leaders within a social system and can help increase the rate of adoption (Rogers, 2003). When a critical mass of early adopters is established, the process of technology diffusion becomes "self-sustaining" (Rogers, 1995, p.

314) and exhibits a snow-ball effect. The process of diffusion spills over from early adopters to the early majority. **Early majority adopters** (34%) interact with peers and move slowly to adopt, preferably after watching earlier users gain success. In comparison, **late majority adopters** (34%) face peer pressure to adopt. **Laggards** (16%) are the last group to adopt an innovation. Laggards hold traditional views, and they are more skeptical about innovations and change agents than the late majority. Thus, laggards tend to decide after looking at whether other members of their social system successfully adopted the innovation. Rogers (2003) also argued that "the individuals or other units in a system, who most need the benefits of a new idea (the less educated, less wealthy), are generally the last to adopt an innovation" (p. 295).

ADOPTER AND DISCONTINUER CHARACTERISTICS

Characterizing different groups of adopters helps target potential users for new innovations (Kotler & Zaltman, 1976; Im & Ha, 2012), predict the growth of innovations (Vijayasarathy, 2004), and develop marketing strategies (De Marez, Vyncke, Berte, Schuurman, & De Moor, 2007; Engel, Blackwell, & Miniard, 1986). Researchers have endeavored to establish the profiles and behavioral characteristics of earlier adopters versus later adopters (Agarwal, Ahuja, Carter, & Gans, 1998; Dee Dickerson & Gentry, 1983; Martinez, Polo, & Flavian, 1998), since Rogers (1962) first argued for the pivotal influence of earlier adopters in determining both the rate and volume of innovation uptake. However, very few empirical studies have examined the characteristics of discontinuers and how these characteristics affect the rate of innovation discontinuance. While businesses are developing retention strategies to keep their users, a homogeneous retention strategy may not work for all discontinuers. A thorough study on discontinuers' characteristics helps SNS providers to identify distinctive segments among discontinuers and develops more effective retention solutions.

This study categorizes individual profiles via demographic, psychographic, and behavioral characteristics. These are characteristics that have proven to have major influences on adoption decisions. Some of them have preliminary proven to be important determinants of discontinuance decisions as well.

Demographic Characteristics

Besides dividing adopters into five categories, Rogers (2003) and Parthasarathy and Bhattacherjee (1998) offered a theoretical and empirical distinction between earlier adopters and later adopters, based on their time of adoption within their social systems. Considerable research lends support to the idea that earlier adopters, when compared to later adopters, are better educated, typically younger (Robertson, Zielinski, & Ward, 1984; Vishwanath & Barnett, 2011), and have more upward social mobility and social status (Chatzoglou & Vraimaki, 2010). Conversely, Rogers (2013) characterized discontinuers "sharing" similar features as laggards or later adopters. They are less educated, less cosmopolitan, and have less contact with change agents with fewer financial resources. However, counter to Rogers's predictions, York and Turcotte (2014) found that socioeconomic status and geographical location explain little of the variation in Facebook discontinuance behavior. While York and Turcotte focused on Facebook, this study references similar demographic characteristics with respect to Twitter use discontinuance.

Behavioral Characteristics

In addition to demographic differences among adopters, individuals in different adopter categories have diverse communication behaviors. In this study, behavioral characteristics include sources of influence, rate of adoption and discontinuance, and motivations for discontinuance.

Sources of influence

Innovation adoption is a social process. Previous research has found that the decision to adopt an innovation largely relies on other adopters in a communication network. In other words, the use of an innovation is largely determined by social consensus (Markus, 1994).

Prior to adopting the innovation, individuals are uncertain about the benefits an innovation will provide. As a result, a potential adopter seeks additional information about the value of the innovation. Research lends support to the notion that earlier adopters are generally known as opinion leaders who drive the rate of the spread of an innovation. They are respected by their peers and become an individual to check with before adopting an innovation (Rogers, 2003). These earlier adopters (i.e., the critical mass) trigger the masses by communicating their adoption to other people and decrease the uncertainty of a new idea by networking and role modeling (Rogers, 2003). Feedback from earlier adopters largely determines the rate of innovation adoption.

In contrast, many studies have argued that innovation discontinuance is an individual process, driven by personal preferences (Burns & Wholey 1993; Greve, 2011; Terlaak & Gong 2008). Terlaak and Gong (2008) explained that innovation discontinuance occurs after individuals have a direct personal experience with the innovation; thus, individuals can make their own decisions to abandon an innovation without relying on others' information.

This study examines whether the decision to discontinuance using Twitter is a social process or individual process.

Rate of adoption and discontinuance

Besides the rate of adoption discussed earlier, the rate of discontinuance is also different between earlier adopters and later adopters. Leuthold (1967) found that later adopters are more likely to discontinue using an innovation than earlier adopters. Similarly, Bishop and Coghenour (1964) found that the rate of discontinuance for Ohio farmers ranged from 14% for the earliest adopters (innovators) to 40% for the laggards. To explain this phenomenon, Parthasarathy and Bhattacherjee (1998) rationalized that earlier adopters have more realistic expectations of innovations because their initial adoption decisions are “based on a rational assessment of the service’s costs and benefits” (p. 365). In contrast, later adopters may have unrealistically high expectations of innovations as their expectations are usually based on opinions from their interpersonal sources, such as friends and peers, rather than their own rational decisions. Additionally, later adopters generally lack technological and cognitive skills to utilize the service extensively, and thus, are more prone to discontinuance (Parthasarathy & Bhattacherjeem, 1998; Rogers, 1995). As a result, a later adopter is believed to be more likely to have a slower rate of adoption, but a faster rate of discontinuance.

Motivations for discontinuance

Previous research has also studied the categories of adopters and their reasons for discontinuance. Lemon and Winer (1995) suggested that reasons for abandoning a service are different between earlier adopters and later adopters. Parthasarathy and Bhattacherjee (1998) found that when earlier adopters choose to discontinue, their discontinuance are due to replacement—the availability of a superior alternative. Indeed, earlier adopters’ psychographic characteristics, such as technological and independent judgment-making ability, help them to rationally compare alternative services (Parthasarathy & Bhattacherjee, 1998; Rogers, 1995).

Hence, earlier adopters' decisions to discontinue using a technology are contingent on locating a superior alternative innovation. Conversely, when later adopters discontinue, as discussed above, it is more likely due to disenchantment. Therefore, it is believed that individuals of different adopter categories have distinct motivations for Twitter use discontinuance.

Psychographic Characteristics

Psychographic characteristics pertain to individuals' values, attitudes, and personalities. These characteristics influence individuals' propensity to adopt or discontinue an innovation.

Perceptions of innovation

Apart from demographic and behavioral characteristics, various technological adoption models have investigated users' perceptions toward an innovation's features, functions, and capabilities. Rogers (2003) identified a complex set of five perceived attributes of technologies that influence individuals' adoption decisions. Those perceived attributes are: (1) the relative advantage of the technology over preceding technologies; (2) its compatibility with other technologies; (3) the complexity in learning to use the technology; (4) the perceived ability to vicariously observe its consumption; and (5) the ability to test the technology on a limited basis. On the other hand, Davis's (1989) Technology Acceptance Model (TAM) studies how users adopt and use an innovation with a more parsimonious approach, focusing on the impact of two antecedent variables: perceived usefulness and perceived ease of use. Perceived usefulness is defined as a subjective evaluation of an innovation's utility in achieving users' goals. The perceived usefulness in is highly comparable to the relative advantage variable from diffusion theory. Perceived ease of use describes the degree to which an innovation is perceived as being simple to understand and use (Davis, 1989). This variable could be considered the corollary to the complexity concept from diffusion theory. Intuitively, users with high levels of perceived usefulness and perceived ease of use have a higher intention to continue using an innovation, whereas users with low levels of these two measures may have a higher intention to discontinue use (Bhattacherjee, 2001). A study by Parthasarathy and Bhattacherjee (1998) indicated that perceived usefulness is a significant predictor of discontinuance behavior. They argued that customer support programs help adopters to get a better understanding about a new service's utility. This in turn increases adopters' perceived usefulness toward the service, thereby, decreasing the chance of discontinuance. However, they did not find perceived ease of use as a significant predictor of discontinuance. This study examines if perceived usefulness and perceived ease of use play a role in Twitter use discontinuance.

Personal innovativeness

Innovativeness has been a key determinant of innovation adoption across many disciplines (e.g., Agarwal & Prasad, 1998; Cowart, Fox, & Wilson, 2008). The aforementioned Rogers's (2003) five adopter categories (i.e., innovators, early adopters, early majority, late majority, and laggards) are largely based on personal innovativeness. Van Braak (2001) described innovativeness as "a relatively-stable, socially constructed, innovation-dependent characteristic that indicates an individual's willingness to change his or her familiar practices" (p. 144). Prior research has also examined the relationship between innovativeness and discontinuance. While Leuthold (1967) and Jorissen (1969) found that the trait of innovativeness is inversely associated with the rate of discontinuance, Cho (2008) showed that discontinuers' innovativeness does not differ from continuing adopters' with respect to Intranet use. This study further examines if users' innovativeness predicts Twitter use discontinuance.

Independent judgment-making

Independent judgment-making is also a critical factor related to adoption. Midgley and Dowling (1978) defined independent judgment-making ability as “the degree to which an individual is receptive to new ideas and makes innovation decisions independently of the communicated experiences of other” (p. 236). In other words, individuals who make independent judgments are more confident in making adoption decisions and less influenced by others. Carlson and Grossbart (1984) found that earlier adopters have a greater ability to form informed judgments about an innovation than later adopters. This study looks at how independent judgment-making ability influence Twitter use discontinuance.

Personality traits

Prior studies found users’ personality traits play an important role in technological adoption (Vishwanath, 2005). This study extends the scope of diffusion study to examine the role of personality differences in innovation discontinuance. To examine personality differences between adopters and discontinuers, this study utilized the Big Five personality trait model (Costa & McCrae, 1992). The model consists of five key traits: extraversion, neuroticism, openness, agreeableness, and conscientiousness. Definition of these traits and their associations with SNS use are as follows:

Extraversion

Extraversion refers to the degree of sociability or withdrawal a person tends to exhibit. Extraverts are typically outgoing and talkative, whereas introverts are quiet and shy. Hunt and Langstedt (2014) found that extraversion predicts technology use. Compared with introverts, several studies found that extraverts are more likely to spend time on SNSs (Rosen & Kluemper, 2008), more likely to be members of Facebook groups (Ross et al., 2009), and have significantly more SNS friends (Amichai-Hamburger & Vinitzky, 2010). That is reasonable since extraverts tend to maintain persistent communication with their friends (Anderson, John, Keltner, & Kring, 2001). However, Hughes, Rowe, Batey, and Lee (2012) argued that the level of extraversion is negatively related to the use of Twitter. They argued that the increased use of anonymity (the use of alias usernames) and the reduced emphasis on social interaction offered by Twitter is more appealing to introverts.

Neuroticism

Neuroticism is defined as a measure of emotional control. Individuals with low levels of neuroticism have a better control of emotions and stability, whereas neurotic individuals are more anxious, insecure, sensitive, and more likely to experience negative emotions (Costa & McCrae, 1992). Regarding adoption decisions, Ryan and Xenos (2011) found that neuroticism is positively correlated with the amount of time spent on Facebook, but Hughes et al. (2012) found a lack of association between neuroticism and the use of Twitter for socializing. Regarding discontinuance decisions, Quercia, Bodaghi, and Crowcroft (2012) found that the discontinuous use of Facebook is likely to occur if a user is neurotic or introverted. Quercia, Kosinski, Stillwell, and Crowcroft's (2011) study on Twitter users supported Quercia et al.'s (2012) argument and pointed out that individuals high in neuroticism withdraw from Twitter during times of stress and they generally report less satisfaction with the support received by their social networks.

Openness

Openness refers to being open to new experiences. Individuals who have a high score in openness tend to be curious, imaginative, and appreciative of diverse views and ideas, while individuals with low openness prefer familiarity and convention (McCrae & Costa, 1987). Openness is featured in a significant number of studies on online behavior, particularly in the context of technological adoption. Openness is positively correlated with SNS usage (Correa, Hinsley, & de Zúñiga, 2010) and information seeking through Twitter (McElroy, Hendrickson, Townsend, & DeMarie, 2007).

Agreeableness

Agreeableness is a measure of how friendly an individual is, with high ratings associated with being kind, sympathetic, and warm. Less agreeable individuals usually have a greater number of online contacts as the Internet provides the means to build friendships that may prove difficult to initiate and maintain offline (Ross et al., 2009). However, agreeableness is generally found to be unrelated to both SNS use (Amichai-Hamburger & Vinitzky, 2010; Correa et al., 2010) and types of users. For example, agreeableness does not have significant difference among Twitter users who are listeners (those who follow many users), popular users (those who are followed by many), highly-read users (those who are often listed in others' reading lists), or influential users (those with a high Klout score) (Quercia et al., 2011).

Conscientiousness

Conscientiousness can be viewed as a measure of trait-oriented work motivation. Conscientious individuals are extremely reliable and tend to be achievers, planners, and hard workers. While some studies have suggested conscientious individuals are inclined to avoid SNSs so they can focus on important tasks (Butt & Phillips, 2008), others found that the use of Twitter for informational purposes is positively related to conscientiousness (Hughes et al., 2012). Gupta (2008) reported that conscientious individuals are more involved in both knowledge sharing and knowledge acquisition activities. Thus, conscientious individuals are frequent SNS users.

While most of the prior studies examine the relationship between personality traits and SNS adoption, this study studies personality traits with respect to Twitter use discontinuance.

DISCONTINUER CATEGORIES— INTERMITTENT DISCONTINUERS AND PERMANENT DISCONTINUERS

Early studies tend to view discontinuance as a one-time complete abandonment of innovations in use. However, some researchers have argued that post-adoption behavior is not simply a binary distinction between use and non-use, but is a wide array of practices enacting varied degrees of engagement with and disengagement from an innovation (Baumer et al., 2013). Abraham and Hayward (1984) suggested the possibility of a "discontinuance and reintroduction" decision-making process (p. 217). They argued that the majority of diffusion studies have incorrectly assumed that after a user discontinues using an innovation, the innovation would then never be reintroduced. In many cases, however, an innovation might just be "temporarily discontinued," and the same individual could later readopt the innovation (p. 217).

In recent years, some opinion leaders have advocated for the idea of taking a social media vacation. For instance, nearly 50,000 people have joined an online challenge— "99 Days of Freedom"—to experience life without Facebook (Aiisha, 2016; Bievens, 2017). In another example, Schoenebeck (2014) found that the Christian period of Lent becomes, for some, an occasion to limit the use of SNSs. In these cases, SNS users "take a break" from the platform rather than "leaving forever." York and Turcotte (2015) suggested that the so-called "Facebook vacation" is an unaddressed type of discontinuance behavior. Similarly, Baumer et al. (2013) found that many respondents described leaving Facebook but return afterwards. These are people who periodically deactivate their accounts but with intentions to return. Moreover, through in-depth interviews, Ravindran, Kuan, Chua, and Goh (2014) found that some Facebook users take a self-imposed break from the site, and temporarily deactivate their accounts due to social network fatigue. Indeed, some discontinuers preserve positive attitudes toward the innovation and express a strong intention to use the technology in the future when they become confident in themselves (Pollard, 2003). Some Facebook users mentioned that they would use the platform in its authentic way if they use it again (Cho, 2015). Hence, SNS use discontinuance can be intermittent rather than permanent, which differs from the innovation discontinuance previously outlined by the Rogers's diffusion of innovations theory. While both intermittent and permanent discontinuers discard the innovation, their post-adoption behavior evolves differently afterward—intermittent discontinuers resume the use of an innovation and permanent discontinuers have no intentions to return. Thus, rejecting an innovation at one stage does not rule out the possibility of readoption at a later point in time.

CRITICISMS ON PRIOR DEFINITIONS OF INTERMITTENT AND PERMANENT DISCONTINUANCE

General Definition

Few studies have conceptualized intermittent discontinuance. Zhou, Yang, and Jin (2018) referred to an intermittent discontinuer as "an individual who has stopped using the innovation and readopts it later on" (p. 494). Likewise, Shen, Li, and Sun (2018) studied post-adoption usage of wearable health information systems and defined intermittent discontinuance as "a state where people neither continuously use the focal information technology, nor entirely abandon it" (p. 2). Ye and Zhang (2017) defined the concept in a more specific way by classifying intermittent discontinuance as a type of adoption: Individual users decide to adopt an innovation, and then discontinue the use of the innovation for weeks up to six months; they resume using the innovation later, and cycle through these stages.

Operational Definition

While prior studies employed both qualitative and quantitative research methods to examine discontinuance, very few came up with a clear and reliable operational definition for discontinuance. Scholars have come up with various timeframes to define these two types of discontinuance. For example, Cho (2005) defined permanent discontinuers as users who stopped using the innovation for the past six months. Xue and Yu (2017) described intermittent discontinuers as those who have used an innovation in the past six months, but occasionally stopped using it for several weeks. York and Turcotte (2015) referred to intermittent discontinuers as those who answered “Yes” to the survey question “have you ever voluntarily taken a break from using Facebook for a period of several weeks or more?” (p. 58). To distinguish intermittent discontinuers from permanent discontinuers, Zhou, Yang, and Jin’s (2018) interview protocol included two dichotomous questions—without specifying the duration of the break— “are you still using [Weibo] now?” and “have you ever stopped using [Weibo]?” (p.487). As can be seen here, the duration of taking a break from SNSs is often defined without much justification. This, consequently, tends to make the classification of intermittent discontinuers and permanent discontinuers arbitrary. Many discontinuance studies might follow a generic approach to define discontinuance, and some might simply reference the operational definitions from other studies without considering the unique nature of one innovation. Each innovation has a different life cycle, turnover rate, and user base, and therefore, the timeframe to define discontinuance should vary from innovation to innovation. That is, the duration of taking a break should be innovation-specific. It is worth noting that the duration of a break can neither be too short—a short period may just be a normal pattern for innovation usage, nor too long—adopters may have already left the platform for a long time. If the timeframe to define discontinuance is too short or too long, the operational definition would not be optimal.

To solve this problem, this study introduces a mathematical approach to assess the duration of a break *D* to represent intermittent discontinuance. Further analytical procedures are presented in Chapter 4. This parameter is informed and generated algorithmically through users' activity levels on Twitter, and so it is specifically defined to study Twitter use discontinuance. This approach avoids arbitrarily taking a duration of time as the cut-off point to define Twitter use discontinuance. Hence, for this study, the definitions of continuing adopters, intermittent discontinuers, and permanent discontinuers are as follows:

- Continuing adopters are individuals who constantly use an innovation and have never taken a break from it more than the duration *D*.
- Intermittent discontinuers are individuals who adopt an innovation and take breaks from it for a period longer than the duration *D*; but later resume to use the innovation, and cycle through these processes.
- Permanent discontinuers are individuals who have not used the innovation for a period much longer than the duration *D.* They completely reject a previously adopted innovation and have no plan to use it again.

Despite recent studies on innovation discontinuance, a systematic investigation on the intermittent discontinuance is lacking. Based to the above definitions, this study first explores the following research question:

RQ1: How frequently are intermittent discontinuance and permanent discontinuance observed among Twitter users?

To better capture the dynamic nature of post-adoption behavior, this study proposes a new classification of three types of innovation users: continuing adopters, intermittent discontinuers, and permanent discontinuers. However, little is known about the distinctive characteristics that drive Twitter users to intermittent and permanent discontinuance, this study aims to explore the following research questions:

> **RQ2: To what extent, are Twitter continuing adopters', intermittent adopters', and permanent adopters' characteristics (demographic, psychographic, behavioral) distinct from each other?**

> **RQ3: What characteristics (demographic, psychographic, behavioral) predict whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer?**

Chapter 3: Understanding Reasons for Discontinuance

Scholarly literature has provided some explanations regarding why users abandon an innovation. Early on, Rogers and Shoemaker (1971) suggested two types of discontinuance: (1) replacement discontinuance, in which an innovation is rejected because a better innovation replaces it, and (2) disenchantment discontinuance, an innovation is abandoned because the adopter is dissatisfied with the innovation's performance or the innovation does not meet the need of an individual. The theoretical explanations of these two types of discontinuance are as follows:

REPLACEMENT DISCONTINUANCE

In a rapidly changing society there are constant waves of innovations. Replacement occurs when users "adopt a better idea that supersedes" the previous innovation (Rogers, 1995, p.182). Displacement effect can serve as an explanation for replacement discontinuance. The focus of displacement effect in media studies usually includes *time* and *functional* displacement. The rationale behind time displacement effect is simple: Time spent with the medium is a zero-sum game (McCombs, 1972; Arrese, & Albarran, 2003). Users shift their media time from an existing medium to a new one. Conversely, functional displacement emphasizes the idea of the "functional alternative" (Taipale, 2013), which explains when a new medium serves similar needs but in a better and efficient manner, users would shift to the new medium (Kayany & Yelsma, 2000; Kaye & Johnson, 2003). For instance, Althaus and Tewksbury (2000) suggested that the Internet is a functional alternative to traditional media. Ramirez, Dimmick, Feaster, and Lin (2008) showed that Instant Messengers displace e-mails and landline telephones. To date, there is a fierce competition among SNSs. For example, Snapchat, a SNS originally built to share ephemeral moments among friends, has taken a significant number of users from Facebook's messenger, especially among 12-to-24 years old users (Statista, 2017).

DISENCHANTMENT DISCONTINUANCE

Disenchantment discontinuance occurs when an adopter is dissatisfied with the innovation's performance (Rogers, 1995). The Uses and Gratifications theory, Expectation Disconfirmation theory, and the Theory of Reasoned Action have been found useful in explaining disenchantment discontinuance.

Scholarly research has drawn upon the Uses and Gratifications theory to study SNS discontinuance. The theory proposes a key distinction between gratifications sought and gratifications obtained (Katz, Blumler, & Gurevitch, 1973; Palmgreen, Wenner, & Rayburn, 1980). Gratifications sought are those gratifications that audiences anticipate obtaining from a medium before they use it. On the other hand, gratifications obtained refer to those gratifications that audiences experience from their exposure to a particular medium. It is worth noting that obtained gratifications may vary from gratifications sought. The discrepancy between these two gratifications would affect the level of satisfaction that individuals experience from the usage of a medium (Palmgreen et al., 1980). Palmgreen and Rayburn (1979) argued that the fulfillment of expected gratifications leads to a recurrent use of the medium; otherwise, audiences would get disappointed and cease utilizing the medium. The disappointment may also lead audiences to search for an alternate medium that can gratify their needs (Quan-Haase & Young, 2010). For instance, Dunne, Lawlor, and Rowley (2010) found that the main reason for young people to use and participate in SNSs is that many of the gratifications they sought (e.g., identity creation and identity management) are connected to the gratifications they obtained—i.e., the rewards that accrue from such actions (e.g., peer acceptance).

Besides the Uses and Gratifications theory, the Expectation Disconfirmation Theory and the Theory of Reasoned Action also address disenchantment discontinuance. These two theories denote the existence of the post-adoption stage (Cho, 2015). Bhattacherjee and Premkumar's (2004) Expectation Disconfirmation Theory explains how expectations toward an innovation can change after their initial acceptance of the innovation, particularly through parameters such as usefulness, satisfaction, confirmation, and continuance intentions. The theory suggests that users' subsequent continuance, as well as discontinuance decisions, depend on whether one is satisfied with the technology and whether his/her expected utility is realized (Bhattacherjee, 2001). On the other hand, the Theory of Reasoned Action posits that behavior is a function of attitudes and subjective norms. The theory contrasts adoption with post-adoption behaviors, suggesting that pre- and post-adoption criteria may significantly differ in many ways (Ajzen & Fishbein, 1980). For example, Zhu and He (2002) found that Internet adoption and Internet use in China are two distinct processes and are influenced by different predictors: Internet adoption is primarily affected by perceived popularity and perceived characteristics of the Internet, but Internet use is solely influenced by perceived need for Internet.

It is worth noting that disenchantment discontinuance is very common: More than 60% of adopters cease using an innovation due to dissatisfaction (Keaveney, 1995). York and Turcotte (2015) found that disenchantment discontinuance is one of the leading motivations for temporary discontinuance of Facebook, followed time burden. Specifically, their research indicated that respondents were dissatisfied with Facebook as its content being "too dramatic" and "boring" (p. 60).

Social Media Fatigue

Besides low-quality content, social media fatigue could be a major contributor to SNS disenchantment discontinuance (Maier et al., 2015; York & Turcotte, 2015).

Despite various positive outcomes that show SNSs are beneficial to users in various aspects in life, negative consequences due to excessive SNS use are also non-negligible. The excessive integration of SNSs in daily routines invades people's daily lives, bringing huge amounts of information, communication, and social support requests. All these forms of stress drive users into an exhausted situation (e.g., Lee, Son, & Kim, 2016; Ravindran et al., 2014). Goasduff and Pettey (2011) proposed the concept of social network fatigue to represent the negative feelings of tiredness, boredom, and burnout that can be induced by SNSs. Literature has drawn on theories regarding extrinsic and intrinsic motivations (Deci, 1975) to explain reasons for SNS discontinuance. Scholars have found that social media fatigue reduces SNS enjoyment (intrinsic benefit), which is one of the most persuasive predictor for people's continued use of SNSs. Thus, social media fatigue negatively influences continuance intention. Empirical studies have found that social media fatigue is one of the major reasons for SNS platform shift, temporary usage retreat, unresponsive interaction, or usage cessation (Luqman, Cao, Masood, & Yu, 2017; Maier et al., 2015; York & Turcotte, 2015). Prior studies have also investigated different determinants of social media fatigue, for example, information overload (Bright, Kleiser, & Grau, 2015), interpersonal comparison (Cramer, Song, & Drent, 2016), and privacy concerns (Gartner, 2010).

Information Overload and Social Burden

In addition, York and Turcotte (2015) showed that most intermittent discontinuers perceived Facebook as a cognitive ("information overload") or social burden ("takes time away from family”). With the rise of SNSs in recent years, the amount of information also increases. As illustrated by “the Zuckerberg’s Law,” the amount of status updates, photos, and other online materials posted on Facebook doubles every year (Bradshaw, 2011). However, individuals have limited capabilities to store and process the flow of information in a limited period of time (Beaudoin, 2008). Information overload refers to when the cognitive threshold is exceeded between the person’s cognitive ability and the endless and invasive postings and activities on information channels (Lee et al., 2016). Many studies have explored information oversupply in the media environment with excessive news or advertisements (Chyi, 2009; Holton & Chyi, 2012; York, 2013). Regarding social burden, Maier and his coauthors (2015) argued that while SNSs facilitate the growth and maintenance of social connections, well-embedded SNS users are expected to offer social support constantly upon request (Ellison, Steinfield, & Lampe, 2007; Krasnova, Wenninger, Widjaja, & Buxmann, 2013). Excessive online social interaction puts pressure on human cognitive processes and causes various communication overload and burdens, such as technostress (i.e., stress caused by working with technology on a daily basis) (Maier et al., 2015). Tarafdar, Tu, and Ragu-Nathan (2010) empirically validated that technostress decreases end-user satisfaction, which determines the duration of an individual’s engagement with a technology.

CRITICISM OF ROGERS AND SHOEMAKER’S REPLACEMENT-DISENCHANTMENT TYPOLOGY

A Call to Extend the Discontinuance Typology

Rogers and Shoemaker (1971) identified that individuals discontinue use of a technological innovation in two situations: disenchantment and replacement. However, Parthasarathy (1995) and Cho (2008) argued that the replacement-disenchantment typology does not adequately represent all the reasons for discontinuance. For example, through a survey with 1,100 U.S. adults, Hawes, Blackwell, and Talarzyk (1976) found that the key reasons leading to service discontinuance includes time constraints, changes in family situations, lost interest, and new alternative interests. Strictly speaking, Rogers and Shoemaker's replacement-disenchantment typology only partially covers the reasons above, without directly addressing reasons such as time constraints, changes in family situations, etc. There is a need to develop a typology that is comprehensive enough to encompass the breadth of reasons for disenchantment. This study calls for a more rigorous categorization—by including indifferent and completion discontinuance as parts of the typology.

Indifferent Discontinuance

The occurrence of underutilization has been widely studied in the information and communications technology literature (Kramer, Walker, & Brill, 2007). Cho (2008) stated that the Rogers and Shoemaker's typology does not incorporate this aspect of discontinuance. To fill this gap, he conceptualized a new type of discontinuance—indifferent discontinuance. Indifferent discontinuance refers to users who "neglect the adopted technology without encountering any problems or feelings of dissatisfaction" (Cho, 2008, p. 21). In contrast to the argument of conscious discontinuance, indifferent discontinuance is a subconscious neglect of an adopted technology. This assumption is based on the limited intellectual capacity in human nature (Weiss, 1999). Cho (2008) argued that indifferent discontinuance could be the most frequent reason for discontinuance.

Besides indifferent discontinuance, Cho (2008) also proposed three additional types of discontinuance. However, these three types of discontinuance are neither built to explain reasons/motivations for Twitter use discontinuance nor designed to examine innovation discontinuance on an individual-level. These types include reserved discontinuance, which states that individuals cease to use a previously adopted innovation but have a strong intention of reusing it if the circumstances are right; partial discontinuance, where users routinely utilize certain features of an innovation but stop using other features; and political discontinuance, in which individuals cease to use a technology due to organizational politics.

Completion Discontinuance

This dissertation also considers a new type of discontinuance—completion discontinuance. Kielmeyer (2003) defined completion discontinuance as a discontinuance that occurs when an innovation has finished serving its purpose and is no longer needed. Completion discontinuance is characterized by the completion of a goal, which could range from a few days or several years or even decades, as perceived by the adopter.

A Call to Enhance the Measurement of Reasons for Discontinuance

Another major criticism of discontinuance studies is that many of them have only investigated users' *primary/main* reason for discontinuance (e.g., Cho, 2008; Parthasarathy & Bhattacherjee, 1998; Parthasarathy, 1995; York & Turcotte, 2015). For instance, even Cho (2008) attempted to measure discontinuance typology in two ways— "categorically and continuously" (p.95), both of the measurements only accounted for users' *primary* reason for discontinuance. Example of his categorical question is as follows:

> Question: Please check the one scenario that best identifies the main reason that you ended your use of Cyworld (a social network service in South Korea).
> 1. I decided to use another technology.
> 2. I become dissatisfied with Cyworld, and have not use similar types of technologies.
> 3. There is no specific reason or critical incident that induced me to stop using Cyworld.
> 4. I am willing to use Cyworld in the future if my situation changes.
> 5. I am selectively using certain features of Cyworld but not all features of it.
>
> — Cho (2008, p. 96)

Each participant was classified as belonging to only one category of discontinuance. Respondents who picked the first option are replacement discontinuers; the second option are disenchantment discontinuers; the third option are indifferent discontinuers; the fourth option are reserved discontinuers; and the last option are partial discontinuers. Cho (2008) also used continuous questions to measure the strength of various reasons for discontinuance. Examples of those measurements are as follows:

Items for replacement discontinuance

1. I ended my use of the system because I found another service that work better.
2. I ended my use of the system because I found an alternative service that had better features.
3. I ended my use of the system because I found other services had more options than the system.
4. I ended my use of the system because I felt that the functional performance of other services was superior.

Items for disenchantment discontinuance

1. I ended my use of the system because I was unhappy with its performance.
2. I ended my use of the system because I was generally dissatisfied with it
3. I ended my use of the system because I was unhappy with one or more features of it
4. I ended my use of the system because I was unhappy with overall functional performance of it

— Cho (2008, p. 97)

Although Cho (2008) also used continuous scales to measure the strength of various reasons for discontinuance, discontinuers are only assigned to the category that they rated the highest score. In many cases, however, multiple reasons cause innovation discontinuance. This study argues that a discontinuer does not exclusively belong to one single discontinuance category, but multiple categories, depending on their reasons for discontinuance.

Several studies employed alternative methods to assess reasons for SNS discontinuance. Instead of utilizing a multiple-choice response format as Cho (2008), York and Turcotte (2015) analyzed an open-ended question, "what made you decide to take a break from using Facebook?"

(p.58). They recorded respondents' verbatim responses and came up with 10 categories to represent motivations for temporary Facebook discontinuance. Besides employing the theoretical discontinuance typology (i.e., disenchantment and replacement), they also included reasons such as privacy concerns and low usage. Although the authors classified each user into one category, the method of content analyzing verbatim responses has the potential to measure multiple users' reasons for discontinuance.

Using another form of categorization, Zhou, Yang, Jin (2018) categorized antecedents of discontinuance into four factors: user-related factors, such as user's habit, time limitation, satisfaction; context-related factors, such as technical disturbance; function-related factors, such as system shortcomings, complexity, and uncertainty; and content-related factors, such as low credibility and low relevance. This study also references their approaches and considers a more comprehensive and rigorous categorization of reasons for discontinuance, by factors (i.e., user-, context-, relationship-, function-, and content-related factors) as well as by discontinuance typology (i.e., disenchantment, replacement, completion, and indifferent discontinuance).

A Call to Refine Disenchantment Discontinuance

Another major criticism of Rogers and Shoemaker's replacement-disenchantment typology is that the discriminatory validity between these two types of discontinuance is questionable. Cho (2008) pointed out that replacement could be the consequence of disenchantment with an adopted innovation. Similarly, Parthasarathy and Bhattacherjee (1998) argued that it is quite possible for a disenchanted discontinuer to quit a service and then adopt another service. Hence, replacement discontinuance and disenchantment discontinuance could coexist. Sharing a similar view, this study argues that the replacement-disenchantment typology is neither mutually exclusive nor exhaustive. While disenchantment can lead to replacement, it is not logical to think the sequence occurs in the opposite direction. Also, a wide range of reasons, from time constraints to functional shortcomings, from privacy concerns to low-quality content, could all be classified under the same umbrella of disenchantment discontinuance. Given the current typology, discontinuers are prone to be disproportionately classified as disenchantment discontinuers. There is a need to extend the typology to one that is more precise. Referencing Zhou et al.'s (2018) study, this study proposes a more granular approach to define discontinuance: by factors (i.e., user-, context-, relationship-, function-, and content-related factors).

INTERMITTENT/PERMANENT DISCONTINUERS AND THEIR REASONS FOR DISCONTINUANCE

As few studies have examined intermittent discontinuers, Zhou, Yang, and Jin's (2018) study of Weibo is the only empirical study to distinguish respective reasons for discontinuance between intermittent and permanent discontinuers. They found that while discontinuers who stop using Weibo because of low usage (similar to indifferent discontinuance discussed above), function-related factors, or content-related factors have a significant tendency to leave permanently. In contrast, users who stop using Weibo due to limited time/resources are more likely to be intermittent discontinuers. They explained that as time and cognitive resources are "volatile" (p. 500), there is a high possibility for users to return when they have more time and feel relieved from SNS exhaustion.

Discontinuers are not a homogeneous group. Intermittent and permanent discontinuers possibly have different reasons for discontinuance. Identifying distinctive motivations for discontinuance between intermittent and permanent discontinuers helps SNS providers to develop an effective retention solution. Previous work on SNS use discontinuance to be the case for Facebook users, but there has not been any analysis of Twitter users at scale. Since Twitter differs from Facebook, people's decisions to leave the two platforms could be very different. It would be beneficial to extend previous work to Twitter. Current empirical research on the association between reasons for discontinuance and type of discontinuers is lacking, thus, to fill the gap in the literature, this study examines respective reasons for intermittent and permanent discontinuers stop using Twitter, addressing the following research questions:

> **RQ4: In general, what are the reasons for intermittent and permanent Twitter use discontinuance?**

> **RQ5: To what extent, are Twitter intermittent discontinuers' and permanent discontinuers' reasons for discontinuance different from each other?**

Chapter 4: The Post-adoption Decision-making Process

Considering the nascent stage of studies examining post-adoption behavior, the term post-adoption, unlike the other concepts of pre-adoption and adoption, has been loosely defined. For some research, post-adoption represents “continued use” (Son & Han, 2011; Ye & Potter, 2011) and “continuous and repeated usage” (Zhou, 2011) of an innovation. Huh and Kim (2008) described the post-adoption behavior as “the subsequent adoption behavior after the first-time adoption.” Parthasarathy and Bhattacherjee (1998) called it as “continued adoption or discontinuance.” As these show, past studies have largely focused on the adoption; few have explored the aspects of discontinuance behavior during the post-adoption period. Yet, it is believed that a person’s belief about the value of an innovation drives both the adoption and discontinuance of an innovation (Burns & Wholey, 1993; Greve, 2011). Just as individuals go through a five-stage process to make behavioral decisions (whether to adopt or not), innovation discontinuance literature suggests that there are also a number of different decision-making processes precede a decision to abandon an innovation (Greve, 1995).

Only a few researchers (e.g., Eichholz & Rogers, 1964; Parthasarathy, 1995) have studied the process of making a discontinuance decision. Parthasarathy (1995) characterized Rogers’s model of adoption as a sequential think-feel-do information processing sequence, which aligns with the Hierarchy of Effects model (Lavidge & Steiner, 1961). The sequence describes a process in which information leads to knowledge, knowledge causes attitude formation, and subsequently leads to a commitment to take an action. Parallel to Rogers’s model of adoption, Parthasarathy (1995) developed a five-step model of discontinuance. Those five stages are: (a) awareness, when the adopter becomes aware of conditions that persuade him or her that the current innovation is inadequate or that better alternatives exist; (b) evaluation, when the adopter processes the information from mass media and/or interpersonal information in order to decide whether or not to continue or discontinue the use of the innovation; (c) trial, when the adopter experiments with other innovations and compares them with the current innovation; (d) decision, when the act of discontinuance occurs; and (e) post-decision, when the discontinuer decides whether the decision made in the previous stage was optimal (Figure 4).

Figure 4: Five-stage Post-adoption Model. Adopted from Parthasarathy (1995).

Unfortunately, thus far, only a few studies have reviewed the Parthasarathy's model (e.g., Cho, 2008; Wang & Butler, 2006). One criticism is that no empirical tests have been done with the above-mentioned discontinuance process. Another criticism is that the model does not clarify whether all discontinuers follow the same process to reach their discontinuance decisions. For example, the third stage (i.e., trial) is applicable to replacement discontinuers who switch to use other innovations only. Moreover, Parthasarathy's model does not consider the possibility of readoption of an innovation. This study argues that discontinuance does not necessarily represent the end-of-life cycle of an innovation but can be just one phase in the post-adoption stage. Therefore, an extended model should consider the differences between the decision-making processes of intermittent discontinuers and permanent discontinuers. Hence, this dissertation seeks to further develop that model and to conduct empirical tests on its applicability.

PROPOSING A NEW MODEL OF DISCONTINUANCE

Referencing Parthasarathy's (1995) post-adoption model, this study proposes a new model for post-adoption period, hoping to adequately examine the decision-making process of how a technology, which is already a part of the routinized everyday activity, is discontinued. Here, the post-adoption decision-making process is conceptualized as a cycle (Figure 5), suggesting that adopters go through stages in sequence. While, in reality, adopters may move forward and backward, or even jump between stages, the cyclical model provides a useful way of understanding the process of innovation discontinuance.

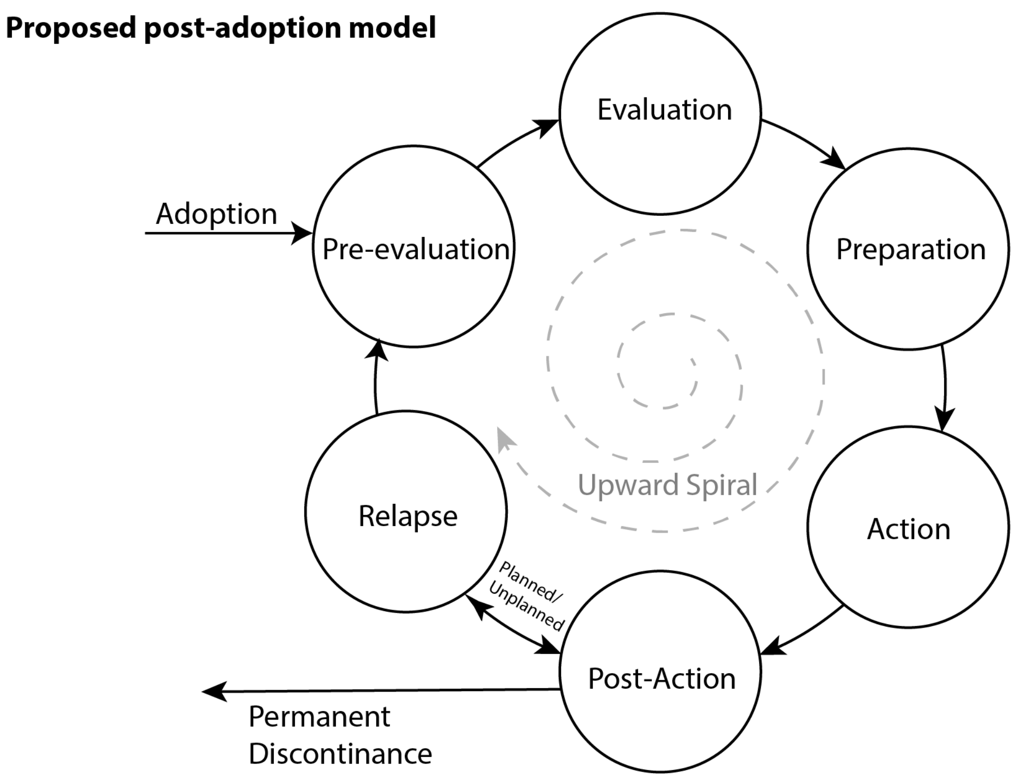

Figure 5: Proposed Post-adoption Decision-making Model.

There are six stages: Stages of pre-evaluation, evaluation, preparation, action (i.e., discontinuance), post-action, and relapse (i.e., readoption).

Pre-evaluation

Pre-Evaluation is the starting point of the model, where adopters become conscious of the innovation and aware of their relationships with the innovation (Cho, 2015). At this stage, adopters have no intention of discontinuing the use of an innovation, either because they are unaware of the existence of better alternatives or they have not developed any dissatisfaction about the innovation yet.

Evaluation

The evaluation stage specifically refers to the stage at which adopters reflect on the benefits and drawbacks of discontinuing. In the context of SNSs, adopters might first search for solutions to reduce disturbance, such as blocking/hiding feeds, or distance themselves from the innovation, such as cutting down on the amount of use. Adopters may evaluate whether the benefits they received through the SNS (e.g., enjoyment, usefulness, and social capital) outweigh the dissatisfaction (e.g., social media fatigue, and privacy concerns) of staying with the SNS. Adopters may also process information from mass media and/or interpersonal information in order to decide how useful the innovation is to their daily lives. They think over what matters to them. However, no commitment of discontinuance has been made yet.

Preparation

During the preparation stage, adopters begin to adjust their usage patterns, such as taking breaks from the innovation, reducing the use of the innovation, deleting the SNS app from their smartphones, or turning off the SNS notifications. Adopters may start to seek out and experiment with better innovations. It is possible that adopters cannot find a superior innovation, despite their initial perceptions that an alternative innovation could be superior. They may end up not discontinuing the current innovation.

Action

This is the stage where discontinuance takes place. Adopters may cancel subscriptions, deactivate/delete accounts, or simply become inactive. They may also switch to another innovation.

Post-action

The post-action stage involves evaluation of the discontinuance choice. Discontinuers may look for reinforcement from their social circle. Some discontinuer may become fully aware of benefits the old innovation provides, or find that the alternate innovation is not as good as the old one. Hence, they readopt the old innovation. Alternatively, discontinuers may feel that opting out of the old innovation remains a good idea after all things are considered.

Relapse

The relapse stage is when discontinuers readopt the innovation. Previous discontinuance is, thus, temporary by nature. In reality, a relapse can be further classified as either planned or unplanned. In a planned scenario, adopters voluntarily take a break from the innovation with an intention to return to the innovation again. In an unplanned scenario, adopters find an unpremeditated need to re-adopt the innovation. For some adopters, they repurpose the use of the innovation.

The upward spiral shows that individuals could go through the post-adoption cycle repeatedly until they come to permanent discontinuance.

This study proposes a new post-adoption decision-making model, which takes discontinuers' planned and unplanned readoption as crucial parts of a post-adoption behavior.

The model aims to provide a structured, comprehensive approach to examine how and why an innovation is discarded or discredited. Intermittent and permanent discontinuers' behavior and cognitive reasoning at each stage are also evaluated, respectively. This study addresses the following research questions:

RQ6: In general, how do users reach their decisions to discontinue Twitter use?

RQ7: To what extent, are Twitter intermittent discontinuers' and permanent discontinuers' post-adoption decision-making processes different from each other?

RQ8: What are the reasons for Twitter readoption for intermittent discontinuers?

RESEARCH DESIGN

Chapter 5: The Mixed-Methods Approach

This study involves several layers of understanding and investigation of Twitter use discontinuance. It conceptualizes and examines the stages of post-adoption decision-making, characteristics that distinguish discontinuers as well as users' reasons for dropping an innovation. Such a series of complex problems require different analytical techniques. Hence, this dissertation utilizes a mixed-methods approach, combining a conventional survey and a computational analysis, to study Twitter use discontinuance. The data triangulation aims to complement and validate findings from both methods (Greene, Caracelli, & Graham, 1989), in which the survey of SNS users could establish part of the initial analytic groundwork by identifying relevant and meaningful questions for inquiry for the subsequent computational analysis of "big data." In turn, the use of Application Programming Interfaces (APIs) and other computational techniques may prompt further integration of the quantitative and qualitative analysis in mixed-methods research designs and help facilitate the understanding of social media as contemporary communicative phenomena (Lomborg & Bechmann, 2014).

SURVEY AND DISCONTINUANCE STUDIES

Survey research has been the most commonly applied method to study innovation discontinuance. For example, Parthasarathy & Bhattacherjee (1998) used a mail survey to examine subscribers' and discontinuers' use and perceptions of online services. Similarly, using secondary data from the 2013 Pew Internet and American Life survey (Rainie et al., 2013), York and Turcotte (2015) studied intermittent discontinuance among Facebook users. Ye and Zhang's

(2017) collaborated with an online survey company and successfully received surveys back from 17,035 Chinese Internet users to explore reasons for discontinuing the use of Weibo.

Survey research is defined as "the collection of information from a sample of individuals through their responses to questions" (Check & Schutt, 2012, p. 160). Given the applicability in exploring and describing human behavior, surveys are frequently used in social and psychological research (Singleton & Straits, 2009). Respondents are usually recruited using conventional survey sampling techniques such as probability-based sample. They are then asked to fill out a questionnaire. Self-reported surveys typically rely on the respondents to recall some levels of detail about their activities and experiences on a medium (Niederdeppe, 2014).

This approach has some key advantages. Survey research can include quantitative research strategies (e.g., a set of predefined numerical rated items), qualitative research strategies (e.g., using open-ended questions to capture and analysis of respondents' verbatim responses), or both. As such, self-administrated surveys can include multiple questions to gather data for correlating media exposure with individual characteristics, opinions, or behavior, such as political participation or health-related behavior. Although self-reported surveys are useful for exploring users' motivations and expectations of a SNS site, they are less useful for accurately capturing online users' responses and behaviors. Several problems may arise through self-reporting (de Vreese & Neijens, 2016). First, respondents must fully understand the meaning of the questions. Challenges arise if the response categories are vague, for example when researchers use the categories such as "seldom," "regularly," or "often" (de Vreese & Neijens, 2016). Second, respondents must be able to recall their experience correctly. Prior (2009) noted this challenge, stating that "respondents may not recall all episodes of the behavior or incorrectly recall them as having occurred during the reference period" (p. 895). This estimation can lead to inaccurate estimates. For example, it has been shown that frequent behavior is often overestimated in self-reports. Social desirability is also a problem because respondents may not want to report the exposure to specific media content, such as low-prestige publications, violence, or pornography (Althaus & Tewksbury, 2007; Clancy, Ostlund, & Wyner, 1979).

Meyer (2004) stated that most diffusion studies have employed survey methodology, gathered data only from adopters, at a single point in time, and usually after the innovation had already diffused in the community. Kee (2017) argued that even though there are practical reasons why diffusion studies have traditionally focused on the quantitative approach with cross-sectional data, existing knowledge of innovation diffusion is constrained by this single methodology. He called for an expansion of the methodological repertoire of diffusion studies.

COMPUTATIONAL RESEARCH AND DISCONTINUANCE STUDIES

Recently, the rapid development of big data research has provided opportunities for diffusion researchers to trace the adoption, implementation, and discontinuation of digital innovations in longitudinal approaches. The ever-increasing use of SNSs has led to the emergence of media-centric digital trace data—data consciously or unconsciously produced by users while interacting with digital tools. The social web has enabled access to social traces at a scale and level of detail, both in breadth and depth, that conventional data collection techniques such as surveys and other user studies could hardly achieve (boyd & Crawford 2012). Moreover, research that involves tracking participants' actual SNS use data through media-centric digital trace data is able to increase measurement validity as well as establish a greater generalizability of results (de Vreese & Neijens, 2016). Another advantage of gathering people information from data sources (e.g., Twitter and blog data) is their "always on" nature. As Taneja and Mamoria

(2012) noted, “all manner of consumption on digital platforms leaves traces, which potentially can provide census-like information on audience behavior” (p. 124). The method allows researchers unobtrusively capture responses and online behaviors (Strohmaier & Wagner, 2014), and therefore, eliminate some of the problems associated with survey instruments. Previous studies have modeled and predicted users’ online behavior based on their social network properties (e.g., Aggarwal, 2011; Goyal, Bonchi, & Lakshmanan, 2010; Murthy, 2015), content of posts (e.g., Agarwal, Liu, Tang, & Yu, 2008), and information flow (e.g., Ver Steeg & Galstyan, 2012).

Studying digital traces and patterns from SNSs with sophisticated computational techniques, such as machine learning, can provide insights into user behavior (Lazer et al., 2009). As a subdomain in computer science, machine learning focuses on constructing algorithms to analyze and learn the hidden patterns in data and, subsequently, make predictions based on these learned analyses (Bishop, 2006). By training machines to learn and repeat the analysis, researchers no longer need to manually execute a particular task. Therefore, the value of machine learning lies in its capability to uncover patterns from data sets that are large, diverse, and fast changing—for instance, social media streams—and to create predictive models to guide future actions.

Regarding social media streams, previous research has demonstrated the potential to use supervised learning—a type of machine learning that creates predictive models from labeled data—to predict Twitter content diffusion and social interaction. For instance, a Twitter study by Jenders, Kasneci, and Naumann (2013) used both “manifest” features (e.g., the number of followers, tweet length, and the number of hashtags) and “latent” features (e.g., sentiment valence and emotional divergence) to predict the virality of tweets. Their results showed that a combination of features covering structural, content-based, and sentiment aspects leads to the best classifier performance. In another example, Petrovic, Osborne, and Lavrenko (2011) found that social features (e.g., the number of followers and following, likes, times the user was listed, and the user's verification status) are reliable predictors of retweetability, while tweet features such as the number of hashtags, URLs, and tweet length improve prediction accuracy. Similarly, Suh, Hong, Pirolli, and Chi (2010) found that the age of the account, the number of followers and following, the presence of URLs and hashtags have a significant impact on retweetability.

Moreover, users' previous online activity and demographic variables have been widely used for discontinuance prediction. Predicting user discontinuance helps devise retention solutions and take appropriate actions. For example, Hadden, Tiwari, Roy, and Ruta (2007) developed a customer discontinuance management framework based on users' features, such as demographic variables, previous activity, and average activity. Similarly, using binomial logistic regression model, Keramati and Ardabili (2011) identified customer dissatisfaction, service usage, switching cost, and demographic variables as key factors in predicting user discontinuance of mobile operators. For SNSs, Kawale et al. (2009) identified two factors that affect user discontinuance in massively multiplayer online role-playing games (MMORPG): Social influence, which is derived from group-play records and personal engagement, which is based on user time records.

However, just like conventional methods, SNS data analyses are not without limitations and pitfalls (boyd & Crawford, 2012). For example, media-centric data sometimes lack background and demographic information about users. Simply reporting metrics of activity per day, or measuring the most active users or most-mentioned users and content, does not necessarily account for why these trends happen and may overlook reasons and behaviors that influence SNS use. Additionally, boyd and Crawford (2012) cautioned, “too often, Big Data enables the practice of apophenia: seeing patterns where none actually exist, simply because enormous quantities of data can offer connections that radiate in all directions” (p. 668). Working with media-centric data can still be subjective, and quantification does not necessarily enable researchers to make claims closer to the objective truth.

The Mixed-Methods Approach and Discontinuance Studies

Although computational methods and user surveys have their own strengths and weaknesses, combining approaches in a single research study could increase researchers’ breadth and depth of understanding while offsetting the weaknesses inherent to using each approach by itself. Doing so also helps researchers make a theoretically informed contribution, thereby bypassing the often-heard criticism that big data research is heavily descriptive and theoretically light (Russell Neuman, Guggenheim, Jang, & Bae, 2014). Researchers can use theories and results from surveys to guide them as they select and construct features for the computational models. Computational methods can help generate new measures for surveys. Accordingly, this study used computational analysis to determine the benchmark (i.e., the duration *D* of a break) that defines whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer. The study then used the benchmark to draft survey questions about Twitter use.

Moreover, one of the goals of this research is to compare intermittent discontinuers and permanent discontinuers. Intermittent discontinuers and permanent discontinuers have distinctive demographic, behavioral, and psychographic characteristics. This study captured these users’ characteristics with a user survey and a computational method. While the user survey captured characteristics in all three perspective, the computational method specifically collected their behavioral characteristics (digital traces) by looking at their Twitter profiles and activities.

Further, this study also examines users' reasons for discontinuance and their discontinuance decision processes with the user survey. Survey methods allow the flexibility to include a wide variety of predefined response options and open-ended questions to assess respondents' emotions, perceptions, and attitudes. Comparatively, computational methods are less applicable to measure users' psychology and cognitive reasoning.

Chapter 6 thoroughly discusses the analytical procedures for each research question.

Chapter 6: Methods

This study utilizes a mixed-methods approach, applying a computational "big data" analysis (Study 1) and a conventional user survey (Study 2). This chapters outlines details for each of the methods.

Study 1 - Computational Approaches

Study 1 used supervised machine learning to study the predictive power of Twitter features in foretelling Twitter use discontinuance. Importantly, Study 1 determined the benchmark (i.e., the duration *D* of a break) to define whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer. The benchmark was used to draft survey questions about Twitter use in Study 2.

Data Collection

Twitter data are readily collectible through an open API. This study employed a method similar to those of Fu and Chan (2013) and Liang and Fu (2015) to generate a random sample of users instead of tweets. The Twitter ID is a unique (numeric) value assigned to every account, and the Twitter IDs have been found to range from 0 to 5,000,000,000 for an account created by March 2016. However, the sparsity of the Twitter user ID space complicates the search process (Gurajala, White, Hudson, Voter, & Matthews, 2016). Thereafter, Twitter's REST API was used to verify whether the Twitter IDs generated were ever assigned, suspended, or protected.

Many Twitter accounts are bots (Varol, Ferrara, Davis, Menczer, & Flammini, 2017) or controlled by teams of humans (e.g., organizational accounts). These accounts are considered as noise when modeling individual-specific phenomena as discontinuance behavior of these accounts could be very different from general individual users. In response, this study used

Botometer, an existing, publicly available tool, to exclude potential bots and organization accounts from the data set. Botometer[2] is a machine learning algorithm trained on thousands of instances of socialbots, from simple to sophisticated, with over 1,000 features, including an account's profile, friends, network structure, temporal activity patterns, language, and sentiment. Varol et al. (2017) suggested that Botometer achieves an 86% accuracy in bot detection and the Pew Research Center conducted independent validation tests of the Botometer system (Wojcik, Messing, Smith, Rainie, & Hitlin, 2018).

Via Twitter's REST API, profiles and tweets (the most recent 3,200 tweets) posted from all public, human accounts were collected at two time periods: in September 2017 and March 2018. This ensures a longitudinal component (over a six-month period) to decide whether the time between tweets is, a permanent discontinuance, a break from Twitter, or just a normalized pattern of behavior for the platform.

Mathematical Approach to Define Discontinuance

In 2015, Twitter stopped disclosing the percentage of its users who took "no discernable user action." Also, the literature does not indicate a clear-cut duration of inactivity to define discontinuance. To develop a definition, this study took a mathematical approach. The analysis included only Twitter accounts that were operated by individuals and have tweeted (or retweeted) at least five times (arguably as users who have *adopted* Twitter) This excluded corporate accounts, operated by bots, or those with little or no content.

Two measures were constructed to account for the duration of inactivity: (1) Average intertweet interval (mean of Δt), which is the average number of days between any two

---

[2] Botometer gives each account a score (0-1) based on how likely the account is to be a bot. Higher scores are more bot-like. Botometer often categorizes "organizational accounts" as bot accounts. The cut-off point for this study was 0.60.

consecutive tweets. The shorter amount of time between a user's tweets, the more intense their tweeting activity generally is (Murthy, Gross, & Pensavalle, 2016); and (2) time since the last tweet (D_L), which represents the time (number of contiguous days) between a user's last tweet to the day of analysis. Figure 6 illustrates the approach with two examples.

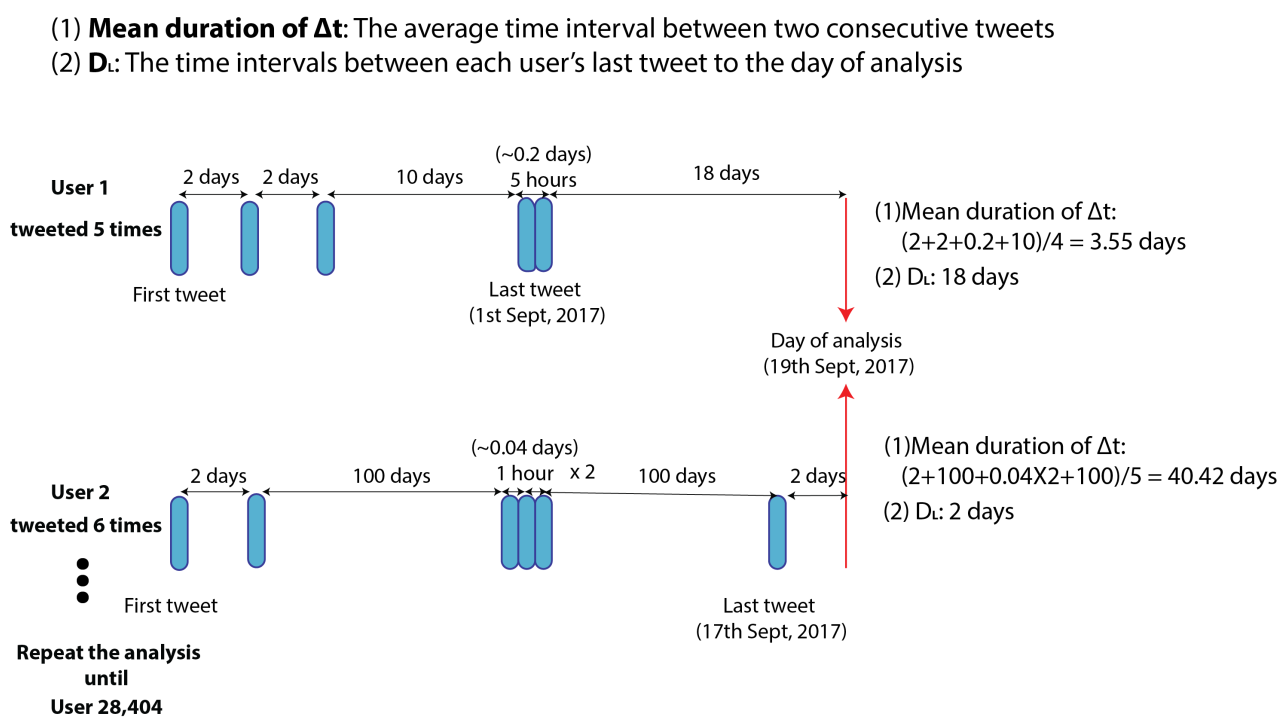

Figure 6: Mathematical Approach to Define Discontinuance.

A preliminary analysis was conducted in September 2017. Tweeting patterns of 28,404 human accounts that tweeted at least five times were examined. To achieve reliable results, this study analyzed the timestamps of all the tweets (up to 3,200 tweets for each user due to the limitation of Twitter API). Figure 7 shows the distribution of the two measures.

The distribution of average intertweet interval measures (average of Δt) and duration from last tweet (D_L) were characterized by power law-like distributions—with characteristic bursts of activity on the left and heavy tail on the right. The sample median of the average intertweet interval was 3.37 days (M = 21.16, SD = 49.23). Although the median gave a general understanding of how long a user might take to tweet again, it did not give a good indication of the distribution of data points as most of the variation is in the tail of the distribution (Murthy et al., 2016). Thus, this study employed the 95th percentile metric, a statistical standard used to discard maximum spikes in the data, to capture a sufficiently long intertweet interval. A 95th percentile metric prevented individuals who tend to take long breaks from being mistakenly considered as permanent discontinuers. As indicated in Figure 7, the 95th percentile of the average intertweet interval (average of Δt) was 103 days. In fact, this duration is similar to the mobile and tech industries' standard for measuring retention, using 90 days or one quarter as the benchmark (Localytics, 2017).

To ensure the average intertweet interval was valid and reliable, the same analytical procedure was repeated with the sample in March 2018 (i.e., after a six-month period). The analysis was updated with new tweets from those 28,404 accounts and their timestamps. Results were similar: The 95th percentile of the average intertweet interval was 104 days.

Based on the analysis, continuing adopters are defined as Twitter users who tweeted continuously and have never taken a break of 103 days or more (since adoption); intermittent discontinuers are individuals who tweeted during the data collection period (i.e., a six-month period) but have taken breaks of more than 103 days since adoption; and permanent discontinuers are individuals who did not tweet for a period much longer than 103 days—this study followed those accounts for a six-month period (i.e., 180 days).

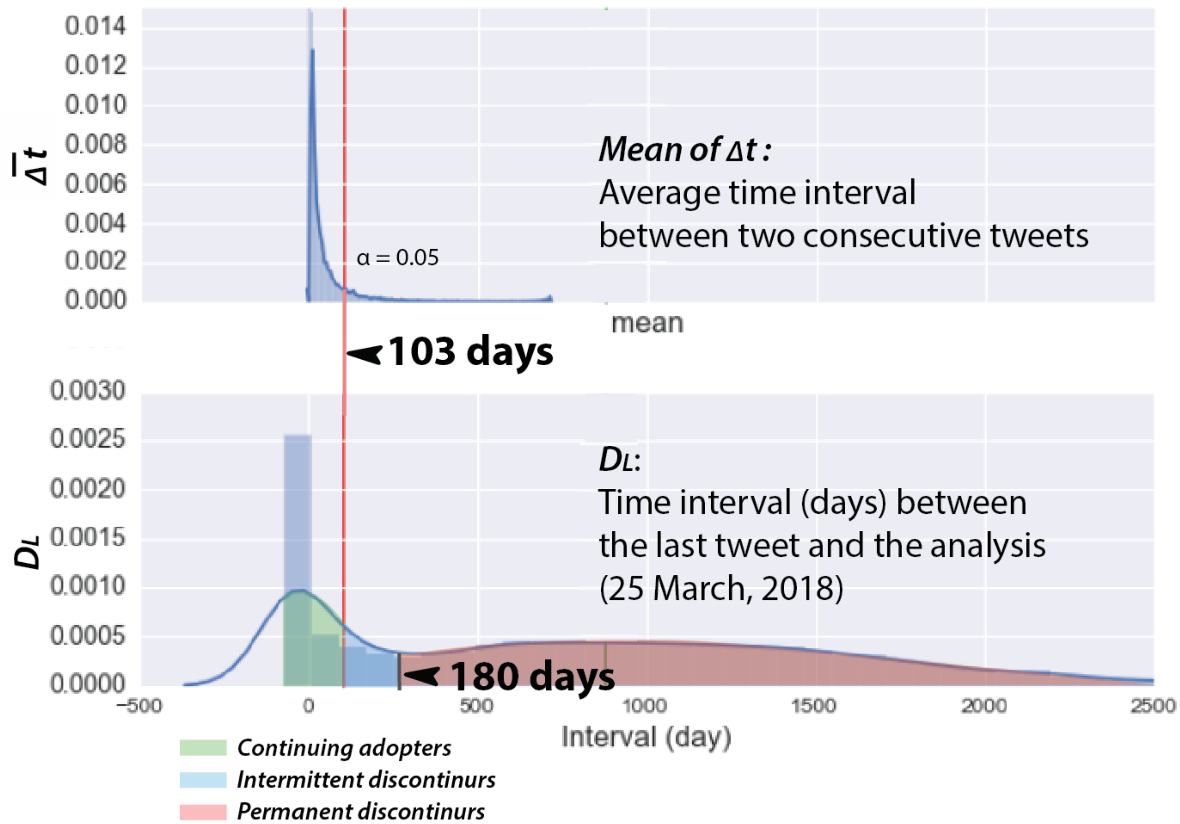

Figure 7: Distributions of Average Intertweet Interval (mean of Δ*t)*, and Time since the Last Tweet (D_L).

Feature Selection

Feature selection is the process of extracting discriminating and relevant attributes that characterize users in a data set. These features are used to train the supervised machine learning model. Briefly discussed in Chapter 5, many studies used both Twitter features (e.g., the number of followers, tweet length, and number of hashtags) to predict users' behavior (Jenders, Kasneci, & Naumann, 2013). This study took a broad range of variables examined in previous research (Castillo, Mendoza, & Poblete, 2011; Gupta, Kumaraguru, Castillo, & Meier, 2014; Nguyen, Li,

& Niederée, 2017) to analyze users' post-adoption behaviors and predict discontinuance. A total of 19 features were from five main categories, including profile, activity, social, interaction, and content features. Table 1 lists all the features.

Each Twitter account was coded for:

Profile features

Profile features were extracted from a user's Twitter profile and consisted of the (1) account longevity, (2) screen name length, whether the user had a (3) description and (4) a profile picture. Account longevity is the time between the date of creation and the date of analysis.

Activity features

Activity features included (5) the average number of tweets across account's lifespan, (6) the average number of likes across account's lifespan, (7) the preferred platform to send out tweets (mobile apps and desktop web), and (8) the proportion of tweets that were retweets. Account's lifespan is the time between the date of creation and date of the last tweet. By tracking the source of tweets, prior work has shown that mobile Twitter users are more likely to be active than non-mobile users, and that tweets made on a mobile device tend to be more conversational and personal (Perreault & Ruths, 2011).

Social features

Social features characterized user's social network: (9) the number of following and (10) followers, and (11) the follower-following ratio. These features indicate the "socialness" of a user.

Table 1: Twitter Features to Predict Discontinuance.

Categories	Features	PseudoNym
Profile features	(1) Account longevity (days)*	ProfileJoinDate
	(2) Screen name length	ProfileNameLen
	(3) Whether the user has a description	ProfileDescription
	(4) Whether the user has a picture	ProfilePic
Activity features	(5) Average number of tweets across account's lifespan**	ActAvgTweet
	(6) Average number of likes across account's lifespan**	ActAvgFav
	(7) Preferred platform to tweet (mobile apps or desktop webs)	ActPlatform
	(8) Proportion of tweets that were retweets	ActRetweetsP
Social features	(9) Number of following	SocialNumFollowees
	(10) Number of followers	SocialNumFollowers
	(11) Followers-to-following ratio	SocialRatios
Interaction features	**Proportion of original tweets that receives:**	
	(13) Retweets	IntGainRetweetP
	(14) Likes	IntGainLikeP
	Proportion of original tweets that contains:	
	(15) Mentions	IntMentions
Content features	(16) Average tweet length	ContentLen
	Proportion of original tweets that contains:	
	(17) Media	ContentMedia
	(18) Hyperlinks	ContentHyperlinks
	(19) Hashtags	ContentHashtags

* Account longevity is the number of days since account creation.
**Average number of tweets across account's lifespan is the total number of tweets posted over the time between the date of creation and the date of the last tweet.

Interaction features

Interaction features characterized the social exchange among Twitter users, including (12) the proportion of original tweets that receives retweets, and (13) the proportion of original tweets that receives likes from others, and (14) the proportion of original tweets contains mentions (i.e., including another user account in the tweet).

Content features

Content features were defined as the explicit content and elements of the tweet, including (16) the average tweet length, the proportion of original tweets that contains (17) media (i.e., images or videos), (18) hyperlinks, and (19) hashtags.

Handling Class Imbalance

Imbalanced data refers to a situation where one class is rare compared to the others in a classification dataset. Imbalanced class distribution in a training set hinders the learning of representative sample instances, especially the minority class instances, and prevents a model from correctly predicting an instance label in a testing set. SMOTE (Chawla, Bowyer, Hall, & Kegelmeyer, 2002) algorithm was used to resolve imbalanced class distribution.

Predictive Models

Via Twitter's REST API, this study collected profiles and tweets (the most recent 3,200 tweets) posted from 28,404 accounts at two time periods: September 2017 and March 2018. To build a prediction model, features from the past are used to infer the state of future. Therefore, this study used accounts' features (X) collected in September 2017 to predict users' discontinuance behavior (corresponding target values Y) in March 2018.

Twitter users were randomly split into training (containing three-fourths of the data) and testing sets (containing one-fourth of the data). The two sets were stratified and contained the same ratio of continuing adopters and discontinuers. Three popular classifiers: Random Forest (Breiman, 2001), Logistic Regression (Cox, 1958), and Gradient Boosting Classifier (Schapire & Freund, 2012) were used to classify each Twitter user. A belief introduction of the classifiers are as follows:

Random Forest

Random forest is an ensemble method. It builds a library of decision trees from a set of random samples. Each decision tree is grown by randomly choosing the variables to split data upon. The classifier predicts a class label by average voting from the decision trees. This method is robust to irrelevant features and can avoid overfitting by constructing an ensemble of trees.

Logistic Regression

Logistic regression uses categorical variables as the dependent variables and a logit function explaining the probability of success or failure. It is the go-to method for binary/multinomial classification problems. The logistic model is robust to noise and can avoid overfitting with regularization.

Gradient Boosting

Gradient boosting machines are a family of powerful machine learning techniques that have shown considerable success in a wide range of practical applications. In gradient boosting, the model consecutively minimizes the loss of the model by adding weak learners using a gradient descent-like procedure.

Model Evaluation

To evaluate model performance, a 10-fold cross-validation was conducted to assess how well the training model generalized to the testing data set. Cross-validation helps avoid overfitting. Prediction results were evaluated using precision, recall, F1-score, and accuracy.

Mathematically,

$$Precision = \frac{tp}{tp + fp}$$

$$Recall = \frac{tp}{tp + fn}$$

$$F1\ score = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn}$$

where *tp* is the number of true positives, *fp* is the number of false positives, *tn* is the number of true negatives, and *fn* is the number of false negatives.

Feature Analysis

Trained classifier provides model features and their importance scores. Feature importance measures how effective a single feature can distinguish classes. The relative importance of a feature is given by its weight or coefficient (depending on the classifier). To enable comparisons between classifiers and across fields, all feature scores were normalized to numbers between 0 and 1. The normalized feature scores were used to rank the features in order of importance—the higher the score, the more important the feature. Using the recursive feature elimination (RFE) procedure, features that did not contribute significantly to the result were recursively eliminated. The recursive process completed when the model reached a desired number of features with high predictive power.

Sensitivity Analysis

Sensitivity analysis was conducted to test the stability and robustness of the findings. Group classification and model training were repeated with seven different sets of inactivity timeframe (based on the 91th to 98th percentile of the average intertweet interval). The order of their top five important features were then compared with those from the 103-180-day inactivity benchmark through Spearman's rank-order correlations. This study took the average of those seven Spearman's correlation coefficients. A high average correlation (> .70) would mean that the top five important features were consistent over different timeframes of inactivity, and the conclusion drawn was not sensitive to the 103-180-day inactivity benchmark.

STUDY 2 – ONLINE SURVEY

A national online survey was conducted in three days in early February 2018. Respondents were recruited through Survey Sampling International (SSI), a national research company that consists of more than 1 million panel members in the United States. SSI administered the survey by sending e-mail invitations to a random subset of its panelists who meet the study's entry criteria. Eligible respondents were those who over the age of 18 and had currently (or previously) owned a Twitter account. To ensure reliable answers, three checking questions[3] were implemented. Surveys deemed incorrect were void. Respondents were informed that their responses would be kept confidential and would not be disclosed to anyone. This study was approved by the Institutional Review Board (IRB) to ensure to had less than minimum risk to target participants (Appendix A).

Pre-test

Two communication scholars reviewed the preliminary questionnaire. Using a draft of the preliminary questionnaire, a pilot study host through Survey Sampling International (SSI) was conducted with 20 respondents from the three user categories (continuing adopters, intermittent discontinuers, and permanent discontinuers), whose responses were excluded from the final study. These respondents commented on the survey design and identified unclear

---

[3] Examples of checking questions include "Please pick none at all for this question" and "Please select strongly disagree for this statement." Respondents were re

questions and responses. The questionnaire was finalized using the feedback from the pilot study and was later loaded into Qualtrics. The survey took about 10 minutes to complete.

Measurement

The survey instrument included questions about Twitter usage, use experience, types of discontinuance, stages of discontinuance, and user attributes. To ensure content reliability and validity, this study adopted established constructs from previous studies. However, given the length of the questionnaire, certain established scales were modified and shortened. Cronbach's alpha values were calculated through the main survey. All Cronbach's alpha values were above the .70 threshold, indicating that the scales had acceptable reliability. The complete questionnaire is attached in Appendix B.

Participants were asked to respond to a variety of seven-point, Likert scales (1 = Strongly Disagree, 7 = Strongly Agree), unless otherwise stated.

Whether the participant is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer

Referencing the computational analysis in Study 1, the duration of 103 days (roughly three months) and the period of Twitter data collection period (i.e., six months) were adopted as criteria to define continuing adopters and discontinuers. Continuing adopters, intermittent discontinuer and permanent discontinuers were separated based on three dichotomous questions: (1) whether they had used Twitter in the past three months, (2) whether they had the intention to use Twitter in the coming six months, (3) whether they had even taken a break from Twitter for a period of three months or more. Continuing adopters were individuals who used Twitter in the past three months and never took a break of three months or more. Intermittent discontinuers referred to individuals who signed in to Twitter at least once in the past three months, had taken a break for three months or more, but returned later. Permanent discontinuers were individuals who did not use Twitter in the past three months and had no intention to use Twitter in the next six months (Table 2).

Table 2: To Define Whether a Participant is a Continuing Adopter, an Intermittent Discontinuer, or a Permanent Discontinuer.

	(1) Have you logged into Twitter during the past three months?	(2) Do you intend to use Twitter in the next six months?	(3) Have you ever voluntarily taken a break from Twitter for a period of three months or more and return to the platform later?
Continuing adopter	Yes	Yes	No
Intermittent discontinuer	Yes or No	Yes	Yes
Permanent discontinuer	No	No	Yes or No

Reasons for discontinuance

Employing a similar coding strategy as York and Turcotte (2015) and Zhou, Yang, and Jin (2018), reasons for Twitter use discontinuance were assessed by content analyzing verbatim responses from the open-ended follow-up question, "*what made you decide to discontinue Twitter use?*" A total of five categories emerged from an inductive coding procedure: user-related, context-related, relationship-related, function-related, and content-related factors, extending the coding categories presented by Zhou, Yang, and Jin (2018). First, if verbatim responses referred to personal dissatisfaction and emotional exhaustions, such as time constraints, boredom, fatigue, burnout, personality mismatch, or privacy concerns, they were coded as **user-related** factors. Moreover, responses including taking a break or leaving Twitter because of low and no usage "without even realizing it" were also coded as user-related. Second, if responses explaining discontinuance due to completion of job or facilitating conditions, such as illness or vacation, these responses were coded as **context-related** factors. Third, responses that cited the lack of social interaction, social influences, or social burden were coded as **relationship-related** factors. For example, they followed their friends or families to other platforms. Fourth, **function-related** factors include respondents who talked about dissatisfaction toward Twitter's design and features, such as the confusing layout and the challenging 140-character limit[4]. This category also includes respondents who replaced Twitter with alternative SNSs such as Facebook, Reddit, or Instagram. Fifth, **content-related** factors consist of dissatisfaction toward content on Twitter, such as low relevance, low credibility, content redundancy, negative/offensive content, too many tweets from U.S. President Donald Trump and other politicians, or too much information. Finally, comments with no clear response were coded in the "no clear response" category.

Four typologies of discontinuance were also considered for the content analysis. Based on previous literature, **disenchantment discontinuance** is attributed to users' dissatisfaction. Sub-factors, which included time burden, social media fatigue, personality mismatch, privacy concerns, a lack of social interaction, social influences, social burden, relative disadvantages, system shortcomings, low content quality, and information overload all indicate disenchantment discontinuance. Sub-factor relative disadvantage was considered as a form of **disenchantment** and **replacement discontinuance**. Sub-factor completion of work is **completion discontinuance**. Finally, sub-factor low usage is considered as a form of **indifferent discontinuance**.

[4] In the hope that it will encourage more people to post, Twitter has doubled the number of characters to 280 characters per tweet since September 2017. Before the time, each tweet only allowed up to a limit of 140 characters.

Two graduate students in communication and psychology studies coded the responses. Reliability tests were performed using a representative sample of the population containing 70 comments, following the recommendation of Riffe, Lacy, and Fico (2005) for 95% level of probability. Interrater reliabilities were calculated (Percent Agreement = 90% and Cohen's Kappa = .80).

Utilization level

Respondents' utilization of Twitter was conceptualized as frequency and duration of use. Participants were asked to report how many days in a week they use (or previously used) Twitter (0 – 7 days) and how much time (in minutes) they normally spend (or previously spent) using it for the days they check (or checked) it. Average time spent per day was transformed using logarithmic 10 transformation to meet the assumption of normality (Tabachnick & Fidell, 2007).

Active/Passive participation

Modified from the online participation scale by Koreleva et al. (2011), six items were used to measure the level of participation. Active use included 1) tweeting their thoughts and feelings, 2) commenting on other people's tweets, 3) retweeting other people's tweets, and 4) liking other people's tweets (Cronbach's $\alpha = .85$, $M = 2.31$, $SD = 0.95$); While passive activity included 5) following news sources, celebrities, and other famous people and 6) clicking on URLs that link out to other websites (e.g., blogs, news sites, etc.) (Cronbach's $\alpha = .72$, $M = 2.91$, $SD = 1.05$). Higher composite scores indicated higher levels of active or passive online participation, respectively.

Perceived usefulness and perceived ease of use

To measure perceived usefulness and perceived ease of use, participants were asked to indicate to what extent they agreed with the following statements: 1) Twitter allows me to seek information more quickly and 2) Twitter allows me to connect with others more easily (Cronbach's α = .75, *M* = 4.59, *SD* = 1.50). In a similar manner, the perceived ease of use was measured with the following statements: 1) Twitter is clear and easy to use and 2) Navigating Twitter requires a lot of mental effort (Cronbach's α = .73, *M* = 4.07, *SD* = 0.80). These items are based on the operationalization of perceived usefulness and perceived ease of use used in the literature on the Technology Acceptance Theory (Venkatesh & Brown, 2001). Higher composite scores indicated higher levels of perceived usefulness and perceived ease of use, respectively.

General satisfaction

To measure general satisfaction, participants were asked to indicate to what extent they felt satisfied with their overall Twitter experience. A higher score represented a higher level of satisfaction (*M* = 4.37, *SD* = 1.78).

Information overload and social burden

The measurements for information overload and social burden were adopted from Maier, Laumer, Eckhardt, and Weitzel (2012). Participants were asked to rate how likely they agreed with each of the statements assessing information overload: 1) I encounter too much information when I search on Twitter and 2) I am overwhelmed by the amount of information available on Twitter (Cronbach's α = .92, *M* = 3.68, *SD* = 1.73); To evaluate social burden, 1) I feel that I care too much about my Twitter-friends' well-being and 2) I feel I spend too much time dealing with my Twitter-friends' problems (Cronbach's α = .77, *M* = 2.28, *SD* = 1.31). Higher composite values indicated higher levels of information overload and social burden, respectively.

Social media fatigue

The scale of emotional exhaustion (Maier et al., 2012) was used to measure social media fatigue. Participants were asked to rate if they agreed with the following statements: 1) I feel burned out using Twitter, and 2) Using Twitter stresses me out (Cronbach's $\alpha = .75$, $M = 2.85$, $SD = 1.65$). A higher composite value indicated a higher level of social media fatigue.

Independent judgment-making

Two statements were employed to measure the extent to which individuals turned to others for opinions on innovations before making decisions. Those two statements were: before registering for an account on Twitter: 1) It was important for me to seek advice from other Twitter users, and 2) I had to find out what other users thought of Twitter (Cronbach's $\alpha = .83$, $M = 5.08$, $SD = 1.65$). Both statements were reverse-coded. A higher composite value indicated a higher level of making independent decisions.

Personal innovativeness

To measure the degree to which an individual is relatively early in adopting new ideas than other members of a social system, three items were adopted from Kim, Mirusmonov, and Lee (2010)'s personal innovativeness scale: 1) When I hear about a new technology, I would look for ways to experiment with it, 2) Among my peers, I am usually the first to try new technologies, and 3) In general, I am hesitant to try new technologies (reverse-coded) (Cronbach's $\alpha = .87$, $M = 4.76$, $SD = 1.30$).

Big Five personality traits

The Berkeley Personality Profile (Harary & Donahue, 1994) was used to measure the Big Five personality traits. Each of the traits was measured with three statements. To measure extroversion, those statements were 1) Prefers to be alone (reverse-coded), 2) Holds back from expressing my opinions (reverse-coded), and 3) Enjoys being part of a group (Cronbach's $\alpha = .71$, $M = 4.29$, $SD = 1.37$). To measure neuroticism, those statements were 1) Becomes stressed out easily, 2) Is calm, even in tense situations (reverse-coded), and 3) Is afraid that I will do the wrong thing (Cronbach's α = .80, *M* = 3.61, *SD* = 1.51). To measure openness, those statements were 1) Does not have a good imagination (reverse-coded), 2) Is interested in many things, and 3) Prefers to stick with things that I know (reverse-coded) (Cronbach's α = .77, *M* = 5.00, *SD* = 0.98). To measure agreeableness, those statements were 1) Trusts others, 2) Contradicts others (reverse-coded), and 3) Values cooperation over competition (Cronbach's α = .79, *M* = 4.83, *SD* = 1.01). To measure conscientiousness, those statements were 1) Completes tasks successfully, 2) Excels in what I do, and 3) Works hard (Cronbach's α = .80, *M* = 5.74, *SD* = 0.89). A higher composite score indicated more of the measured personality trait.

Demographic information

Respondents were also asked for their basic demographic information: gender, age, ethnicity, and education level. After the descriptive analysis, ethnicity and education were collapsed into two categories—non-white and white, no college and college—for inferential analysis.

Measures for the Post-adoption Decision-making Process

Evaluation

To evaluate the stage of evaluation, respondents were asked to gauge how likely the following statements were to resonate with them before they decided to quit Twitter: 1) I talked to others about my decision to stop using Twitter, 2) I found out what friends who had already stopped using Twitter thought, 3) I was aware of alternative SNSs, and 4) I searched for solutions to reduce, if any, disturbance on Twitter.

Preparation

For the stage of preparation (before they stopped using Twitter), respondents were asked to rate if they agreed with the following statements: 1) I started to try out other forms of social media, 2) I reduced my usage of Twitter, 3) I took several Twitter breaks, and 4) I logged into Twitter, but I reduced my participation in the conversations.

Action

Regarding the stage of action, respondents were asked if they did the following when they quit using Twitter: 1) I informed others I was leaving Twitter in my last tweet, 2) I informed others I was switching to other platforms in my last tweet, 3) I backed up all the tweets I had previously posted, 4) I deleted all the tweets on my timeline, 5) I switched my Twitter account status to private/protected, 6) I deactivated my Twitter account, and 7) I deleted my Twitter account.

Post-action

For the post-action stage, respondents were asked how much they agreed with the following statements: After I left Twitter,1) I did not want to be the first person I knew to stop using Twitter, 2) I regretted quitting Twitter, and 3) I thought my decision to stop using Twitter was hasty.

Relapse

Respondents were asked if they used Twitter again after stop using it for three months or more. If they did, they were asked to indicate the reasons for readoption, which included four pre-defined choices, such as 1) I thought Twitter was still worth using, 2) My work/class required me to use Twitter again, 3) My friends asked me to use Twitter again, or 4) Other. Respondents could choose multiple options. For those who picked "other," they were further directed to answer an open-ended question— "*why you decided to return to Twitter again after the break?*"

Continuance commitment

Three questions were asked to measure the degree of continuance commitment after they re-adopted using Twitter: 1) It was very hard for me to stop using Twitter, even if I wanted to, 2) Twitter was a matter of necessity as much as desire, and 3) I thought about quitting Twitter again.

ANALYTICAL PROCEDURES

Study 1 consisted of 19 independent variables and Study 2 was conducted with 22 independent variables. As Long (1997) argued, a minimum of 10 observations for each variable is required for testing a maximum likelihood model (such as logistic regressions). Given the number of observations in this data set (Study 1: N = 28,404 and Study 2: N = 419), the data set was sufficient to support the variables. The traditional .05 criterion of statistical significance was employed for all tests.

Both computational approach (Study 1) and user survey (Study 2) were used to examine the proportion of and characteristic differences among continuing adopters, intermittent and permanent discontinuers, addressing RQ1, RQ2, and RQ3. User survey (Study 2) answered RQ4 to RQ8. Analytical procedures and statistical approaches used to answer each of the research questions are as follows:

To address **RQ1,** *"how frequently are intermittent discontinuance and permanent discontinuance observed among Twitter users?*" Twitter data (Study 1) and survey data (Study 2) were analyzed and descriptive statistics were generated.

To answer **RQ2**, *"to what extent, are Twitter continuing adopters', intermittent adopters', and permanent adopters' characteristics (demographic, psychographic, behavioral)* *distinct from each other?"* Study 1 employed Kruskal-Wallis *H* tests and Dunn's pairwise comparisons to evaluate whether the medians of users' profile, activity, social, interaction, and content features (Table 1) were significantly different across the groups. Twitter data (e.g., number of followers) usually follow power law-like distributions. The Kruskal-Wallis *H* test is a rank-based nonparametric test and considered as an alternative to the one-way analysis of variance (ANOVA) test. It does not assume normality in the data and is much less sensitive to outliers. Meanwhile, chi-squared tests of independence were used to examine the relationship between categorical variables (i.e., description, profile picture, mobile apps, and desktop webs) and the group memberships.

For Study 2, chi-squared tests of independence tests were used to examine the relationship between categorical demographic variables (i.e., gender, ethnicity, and education). One-way ANOVA tests were used to check if any demographic (i.e., age), behavioral (i.e., utilization level, online participation scale), and psychographic variables (i.e., perceived usefulness, perceived ease of use, satisfaction, information overload, social burden, social media fatigue, independent judgment-making, innovativeness, extraversion, neuroticism, openness, and agreeableness) were significantly different among the groups. Levene's tests were used to test the homogeneity of variances assumption. If the assumption of homogeneity of variances was met, a one-way ANOVA test was performed for that variable and used a Tukey's post hoc test. Alternatively, a Welch's ANOVA instead of a one-way ANOVA was carried out. A Games-Howell post hoc test was then used if the assumption of homogeneity of variances was not met.

To address **RQ3**, *"what characteristics (demographic, psychographic, behavioral) predict whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a* *permanent discontinuer?"* Computational analysis of the "big data" data sets drawn from Twitter (Study 1) and survey measures (Study 2).

In Study 1, supervised machine learning (with three classifiers: Random Forest, Logistic Regression, and Gradient Boosting Classifier) used accounts' features (*X*) collected in September 2017 to predict users' discontinuance behavior (corresponding target values *Y*) in March 2018. The trained classifier then identified the top five features that were highly discriminative and relevant to distinguish these three user groups. These five features were considered as media-centric behavioral factors that predict intermittent discontinuance and permanent discontinuance. Sensitively analysis was then carried out to check the robustness of the model.

Study 2 employed bivariate correlations, a multinomial logistic regression, and a binary logistic regression. Bivariate correlations were first conducted to test the relationship among variables (Table 3). Pallant (2007) referred that the bivariate correlation of .70 indicates a higher probability of multicollinearity. No independent variables were highly correlated (all less than .70). To guard against multicollinearity, the variance inflation factor score (VIF) for each variable in each model was examined. No VIF statistic for any variable was above 2.2 (tolerance not below 0.45), suggesting that multicollinearity was not a problem for these regression models (Menard, 1995; Myers, 1990). An examination of the Mahalanobis distance scores indicated no multivariate outliers. Residual and scatter plots indicated the assumptions of normality, linearity, and homoscedasticity were all satisfied.

Table 3: Bivariate Correlations between Independent Variables (N = 419).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Days per week		.47***	.50***	.40***	.47***	.13**	.54***	-.05	.18***	-.09	-.15**	.06	.02	-.03	.05	-.01	-.10*
2. Minutes spent per day			.47***	.35***	.30***	.25***	.33***	.10*	.36***	.13**	-.26***	-.04	-.04	.01	-.03	-.00	-.04
3. Active online participation				.41***	.38***	.22***	.41***	.02	.39***	.09	-.29***	.12*	.04	.06	-.00	-.04	-.01
4. Passive online participation					.44***	.20***	.41***	-.02	.23***	.01	-.30***	.13**	.00	-.03	.02	.07	.03
5. Perceived usefulness						.25***	.69***	-.13**	.15**	-.14**	-.21***	.12*	.05	-.02	.09	.09	.02
6. Perceived ease of use							.18***	.21***	.26***	.18***	-.16**	-.03	-.10	.00	.01	.01	.06
7. Satisfaction								-.23***	.12*	-.29***	-.20***	.10*	.06	-.04	.04	.08	.06
8. Information overload									.30***	.38***	-.03	-.16**	-.10*	.13**	-.11*	.03	-.14**
9. Social burden										.40***	-.31***	-.01	-.03	.12*	-.15**	-.07	-.20***
10. Social media fatigue											-.09	-.10	-.11*	.20**	-.13**	-.09	-.15**
11. Independent judgment-making												.09	.12*	-.03	-.03	.02	.01
12. Innovativeness													.18***	-.17***	.34***	.05	.25***
13. Extraversion														-.33***	.30***	.34***	.22***
14. Neuroticism															-.30***	-.25***	-.29***
15. Openness																.10*	.36***
16. Agreeableness																	.21**
17. Conscientiousness																	

* $p < .05$ ** $p < .01$ *** $p < .001$

A multinomial logistic regression model and also a binary logistic regression were performed to predict user categories based on their demographic (i.e., age, gender, ethnicity, and education), psychographic (i.e., perceived usefulness and perceived ease of use, satisfaction, information overload, social burden, social media fatigue, independent judgment-making, innovativeness, extraversion, neuroticism, openness, and agreeableness), and behavioral (i.e., utilization level and online participation scale) characteristics. The multi-nominal logistic model is a more general version of the binary logistic model and uses several binary logistic regression models to compare categories (continuing adopters = 0 as the reference group, intermittent discontinuers = 1, and permanent discontinuers = 2). The independent variable can be either continuous or categorical variables. The probability range of each dependent variable is from 0 to 1. Thus, the first step was to test whether intermittent discontinuers and permanent discontinuers are different from continuing adopters (the reference group). The second step was to use a binary logistic regression to compare the predictors between permanent discontinuers and intermittent discontinuers (the reference group).

To address **RQ4**, *"in general, what are the reasons for intermittent and permanent Twitter use discontinuance?"* Twitter use discontinuance were assessed by content analyzing verbatim responses from the open-ended follow-up question, "*what made you decide to discontinue Twitter use?*" descriptive analysis was conducted.

To address **RQ5,** *"to what extent, are Twitter intermittent discontinuers' and permanent discontinuers' reasons for discontinuance different from each other?"* Two independent samples *Z*-statistics were used to test the significance between the groups' differences.

To address **RQ6**, "*in general, how do users reach their decisions to discontinue Twitter use?*" Survey questions related to each of the stages in the post-adoption process (i.e., evaluation, preparation, action, post-action, and relapse) were evaluated. A descriptive analysis examined how discontinuers perceive and engage in specific behaviors at each stage.

To address **RQ7**, *"to what extent, are Twitter intermittent discontinuers' and permanent discontinuers' post-adoption decision-making processes different from each other?"* Two independent samples *t*-tests were performed to investigate if intermittent and permanent discontinuers take different behavioral and cognitive approaches at each stage.

To address RQ8, "*what are the reasons for Twitter readoption for intermittent discontinuers?*" Answers were assessed by content analyzing verbatim responses from the open-ended follow-up question, "why you decided to return to Twitter again after the break?" when respondents picked other besides the four pre-defined choices, such as because of work or friends.

Table 4 summarizes the statistical approaches used for each research question.

Table 4: Analytical Procedures for Each Research Question.

	Research questions	Dimensions	Major analytical procedures: Study1 (Computational approach)	Major analytical procedures: Study 2 (Survey approach)
RQ1	How frequently are intermittent discontinuance and permanent discontinuance observed among Twitter users?		Computational analysis determines the benchmark (i.e., the duration *D* of a break) to define whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer.	The benchmark generated from the computational approach was used to draft survey questions about Twitter use in survey.
RQ2	To what extent, are Twitter continuing adopters', intermittent adopters', and permanent adopters' characteristics (demographic, psychographic, behavioral) distinct from each other?	User' characteristics	Chi-squared tests of independence were used to examine the relationship between categorical variables (i.e., description, profile picture, mobile apps, and desktop webs) among the groups. Kruskal-Wallis *H* tests and Dunn's pairwise comparisons were used to to evaluate whether the medians of other users' profile, activity, social, interaction, and content features were significantly different across the groups.	Chi-squared tests of independence tests were used to examine the relationship between categorical demographic variables (i.e., gender, ethnicity, and education). One-way ANOVA tests/ a Welch's ANOVA were used to examine if there were significant differences among continuing adopters, intermittent discontinuers, or permanent discontinuers' characteristics (demographic, psychographic, behavioral).
RQ3	What characteristics (demographic, psychographic, behavioral) predict whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer?		Supervised machine learning (with three classifiers: Random Forest, Logistic Regression, and Gradient Boosting Classifier) used accounts' features (*X*) collected in September 2017 to predict users' discontinuance behavior (corresponding target values *Y*) in March 2018. Sensitively analysis was carried out to check the robustness of the model.	A multinomial logistic regression, and a binary logistic regression were used to predict the users' discontinuance behavior.

Table 4 – Continued

Research questions		Dimensions	Major analytical procedures	
			Study1 (Computational approach)	Study 2 (Survey approach)
RQ4	In general, what are the reasons for intermittent and permanent Twitter use discontinuance?	Reasons for discontinuance		Verbatim responses from survey's open-ended questions were content analyzed. Descriptive findings were reported.
RQ5	To what extent, are Twitter intermittent discontinuers' and permanent discontinuers' reasons for discontinuance different from each other?			Two independent samples *Z*-tests were used to examine if there were significant differences among intermittent and permanent discontinuers.
RQ6	In general, how do users reach their decisions to discontinue Twitter use?	Decision-making processes of discontinuance		Respondents were asked to rate if they agreed with a series of pre-defined behavioral statements. Descriptive findings were reported.
RQ7	To what extent, are Twitter intermittent discontinuers' and permanent discontinuers' post-adoption decision-making processes different from each other?			Two independent samples *t*-tests were used to examine if there were significant differences among intermittent and permanent discontinuers.
RQ8	What are the reasons for Twitter readoption for intermittent discontinuers?			Verbatim responses from survey's open-ended questions were content analyzed. Descriptive findings were reported.

RESULTS

Chapter 7: Study 1 - Computational Analysis

TWITTER ACCOUNT PROFILES

Through Twitter REST API, 98,575 valid Twitter accounts were collected in September 2017. The date of creation for these accounts ranged from November 2006 to March 2016. All the content (13.2 million public tweets) was posted by 49,287 users (50.1% of the accounts). The other half of the accounts contained no content (43.6%) or they were protected by privacy settings (6.4%). Thus, their tweets were not accessible. Among all these accounts, only one-third (33.9%) tweeted five times or more. The sample showed a similar inactivity as Twopcharts reported. This website monitors the activity level of Twitter accounts and it found that 44% of existing Twitter accounts had never tweeted once and 5.1% were "private" accounts (The Wall Street Journal, 2014).

Further, through the use of Botometer API, this study identified that 15% of these accounts were operated by bots or organizations. The finding was consistent with prior research that estimated that between 9% to 15% of active Twitter accounts were bots (Varol, Ferrara, Davis, Menczer, & Flammini, 2017). The following analysis included accounts with more than five tweets and excluded bot-like accounts. The final sample consisted of 28,404 accounts (Figure 8).

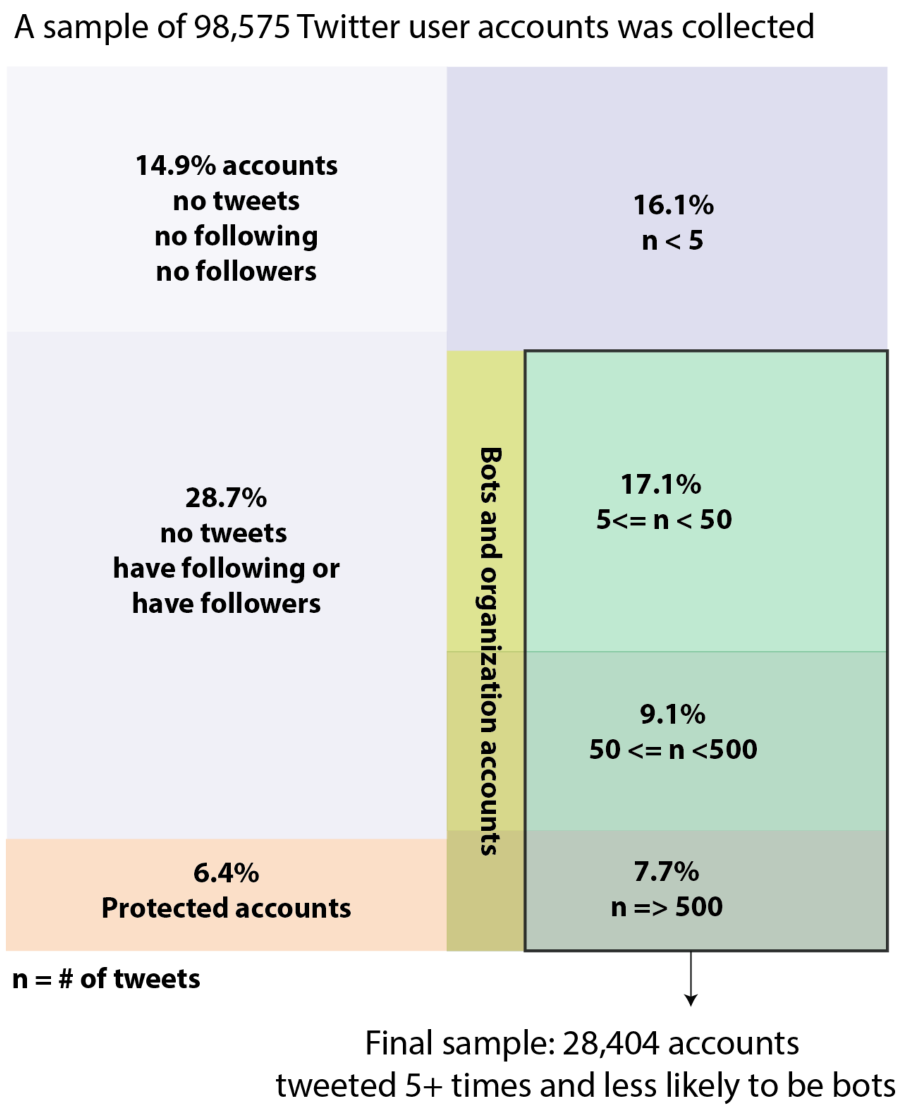

Figure 8: Profile of Twitter Accounts

Differences Among Continuing Adopters, Intermittent Discontinuers, and Permanent Discontinuers

RQ1 asked, "*how frequently are intermittent discontinuance and permanent discontinuance observed among Twitter users?*" Classification was based on the 103-day benchmark (discussed in Chapter 6). Among the 284,404 accounts, 8.10% were continuing adopters, 14.90.41% were intermittent discontinuers, and 77.00% of the accounts were permanent discontinuers. Therefore, the majority of Twitter accounts showed prolonged inactivity.

RQ2 asked, "*to what extent, are Twitter continuing adopters', intermittent adopters', and permanent adopters' characteristics (demographic, psychographic, behavioral) distinct from each other?*" Chi-squared tests of independence revealed that there were relationships between all categorical variables (i.e., description, profile picture, mobile apps, and desktop webs) and their group memberships. Similarly, Kruskal-Wallis *H* tests revealed that there were significant differences in *all* other features among the groups ($p < .001$, adjusted using the Bonferroni correction). Table 5 summarizes the mean rank for each.

Regarding profile features, chi-squared tests of independence revealed that there were relationships between whether an account has a description, $\chi^2_{(2)} = 185.74$, $p < .001$, and a profile picture, $\chi^2_{(2)} = 248.49$, $p < .001$ with their group memberships. Compared to continuing adopters and intermittent discontinuers, permanent discontinuers were less likely to have a profile picture and a description. These findings suggest that permanent discontinuers make less of an effort to curate their online profiles.

Regarding activity features, Dunn's pairwise tests revealed, compared with intermittent discontinuers and permanent discontinuers, continuing adopters had significantly more tweets (*mean rank* = 9,531.26) and likes (*mean rank* = 9,941.74) across the accounts' lifespan, which was defined as the time between the date of creation and date of the last tweet. Surprisingly, intermittent discontinuers showed significantly fewer tweets across the accounts' lifespan (*mean rank* = 5,226.47) than permanent discontinuers did (*mean rank* = 6,393.47).

On the other hand, the use of devices had significant differences among user groups. Continuing adopters (*mean rank* = 7,082.45) and intermittent discontinuers (*mean rank* = 6,903.54) were more likely to tweet from mobile devices, such as smartphones and tablets, than permanent discontinuers (*mean rank* = 6,303.85); while permanent discontinuers (*mean rank* = 6,640.83) were more likely to tweet from non-mobile devices, such as personal computers, than continuing adopters (*mean rank* = 5,617.05) and intermittent discontinuers (*mean rank* = 6,033.82). This finding was consistent with Perreault and Ruth's (2011), which found that Twitter users on personal computers were more active than non-mobile users.

Regarding social and interaction features, as expected, continuing adopters were significantly more likely to gain followers, make connections, and have a higher follower-following ratio. Further, their tweets were more likely to receive likes and be retweeted. In contrast, permanent discontinuers had the lowest number of all these features. These findings showed that continuing adopters are frequent content creators and are more likely to interact with others. One interesting finding was that intermittent discontinuers (mean rank = 7,423.29) were more likely to embed mentions in their tweets, than continuing adopters (mean rank = 6,968.93) and permanent discontinuers (mean rank = 6,211.25).

Regarding content features, compared to continuing adopters and intermittent discontinuers, permanent discontinuers were significantly less likely to embed media (e.g., videos, photos), hyperlinks, and hashtags in their tweets. Moreover, their tweets were generally shorter.

Table 5: Kruskai-Wallis H Tests for Twitter data (N = 28,404).

	User categories			Kruskai-Wallis
	Continuing adopters (n = 2,380)	**Intermittent discontinuers (n = 4,377)**	**Permanent discontinuers (n = 21,644)**	
		Mean Rank		**H**
Profile features				
# of day registered (until Jan. 2018)	6,494.23 ^{b}	7,303.38 ^{a}	6,287.69 ^{b}	122.87 ***
Length of name	5,929.70 ^{c}	6,295.42 ^{b}	6,553.56 ^{a}	32.08 ***
Description (No = 0)[1]	6,936.59 ^{a}	6,851.67 ^{a}	6,330.37 ^{b}	185.74 ***
Profile picture (No = 0)[1]	7,226.83 ^{a}	6,917.57 ^{b}	6,285.13 ^{c}	248.49 ***
Activity features				
Tweet across lifespan ($\log_{10}$)	9,351.26 ^{a}	5,226.12 ^{c}	6,393.47 ^{b}	871.52 ***
Favorite across lifespan ($\log_{10}$)	9,941.74 ^{a}	7,582.17 ^{b}	5,852.20 ^{c}	1,428.52 ***
Platform (mobile apps)[1] (No = 0)	7,082.45 ^{a}	6,903.54 ^{a}	6,303.85 ^{b}	104.48 ***
Platform (desktop webs)[1] (No = 0)	5,617.05 ^{c}	6,033.82 ^{b}	6,640.83 ^{a}	178.90 ***
Retweets proportion	8,803.84 ^{a}	7,922.13 ^{b}	5,908.61 ^{c}	985.54 ***
Social features				
Number of following ($\log_{10}$)	9,776.42 ^{a}	8,058.93 ^{b}	5,774.00 ^{c}	1555.23 ***
Number of followers ($\log_{10}$)	10,512.05 ^{a}	8,148.25 ^{b}	5,675.04 ^{c}	2,129.08 ***
Follower-following ratio ($\log_{10}$)	8,242.46 ^{a}	6,104.80 ^{b}	5,414.76 ^{c}	924.38 ***
Interaction features				
Received retweet	9,222.40 ^{a}	7,823.31 ^{b}	5,882.56 ^{c}	1,228.52 ***
Received "likes"	9,709.92 ^{a}	8,069.31 ^{b}	5,779.21 ^{c}	1,593.06 ***
Mentions	6,968.93 ^{b}	7,423.29 ^{a}	6,211.25 ^{c}	197.93 ***
Content features				
Avg. length	8,018.03 ^{a}	7,792.14 ^{b}	6,021.31 ^{c}	579.00 ***
Media	8,283.10 ^{a}	7,806.35 ^{b}	5,989.28 ^{c}	748.81 ***
Hyperlinks	8,307.75 ^{a}	8,240.77 ^{a}	5,898.74 ^{b}	987.99 ***
Hashtags	7,747.44 ^{a}	8,007.34 ^{a}	6,007.56 ^{b}	656.22 ***

$^*p < .05$ $^{**}p < .01$ $^{***}p < .001$

[1]Chi-squared tests were used to examine the association between categorical variables: Description, profile picture, mobile apps, and desktop webs.

Subscripts *a, b, c* indicate statistical significant differences between the mean rankings.

To address **RQ3**, **"***what characteristics (demographic, psychographic, behavioral) predict whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer?"* Random forest, gradient boosting, and logistic regression classifiers were used to train the discontinuance prediction model. After employing SMOTE algorithm to resolve the biased of imbalanced class distribution, all three predictive models achieved reasonably high prediction accuracies (in the ranges of 75% to 92%). The prediction accuracies were significantly better than random guessing (33.3% for three-class classification), confirming that it was possible to classify whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer. Table 6 presents the prediction results (i.e., precision, recall, F1-score, and overall accuracy).

Table 6: Classifiers' Performance.

	Precision	**Recall**	**F1-score**	**Accuracy**
Random Forest	.91	.91	.91	.92
Gradient Boosting	.86	.86	.86	.85
Logistic Regression	.76	.75	.75	.75

IMPORTANT FEATURES

Best performances were achieved using the Random Forest classifier. Its high F1-score (i.e., .91, the weighted average of precision and recall) demonstrated a strong model performance in terms of both sensitivity and specificity. Table 7 shows the classification performance for Random Forest Classifier for each target group. In fact, the success of machine learning algorithms is highly dependent on features that were used. The strong model performance indicates that the features selected in this study are highly discriminative and relevant that can be used to distinguish three groups. This suggests that Twitter features discussed above are effective at predicting whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer.

Table 7: Classification Performance of the Random Forest Classifier.

	Precision	**Recall**	**F1-score**
Continuing adopters (0)	.92	.96	.94
Intermittent discontinuers (1)	.90	.89	.90
Permanent discontinuers (2)	.94	.88	.91

Recursive feature selection identified the top five features that were highly discriminative and relevant to distinguish these three user groups. In the order of their importance, they were (1) the average number of tweets across account's lifespan, (2) the number of followers, (3) the proportion of original tweets that receives likes, (4) the average number of likes across account's lifespan, and (5) the proportion of original tweets that contains hyperlinks. These five features totally achieved 84.12% accumulated model accuracy (Table 8), answering **RQ3**.

Table 8: The Top Five Features Importance Scores.

	Features	**Description**	**Feature importance**	**Accumulated model accuracy**
1	ActAvgTweet	Average number of tweets across account's lifespan**	.16	58.50%
2	Followers_count	Number of followers	.14	75.07%
3	IntGainLikeP	Proportion of original tweets that receives likes	.09	79.30%
4	ActAvgFav	Average number of likes across account's lifespan**	.08	83.02%
5	ContentHyperlinks	Proportion of original tweets that contains hyperlinks	.07	84.12%

Finally, this study carried out a sensitivity analysis to test the robustness of the model. Random Forest classification was performed on seven different inactivity benchmarks (based on the 91th to 98th percentile of the average intertweet intervals (ITI)). The top five features derived from each benchmark were reported in Table 9. The Spearman's correlation coefficients between the ranking of those top five features for each benchmark and that of the 103-180-day benchmark ranged from .26 to 1.00. The average correlation coefficient was .74. This indicated that the model was insensitive to the choice of benchmark and the prediction model was reasonably stable and robust.

Table 9: Sensitivity Analysis.

Set	Percentile of the average ITI	Respective timeframe (days)	Top five important features					r_s
			1st	2nd	3rd	4th	5th	
1	91st	60-140	ActAvgTweet	Followers_count	IntGainLikeP	ActAvgFav	ContentHyperlinks	1.00
2	92nd	73-150	ActAvgTweet	Followers_count	IntGainLikeP	ContentHyperlinks	ActAvgFav	.26
3	93rd	82-160	ActAvgTweet	Followers_count	IntGainLikeP	ActAvgFav	ContentHashtags	1.00
4	94th	92-170	ActAvgTweet	Followers_count	ActAvgFav	ContentHashtags	ContentHyperlinks	.60
The 103-180-day benchmark	95th	103-180	ActAvgTweet	Followers_count	IntGainLikeP	ActAvgFav	ContentHyperlinks	
5	96th	122-200	ActAvgTweet	ActAvgFav	Followers_count	ActAvgFav	ContentHyperlinks	.70
6	97th	145-220	ActAvgTweet	Followers_count	ContentMedia	IntGainRetweetP	ContentHyperlinks	.70
7	98th	185-250	ActAvgTweet	ActAvgFav	ContentHyperlinks	IntGainLikeP	ActRetweetsP	.90
							Average =	.74

r_s is the Spearman's correlation coefficients.
ActAvgTweet is the average number of tweets across account's lifespan.
Followers_count is the number of followers.
IntGainLikeP is the proportion of original tweets that receives likes.
ActAvgFav is the average number of likes across account's lifespan.
ContentHyperlinks is the proportion of original tweets that contains hyperlinks.
ActRetweetsP is the proportion of tweets that were retweets.
IntGainRetweetP is the proportion of original tweets got retweeted.
ContentMedia is the proportion of original tweets that contains media (e.g., video and photos).

Chapter 8: Study 2 – User Survey

Respondent Profiles

A survey of 450 Twitter users was conducted in February 2018. As a part of data cleaning, 31 respondents who either failed or did not answer the attentiveness questions were dropped from the data set. The final sample consisted of 419 individuals.

The sample's demographic characteristics were compared to Twitter demographics reported by the Pew Research Center (Smith & Anderson, 2018). Table 10 shows the comparison. Of the sample, the mean age was 35.8 (*SD* = 10.8), ranging from 19 to 82. In terms of gender, 44.7% of the respondents were male and 55.3% were female, which is slightly different from Twitter's demographic—of which 48.7% were male and 51.9% were female (Smith & Anderson, 2018). The vast majority of the sample was white (74.9%), followed by 8.1% black/African-American, 6.3% Asian, 6.3% Hispanic/Latino, 2.8% multi-racial, and 1.1% Native American. Most of the respondents (40.1%) were college graduates. It aligns with the findings from the Pew's study, which reports that 38% of Twitter users were college graduates. Overall, the sample is reasonably representative of the Twitter U.S. population in terms of age, gender, race, and education.

Twitter Use

Respondents were asked to report when was the last time they *signed into* Twitter. Results shows that a substantial majority of respondents (81.4%) logged into Twitter at least once in the past three months. Meanwhile, 10% reported that the last time they logged in was three to 12 months ago. Some respondents (6.2%) said the last time they signed into Twitter was more than a year ago and a few of the respondents (2.4%) could not recall when was the last time they signed in.

Table 10: Demographic Profile of Survey Respondents and Twitter Users.

	Respondents Survey (Feb. 2018) (%)	**Twitter users* (Jan. 2018) (%)**
Age:		
18-29	38.2	43.4
30-49	44.6	33.1
50-64	10.7	17.7
65+	6.4	5.8
Gender:		
Male	44.7	48.1
Female	55.3	51.9
Race/Ethnicity:		
White	74.9	67.8
Non-white	25.1	32.2
Education:		
High school or less	24.8	29.9
Some college	35.1	32.1
College graduate	40.1	38.0

* Data was derived from the Pew Research Center's *Social Media Use in 2018* report (Smith & Anderson, 2018)

Regarding when was the last time the respondents *posted on* Twitter, more than half of the respondents (55.1%) said they tweeted at least once in the last three months, followed by 18.1%, who said their last tweet was posted three to 12 months ago. Meanwhile, 15.9% of the respondents reported that their last tweet occurred more than a year ago. One out of ten (10%) respondents said they had never posted before. Finally, 2% could not recall when was the last time they posted.

Regarding why they first started using Twitter, 56% of the respondents said it was for social networking, and 50.6% said they used it for news/information. For those who used Twitter for news, a vast majority (80.1%) reported that they used Twitter specifically for breaking news, followed by politics (67.5%), entertainments (61.3%), and sports (39.6%). Roughly a quarter

(25.5%) said used Twitter to express their personal thought (25.5%), and 11.9% used it for work/study. These findings were consistent with Blank's (2017) study, which indicated that socializing and information seeking were the top two activities for Twitter users.

When asked whether friends, family, or mass media influenced their decisions to start using Twitter, nearly two-thirds of them (64.7%) said their friends played a role. Family (19.6%) and co-workers (15.8%) also influenced their decisions. Comparatively, mass media played a less important role, with only 13.3% attributing their decisions to online reviews and 10.5% to advertisements for Twitter.

Differences Among Continuing Adopters, Intermittent Discontinuers, and Permanent Discontinuers

RQ1 asked, *"how frequently are intermittent discontinuance and permanent discontinuance observed among Twitter users?"* Among all respondents (N = 419), 166 (39.6%) were continuing adopters, 194 (46.3%) were intermittent discontinuers, and 59 (14.1%) were permanent discontinuers.

RQ2 asked, "*to what extent, are Twitter continuing adopters', intermittent adopters', and permanent adopters' characteristics (demographic, psychographic, behavioral) distinct from each other?*" Chi-squares tests and one-way ANOVA tests revealed significant differences among the three groups for 12 variables. Table 11 summarizes the mean and standard deviation for each.

Four demographic variables were examined. Chi-square tests of independence showed a relationship between gender and group memberships, $\chi^2_{(2)} = 9.35$, $p < .05$. Females were more likely to be permanent discontinuers than continuing adopters.

For Twitter use, results showed significant differences between continuing adopters and discontinuers in terms of number of day(s) per week, $F(2, 416) = 60.61$, $p < .001$, minute(s) per day, Welch's $F(2, 416) = 4.53$, $p < .05$, and active online participation scale, Welch's $F(2, 416) = 9.60$, $p < .001$. Alternatively, passive online participation had significant differences among these three groups, $F(2, 416) = 15.91$, $p < .001$. Continuing adopters had the highest scores for passive online participation ($M = 3.21$, $SD = 1.00$), followed by intermittent discontinuers ($M = 2.80$, $SD = 0.98$), and permanent discontinuers ($M = 2.40$, $SD = 1.13$). As expected, continuing adopters had a higher utilization level and online participation than discontinuers. However, surprisingly, intermittent discontinuers differed from permanent discontinuers only in the level of passive participation. There were no other significant variations in terms of behavioral measures.

For innovation perceptions, there were significant differences in terms of perceived usefulness, Welch's $F(2, 416) = 43.62$, $p < .001$, and satisfaction, Welch's $F(2, 416) = 31.74$, $p < .001$, among these three groups. Continuing adopters had the highest scores for perceived usefulness and satisfaction, followed by intermittent discontinuers, and permanent discontinuers. Intermittent discontinuers ($M = 3.19$, $SD = 1.65$) and permanent discontinuers ($M = 3.08$, $SD = 1.88$) both reported a higher level of social media fatigue, compared with continuing adopters ($M = 2.39$, $SD = 1.45$), Welch's $F(2, 416) = 12.62$, $p < .001$. Permanent discontinuers ($M = 4.14$, $SD = 1.76$) reported a significant higher level of information overload than continuing adopters ($M = 3.40$, $SD = 1.59$), Welch's $F(2, 416) = 4.87$, $p < .01$. There was no significant difference in terms of social burden among three groups, $F(2, 416) = .40$, $p > .05$.

For personality traits, intermittent discontinuers ($M = 5.19$, $SD = 1.54$) and permanent discontinuers ($M = 5.66$, $SD = 1.54$) had a significantly higher independent judgment scale than continuing adopters ($M = 4.74$, $SD = 1.75$), Welch's $F(2, 416) = 7.66$, $p < .001$. There was no significant difference between intermittent and permanent discontinuers in terms of independent judgment scale. However, intermittent discontinuers (M = 4.93, SD = 1.18) had a significant higher level of innovativeness than permanent discontinuers (M = 4.42, SD = 1.48), Welch's $F(2, 416) = 3.78$, $p < .05$. One-way ANOVA tests demonstrated that there were no significant differences between any Big Five personality traits among three groups.

ASSOCIATIONS AMONG MAIN CONSTRUCTS AND PREDICTING INTERMITTENT AND PERMANENT DISCONTINUANCE

To answer **RQ3**, "*what characteristics (demographic, psychographic, behavioral) predict whether a Twitter user is a continuing adopter, an intermittent discontinuer, or a permanent discontinuer?"* A multinomial logistic regression analysis with "continuing adopters" as a reference category was employed to predict the odds of intermittent and permanent discontinuance (Table 12). A test of full model versus an intercept-only model (null model) was statistically significant ($LR\ \chi^2 = 601.4$, $p < 0.001$), indicating that the predictors reliably distinguished these three groups. Non-significant deviance and Pearson scores and a Nagelkerke's R^2 of .50 (indicating a moderate relationship between prediction and the grouping) further supported that the logistic model was more effective than the null model.

Table 11: Descriptive Statistics and One-way ANOVA Tests for Survey Respondents.

	All respondents (N = 419)		User categories						One-way ANOVA F
			Continuing adopters (n = 166)		**Intermittent discontinuers (*n* = 194)**		**Permanent discontinuers (*n* = 59)**		
	M	***(SD)***	***M***	***(SD)***	***M***	***(SD)***	***M***	***(SD)***	
Demographic									
Gender (male = 0)[1]	.55		.51 ^{a}		.60 ^{ab}		.73 ^{b}		9.35 *
Education[1] (no college = 0)	.51		.58		.48		.41		6.91
Ethnicity [1] (non-white = 0)	.75		.78		.72		.78		2.09
Age	35.79	(10.8)	36.04	(10.65)	36.35	(11.07)	33.22	(9.74)	2.00
Twitter use									
# of day registered (until Jan. 2018)	2,251	(1,095)	2,140	(1,156)	2,282	(1,088)	2,461	(903)	^{w}2.35
Days per week	3.22	(2.53)	4.67 ^{a}	(2.29)	2.45 ^{b}	(2.20)	1.66 ^{b}	(2.22)	60.61 ***
Minutes spent per day($\log_{10}$)	19.05	(23.37)	23.12 ^{a}	(25.97)	17.33 ^{b}	(20.71)	13.26 ^{b}	(22.38)	^{w}4.53 *
Active online participation	2.31	(0.95)	2.52 ^{a}	(1.01)	2.24 ^{b}	(0.91)	1.95 ^{b}	(0.81)	^{w}9.60 ***
Passive online participation	2.91	(1.05)	3.21 ^{a}	(1.00)	2.80 ^{b}	(0.98)	2.40 ^{c}	(1.13)	15.91 ***
Innovation perceptions									
Perceived usefulness	4.59	(1.50)	5.20 ^{a}	(1.20)	4.46 ^{b}	(1.45)	3.29 ^{c}	(1.49)	^{w}43.62 ***
Perceived ease of use	4.07	(0.80)	4.08 ^{ab}	(0.74)	4.15 ^{a}	(0.84)	3.81 ^{b}	(0.74)	4.32 *
Satisfaction	4.37	(1.78)	5.29 ^{a}	(1.40)	4.03 ^{b}	(1.68)	2.92 ^{c}	(1.62)	^{w}62.11 ***
Information overload	3.68	(1.73)	3.40 ^{b}	(1.59)	3.78 ^{ab}	(1.81)	4.14 ^{a}	(1.76)	^{w}4.87 **
Social burden	2.28	(1.31)	2.34	(1.42)	2.22	(1.23)	2.31	(1.31)	0.40
Social media fatigue	2.85	(1.65)	2.39 ^{b}	(1.45)	3.19 ^{a}	(1.65)	3.08 ^{a}	(1.88)	^{w}12.62 ***
Personality traits									
Independent judgment-making	5.08	(1.65)	4.74 ^{b}	(1.75)	5.19 ^{a}	(1.54)	5.66 ^{a}	(1.54)	^{w}7.66 ***
Innovativeness	4.76	(1.30)	4.69 ^{ab}	(1.34)	4.93 ^{a}	(1.18)	4.42 ^{b}	(1.48)	^{w}3.78 *
Extraversion	4.29	(1.37)	4.21	(1.31)	4.38	(1.38)	4.20	(1.48)	0.76
Neuroticism	3.61	(1.51)	3.56	(1.54)	3.59	(1.49)	3.80	(1.53)	0.54
Openness	5.00	(0.98)	4.97	(0.98)	5.02	(0.94)	4.97	(1.09)	0.15
Agreeableness	4.83	(1.01)	4.83	(0.96)	4.86	(1.01)	4.68	(1.13)	0.77
Conscientiousness	5.74	(0.89)	5.63	(0.87)	5.79	(0.90)	5.89	(0.93)	2.52

* $p < .05$ ** $p < .01$ *** $p < .001$

Subscripts *a, b, c* indicate statistical significant differences between the means.

Subscript *w* represents *Welch's adjusted F* ratios and *post hoc* comparisons were conducted utilizing *Games-Howell* tests.

[1] Chi-squared tests were used to examine the association between categorical variables: Gender, education, and ethnicity.

Results demonstrated that six predictors significantly distinguished intermittent discontinuers from continuing adopters: education (*OR* = 1.79, $p < .05$), days per week (*OR* = 0.69, $p < .001$), satisfaction (*OR* = 0.74, $p < .05$), independent judgment-making scale (*OR* = 1.23, $p < .05$), social media fatigue (*OR* = 1.40, $p < .01$), and innovativeness (*OR* = 1.28, $p < .05$). In other words, the odds of being an intermittent discontinuer (as opposed to a continuing adopter) increases when the respondent does not have a college degree, uses Twitter on fewer days per week, is less satisfied with Twitter, is more capable of making independent judgment, is more innovative, and experiences a higher level of social media fatigue.

On the other hand, seven predictors significantly distinguished permanent discontinuers from continuing adopters: Age (*OR* = 0.95, $p < .05$), days per week (*OR* = 0.74, $p < .01$), satisfaction (*OR* = 0.59, $p < .01$), independent judgment-making scale (*OR* = 1.43, $p < .05$), number of days since adopting Twitter (*OR* = 0.84, $p < .05$), social burden (*OR* = 1.54, $p < .05$), and conscientiousness (*OR* = 1.85, $p < .05$). In short, the odds of being a permanent discontinuer (as opposed to a continuing adopter) increases when the respondent is younger, uses Twitter on fewer days per week, is less satisfied with Twitter, is more capable of making independent judgment, has a shorter history with Twitter, experiences a higher level of social burden, and is more conscientious.

Among those four blocks of independent variables (i.e., demographics, Twitter use, innovation perceptions, and personality traits), variables of innovation perceptions contributed significantly more to the multinomial logistic regression model than the other blocks, $F(2,12) = 699.16$, $p < .001$). Variables of innovation perceptions accounted for 32% of the variation.

Binary logistic regression analysis with "intermittent discontinuers" as a reference category was employed to predict the odds of being a permanent discontinuer (Table 13). A test of the full model versus an intercept-only model (null model) was statistically significant, *LR* χ^2 = 205.91, $p < .001$, indicating that the full model fits significantly better than the null model. The model explained 36.0% (Nagelkerke R^2) of the variance and correctly classified 82% of the cases. Adjusted odds ratios, indicating changes in odds resulting from unit changes in the independent variables, are presented in Table 13. Results showed that permanent discontinuers tend to be younger (*OR* = 0.95, $p < .01$), non-white (*OR* = 0.26, $p < .05$), report a higher level of social burden (*OR* = 1.84, $p < .001$), and are less innovative (*OR* = 0.63, $p < .01$) than intermittent discontinuers.

Among those four blocks of independent variables (i.e., demographics, Twitter use, innovation perceptions, and personality traits), variables of innovation perceptions contributed significantly more to the binary logistic regression model than other blocks, $F(2,6) = 237.34$, $p < .001$). Variables of innovation perceptions accounted for 21% of the variation to predict the odds of being a permanent discontinuer.

Table 12: Multinomial Logistic Regression Predicting Intermittent Discontinuers and Permanent Discontinuers (Only the Final Model is Shown).

	Reference category: continuing adopters (n = 166)								
	Intermittent discontinuers (n = 194)				Permanent discontinuers (n = 59)				Incremental R^2 *Model* χ^2
	B	(SE)	OR	95 % CI	*B*	(SE)	OR	95 % CI	
Intercept (constant)	127.18	(89.11)			350.52 *	(141.60)			
Demographic									
Gender (male = 0)	-0.07	(0.28)	0.94	(0.54 – 1.63)	-0.80	(0.46)	0.45	(0.18 – 1.10)	
Education (no college = 0)	0.58 *	(0.27)	1.79	(1.06 – 3.02)	0.67	(0.40)	1.95	(0.89 – 4.28)	
Ethnicity (non-white = 0)	0.23	(0.32)	1.26	(0.68 – 2.34)	-0.96	(0.53)	0.38	(0.14 – 1.07)	.06
Age	0.00	(0.01)	1.00	(0.97 – 1.03)	-0.05 *	(0.02)	0.95	(0.91 – 0.99)	564.67***
Twitter use									
# of day registered (until Jan. 2018)	-0.07	(0.04)	0.94	(0.86 – 1.02)	-.017 *	(0.07)	0.84	(0.73 – 0.96)	
Days per week	-0.37 ***	(0.07)	0.69	(0.61 – 0.80)	-0.30 **	(0.12)	0.74	(0.59 – 0.93)	
Minutes spent per day($\log_{10}$)	0.42	(0.07)	1.53	(0.77 – 3.05)	-0.59	(0.51)	0.56	(0.21 – 1.50)	
Active online participation	0.20	(0.18)	1.23	(0.86 – 1.74)	0.27	(0.31)	1.31	(0.71 – 2.40)	.28
Passive online participation	-0.12	(0.15)	0.88	(0.66 – 1.19)	-0.04	(0.23)	0.96	(0.61 – 1.50)	719.77***
Innovation perceptions									
Perceived usefulness	-0.02	(0.13)	0.99	(0.76 – 1.28)	-0.29	(0.18)	0.75	(0.52 – 1.07)	
Perceived ease of use	0.31	(0.19)	1.37	(0.94 – 1.98)	-0.28	(0.29)	0.76	(0.43 – 1.33)	
Satisfaction	-0.30 *	(0.12)	0.74	(0.59 – 0.95)	-0.53 **	(0.17)	0.59	(0.42 – 0.82)	
Information overload	0.02	(0.09)	1.02	(0.85 – 1.23)	0.15	(0.13)	1.16	(0.90 – 1.49)	
Social burden	-0.13	(0.13)	0.88	(0.68 – 1.14)	0.43 *	(0.19)	1.54	(1.06 – 2.23)	.32
Social media fatigue	0.34 **	(0.10)	1.40	(1.14 – 1.72)	0.14	(0.14)	1.15	(0.87 – 1.53)	699.16***
Personality traits									
Independent judgment-making	0.21 *	(0.09)	1.23	(1.03 – 1.46)	0.36 *	(0.14)	1.43	(1.09 – 1.88)	
Innovativeness	0.24 *	(0.11)	1.28	(1.02 – 1.60)	-0.16	(0.17)	0.85	(0.61 – 1.20)	
Extraversion	0.17	(0.11)	1.19	(0.96 – 1.47)	0.20	(0.17)	1.22	(0.88 – 1.69)	
Neuroticism	0.03	(0.11)	1.03	(0.84 – 1.26)	0.02	(0.15)	1.02	(0.75 – 1.38)	
Openness	0.02	(0.16)	1.02	(0.75 – 1.38)	0.15	(0.23)	1.17	(0.74 – 1.84)	
Agreeableness	0.03	(0.14)	1.03	(0.78 – 1.36)	-0.11	(0.22)	0.90	(0.59 – 1.37)	.09
Conscientiousness	0.24	(0.18)	1.27	(0.90 – 1.80)	0.60 *	(0.26)	1.85	(1.09 – 3.02)	803.50**
Model χ^2 (*df*)	601.4 ***	(44)							
R^2 (Nagelkerke)	.50								
R^2 (Cox and Snell)	.43								

B Unstandardized regression coefficient, *SE* standard error, OR odd ratio, *CI* confidence interval for *OR*

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

Table 13: Binary Logistic Regression Predicting Intermittent Discontinuers and Permanent Discontinuers (Only the Final Model is Shown).

	Reference category: Intermittent discontinuers (n = 194)					
	Permanent discontinuers (n = 59)					
	B		(SE)	OR	95 % CI	Incremental R^2 Model χ^2
Intercept (constant)	237.20		(134.59)			
Demographic						
Gender (male = 0)	-0.56		(0.42)	0.57	(0.25 – 1.29)	
Education (no college = 0)	-0.02		(0.37)	0.98	(0.47 – 2.03)	
Ethnicity (non-white = 0)	-1.34	*	(0.49)	0.26	(0.10 – 0.69)	.06
Age	-0.05	**	(0.02)	0.95	(0.92 – 0.99)	263.88*
Twitter use						
# of day registered (until Jan. 2018)	-0.12		(0.07)	0.89	(0.78 – 1.01)	
Days per week	0.09		(0.12)	1.10	(0.88 – 1.38)	
Minutes spent per day ($\log_{10}$)	-1.00		(0.50)	0.37	(0.14 – 0.98)	
Active online participation	0.11		(0.29)	1.12	(0.63 – 2.00)	.11
Passive online participation	0.11		(0.22)	1.12	(0.73 – 1.71)	255.45**
Innovation perception						
Perceived usefulness	-0.30		(0.17)	0.74	(0.53 – 1.03)	
Perceived ease of use	-0.50		(0.26)	0.61	(0.36 – 1.01)	
Satisfaction	-0.24		(0.16)	0.78	(0.58 – 1.06)	
Information overload	0.11		(0.11)	1.12	(0.89 – 1.40)	
Social burden	0.61	***	(0.18)	1.84	(1.29 – 2.61)	.21
Social media fatigue	-0.21		(0.13)	0.81	(0.63 – 1.04)	237.34***
Personality traits						
Independent judgment-making	0.15		(0.14)	1.16	(0.89 – 1.52)	
Innovativeness	-0.46	**	(0.16)	0.63	(0.46 – 0.87)	
Extraversion	0.03		(0.15)	1.03	(0.77 – 1.38)	
Neuroticism	-0.01		(0.14)	0.99	(0.75 – 1.30)	
Openness	0.11		(0.22)	1.12	(0.72 – 1.72)	
Agreeableness	-0.15		(0.20)	0.86	(0.58 – 1.28)	.08
Conscientiousness	0.37		(0.24)	1.45	(0.91 – 2.32)	259.95*
Model χ^2 (*df*)	205.91	***	(22)			
H—L χ^2 (*df*)	5.70		(8)			
R^2 (Nagelkerke)	.36					
R^2 (Cox and Snell)	.24					

B Unstandardized regression coefficient, *SE* standard error, OR odd ratio, *CI* confidence interval for *OR*
$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

Reasons For Discontinuance

RQ4 asked, *"in general, what are the reasons for intermittent and permanent Twitter use discontinuance?"* Intermittent discontinuers and permanent discontinuers gave 370 and 141 responses to the open-ended question in the survey, respectively. Table 14 presents the frequencies of these reasons in five factors (i.e., user-, context-, relationship-, function-, content-related factors), and four discontinuance typologies (i.e., disenchantment, replacement, indifferent, and completion), with verbatim quotes for each.

For both groups of discontinuers, user-related factors were the most common reasons for Twitter use discontinuance (49.48% for intermittent discontinuers and 52.54% for permanent discontinuers). Specifically, roughly a quarter (23.20%) of the intermittent discontinuers stated that low usage was one of their reasons for taking a break from Twitter. In addition, approximately one-third (32.20%) of the permanent discontinuers left Twitter because of a lack of interest.

Function-related factors were the second most common motivation for permanent Twitter use discontinuance (45.76%). Many (28.82%) permanent discontinuers were dissatisfied with some features of Twitter, such as commenting that its layout is "too confusing" and "messy." Therefore, 35.59% dropped Twitter and turned to other SNSs, such as Facebook, Instagram, or Reddit. Among intermittent discontinuers, function-related factors were only the fourth reason for discontinuance.

More intermittent discontinuers reported content-related reasons for discontinuance, making them the second most common motivation for the group. Many of them (45.36%) were disenchanted with the quality of content on Twitter and overwhelmed by the constant streaming of information. One interesting finding was that 17.01% of the intermittent discontinuers took a break from the platform because of Donald Trump and debates related to him. Content-related factors were the third major reason for permanent discontinuers. Roughly a quarter (25.42%) of permanent discontinuers said low relevance was the reason for dropping the platform.

Context-related factors accounted for 17.53% of intermittent discontinuance and 3.39% of permanent discontinuance. While some discontinuers (12.89% for intermittent discontinuers and 3.39% for permanent discontinuers) reported that they did not sign in to Twitter because they were sick or on vacation, a few of them (4.64% for intermittent discontinuers and 1.69% for permanent discontinuers) left Twitter as they had completed their work that required Twitter.

Relationship-related factors were the least common reason for intermittent discontinuers (14.43%). Results revealed that very few respondents discontinued their Twitter use because of social burden (1.55% for intermittent discontinuers and 3.39% for permanent discontinuers).

Association Between Reasons For Discontinuance and Type of Discontinuers

Factors

As shown in Table 14, compared with intermittent discontinuers, permanent discontinuers were significantly more likely to mention relationship-related factors (10.99% difference, $z = -1.97$, $p < 0.05$) and function-related factors (30.81% difference, $z = -4.99$, $p < 0.001$) as reasons for discontinuance. In contrast, intermittent discontinuers reported more context-related factors as the reason for discontinuance (14.14% difference, $z = 2.37$, $p < 0.01$). Intermittent discontinuers and permanent discontinuers were equally likely to report user-related and content-related factors as reasons for discontinuance. As discussed about, these two factors are major reasons for discontinuance for both groups.

Discontinuance Typologies

Regarding discontinuance typologies, most of the sub-factors related to disenchantment discontinuance showed insignificant variations between two groups. Compared with intermittent discontinuers, permanent discontinuers were more likely to report a lack of interest (22.41% difference, $z = -4.22$, $p < 0.001$), social influence (8.41% difference, $z = -2.20$, $p < 0.05$), system shortcomings (23.66% difference, $z = -5.15$, $p < 0.001$), and low relevance (14.08% difference, $z = -2.68$, $p < 0.01$) as reasons for discontinuance. On the contrary, compared with permanent discontinuers, intermittent discontinuers were significantly more likely to state information overload (11.12% difference, $z = 1.99$, $p < .05$) as an explanation for discontinuance.

Relative disadvantage is a combined form of discontinuance—disenchantment and replacement discontinuance. Permanent discontinuers were more likely to feel dissatisfied and replace Twitter with other SNS platforms (22.70% difference, $z = -3.96$, $p < 0.001$).

Regarding indifferent discontinuance (i.e., low usage), intermittent discontinuers were more likely to say they forgot to use Twitter (14.73% difference, $z = 2.49$, $p < 0.05$). Finally, for completion discontinuance (i.e., completed their work), there was no significant difference between the two types of discontinuers, $z = 1.02$, $p > .05$.

Table 14: Comparison of Reasons for Twitter use discontinuance between Intermittent Discontinuers and Permanent Discontinuers.

Factors & Sub-factors	Frequency (%)[#] Intermittent discontinuers (n = 194)		Permanent discontinuers (n = 59)		Z-score		Verbatim Quotes
User-related	**96**	**(49.48%)**	**31**	**(52.54%)**	-0.41		
Low usage[3]	45	(23.20%)	5	(8.47%)	2.49	*	It just doesn't interest me and I forget about it. It wasn't really a conscious decision.
Social media fatigue							
Usage exhaustion[1]	32	(16.49%)	10	(16.95%)	-0.08		I took a break from Twitter just to get away from all the drama and constant checking up on people for a few times a day. I got a little bit burned out.
Lack of Interest[1]	19	(9.79%)	19	(32.20%)	-4.22	***	I tend to get very bored with Twitter.
Burden on time[1]	24	(12.37%)	7	(11.86%)	0.10		I can't open Twitter due to my busy schedule.
Personality mismatch[1]	2	(3.39%)	1	(1.69%)	-0.41		As an introvert, I did not want to share my feelings online.
Privacy concerns[1]	1	(1.69%)	1	(1.69%)	-0.90		On top of that they probably spy on you and share the information with the government and other organizations.
Context-related	**34**	**(17.53%)**	**3**	**(3.39%)**	**2.37**	**	
Facilitating conditions	25	(12.89%)	2	(3.39%)	2.07	*	There was a time when I was so ill that I could barely see, let alone interact with others.
Completion of work[4]	9	(4.64%)	1	(1.69%)	1.02		I stopped using an account because it was related to a job that I was no longer doing.
Relationship-related	**28**	**(14.43%)**	**15**	**(25.42%)**	**-1.97**	*	
Lack of social interaction[1]	19	(9.79%)	5	(8.47%)	0.30		I felt that I wasn't connecting with people on Twitter.
Social influences[1]	10	(5.15%)	8	(13.56%)	-2.20	*	My children don't use it much anymore.
Social burden[1]	3	(1.55%)	2	(3.39%)	-0.89		I had to cut some people off and twitter was big in school.
Function-related	**29**	**(14.95%)**	**27**	**(45.76%)**	**-4.99**	***	
Relative disadvantages [2]	25	(12.89%)	21	(35.59%)	-3.96	***	Facebook has more to do on it than Twitter.
System shortcomings[1]	10	(5.15%)	17	(28.81%)	-5.15	***	I don't like the layout or the way the information is presented.
Content-related	**88**	**(45.36%)**	**25**	**(42.37%)**	**0.40**		
Information overload[1]	38	(19.59%)	5	(8.47%)	1.99	*	I took a break from Twitter as the constant flow of information and idiocy surrounding politics was straining my eyes and my minds.
Avoiding politics & Trump[1]	33	(17.01%)	9	(15.25%)	0.32		All the drama that comes with politics and trump really makes me not engage in Twitter debates which seem tiresome and anxiety producing.

Table 14 – Continued

Factors & Sub-factors	Frequency (%)[#] Intermittent discontinuers (n = 194)		Permanent discontinuers (n = 59)		Z-score		Verbatim Quotes
Low content quality							
Negative/ Offensive content[1]	27	(13.92%)	7	(11.86%)	0.40		There was a lot of negative postings from people I was following.
Low relevance[1]	22	(11.34%)	15	(25.42%)	-2.68	**	Twitter also has a trending section that is full of very random topics that do not really pertain to my life at all and I did not find very humorous.
Low credibility[1]	13	(6.70%)	4	(6.78%)	-0.02		Twitter is full of spam and fake accounts.
Content redundancy[1]	13	(6.70%)	3	(5.08%)	0.45		It seems like the people I do see are just saying the same things on Facebook so why do I need two places.
No clear response	3	(1.55%)	0	(0.00%)	0.96		
Total number of comment	370		141				

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

Each respondent could mention multiple reasons for discontinuance.

1. Burden on time, social media fatigue, not matching users' personality/style, privacy concerns, lack of social interaction, social influences, social burden, relative disadvantages, system shortcomings, low content quality, and information overload were considered as forms of disenchantment discontinuance.
2. Relative disadvantage was considered as a combination of disenchantment and replacement discontinuance.
3. Low usage was considered as a form of indifferent discontinuance.
4. Completion of work was considered as a form of completion discontinuance.

THE POST-ADOPTION DECISION-MAKING PROCESS

One of the goals of the current study is to understand the post-adoption decision-making process. Table 15 summarizes the results for **RQ6** and **RQ7**.

RQ6 asked, "*In general, how do users reach their decisions to discontinue Twitter use?*" A descriptive analysis showed that at the stage of evaluation, Twitter discontinuers rarely talked to (M = 2.04, SD = 1.68) or consulted with others (M = 2.22, SD = 1.68) about their discontinuance decisions at the stage of evaluation. At the stage of preparation, discontinuers reported they cut down usage (M = 5.70 SD = 1.68), take a break (M = 4.74, SD = 2.07), and reduce their online participation (M = 4.33, SD = 2.11) before they officially stopped using Twitter. Very few Twitter discontinuers took specific actions at this stage of action. It is believed that most of them would just leave their accounts idle and inactive. At the stage of post-action, in general, Twitter discontinuers did not show regret to be the first in their social group to stop using Twitter (intermittent: M = 1.84, SD = 1.39; permanent: M = 1.86, SD = 1.25). Most of them did not regret quitting Twitter (intermittent: M = 1.63, SD = .398; permanent: M = 1.71, SD = 1.02), and did not think their decisions to quit Twitter was hasty (intermittent: M = 1.81, SD = 1.33; permanent: M = 1.76, SD = 1.21).

RQ7 asked, "*to what extent, are Twitter intermittent discontinuers' and permanent discontinuers' post-adoption decision-making processes different from each other?*" Independent sample t-tests revealed that, at the stage of evaluation, permanent discontinuers (M = 4.78, SD = 2.05) were significantly more likely to seek alternative SNSs than intermittent discontinuers (M = 3.59, SD = 2.46), $t(251) = -2.32$, $p < .05$. In contrast, intermittent discontinuers (M = 4.12, SD = 2.16) were also significantly more likely to search for solutions to reduce disturbance than permanent discontinuers (M = 3.90, SD = 2.56), $t(251) = -1.62$, $p < .05$.

At the stage of preparation, permanent discontinuers ($M = 4.66$, $SD = 2.03$) were significantly more likely to try out other forms of SNSs than intermittent discontinuers ($M = 3.69$, $SD = 2.01$), $t(251) = -2.19$, $p < .05$.

At the stage of action, a few permanent discontinuers would announce their decisions to leave (3.39%), back up their tweets (3.39%), deactivated (6.78%), or deleted their Twitter account (6.78%), but no intermittent discontinuers reported taking these actions. While there was a slightly higher portion of discontinuers changed their Twitter accounts to "private"/ "protected" setting (9.30% for intermittent discontinuers and 5.08% for permanent discontinuers), there were no significant differences between the groups (4.22% difference, $z = 1.02$, $p > .05$)

REASONS FOR READOPTION

RQ8 asked, "what are the reasons for Twitter readoption for intermittent discontinuers?" Intermittent discontinuers said they readopted Twitter for friends (52.4%), and for their work/study (40.5%). One-third readopted Twitter because they thought Twitter was still useful in the same way. More than half of the respondents (54.2%) who selected "other" explained in the open-ended follow-up question that they rejoined Twitter after a voluntary break. A respondent mentioned the planned break was a "self-imposed SNS detox." Many later felt more prepared to focus on things, so they felt "ready to use Twitter again." Several said they returned and repurposed their use of Twitter "with a more clear intent" or practiced a "purposeful stay" on Twitter. Some did it by "deleting people who they found disturbing."

Also, many explained that relationship-related factors as reasons to use Twitter again. Many of them stated that they felt "disconnected from friends" or "missing out things their friends posted" when they left Twitter. Many of the respondents signed in to Twitter only when breaking news happened. Trump has been one of the major reasons for Twitter users to abandon Twitter. However, for some respondents, Trump was the reason they rejoined the community, mentioning “it really wasn’t until Trump that I became interested in it and started to see it as a valuable tool for other matters that concerned me as well.” For others, because of the presence of Trump on Twitter, they realized that Twitter could be “a very effective method of making change.”

Finally, for the measures of continuance commitment, intermittent discontinuers generally disagreed with the statement “Twitter was a matter of necessity” (M = 2.13, SD = 1.81). It was not hard for them to stop using Twitter again (M = 2.00, SD = 1.41). In fact, many intended to take a break or leave Twitter in the future (M = 4.50, SD = 1.77). This implies that readoption does not necessarily mean complete satisfaction toward the innovation. For most, readoption is just a temporal decision to fulfill a short-term needs and gratifications. A readoption does not generate continuance commitment and loyalty to the platform.

Table 15: The Post-adoption Decision-making Process.

	All discontinuers ($n = 253$)	Intermittent discontinuers ($n = 194$)	Permanent discontinuers ($n = 59$)	
Evaluation - Before I decided to quit Twitter… (1 = strongly disagree 7 = strongly agree)		*Mean (SD)*		*t*
1. I talked to others about my decision to stop using Twitter.	2.04 (1.68)	1.94 (1.68)	2.36 (1.68)	-1.13
2. I found out what friends who had already stopped using Twitter thought.	2.22 (1.68)	2.19 (1.71)	2.32 (1.68)	-0.363
3. I was aware of alternative SNSs.	3.87 (2.26)	3.59 (2.46)	4.78 (2.05)	-2.32 *
4. I searched for solutions to reduce, if any, disturbance on Twitter.	3.95 (2.36)	4.12 (2.16)	3.90 (2.56)	1.62 *
Preparation - Before I stopped using Twitter… (1 = strongly disagree 7 = strongly agree)				
1. I started to try other forms of social media.	3.92 (2.00)	3.69 (2.01)	4.66 (2.03)	-2.19 *
2. I reduced my usage of Twitter.	5.70 (1.68)	5.84 (1.67)	5.25 (1.70)	1.59
3. I took several Twitter breaks.	4.74 (2.07)	4.88 (2.06)	4.27 (2.18)	1.29
4. I logged into Twitter, but I reduced my participation.	4.33 (2.11)	4.34 (2.19)	4.32 (2.11)	0.46
Action - I quitted Twitter and … (Yes/No)		Answer with "Yes" (%)		*z*
1. I informed others I was leaving Twitter in my last tweet.	2 (0.79)	0 (0.00)	2 (3.39)	-2.57 *
2. I informed others I was switching to other platforms in my last tweet.	7 (2.77)	6 (3.09)	1 (1.69)	0.57
3. I backed up all the tweets I had previously posted.	2 (0.79)	0 (0.00)	2 (3.39)	-2.57 *
4. I deleted all the tweets on my timeline.	9 (3.56)	6 (3.09)	3 (5.08)	-0.72
5. I switched my Twitter account status to "private"/ "protected."	21 (8.30)	18 (9.30)	3 (5.08)	1.02
6. I deleted my Twitter account.	4 (1.58)	0 (0.00)	4 (6.78)	-3.66 ***
Post-Action - After I left Twitter, I realized… (1 = strongly disagree 7 = strongly agree)		*Mean (SD)*		*t*
1. I did not want to be the first person I knew to stop using Twitter.	1.84 (1.29)	1.84 (1.39)	1.86 (1.25)	-0.07
2. I regretted quitting Twitter.	1.63 (1.01)	1.63 (.98)	1.71 (1.02)	-0.39
3. I thought my decision to stop using Twitter was hasty.	1.81 (1.28)	1.81 (1.33)	1.76 (1.22)	0.18
Relapse - I readopted Twitter because… (Check all that apply)		%		
- I thought Twitter was still worth using.		29.64		
- My work/class required me to use Twitter again.		40.53		
- My friends asked me to use Twitter again.		52.42		
- Other (followed by an open-ended question for elaboration)		32.56		
Continuance Commitment - After I readopted using Twitter… (1 = strongly disagree 7 = strongly agree)		*Mean (SD)*		
1. It was very hard for me to stop using Twitter, even if I wanted to.		2.13 (1.81)		
2. Twitter was a matter of necessity as much as desire.		2.00 (1.41)		
3. I thought about taking a break/quitting Twitter again in the future.		4.50 (1.77)		

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

DISCUSSION AND CONCLUSION

Chapter 9: The Bigger Picture

Thousands of studies have examined and substantiated the diffusion of innovations theory. However, most research has only emphasized the adoption dimension of the diffusion process. Innovation discontinuance, a vital facet of the diffusion process, is largely overlooked. Using Twitter as a case of study, this dissertation (1) identifies differences among continuing adopters, intermittent discontinuers, and permanent discontinuers; (2) investigates the underlying association between different types of discontinuers and reasons for discontinuance; (3) builds a discontinuance prediction model; and (4) proposes a new conceptual model to illustrate the post-adoption decision-making process.

Discussion of Key Findings

Twitter's role as a megaphone for the U.S. president, brands, and celebrities has little effect in boosting the platform's shrinking user base and advertising revenue. The number of inactive Twitter accounts and the rate of Twitter use discontinuance are staggering (Hwong, 2017; Nielsen Online, 2009). The computational analysis in Study 1 treated tweeting activity as a proxy for continuous adoption. Analyzing nearly 100,000 Twitter accounts, Study 1 revealed that less than 3% of Twitter accounts belong to continuing adopters. This explains the platform's temporal instability—arguably a quarter of the Twitter's user base is composed of intermittent discontinuers and permanent discontinuers, aside from the fact that millions of other accounts are operated by bots or have never tweeted before.

The user survey in Study 2 considered signing in to the platform as an indication of continuous usage. Study 2 revealed that 39.6% of the respondents were continuing adopters, and more respondents (46.3%) were intermittent discontinuers, who once left Twitter for a break but resumed use at a later time. The variation in measurement partly explains why these two studies did not generate consistent results in terms of the proportion of Twitter continuing adopters, intermittent discontinuers, and permanent discontinuers.

While Rogers's (1995) diffusion of innovations theory conceptualized discontinuance as a one-time decision to completely abandon an innovation in use, this study extends the definition of discontinuance to include intermittent discontinuance. As suggested by the findings, intermittent discontinuers, unlike permanent discontinuers, maintained a positive perception (i.e., perceived usefulness and perceived ease of use) and overall satisfaction with Twitter. This is in line with previous research that suggested that innovation utility/usefulness measures are highly predictive of individuals' intention to continue using the platform (Davis, 1989). Yet, despite an understanding of the utilitarian value of Twitter, intermittent discontinuers are more likely to report information overload than permanent discontinuers as a reason for discontinuance. The root causes of their information overload include tweets from trolls, politically driven mass media, and advertising. Therefore, they take long breaks away from Twitter to cope with the stress. As such, intermittent discontinuance can be understood as a temporal settlement of the constant interplay between Twitter's utilitarian performance and social media fatigue, which is consistent with Cho's (2015) argument with respect to Facebook discontinuance as an adaptive response strategy employed by users to avoid a stressful situation.

While Rogers's innovation-decision process is conceptualized as "an uncertainty reduction process" (2003, p. 232), this study suggests that the post-adoption decision-making process is "a disturbance-coping process." The findings of this study confirmed that discontinuance is not the end of the diffusion process but one of the stages in the post-adoption process. The post-adoption decision-making process could be portrayed in a manner analogous to the adoption process but, depending on the type of discontinuance—intermittent or permanent—the respective decision-making process could be quite different. For intermittent discontinuers, the movement through different stages of the post-adoption model is neither linear nor unitary, but cyclical, involving multiple stages: pre-evaluation, evaluation, preparation, action (i.e., discontinuance), post-action, and relapse (i.e., readoption) over time.

Unlike adoption, which often involves social learning and social influence, discontinuance is more likely to be an individual decision. When users adopt an innovation, they usually confront risks and uncertainties about the unexpected consequences of the innovation at the implementation stage. To reduce those uncertainties, many of them seek advice and opinions from their peers. In contrast, before users choose to discontinue, they usually have had a direct experience with the benefits and limitations the innovation provides. Thus, they seldom consult with friends before they decide to discontinue at the stage of evaluation.

In theory, the post-adoption decision-making model of the incumbent innovation could overlap to some degree with an innovation-decision process of another innovation. This explains why many discontinuers seeking superior alternatives to Twitter reduce their Twitter usage at the stage of preparation of the post-adoption model—they spend more time exploring other innovations, such as Instagram and Reddit, at the stage of trial in the adoption model.

At the stage of action, most Twitter discontinuers let their accounts remain idle and inactive, without taking specific actions such as erasing content, deleting accounts, or archiving messages. For some discontinuers, an idle account serves as a gateway should they decide to return in the future. For others, unplugging from the platform completely could mean losing touch with family and friends, and they are not fully prepared for it. Another explanation for not taking specific action is that, compared to signing up a SNS account, deleting an account appears laborious and is not always foolproof. Instructions and links to delete accounts are usually hidden in pages and come with long explanations. Twitter, for example, does not allow users to delete data instantly but places the account in a queue for 30 days before permanent deletion. Even after deleting the account, the company claims that some content may still be viewable on Twitter for a few days and some tweets may still be indexed by Google and Bing and remain searchable.

In fact, discontinuance and subsequent readoption are often planned. Temporary discontinuance often serves as a short-term break for users to reflect on the positives and negatives of being connected with the platform. In recent years, “social media detox” has become very popular among frequent SNS users who experience social media fatigue. The detox period usually results in positive changes of SNS behavior. To manage social media stress, survey respondents reported that they would remove the disturbance by cleaning up profiles and unfollowing people or businesses that push annoying content. Therefore, users’ readoption often comes with the hope for a purposeful and long-lasting stay. Results also revealed that social factors play a critical role in unplanned Twitter readoption. While leaving SNSs may reduce social stress, it comes with the cost of making one feel disconnected from the community and less satisfied (Sheldon, Abad, & Hinsch, 2011). Some discontinuers may realize the tradeoff between social connection and social burden, and later choose to resume Twitter use as they value the social connection more.

However, readoption to Twitter does not necessarily mean complete satisfaction toward the innovation. Intermittent discontinuers generally showed a low level of continuance commitment. It is believed that for most users, readoption is just a temporal decision to fulfill a short-term needs and gratifications. Readoption does not generate loyalty to the platform.

While many diffusion studies have focused on the differences between earlier adopters and later adopters, this study enriches the understanding of such variations by distinguishing the two types of discontinuers. The findings of this study showed that permanent discontinuers are more likely to leave the platform because of its functional shortcomings, such as the layout, the hashtags/mentions, or the 140-character limit. Twitter data analysis revealed that permanent discontinuers are less likely to craft their tweets and seldom use Twitter affordances—contextual (e.g., hashtags), interactional (e.g., mentions and retweets), and informational (e.g., text, URLs, videos, and photos) (Tanupabrungsun and Hemsley, 2018) in their tweet exchange. Instead, they are more likely to replace Twitter with alternative platforms once they realized that Twitter does not meet their need and gratifications. They would seek and try alternatives before they discontinued Twitter use. In fact, permanent discontinuers' personal characteristics may help explain their discontinuance behavior. Results revealed that permanent discontinuers have a lower score in personal innovativeness but a higher score in independent judgment-making. While innovativeness reflects a person's propensity to experience and experiment with an innovation (Hirschman, 1980), a lower score in the trait could mean the individual is less likely to search for technical solutions to address the functional shortcomings s/he encountered. Meanwhile, a high score in independent judgment-making means an individual is less likely to rely on others for help or advice when solving technical problems. Hence, discontinuers with low innovativeness and high independent judgment-making prefer to leave Twitter permanently and use alternative SNSs that they think are better.

Moreover, compared with intermittent discontinuers, permanent discontinuers tend to be younger and more likely to be early adopters. This finding is in line with the previous report from Gartner, a research and advisory firm providing information technology consultation, which found that younger people get bored with SNSs more easily and early adopters experience social media fatigue more frequently (Goasduff & Pettey, 2011). Thus, younger people usually selectively choose SNSs to combat SNS exhaustion and permanently left those platforms they are dissatisfied with.

On the other hand, intermittent discontinuers are more likely to report that, since their initial adoption, they have rarely used Twitter (i.e., low usage). Intermittent discontinuers usually have the fewest tweets across their account's lifespan among the three groups. This indicates that they keep Twitter at their disposal and use the microblogging service only when they need it. Many of them, for instance, maintained a Twitter account to get breaking news or information on some niche topics.

The reasons for discontinuance usually vary among discontinuers. Besides user- and function-related factors discussed earlier, quite a few respondents also mentioned content quality as a reason for discontinuance in the open-ended question. Since Trump took office, Twitter has become a channel for official statements (Landers, 2017). His influential Twitter presence has attracted substantial attention, turning the platform into a public sphere for vicious political debates. Some respondents followed Trump and re-joined the platform, but more respondents (17.01% intermittent discontinuers and 15.25% permanent discontinuers) decided to disengage from the platform as the amount of hatred, prejudice, racism, and misogyny become unbearable. Twitter users who constantly encounter ideologically incongruent content have a significantly lower level of Twitter satisfaction and, therefore, stop using the SNS temporarily or permanently.

Also, reasons for discontinuance usually vary from innovation to innovation. Surprisingly, unlike Facebook discontinuers (York & Turcotte, 2015), Twitter discontinuers are not as likely to mention privacy and social burden concerns as reasons for leaving the platform. Twitter users may be oblivious to privacy risks and comfortable sharing their personal information on Twitter because of the way the platform is designed. One major distinction between Twitter and Facebook is that messages posted on Twitter are public by default—tweets can be easily searched and aggregated, but Facebook content is usually set as "private" with the intention to be shared only with friends and family. Also, Twitter is organized around shared interests, instead of personal relationships. The main purpose of Twitter is usually for gathering and spreading information, instead of relationship building and maintenance.

THEORETICAL IMPLICATIONS

This study extends the diffusion of innovations theory through an examination of the post-adoption decision-making process. While early studies approached discontinuance as a one-time, complete abandonment of an innovation in use, this study extends the concept by examining two types of discontinuance: intermittent and permanent. The concept of intermittent discontinuance leads to the development of a new post-adoption decision-making model. This cyclical model consists of six stages: (1) pre-evaluation, when adopters become aware of their relationships with the innovation; (2) evaluation, when adopters reflect on the benefits and drawbacks of continuing and discontinuing; (3) preparation, when adopters adjust their usage patterns; (4) action, when adopters discontinue using the innovation; (5) post-action, when discontinuers evaluate their discontinuance decisions and look for affirmation; (6) relapse, when discontinuers readopt the innovation. Adopters can go through the post-adoption cycle repeatedly until they come to a permanent discontinuance.

This multi-stage model provides a systematic framework to explore and compare behavior and cognitive reasoning among intermittent and permanent discontinuers at each stage. This study tested the proposed model and the results provided empirical support for the applicability and usefulness of this framework. As a result, this study presents a preliminary yet holistic picture regarding the post-adoption process, an untold yet important story most diffusions studies missed.

To address the arbitrariness of defining inactivity, this study introduces a mathematical approach to generate the benchmark, based on an innovation's own life cycle and its user base. This study also refines and extends Rogers and Shoemaker's (1971) replacement-disenchantment typology and suggests a more comprehensive and rigorous categorization of reasons for discontinuance, by factors (i.e., user-, context-, relationship-, function-, and content-related factors) and by discontinuance typologies (i.e., disenchantment, replacement, completion, and indifferent discontinuance).

PRACTICAL IMPLICATIONS

Understanding users' motivations for adoption as well as discontinuance is necessary for effectively developing, implementing, using and evaluating SNSs. This study advises SNS providers not to view all discontinuers as a homogeneous group but to identify factors distinguishing different types of discontinuers. Developing tailor-made retention solutions may help a SNS to become more relevant and achieve cost-effectiveness, while delivering a better user experience.

Specifically, individuals who leave a SNS due to function- and relationship-related factors are usually permanent discontinuers. SNS providers should innovate and address shortcomings in design, as those problems often lead to permanent discontinuance. To sustain growth, SNS providers need to anticipate and adapt to changes constantly. For example, Twitter introduced new discovery tools and expanded character limits in the hope to stay competitive. Second, individuals who stop using an innovation due to dissatisfaction are more likely to initiate negative word of mouth among other adopters (Parthasarathy, 1995). Hence, SNS providers should note that social influence (i.e., relationship-related factors) could possibly turn Twitter users away permanently. To counter the adverse effects of disenchantment discontinuance, SNS providers should invest in better technical support. This would help novice users take advantage of the platform and build realistic expectations for the service. Third, content quality was a concern for intermittent discontinuers. Appropriate levels of content moderation and other mechanisms to filter fake news, curb harassment, and reduce incivility may help retain users before the exodus begins.

LIMITATIONS AND FUTURE RESEARCH

Despite these theoretical and practical contributions, this study is not without limitations. Perhaps the biggest challenge is the methodological difficulty in defining adoption and discontinuance in SNS research. "Adoption" refers to a definable act of decision (conscious or subconscious) on the users' part, and diffusion studies in marketing and telecommunication often use "hard data" such as purchase or subscription records to define adoption. However, for SNS studies, locating such actions and interpreting them are not that straight forward. While the computational analysis in Study 1 treated tweeting activity as a proxy for continuous adoption, the user survey in Study 2 considered signing in to the platform as an indication of continuous usage. This variation in measurement could explain the inconsistent results in terms of the proportion of Twitter continuing adopters, intermittent discontinuers, and permanent discontinuers in Study 1 and Study 2. The operational definition of Study 1 might overlook active lurkers on Twitter, who were mostly silent (i.e., they rarely post anything), but used the platform regularly to receive information. Study 2 might overestimate the number of adopters, as a simple access (i.e., log in or visit) to the platform does not imply making "full use of" a SNS, which is the emphasis in the definition of adoption (Rogers, 1983, p.21).

As Twitter login history is not available to researchers, tweeting is arguably the closest resemblance of twitter activity. While the sustainability of a SNS depends not only on people joining, but also on people staying and contributing, visible content creation and online interaction are pivotal indications for the SNS growth or decline. Further research could consider modeling SNS activity in two forms—passive and active. Research could recruit respondents who are willing to disclose their Twitter IDs. A comparison of activity metrics among active users, lurkers, and discontinuers could provide valuable insights into discontinuance studies.

Second, given the nascent stage of studies examining post-adoption behaviors, many questions have not yet been addressed. While this study proposes a multi-stage post-adoption decision-making model, discontinuance is the focus of this study. Other stages, such as the stage of relapse, have not been fully examined. Specifically, future research should examine the nature of readoption: What is the average number of relapses before a user completely abandons a SNS? What personal and social factors affect and predict the number of relapses before a discontinuance becomes permanent? What are the behavioral, attitudinal, and perceptional differences between initial adoption and readoption? Furthermore, although this study examines the characteristics of intermittent and permanent discontinuers, their distinctive roles in the diffusion process have not been thoroughly discussed. For example, compared with permanent discontinuers, do intermittent discontinuers have the same influence in discouraging potential and current users from using a SNS? Or do intermittent discontinuers take up a moderating role between adopters and discontinuers? Future projects should address these questions.

Third, the empirical focus of this study is on one singular SNS and its U.S. users. Although Twitter is one of the most popular SNSs, it may not be an accurate representation of other SNS platforms, such as Facebook, Instagram, etc. SNSs differ from one another in terms of their affordances, purposes, and user bases. While advertisers and marketers tend to target their customers through multiple SNS platforms simultaneously, they should be aware that SNS discontinuance could occur on different platforms for different reasons. Moreover, as the use of SNSs is not confined by geographical boundaries, it is imperative for researchers to examine users from diverse cultural backgrounds and geographical areas. For instance, discontinuers from individualist cultures may value autonomy more. In that sense, maintaining interpersonal relations online may not be such a strong goal for them compared to discontinuers from collectivist cultures. Cultural factors should be taken into consideration to understand global SNS discontinuance. Further studies on cross-platform and cross-cultural comparisons are encouraged.

Fourth, regarding the methodology, the main results of this study are based on a classification predictive model to estimate the probability of Twitter use discontinuance within a certain timeframe (e.g., the next three months for this study). The multi-class classification (continuing adopters and discontinuers) is normally what is needed as usually companies are interested in targeting users with the highest possibility of discontinuance. However, other methodological approaches have other advantages and may serve as alternative models in specific conditions. For example, survival analysis could be a good alternative. Survival analysis models the occurrence and timing of events and helps to understand how time-varying variables interact. For this study, survival analysis could have helped predicting not only if a Twitter user would discontinue but also how long until s/he are expected to leave.

Finally, although the period of inactivity used to define discontinuance in this study was innovation-specific, there is no guarantee that discontinuers would not resume using Twitter in the future. The cross-sectional nature of the current survey restricts a temporal analysis and is less likely to capture a long-term phenomenon. Computational analysis is helpful for longitudinal study but is also constraint by the API rate limit. For example, this study could only collect the most recent 3,200 tweets from users. Future studies are encouraged to use longitudinal data to examine users' readoption behavior. Ideally, the longitudinal approach would begin from the first stage of the adoption model (i.e., the knowledge stage) to the last stage of the post-adoption decision-making model, until the very end of the product's life cycle.

CONCLUSION

In the real world, only a few innovations sustain their user bases and become institutionalized, while many end up being fads (Strang & Macy, 2001). Understanding innovation discontinuance and its relation to adoption could yield theoretical insights into the temporal instability of an innovation, and why and how an innovation is discarded or discredited. This study identified significant demographic, behavioral, and psychographic differences among Twitter continuing adopters, intermittent discontinuers, and permanent discontinuers. Reasons for discontinuance vary across the three groups of users.

This dissertation should not close without acknowledging that, in some cases, innovation discontinuance is reasonable and even desirable for SNS users. A major criticism of Rogers's innovation diffusion process has been its pro-innovation emphasis. The argument that all users should adopt an innovation has been challenged by many scholars. For instance, Bunch and Lopez (1995) stated that discontinuance is not always negative. In the context of agricultural technologies, they believed that many farming technologies are discarded because farmers' needs for technologies changed. Similarly, many SNSs users adopt but eventually drop a platform because they no longer need it. For SNS providers, knowing why users abandon certain SNSs can provide insights into their technological shortcomings, and ultimately, lead to the creation of higher-quality digital platforms.

APPENDICES

Appendix A - IRB Approval

OFFICE OF RESEARCH SUPPORT

THE UNIVERSITY OF TEXAS AT AUSTIN

P.O. Box 7426, Austin, Texas 78713 · Mail Code A3200
(512) 471-8871 · FAX (512) 471-8873

FWA # 00002030

Date: 01/09/18

PI: Hsiang I Chyi

Dept: Journalism

Title: Building an Innovation Discontinuance Model: The Case of Twitter

Re: IRB Exempt Determination for Protocol Number 2017-11-0130

Dear Hsiang I Chyi:

Recognition of Exempt status based on 45 CFR 46.101(b)(2).

Qualifying Period: 01/09/2018 to 01/08/2021. *Expires 12 a.m. [midnight] of this date.*
A continuing review report must be submitted in three years if the research is ongoing.

Responsibilities of the Principal Investigator:

Research that is determined to be Exempt from Institutional Review Board (IRB) review is not exempt from ensuring protection of human subjects. The Principal Investigator (PI) is responsible for the following throughout the conduct of the research study:

1. Assuring that all investigators and co-principal investigators are trained in the ethical principles, relevant federal regulations, and institutional policies governing human subject research.

2. Disclosing to the subjects that the activities involve research and that participation is voluntary during the informed consent process.

3. Providing subjects with pertinent information (e.g., risks and benefits, contact information for investigators and ORS) and ensuring that human subjects will voluntarily consent to participate in the research when appropriate (e.g., surveys, interviews).

4. Assuring the subjects will be selected equitably, so that the risks and benefits of the research are justly distributed.

5. Assuring that the IRB will be immediately informed of any information or unanticipated problems that may increase the risk to the subjects and cause the category of review to be reclassified to expedited or full board review.

OFFICE OF RESEARCH SUPPORT

THE UNIVERSITY OF TEXAS AT AUSTIN

P.O. Box 7426, Austin, Texas 78713 · Mail Code A3200
(512) 471-8871 · FAX (512) 471-8873

FWA # 00002030

Date: 01/09/18
PI: Hsiang I Chyi
Dept: Journalism
Title: Building an Innovation Discontinuance Model: The Case of Twitter

Re: IRB Exempt Determination for Protocol Number 2017-11-0130

Dear Hsiang I Chyi:

Recognition of Exempt status based on 45 CFR 46.101(b)(2).

Qualifying Period: 01/09/2018 to 01/08/2021. *Expires 12 a.m. [midnight] of this date.*
A continuing review report must be submitted in three years if the research is ongoing.

Responsibilities of the Principal Investigator:

Research that is determined to be Exempt from Institutional Review Board (IRB) review is not exempt from ensuring protection of human subjects. The Principal Investigator (PI) is responsible for the following throughout the conduct of the research study:

1. Assuring that all investigators and co-principal investigators are trained in the ethical principles, relevant federal regulations, and institutional policies governing human subject research.

2. Disclosing to the subjects that the activities involve research and that participation is voluntary during the informed consent process.

3. Providing subjects with pertinent information (e.g., risks and benefits, contact information for investigators and ORS) and ensuring that human subjects will voluntarily consent to participate in the research when appropriate (e.g., surveys, interviews).

4. Assuring the subjects will be selected equitably, so that the risks and benefits of the research are justly distributed.

5. Assuring that the IRB will be immediately informed of any information or unanticipated problems that may increase the risk to the subjects and cause the category of review to be reclassified to expedited or full board review.

Appendix B - Online Survey

B1. Consent Form

Identification of Investigator and Purpose of Study

You are invited to participate in a research study regarding Twitter usage. The study is being conducted by Margaret YM Ng, an Ph.D. candidate in the School of Journalism in the Moody College of Communication at The University of Texas at Austin, 300 W. Dean Keeton St., Austin, TX 78712.

The purpose of this research study is to examine how people adopt and quit Twitter. Your participation in the study will contribute to a better understanding of the how people use social media. You are free to contact the investigator at the above address and phone number to discuss the study.

If you agree to participate:

- The survey will take approximately 10 minutes of your time.
- You have at least one Twitter account.
- You will be asked to take a set of survey questions regarding to your Twitter usage, personality, and demographics.

Risks/Benefits/Confidentiality of Data

There are no risks to participating in this project beyond what is experienced in everyday life. There will be no costs for participating, nor will you benefit from participating. No identifying information about you (including name or email address) will be collected, so no one will be able to connect you to the research. Your Twitter accounts will not be shared with anyone outside of the research team, will be removed from the data set, and will not be linked to survey responses.

Participation or Withdrawal

Your participation in this study is voluntary. You may decline to answer any question and you have the right to withdraw from participation at any time. Withdrawal will not affect your relationship with The University of Texas in any way. If you do not want to participate, either simply stop participating or close the browser window.

If you do not want to receive any more reminders, you may email me at margaretnym@utexas.edu.

Contacts

If you have any questions about the study or need to update your email address contact the researcher Margaret YM Ng at 512.710.3715 or send an email to margaretnym@utexas.edu. This study has been reviewed by The University of Texas at Austin Institutional Review Board and the study number is **2017-11-0130**

Questions about your rights as a research participant

If you have questions about your rights or are dissatisfied at any time with any part of this study, you can contact, anonymously if you wish, the Institutional Review Board by phone at (512) 471-8871 or email at orsc@uts.cc.utexas.edu.

Please read each questions and statements carefully. There are checking questions along the survey. Survey with contradicted answers for checking questions would be void.

By clicking [CONTINUE] I consent to participate in this study. By taking this survey, I indicate my consent to participate in this study.

Thank you.

Please print a copy of this document for your records.

B2. QUESTIONNAIRE

Twitter Use

Gen1. Do you have a Twitter account?
- Yes
- No

Skip To: Gen2 If Do you have a Twitter account? = Yes
Skip To: End of Survey If Do you have a Twitter account? = No

Please answer with the option that best reflects your real Twitter usage behavior. It ***will not affect*** your chance to get the bonus.

Gen4. Have you logged into Twitter during the past three months?
- Yes
- No

Skip To: Gen6a If Please answer with the option that best reflects your real Twitter usage behavior. It will not af... = No
Skip To: Gen5 If Please answer with the option that best reflects your real Twitter usage behavior. It will not af... = Yes

Gen5. Have you posted on Twitter during the past three months?
- Yes
- No

Skip To: Gen7 If Please answer with the option that best reflects your real Twitter usage behavior. It will not af... = Yes
Skip To: Gen6b If Please answer with the option that best reflects your real Twitter usage behavior. It will not af... = No

Gen6a. When was the last time you logged into Twitter?
- 3 - 6 months ago
- 6 -12 months ago
- 1 - 2 years ago
- More than 2 years ago
- I cannot recall

Gen6b. When was the last time you posted on Twitter?
(If you don't remember, you can check the date of your last tweets)
- I have never posted before
- 3 months ago
- 6 months ago
- 12 months ago
- More than 2 years ago
- I cannot recall

Break1. Have you ever voluntarily taken a break from Twitter for a period of **three months** or more and return to the platform later?

- Yes
- No

Skip To: Break2 If Have you ever voluntarily taken a break from Twitter for a period of three months or more? = Yes
Skip To: End of Block If Have you ever voluntarily taken a break from Twitter for a period of three months or more? = No

Break2. Why did you decide to take a break for **a period of three months or more** from Twitter? (open-ended, min. 250 characters)

____

____

Gen7. Do you intend to use Twitter in the next six months?

- Yes
- No

Display This Question: Do you intend to use Twitter in the next six month? = No

Gen7_1: What were your reasons for stop using Twitter? (open-ended, min. 250 characters)

____

____

Stages of Discontinuance

We would like to know about the process you went through when quitting Twitter. On a scale of 1(*Strongly Disagree)* to 7(*Strongly Agree)*, rate how well the following statements apply to you.

Recalling my experience of taking a break/leaving Twitter,

Evaluation Before I decided to quit Twitter…

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
1. I talked to others about my decision to stop using Twitter.	○	○	○	○	○	○	○
2. I found out what friends who had already stopped using Twitter thought.	○	○	○	○	○	○	○
3. I was aware of alternative SNSs.	○	○	○	○	○	○	○
4. I searched for solutions to reduce, if any, disturbance on Twitter.	○	○	○	○	○	○	○

Preparation Before I stopped using Twitter…

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
1. I started to try other form of social media.	○	○	○	○	○	○	○

2. I reduced my usage of Twitter.	○	○	○	○	○	○	○
3. I took several Twitter breaks.	○	○	○	○	○	○	○
4. I logged into Twitter, but I reduced my participation.	○	○	○	○	○	○	○

Action I quitted Twitter and … (Yes/No) (Check all that apply)

	No (1)	Yes (2)
1. I informed others I was leaving Twitter in my last tweet.	○	○
2. I informed others I was switching to other platforms in my last tweet.	○	○
3. I backed up all the tweets I had previously posted.	○	○
4. I deleted all the tweets on my timeline.	○	○
5. I switched my Twitter account status to "private"/ "protected."	○	○
6. I deactivated my Twitter account.	○	○
7. I deleted my Twitter account.	○	○

Post-Action After I left Twitter, I did realize that…

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
1. I did not want to be the first person I knew to stop using Twitter.	○	○	○	○	○	○	○
2. I regretted quitting Twitter.	○	○	○	○	○	○	○
3. I thought my decision to stop using Twitter was hasty.	○	○	○	○	○	○	○

I readopted Twitter after taking a break.

- Yes (to **Relapse**)
- No (skip **Relapse**)

Skip To: Relapse _why If I did once readopt Twitter after I thought I quitted Twitter. = Yes
Skip To: End of Block If I did once readopt Twitter after I thought I quitted Twitter. = No

Relapse

I readopted Twitter because… (Check all that apply)

- I thought Twitter was still worth using.
- My work/class required me to use Twitter again.
- My friends asked me to use Twitter again.
- Other: ____

RelapseOther: Why you decided to **return to Twitter** again after the break? (open-ended, min. 250 characters)

____

____

Continuance Commitment

After I readopted using Twitter...

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
1. It was very hard for me to stop using Twitter, even if I wanted to.	○	○	○	○	○	○	○
2. Twitter was a matter of necessity as much as desire.	○	○	○	○	○	○	○
3. I thought about quitting Twitter again in the near future.	○	○	○	○	○	○	○

Twitter Activity

Please report your current experience with Twitter. If you have already quitted Twitter, please recall your previous experience when you most engaged with Twitter.

Exp1. In a typical week, how often do/did you use Twitter?

-	0 1 2 3 4 5 6 7
Number of days per week	

Exp2. On average, how much time do/did you spend using Twitter each time you logged in?

	0 10 20 30 40 50 60 70 80 90 100110120
minute(s)	

Exp3. When using Twitter, I often…

	None at all (1)	A little (2)	A moderate amount (3)	A lot (4)	A great deal (5)
Active Online Participation Scale (modified from Koreleva, et al., 2011)					
1. **Tweet** my thoughts and feelings	○	○	○	○	○
2. **Comment** on other people's tweets	○	○	○	○	○
3. **Retweet** other people's tweets	○	○	○	○	○
4. **"Like"** other people's tweets	○	○	○	○	○
Passive Online Participation Scale (modified from Koreleva, et al., 2011)					

5. **Follow** news sources, celebrities, and other famous people	○	○	○	○	○
6. **Click on URLs** that link out to other websites (e.g., blogs, news sites, etc.)	○	○	○	○	○

Recall from your experience,
FJoin_Why: Why did you start using Twitter in the first place? (check all that apply)

- For expressing my personal thought
- For access to the news
- For social networking
- For work/study
- Other _____

Display This Question:

If Recall from your experience, Why did you start using Twitter in the first place? = For access to information/news

Fjoin_why_news Through Twitter, what kind of information/news you frequently get access to? **(Check all that apply)**

- Breaking news
- Politics
- Economy
- Sports
- Health
- Crimes/Disasters
- Technology
- Entertainments
- Other: ____

FJoin_Inf. Did any of the following influence your decision to start using Twitter? (Check all that apply)

- Online review about Twitter
- Advertisements for Twitter
- Family
- Friends
- Co-workers
- Other _____

Twitter Experience

Below are statements regarding your personality. On a scale of 1 (Strongly disagree) to 7 (Strongly agree), rate how well the following statements apply to you.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Perceived usefulness (Venkatesh & Brown, 2001)							
1. Twitter allows me to **seek information** more quickly.	○	○	○	○	○	○	○
2. Twitter allows me to **connect with others** more easily.	○	○	○	○	○	○	○
Perceived ease of use (Venkatesh & Brown, 2001)							
3. Twitter is **clear and easy** to use.	○	○	○	○	○	○	○
4. Navigating Twitter requires a lot of **mental efforts**.	○	○	○	○	○	○	○
Satisfaction							
5. I feel **satisfied** with my overall Twitter experience.	○	○	○	○	○	○	○

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Information overload							

1. I encounter **too much information** when I search on Twitter.							
2. I am **overwhelmed** by the amount of information available on Twitter.							

Social overload (Maier, Laumer, Eckhardt, & Weitzel, 2012)

3. I feel that I **care too much** about my Twitter-friends' well-being.							
4. I feel I **spend too much time** dealing with my Twitter-friends' problem.							

Emotional Exhaustion (Maier et al., 2012)

5. I feel **burned out** for using Twitter.							
6. Using Twitter **stresses** me out.							

User attributes

On a scale of 1(*Strongly Disagree)* to 7(*Strongly Agree)*, rate how well the following statements apply to you.

IJM_A. Independent Judgment-making (Adoption)
Before I registered an account on Twitter, it was important for me to

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
1. **Seek advice** from other Twitter users. *	○	○	○	○	○	○	○
2. Find out what **other users thought** of Twitter. *	○	○	○	○	○	○	○

Innovativeness (Kim & Mirusmonov, 2010)

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
1. When I hear about a new technology, I would **look for ways to experiment** with it.	○	○	○	○	○	○	○
2. Among my peers, I am usually the **first to try new technologies.**	○	○	○	○	○	○	○
3. In general, I am **hesitant** to try new technologies.*	○	○	○	○	○	○	○

Big Five Inventory (BF)
I see myself as someone who:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Extraversion							
1. Prefers to be alone.*	○	○	○	○	○	○	○
2. Holds back from expressing my opinions. *	○	○	○	○	○	○	○
3. Enjoys being part of a group.	○	○	○	○	○	○	○
Neuroticism							
4. Becomes stressed out easily.	○	○	○	○	○	○	○
5. Is calm, even in tense situations. *	○	○	○	○	○	○	○
6. Is afraid that I will do the wrong thing.	○	○	○	○	○	○	○
Openness							
7. Does not have a good imagination. *	○	○	○	○	○	○	○
8. Is interested in many things.	○	○	○	○	○	○	○
9. Prefers to stick with things that I know. *	○	○	○	○	○	○	○
Agreeableness							
10. Trusts others.	○	○	○	○	○	○	○
11. Contradicts others. *	○	○	○	○	○	○	○
12. Values cooperation over competition.	○	○	○	○	○	○	○
Conscientiousness							
13. Completes tasks successfully.	○	○	○	○	○	○	○
14. Excels in what I do.	○	○	○	○	○	○	○

15. Works hard. ○ ○ ○ ○ ○ ○ ○

*** Reverse coding**

Demographics and SES Questions

Below are statements regarding your demographics.

a. What is your gender?

1 Male
2 Female

b. What is your age? ____________________

c. Which of the following best describes your race?

1 White (e.g., Caucasian, European, Irish, Italian, Arab, Middle Eastern)
2 Black or African-American (e.g., Negro, Kenyan, Nigerian, Haitian)
3 Asian or Asian-American (e.g., Asian Indian, Chinese, Filipino, Vietnamese or other Asian origin groups)
4 Native American/American Indian/Alaska Native
5 Pacific Islander/Native Hawaiian
6 Hispanic/Latino (e.g., Mexican, Puerto Rican, Cuban)
7 Some other race (please specify ______________________)

d. What is your household income before taxes?

1 Less than $20,000
2 20,001 to under $40,000
3 40,001 to under $60,000
4 60,001 to under $80,000
5 80,001 to under $100,000
6 $100,001 or more

e. What is the highest level of school you have completed or the highest degree you have received?

1 Less than high school
2 Completed High School
3 Some college, no degree (includes community college)
4 Two-year associate degree from a college or university
5 Four-year college or university degree/Bachelor's degree (e.g., BS, BA, AB)
6 Postgraduate or professional degree, including master's, doctorate, medical or law degree (e.g., MA, MS, PhD, MD, JD)

Thank you for taking the time to complete this questionnaire. Your help is greatly appreciated.

References

Abraham, S. C. S., & Hayward, G. (1984). Understanding discontinuance: Towards a more realistic model of technological innovation and industrial adoption in Britain. *Technovation*, *2*, 209–231. doi:10.1016/0166-4972(84)90004-X

Abrahamson, E., & Rosenkopf, L. (1993). Institutional and competitive bandwagons: Using mathematical modeling as a tool to explore innovation diffusion. *Academy of Management Review*, *18*, 487–517. doi: 10.5465/AMR.1993.9309035148

Agarwal, N., Liu, H., Tang, L., & Yu, P. S. (2008). Identifying the influential bloggers in a community. *Proceedings of the 2008 International Conference on Web Search and Data Mining*, *USA*, 207–218. doi: 10.1145/1341531.1341559

Agarwal, R., Ahuja, M., Carter, P. E., & Gans, M. (1998). Early and late adopters of IT innovations: extensions to innovation diffusion theory. *Proceedings of the Diffusion Interest Group in Information Technology* Conference, 1–18.

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information systems research*, *9*, 204–215. doi:10.1287/isre.9.2.204

Aggarwal, C. C. (2011). An introduction to social network data analytics. *Social network data analytics* (pp. 1–15). Boston, MA: Springer.

Ahn, J. H., Han, S. P., & Lee, Y. S. (2006). Customer churn analysis: Churn determinants and mediation effects of partial defection in the Korean mobile telecommunications service industry. *Telecommunications Policy*, *30*, 552–568. doi:10.1016/j.telpol.2006.09.006

Aiisha, L. (2015, November 29). My breakup with social media. *Huffpost*. Retrieved from https://www.huffingtonpost.com/laura-aiisha-/my-break-up-with-social-m_b_8672308.html

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behaviour*. Upper Saddle River, NJ: Prentice Hal

Allan, R. (2016, December 6). Bye, users! Twitter's retention rate is worse than you think. *Medium*. Retrieved from https://medium.com/@sm_app_intel/bye-users-twitters-retention-rate-is-worse-than-you-think-229b406887c4#.tqi4xqkkf

Althaus, S. L., & Tewksbury, D. H. (2000). Patterns of Internet and traditional news media use in a networked community. *Political Communication*, *17*, 21–45. doi:10.1080/105846000198495

Althaus, S. L., & Tewksbury, D. H. (2007). *Toward a new generation of media use measures for the ANES.* (Report No. ne011903). Retrieved from American National Election Studies website:

https://www.researchgate.net/profile/Scott_Althaus/publication/265199906_Toward_a_New_Generation_of_Media_Use_Measures_for_the_ANES/links/5626589608aeabddac92f363.pdf

Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in Human Behavior*, *26*, 1289–1295. doi:10.1016/j.chb.2010.03.018

Anderson, C., John, O. P., Keltner, D., & Kring, A. M. (2001). Who attains social status? Effects of personality and physical attractiveness in social groups. *Journal of personality and Social Psychology*, *81*, 116–132. doi:10.1037/0022-3514.81.1.116

Anil Kumar, D., & Ravi, V. (2008). Predicting credit card customer churn in banks using data mining. *International Journal of Data Analysis Techniques and Strategies*, *1*, 4–28. doi:10.1504/IJDATS.2008.02002

Arrese, A., & Albarran, A. B. (2003). *Time and media markets*. Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Barnett, H. G. (1953). *Innovation: The basis of cultural change*. New York, NY: McGraw-Hill

Baumer, E. P., Adams, P., Khovanskaya, V. D., Liao, T. C., Smith, M. E., Schwanda Sosik, V., & Williams, K. (2013). Limiting, leaving, and (re) lapsing: an exploration of facebook non-use practices and experiences. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, *USA*, 3257–3266. doi:10.1145/2470654.2466446

Beaudoin, C. E. (2008). Explaining the relationship between Internet use and interpersonal trust: Taking into account motivation and information overload. *Journal of Computer-Mediated Communication*, *13*, 550–568. doi:10.1111/j.1083-6101.2008.00410.x

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 351–370. doi:10.2307/3250921

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly*, *28*, 229–254. doi: 10.2307/25148634

Bievens, B. (2017, April 3). Why I did a social media cleans. *Odys*sey. Retrieved from https://www.theodysseyonline.com/my-social-media-cleanse-experiement

Black, W. (1983). Discontinuance and diffusion: Examination of the post adoption decision process. *Advances in Consumer Research*, *10*, 356–361.

boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication & Society*, *15*, 662–679. doi:10.1080/1369118X.2012.678878

Bradshaw, T. (2011, March). The fickle value of friendship. *Financial Times*. Retrieved from https://www.ft.com/content/240f19d4-5afc-11e0-a290-00144feab49a

Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5–32. doi:10.1023/A:1010933404324

Bright, L. F., Kleiser, S. B., & Grau, S. L. (2015). Too much Facebook? An exploratory examination of social media fatigue. *Computers in Human Behavior*, *44*, 148–155. doi:10.1016/j.chb.2014.11.048

Bruns, A. (2013). Faster than the speed of print: Reconciling 'big data' social media analysis and academic scholarship. *First Monday*, *18*. doi:10.5210/fm.v18i10.4879

Bruns, A., & Burgess, J. (2012). Researching news discussion on Twitter: New methodologies. *Journalism Studies*, *13*, 801–814. doi:10.1080/1461670X.2012.664428

Bunch, L. R., & Lopez, G. (1996). Soil recuperation in Central America: Sustaining innovation after intervention. Gatekeeper Series No. 55. London: Sustainable Agriculture Program, International Institute for Environment and Development.

Burns, L. R., & Wholey, D. R. (1993). Adoption and abandonment of matrix management programs: Effects of organizational characteristics and interorganizational networks. *Academy of Management Journal*, *36*, 106-138. doi: 10.2307/256514

Butt, S., & Phillips, J. G. (2008). Personality and self-reported mobile phone use. *Computers in Human Behavior*, *24*, 346–360. doi:10.1016/j.chb.2007.01.019

Carlson, L., & Grossbart, S. L. (1984). Toward a better understanding of inherent innovativeness. *Proceedings of the American Marketing Association Educator's Conference*, *USA*, *50*, 88–91.

Castillo, C., Mendoza, M., & Poblete, B. (2011). Information credibility on twitter. *Proceedings of the 20th International Conference on World Wide Web*, *India*, 675–684. doi:10.1145/1963405.1963500

Chatzoglou, P. D., & Vraimaki, E. (2010). Investigating Internet usage as innovation adoption: A quantitative study. *Journal of Information, Communication and Ethics in Society*, *8*, 338–363. doi:10.1108/14779961011093345

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, *16*, 321–357. doi:10.1613/jair.953

Check, J., & Schutt, R. K. (2012). Survey research. In J. Check & R. K. Schutt (Eds.). *Research methods in education.* (pp. 159–185). Thousand Oaks, CA: Sage Publications.

Chen, G. M. (2015). Why do women bloggers use social media? Recreation and information motivations outweigh engagement motivations. *New Media & Society*, *17*, 24–40. doi:10.1177/1461444813504269

Cho, I. H. (2008). *The nature and determinants of Intranet discontinuance after mandatory adoption* (Doctoral dissertation). Retrieved from ProQuest dissertations publishing. (3518745)

Cho, I. H. (2015). Facebook discontinuance: Discontinuance as a temporal settlement of the constant interplay between disturbance and coping. *Quality & Quantity*, *49*, 1531-1548. doi: 10.1007/s11135-015-0225-x

Chyi, H. I. (2009). Information surplus in the digital age: Impact and implications. In Z. Papacharissi (Ed.), *Journalism and citizenship: New agendas in communication* (pp. 91–107). New York, NY: Routledge

Clancy, K. J., Ostlund, L. E., & Wyner, G. A. (1979). False reporting of magazine readership. *Journal of Advertising Research*, *19*, 23–30.

Correa, T., Hinsley, A. W., & de Zúñiga, H. G. (2010). Who interacts on the Web? The intersection of users' personality and social media use. *Computers in Human Behavior*, *26*, 247–253. doi:10.1016/j.chb.2009.09.003

Costa, P. T., & McCrae, R. R. (1992). Four ways five factors are basic. *Personality and Individual Differences*, *13*, 653–665. doi:10.1016/0191-8869(92)90236-I

Cowart, K. O., Fox, G. L., & Wilson, A. E. (2008). A structural look at consumer innovativeness and self-congruence in new product purchases. *Psychology & Marketing*, *25*, 1111–1130. doi:10.1002/mar.20256

Cox, D. R. (1958). The regression analysis of binary sequences. *Journal of the Royal Statistical Society. Series B (Methodological)*, *20*, 215–242.

Cramer, E. M., Song, H., & Drent, A. M. (2016). Social comparison on Facebook: Motivation, affective consequences, self-esteem, and Facebook fatigue. *Computers in Human Behavior*, *64*, 739–746. doi:10.1016/j.chb.2016.07.049

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*, 319–340, doi:10.2307/249008

Davis, C. A., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. (2016, April). Botornot: A system to evaluate social bots. *Proceedings of the 25th International Conference Companion on World Wide Web*, 273–274. doi:10.1145/2872518.2889302

Dearing, J. W. (2009). Applying diffusion of innovation theory to intervention development. *Research on Social Work Practice*, *19*, 503–518. doi:10.1177/1049731509335569

Deci, E. L. (1975). *Intrinsic motivation*. New York, NY: Plenum

Dee Dickerson, M., & Gentry, J. W. (1983). Characteristics of adopters and non-adopters of home computers. *Journal of Consumer Research*, *10*, 225–235. doi:10.1086/208961

DeFleur, M. (1965). Mass communication and social change. *Social Forces*, *44*, 314–326.

De Marez, L., Vyncke, P., Berte, K., Schuurman, D., & De Moor, K. (2007). Adopter segments, adoption determinants and mobile marketing. *Journal of Targeting, Measurement and Analysis for Marketing*, *16*, 78–95. doi:10.1057/palgrave.jt.5750057

de Vreese, C. H., & Neijens, P. (2016). Measuring media exposure in a changing communications environment. *Communication Methods and Measures*, *10*, 69–80. doi:10.1080/19312458.2016.1150441

Dror, G., Pelleg, D., Rokhlenko, O., & Szpektor, I. (2012). Churn prediction in new users of Yahoo! answers. *Proceedings of the 21st International Conference on World Wide Web*, *USA*, 829–834. doi:10.1145/2187980.2188207

Dunne, Á., Lawlor, M. A., & Rowley, J. (2010). Young people's use of online social networking sites–a uses and gratifications perspective. *Journal of Research in Interactive Marketing*, *4*, 46–58. doi:10.1108/17505931011033551

Eichholz, G., & Rogers, E. M. (1964). Resistance to the adoption of audio-visual aids by elementary school teachers: Contrasts and similarities to agricultural innovation. In M. B. Miles (Eds), *Innovation is Education* (pp. 299–316). New York, NY: Columbia University, Teachers College Bureau or Publications.

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. *Journal of Computer Mediated Communication, 12*, 1143–1168. doi:10.1111/j.1083-6101.2007.00367.x

Engel, J. F., Blackwell, R. D., & Miniard, P. W. (1986). *Consumer behavior.* Chicago, IL: Dryden Press.

Fader, P. S., & Hardie, B. G. (2007). How to project customer retention. *Journal of Interactive Marketing*, 21, 76–90. doi:10.1002/dir.20074

Fu, K. W., & Chan, C. H. (2013). Analyzing online sentiment to predict telephone poll results. *Cyberpsychology, Behavior, and Social Networking*, *16*, 702–707. doi: doi:10.1089/cyber.2012.0375

Gartner. (2010, April). Gartner privacy survey. *Gartner*. Retrieved from https://www.gartner.com/doc/1361613/gartner-privacy-survey

Goasduff, L., & Pettey, C. (2011 August). Gartner survey highlights consumer fatigue with social media. *Gartner*. Retrieved from https://www.gartner.com/newsroom/id/1766814

Goyal, A., Bonchi, F., & Lakshmanan, L. V. (2010). Learning influence probabilities in social networks. *Proceedings of the 3rd ACM International Conference on Web Search and Data Mining*, USA, 241–250. doi: 10.1145/1718487.1718518

Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational Evaluation and Policy Analysis*, *11*, 255–274. doi:10.3102/01623737011003255.

Greve, H. R. (1995). Jumping ship: The diffusion of strategy abandonment. *Administrative Science Quarterly*, 444–473. doi:10.2307/2393793

Greve, H. R. (2011). Fast and expensive: The diffusion of a disappointing innovation. *Strategic Management Journal*, *32*, 949–968. doi:10.1002/smj.922

Gupta, A., Kumaraguru, P., Castillo, C., & Meier, P. (2014). Tweetcred: Real-time credibility assessment of content on twitter. *International Conference on Social Informatics*, *Berlin*, 228–243. doi:10.1007/978-3-319-13734-6_16

Gupta, B. (2008). Role of personality in knowledge sharing and knowledge acquisition behavior. *Journal of the Indian Academy of Applied Psychology*, *34*, 143–149.

Gurajala, S., White, J. S., Hudson, B., Voter, B. R., & Matthews, J. N. (2016). Profile characteristics of fake Twitter accounts. *Big Data & Society*, *3*(2), 2053951716674236. doi:2053951716674236

Hadden, J., Tiwari, A., Roy, R., & Ruta, D. (2007). Computer assisted customer churn management: State-of-the-art and future trends. *Computers & Operations Research*, *34*, 2902–2917. doi:10.1016/j.cor.2005.11.007

Harting, J., Rutten, G. M., Rutten, S. T., & Kremers, S. P. (2009). A qualitative application of the diffusion of innovations theory to examine determinants of guideline adherence among physical therapists. *Physical Therapy*, *89*, 221–232. doi:10.2522/ptj.20080185

Hawes, D. K., Blackwell, R. D., & Talarzyk, W. W. (1976). Consumer decisions to reduce or stop using products and services: Preliminary results of a nationwide study. *Proceedings of Association for Consumer Research North American Advances*, *USA*, *3*, 102–109.

Highfield, T., Harrington, S., & Bruns, A. (2013). Twitter as a technology for audiencing and fandom: The# Eurovision phenomenon. *Information, Communication & Society*, *16*, 315–339. doi:10.1080/1369118X.2012.756053

Hirschman, E. C. (1980). Innovativeness, novelty seeking, and consumer creativity. *Journal of Consumer Research*, *7*, 283–295. doi:10.1086/208816

Holton, A. E., & Chyi, H. I. (2012). News and the overloaded consumer: Factors influencing information overload among news consumers. *Cyberpsychology, Behavior, and Social Networking*, *15*, 619–624. doi:10.1089/cyber.2011.0610

Hughes, D. J., Rowe, M., Batey, M., & Lee, A. (2012). A tale of two sites: Twitter vs. Facebook and the personality predictors of social media usage. *Computers in Human Behavior*, *28*, 561–569. doi:10.1016/j.chb.2011.11.001

Hunt, D. S., & Langstedt, E. (2014). The influence of personality factors and motives on photographic communication. *The Journal of Social Media in Society, 3*, 42–64.

Hwong, C. (2017, May 4). Chart of the week: Which social media platforms are losing users?. *Verto Analytics*. Retrieved from http://www.vertoanalytics.com/chart-week-social-media-networks-churn/

Im, H., & Ha, Y. (2012). Who are the users of mobile coupons? A profile of US consumers. *Journal of Research in Interactive Marketing*, *6*, 215–232. doi:10.1108/17505931211274688

Jarvenpaa, S. L., Knoll, K., & Leidner, D. E. (1998). Is anybody out there? Antecedents of trust in global virtual teams. *Journal of Management Information Systems*, *14*, 29–64. doi:10.1080/07421222.1998.11518185

Java, A., Song, X., Finin, T., & Tseng, B. (2007). Why we twitter: Understanding microblogging usage and communities. *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis*, *USA*, 56–65. doi: 10.1145/1348549.1348556

Jenders, M., Kasneci, G., & Naumann, F. (2013). Analyzing and predicting viral tweets. *Proceedings of the 22nd International Conference on World Wide Web*, *Brazil*, 657–664. doi:10.1145/2487788.2488017

Jorissen, M. W. (1969). *Discontinuance of Innovations by Farmers in Minas Gerais. Brazil* (Unpublished master's thesis). Michigan State University, Lansing, MI.

Katz, E., Blumler, J. G., & Gurevitch, M. (1973). Uses and gratifications research. *The Public Opinion Quarterly*, *37*, 509–523.

Katz, E., & Lazarsfeld, P. (1955*). Personal influence*. New York, NY: Free Press

Kawale, J., Pal, A., & Srivastava, J. (2009). Churn prediction in MMORPGs: A social influence based approach. *Proceedings of International Conference on Computational Science and Engineering*, *USA*, *4,* 423–428. doi: 10.1109/CSE.2009.80

Kawamoto, T. (2013). A stochastic model of tweet diffusion on the Twitter network. *Physica A: Statistical Mechanics and its Applications*, *392*, 3470–3475. doi:10.1016/j.physa.2013.03.048

Kayany, J. M., & Yelsma, P. (2000). Displacement effects of online media in the socio-technical contexts of households. *Journal of Broadcasting & Electronic Media*, *44*, 215-229. doi:10.1207/s15506878jobem4402_4

Kaye, B. K., & Johnson, T. J. (2003). From here to obscurity?: Media substitution theory and traditional media in an on-line world. *Journal of the American Society for Information Science and Technology*, 54, 260-273. doi: 10.1002/asi.10212

Keaveney, S. M. (1995). Customer switching behavior in service industries: An exploratory study. *The Journal of Marketing*, 71–82. doi:10.2307/1252074

Kee, K.F. (2017). Adoption and diffusion. In C. Scott & L. Lewis (Eds.), *The international encyclopedia of organizational communication Volume 1* (pp. 41-54). Chichester, UK: Wiley-Blackwell

Keramati, A., & Ardabili, S. M. (2011). Churn analysis for an Iranian mobile operator. *Telecommunications Policy*, *35*, 344–356. doi:10.1016/j.telpol.2011.02.009

Khalifa, M., & Liu, V. (2007). Online consumer retention: contingent effects of online shopping habit and online shopping experience. *European Journal of Information Systems*, *16*, 780–792. doi:10.1057/palgrave.ejis.3000711

Kielmeyer, G. M. (2003). *Discontinuance of innovations: Social network characteristics, product attributes, and adopter traits related to post-adoption behavior* (Doctoral dissertation). Retrieved from University of Illinois at Urbana-Champaign, Urbana and Champaign, IL

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human Behavior*, *26*, 310–322. doi:10.1016/j.chb.2009.10.013

Kim, S., Choi, D., Lee, E., & Rhee, W. (2017). Churn prediction of mobile and online casual games using play log data. *PloS One*, *12*, e0180735. doi:10.1371/journal.pone.0180735

Kim, H. S., & Yoon, C. H. (2004). Determinants of subscriber churn and customer loyalty in the Korean mobile telephony market. *Telecommunications Policy*, *28*, 751–765. doi:10.1016/j.telpol.2004.05.013

Koroleva, K., Krasnova, H., Veltri, N. F., & Günther, O. (2011). It's all about networking! Empirical investigation of social capital formation on social network sites. *Proceedings of the 32nd International Conference on Information Systems. Shanghai, China*. 1–20. doi:10.7892/boris.47120

Kotler, P., & Zaltman, G. (1976). Targeting prospects for a new product. *Journal of Advertising Research*, *16*, 7–20.

Kramer, B. S., Walker, A. E., & Brill, J. M. (2007). The underutilization of information and communication technology-assisted collaborative project-based learning among international educators: A Delphi study. *Educational Technology Research and Development*, *55*, 527-543. doi: 10.1007/s11423-007-9048-3

Krasnova, H., Wenninger, H., Widjaja, T., & Buxmann, P. (2013 February). Envy on Facebook: A hidden threat to users' life satisfaction?. *Proceedings of the 11th International Conference on Wirtschaftsinformatik (WI2013)*. *Germany*. 1–16. doi:10.7892/boris.47080

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media?. *Proceedings of the 19th International Conference on World Wide Web*, USA, 591–600. doi: 10.1145/1772690.1772751

Landers, E. (2017, June 6). White House: Trump's tweets are "official statements." *CNNPolitics.* Retrieved from https://www.cnn.com/2017/06/06/politics/trump-tweets-official-statements/index.html

Lavidge, R.C. & Steiner, G.A. (1961). A model for predictive measurements of advertising effectiveness. *Journal of Marketing*, *25*, 59–62.

Lazer, D., Pentland, A. S., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., ... & Jebara, T. (2009). Life in the network: The coming age of computational social science. *Science*, *323*, 721–723. doi: 10.1126/science.1167742

Lee, A. R., Son, S. M., & Kim, K. K. (2016). Information and communication technology overload and social networking service fatigue: A stress perspective. *Computers in Human Behavior*, *55*, 51–61. doi:10.1016/j.chb.2015.08.011

Lee, P. S., & Leung, L. (2008). Assessing the displacement effects of the Internet. *Telematics and Informatics*, *25*, 145–155. doi:10.1016/j.tele.2006.08.002

Leuthold, F. O. (1968). *Discontinuance of improved farm innovations by Wisconsin farm operators* (Unpublished doctoral dissertation) University of Wisconsin, Madison, WI.

Liang, H., & Fu, K. W. (2015). Testing propositions derived from Twitter studies: Generalization and replication in computational social science. *PloS One*, *10(8)*, e0134270. doi:10.1371/journal.pone.0134270

Liu, Y., Kliman-Silver, C., & Mislove, A. (2014). The tweets they are a-changin: Evolution of Twitter users and behavior. *Proceedings of International Conference on Web and Social Media, USA*, *13*, 305–314.

Localytics. (2017, March 21). *Mobile apps: What's a good retention rate?*. Retrieved from http://info.localytics.com/blog/mobile-apps-whats-a-good-retention-rate

Lomborg, S., & Bechmann, A. (2014). Using APIs for data collection on social media. *The Information Society*, *30*, 256-265. doi:10.1080/01972243.2014.915276

Long, J. S. (1997). Regression models for categorical and limited dependent variables. *Advanced quantitative techniques in the social sciences*. London: SAGE Publications.

Luqman, A., Cao, X., Ali, A., Masood, A., & Yu, L. (2017). Empirical investigation of Facebook discontinues usage intentions based on SOR paradigm. *Computers in Human Behavior*, *70*, 544–555. doi:10.1016/j.chb.2017.01.020

Maier, C., Laumer, S., Eckhardt, A., & Weitzel, T. (2012). When social networking turns to social overload: Explaining the stress, emotional exhaustion, and quitting behavior from social network sites' users. *Proceedings of the 20th European Conference on Information Systems*, *Spain*.

Maier, C., Laumer, S., Eckhardt, A., & Weitzel, T. (2015). Giving too much social support: Social overload on social networking sites. *European Journal of Information Systems*, *24*, 447–464. doi:10.1057/ejis.2014.3

Markus, M. L. (1987). Toward a “critical mass” theory of interactive media: Universal access, interdependence and diffusion. *Communication Research*, *14*, 491–511. doi:10.1177/009365087014005003

Markus, M. L. (1994). Electronic mail as the medium of managerial choice. *Organization science*, *5*(4), 502-527. doi:10.1287/orsc.5.4.502

Martinez, E., Polo, Y., & Flavian, C. (1998). The acceptance and diffusion of new consumer durables: differences between first and last adopters. *Journal of Consumer Marketing*, *15*, 323–342. doi:10.1108/07363769810225975

McCombs, M. E. (1972). Mass media in the marketplace. *Journalism and Communication Monographs*, *24*, 1–103.

McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, *52*, 81–90. doi:10.1037/0022-3514.52.1.81

McElroy, J. C., Hendrickson, A. R., Townsend, A. M., & DeMarie, S. M. (2007). Dispositional factors in Internet use: Personality versus cognitive style. *MIS Quarterly*, 809–820. doi:10.2307/25148821

Menard, S. (1995). *Applied logistic regression analysis*. Thousand Oaks, CA: Sage.

Meyer, G. (2004). Diffusion methodology: Time to innovate?. *Journal of Health Communication*, *9*, 59–69. doi:10.1080/10810730490271539

Midgley, D. F., & Dowling, G. R. (1978). Innovativeness: The concept and its measurement. *Journal of Consumer Research*, *4*, 229-242. doi:10.1086/208701

Murthy, D. (2015). Twitter and elections: Are tweets, predictive, reactive, or a form of buzz?. *Information, Communication & Society*, *18*, 816–831. doi:10.1080/1369118X.2015.1006659

Murthy, D., Gross, A., & Pensavalle, A. (2015). Urban social media demographics: An exploration of Twitter use in major American cities. *Journal of Computer-Mediated Communication*, *21*, 33-49. doi:10.1111/jcc4.12144

Myers, R. H. (1990). *Classical and modern regression with applications* (2nd Eds.). N. Scituate, MA: Duxbury Press

Nielsen Online (2009, April 30). *Update return of the Twitter quitters*. Retrieved from http://www.nielsen.com/us/en/insights/news/2009/update-return-of-the-twitter-quitters

Newell, J., Genschel, U., & Zhang, N. (2014). Media discontinuance: Modeling the diffusion "S" curve to declines in media use. *Journal of Media Business Studies*, *11*, 27–50.

Newman, N. (2009). *The rise of social media and its impact on mainstream journalism*. Oxford, UK: Reuters Institute for the Study of Journalism. Retrieved from https://reutersinstitute.politics.ox.ac.uk/sites/default/files/2017-11/The%20rise%20of%20social%20media%20and%20its%20impact%20on%20mainstream%20journalism.pdf

Niederdeppe, J. (2014). Conceptual, empirical, and practical issues in developing valid measures of public communication campaign exposure. *Communication Methods and Measures*, *8*, 138–161. doi:10.1080/19312458.2014.903391

Nguyen, T. N., Li, C., & Niederée, C. (2017). On early-stage debunking rumors on Twitter: Leveraging the wisdom of weak learners. In G. Ciampaglia, A. Mashhadi, & T. Yasseri (Eds). *Lecture Notes in Computer Science*: *Vol. 10540*. *Social Informatics* (pp.141–158). Cham: Springer. doi:10.1007/978-3-319-67256-4_13

Oliver, T.A. (1997). *Satisfaction: A Behavioral Perspective on the Consumer*. Boston, MA: McGraw-Hill

Olson, P. (2013). Teenagers say goodbye to Facebook and hello to messenger apps. *The Guardian*. Retrieved from http://www.theguardian.com/technology/2013/nov/10/teenagers-messenger-apps-facebook-exodus

Osipow, S. H., Doty, R. E., & Spokane, A. R. (1985). Occupational stress, strain, and coping across the life span. *Journal of Vocational Behavior*, *27*, 98–108. doi:10.1016/0001-8791(85)90055-7

Owyang, J. (2012, August 17). Social networks: Premium vs freemium. [Web log post]. Retrieved from http://www.web-strategist.com/blog/2012/08/17/social-networks-premium-vs-freemium/

Page, C. (2014, April 14). Twitter has almost 430 million inactive users. *The Inquirer*. Retrieved from https://www.theinquirer.net/inquirer/news/2339684/twitter-has-almost-430-million-inactive-users

Pallant, J. (2007). *SPSS Survival Manual*. Berkshire: Open University Press.

Palmgreen, P., & Rayburn, J. D. (1979). Uses and gratifications and exposure to public television: A discrepancy approach. *Communication Research*, *6*, 155–179. doi:10.1177/009365027900600203

Palmgreen, P., Wenner, L. A., & Rayburn, J. D. (1980). Relations between gratifications sought and obtained: A study of television news. *Communication Research*, *7*, 161–192. doi:10.1177/009365028000700202

Park, J. H. (2014). The effects of personalization on user continuance in social networking sites. *Information Processing & Management*, *50*, 462–475. doi:10.1016/j.ipm.2014.02.002

Park, C. S., & Kaye, B. K. (2017). The tweet goes on: Interconnection of Twitter opinion leadership, network size, and civic engagement. *Computers in Human Behavior, 69*, 174–180. doi:10.1016/j.chb.2016.12.021

Parthasarathy, M. (1995). *The impact of discontinuance on the subsequent adoption of an innovation: Theoretical foundation and empirical analysis* (Unpublished doctoral dissertation). University of Nebraska–Lincoln, Lincoln, NE.

Parthasarathy, M., & Bhattacherjee, A. (1998). Understanding post-adoption behavior in the context of online services. *Information Systems Research*, *9*, 362–379. doi/10.1287/isre.9.4.362

Perreault, M., & Ruths, D. (2011). The effect of mobile platforms on Twitter content generation. *Proceedings of the 5th International Conference on Web and Social Media*, *Spain*, 289–296.

Petrovic, S., Osborne, M., & Lavrenko, V. (2011). RT to win! Predicting message propagation in Twitter. In *Proceedings of International Conference on Web and Social Media, Spain*, 586–589.

Peshin, R., & Dhawan, A. K. (2009). *Integrated pest management: Innovation-development process*. New York, NY: Springer. doi: 10.1007/978-1-4020-8992-3

Pollard, C. (2003). E-service adoption and use in small farms in Australia: Lessons learned from a government-sponsored programme. *Journal of Global Information Technology Management*, *6*, 45–63. doi:10.1080/1097198X.2003.10856349

Prior, M. (2009). Improving media effects research through better measurement of news exposure. *The Journal of Politics*, *71*, 893–908. doi:10.1017/S0022381609090781

Quan-Haase, A., & Young, A. L. (2010). Uses and gratifications of social media: A comparison of Facebook and instant messaging. *Bulletin of Science, Technology & Society*, *30*, 350–361. doi:10.1177/0270467610380009

Quercia, D., Bodaghi, M., & Crowcroft, J. (2012, June). Loosing friends on Facebook. *Proceedings of the 2012 Annual ACM Web Science Conference*, USA, 251–254. doi: 10.1145/2380718.2380751

Quercia, D., Kosinski, M., Stillwell, D., & Crowcroft, J. (2011, October). Our Twitter profiles, our selves: Predicting personality with Twitter. *Proceedings of the 2011 IEEE Third International Conference on Social Computing, USA*, 180–185. doi:10.1109/passat/socialcom.2011.26

Raacke, J., & Bonds-Raacke, J. (2008). MySpace and Facebook: Applying the uses and gratifications theory to exploring friend-networking sites. *Cyberpsychology & Behavior*, *11*, 169–174. doi:10.1089/cpb.2007.0056

Rainie, L., Smith, A. & Duggan, M. (2013). Coming and going on Facebook. *Pew Research Center's Internet and American Life Project.* Retrieved from http://www.pewinternet.org/2013/02/05/coming-and-going-on-facebook/

Ramirez, A., Dimmick, J., Feaster, J., & Lin, S. F. (2008). Revisiting interpersonal media competition: The gratification niches of instant messaging, e-mail, and the telephone. *Communication Research*, *35*, 529–547. doi:10.1177/0093650208315979

Ratts, M. J., & Wood, C. (2011). The fierce urgency of now: Diffusion of innovation as a mechanism to integrate social justice in counselor education. *Counselor Education and Supervision*, *50*, 207–223. doi:10.1002/j.1556-6978.2011.tb00120.x

Ravindran, T., Kuan, Y., Chua, A., & Goh, D. H-L. (2014). Antecedents and effects of social network fatigue. *Journal of the Association for Information Science and Technology*, *65*, 2306–2320. doi:10.1002/asi.23122

Rice, R. E. (2009). Diffusion of innovations: Theoretical extensions. In R. Nabi, & M. B. Oliver (Eds.), *Handbook of Media Effects* (pp. 489–503). Thousand Oaks, CA: Sage.

Riff, D., Lacy, S., & Fico, F. (2014). *Analyzing media messages: Using quantitative content analysis in research (3rd ed.)*. New York, NY: Routledge.

Robertson, T., Zielinski, J., & Ward, S. (1984). *Consumer behavior*. Glenview, IL: Scott Foresman and Company.

Rogers, E. M. (1962). *Diffusion of innovations* (1st ed.). New York, NY: Free Press.

Rogers, E. M. (1983). *Diffusion of innovations* (3rd ed.). New York, NY: Free Press.

Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). New York, NY: Free Press.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Free Press.

Rogers, E. M., & Shoemaker, F. F. (1971). *Communication of innovations: A cross-cultural approach*. New York, NY: Free Press.

Rogers, M., Chapman, C., & Giotsas, V. (2012). Measuring the diffusion of marketing messages across a social network. *Journal of Direct, Data and Digital Marketing Practice*, *14*, 97–130. doi:10.1057/dddmp.2012.25

Rosen, P. A., & Kluemper, D. H. (2008). The impact of the big five personality traits on the acceptance of social networking website. *Proceedings of Americas Conference on Information Systems*, *Canada,* 274.

Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior*, *25*, 578–586. doi:10.1016/j.chb.2008.12.024

Russell Neuman, W., Guggenheim, L., Mo Jang, S., & Bae, S. Y. (2014). The dynamics of public attention: Agenda setting theory meets big data. *Journal of Communication*, *64*, 193–214. doi:10.1111/jcom.12088

Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. *Computers in Human Behavior*, *27*, 1658–1664. doi:10.1016/j.chb.2011.02.004

Schapire, R. E., & Freund, Y. (2012). *Boosting: Foundations and algorithms*. Cambridge, MA: MIT Press.

Schoenebeck, S. Y. (2014). Giving up Twitter for Lent: how and why we take breaks from social media. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, *Canada*, 773–782. doi: 10.1145/2556288.2556983

Sheldon, K. M., Abad, N., & Hinsch, C. (2011). A two-process view of Facebook use and relatedness need-satisfaction: Disconnection drives use, and connection rewards it. *Psychology of Popular Media Culture, 1*, 2-15. doi:10.1037/2160-4134.1.S.2

Shen, X.-L., Li, Y.-J., & Sun, Y. (2018). Wearable health information systems intermittent discontinuance: A revised expectation-disconfirmation model. *Industrial Management & Data Systems*. Online first: https://www.emeraldinsight.com/doi/abs/10.1108/IMDS-05-2017-0222.

Singleton R. A. & Straits B. C. (2009) *Approaches to social research.* New York, NY: Oxford University Press.

Smith, A., & Anderson, M. (2018, March). Social media use in 2018. *Pew Research Center*. Retrieved from http://assets.pewresearch.org/wp-content/uploads/sites/14/2018/03/01105133/PI_2018.03.01_Social-Media_FINAL.pdf

Son, M., & Han, K. (2011). Beyond the technology adoption: Technology readiness effects on post-adoption behavior. *Journal of Business Research*, *64*, 1178–1182. doi:10.1016/j.jbusres.2011.06.019

Statista. (2017 August). Chart: Facebook is coming after snapchat from all sides. Retrieved from https://www.statista.com/statistics/740618/messenger-app-chat-usage-usa/

Strang, D., & Macy, M. W. (2001). In search of excellence: Fads, success stories, and adaptive emulation. *American Journal of Sociology*, *107*, 147–182. doi:10.1086/323039

Strohmaier, M., & Wagner, C. (2014). Computational social science for the World Wide Web. *IEEE Intelligent Systems*, *29*, 84–88. doi:10.1109/MIS.2014.80

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be retweeted? Large scale analytics on factors impacting retweet in Twitter network. *Proceedings of the IEEE Second International Conference on Social Computing*, *USA*, 177–184. doi:10.1109/SocialCom.2010.33

Swan, J. E., & Oliver, R. L. (1989). Postpurchase communications by consumers. *Journal of Retailing*, *65*, 516–534

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics*. Boston, MA: Pearson Education.

Taipale, S. (2013). The relationship between Internet use, online and printed newspaper reading in Finland: Investigating the direct and moderating effects of gender. *European Journal of Communication*, *28*, 5–18. doi:10.1177/0267323112453672

Taneja, H., & Mamoria, U. (2012). Measuring media use across platforms: Evolving audience information systems. *International Journal on Media Management*, *14*, 121–140. doi:10.1080/14241277.2011.648468

Tanupabrungsun, S., & Hemsley, J. (2018). Studying celebrity practices on twitter using a framework for measuring media richness. *Social Media + Society*, *4*, 205630511876336. doi:1177/2056305118763365

Tarafdar, M., Tu, Q., & Ragu-Nathan, T. S. (2010). Impact of technostress on end-user satisfaction and performance. *Journal of Management Information Systems*, *27*, 303–334. doi:10.2753/mis0742-1222270311

Terlaak, A., & Gong, Y. (2008). Vicarious learning and inferential accuracy in adoption processes. *Academy of Management Review*, *33*(4), 846–868. doi: 10.5465/amr.2008.34421979

Terlaak, A., Gong, Y., & Kim, J. H. (2008). Post-adoption regret and biased vicarious learning in innovation abandonment bandwagons. *Proceedings of Academy of Management*, *USA*, 1–6. doi: 10.5465/AMBPP.2008.33660306

Trefis (2017, July 26). Twitter's Q2 revenue likely to decline, though MAUs might improve. *Forbes*. Retrieved from https://www.forbes.com/sites/greatspeculations/2017/07/26/twitters-q2-revenue-likely-to-decline-though-maus-might-improve/#1f1544b238a7

Valenzuela, S., Park, N., & Kee, K. F. (2009). Is there social capital in a social network site?: Facebook use and college students' life satisfaction, trust, and participation. *Journal of Computer-Mediated Communication*, *14*, 875–901. doi:10.1111/j.1083-6101.2009.01474.x

Van Braak, J. (2001). Individual characteristics influencing teachers' class use of computers. *Journal of Educational Computing Research*, *25*, 141–157. doi:10.2190/81YV-CGMU-5HPM-04EG

Varol, O., Ferrara, E., Davis, C. A., Menczer, F., & Flammini, A. (2017). Online Human-Bot Interactions: Detection, estimation, and characterization. *Proceedings of the International Conference on Web and Social Media*, *Canada*, 1–11. doi:arxiv:1703.03107

Venkatesh, V., & Brown, S. A. (2001). A longitudinal investigation of personal computers in homes: Adoption determinants and emerging challenges. *MIS Quarterly*, 71–102. doi: 10.2307/3250959

Ver Steeg, G., & Galstyan, A. (2012). Information transfer in social media. *Proceedings of the 21st International Conference on World Wide Web*, *France*, 509–518. doi:10.1145/2187836.2187906

Vijayasarathy, L. R. (2004). Predicting consumer intentions to use online shopping: The case for an augmented technology acceptance model. *Information & Management*, *41*, 747–762. doi:10.1016/j.im.2003.08.011

Vishwanath, A. (2005). Impact of personality on technology adoption: An empirical model. *Journal of the Association for Information Science and Technology*, *56*, 803-811. doi:10.1002/asi.20169

Vishwanath, A., & Barnett, G. A. (2011). *The diffusion of innovations. A communication science perspective*. New York, NY: Peter Lang.

Wang, W., & Butler, J. E. (2006). System deep usage in post-acceptance stage: a literature review and a new research framework. *International Journal of Business Information Systems*, *1*, 439–462. doi:10.1504/IJBIS.2006.008959

Wojcik, S., Messing, S., Smith, A., Rainie, L., Hitlin, P., (2018, April). Bots in the Twittersphere. *Pew Research Center*. Retrieved from http:// assets.pewresearch.org/wp-content/uploads/sites/14/2018/04/01120759/PI_2018.04.09_Twitter-Bots_FINAL.pdf

Xie, Y., Li, X., Ngai, E. W. T., & Ying, W. (2009). Customer churn prediction using improved balanced random forests. *Expert Systems with Applications*, *36*, 5445–5449. doi:10.1016/j.eswa.2008.06.121

Ye, C., & Potter, R. (2011). The role of habit in post-adoption switching of personal information technologies: An empirical investigation. *Communications of the Association for Information Systems*, 28, 585–610. Retrieved from http://aisel.aisnet.org/cais/vol28/iss1/35/

Ye, Y., & Zhang, M. (2017). Intermittent use of social media: Facebook and Weibo use, their predictors and social and political implications. In K. Xue, M. Yu (Eds.), *New Media and Chinese Society. Vol. 5. Communication, Culture and Change in Asia* (pp. 75–93). Singapore: Springer. doi:10.1007/978-981-10-6710-5

York, C. (2013). Overloaded by the news: Effects of news exposure and enjoyment on reporting information overload. *Communication Research Reports*, *30*, 282–292. doi:10.1080/08824096.2013.836628

York, C., & Turcotte, J. (2015). Vacationing from Facebook: Adoption, temporary discontinuance, and readoption of an innovation. *Communication Research Reports*, *32*, 54–62. doi:10.1080/08824096.2014.989975

Zhang, S., Zhao, L., Lu, Y., & Yang, J. (2015). Get tired of socializing as social animal? An empirical explanation on discontinuous usage behavior in social network services. *Proceedings of Pacific Asia Conference on Information Systems, Singapore,* 125. Retrieved from http://aisel.aisnet.org/pacis2015/125

Zhou, T. (2011). An empirical examination of users' post-adoption behaviour of mobile services. *Behaviour & Information Technology*, *30*, 241–250. doi:10.1080/0144929X.2010.543702

Zhou, Z., Yang, M., & Jin, X. L. (2018). Differences in the Reasons of Intermittent versus Permanent Discontinuance in Social Media: An Exploratory Study in Weibo. *Proceedings of the 51st Hawaii International Conference on System Sciences*, *USA*, 493–502.

Zhu, J. J., & He, Z. (2002). Perceived characteristics, perceived needs, and perceived popularity: Adoption and use of the Internet in China. *Communication Research*, *29*, 466–495. doi:10.1177/0093650202029004005

Vita

Yee Man (Margaret) Ng obtained a B.S.Sc. degree in Journalism and Communication from the Chinese University of Hong Kong and a M.A. in Journalism from the University of Missouri. She is a media researcher with certified industrial training in data science and database tools. Her primary area of study examines how rapidly evolution of technology is transforming interpersonal and social interactions, with an emphasis on how technological changes induce psychological effects such as bewilderment and insecurity. Ng has taught multiple courses on multimedia storytelling. She worked as a data journalist and graphic designer for several news organizations in the United States, Hong Kong, China, and Singapore. She has received several fellowships and research awards, including the Jesse H. Jones Endowed Centennial Fellowship, OpenNews Scholarship, White House Correspondents' Association Scholarship, University of Texas Dissertation Writing Fellowship, and multiple top research paper awards from the Association for Education in Journalism and Mass Communication. Ng will join the Department of Journalism at the University of Illinois Urbana-Champaign as an assistant professor in the fall of 2018.

Permanent address (or email): margaretnym@utexas.edu

This dissertation was typed by the author.