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# Older adults' use of various types of technology: A typology approach

Sangbo Nam  
*Iowa State University*

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**Older adults' use of various types of technology: A typology approach**

by

**Sangbo Nam**

A dissertation submitted to the graduate faculty  
in partial fulfillment of the requirements for the degree of

**DOCTOR OF PHILOSOPHY**

Major: Human Development and Family Studies

Program of Study Committee:  
Megan Gilligan, Co-major Professor  
Jennifer Margrett, Co-major Professor  
Jeong Eun Lee  
Peter Martin  
Daniel Russell

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2018

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**ABSTRACT**

Developed in the late 1990s, the modernization theory of aging posited that older adults were in danger of losing control and power over their lives because they could not keep up with technological progress. Early concerns about the age-related digital divide focused more on the access to technology; however, the age-related digital divide is a complex and multidimensional phenomenon. Previous works on technology use are not without substantial inconsistencies, and the research findings on antecedents and consequences of technology use remain especially equivocal. Without refining technology construct, inconsistent findings could hinder the understanding of different associations among distinct forms of technology used by older adults.

This dissertation consists of three studies that examined predictors of refined technology construct health-related information technology (HIT), work-related information technology (WIT), communications technology (CT), entertainment technology (ET) and patterns of technology use in older populations, using the data from the most recent wave (2011) of the Wisconsin Longitudinal Study (WLS). I further explored patterns of technology use in older populations that have been overlooked in previous studies.

Results from the first study showed sets of factors (i.e., individual characteristics, social roles, and personality traits) differently predicted each type of technology use. Older women were more likely to use HIT and CT, but less likely to use WIT. However, there were no gender differences in ET use. Older adults with higher subjective health predicted the use of WIT, CT, and ET, but not HIT. Among the Big Five personality traits, openness predicted all types of technology use, higher agreeableness was associated with less use of both HIT and WIT, and less conscientiousness was associated with less use of ET.



In the second study, I applied latent class analysis to find the best fitting model to explain the patterns of technology use in older populations. It yielded a three-class model, where each class was identified as multi-users, selective users, and non-users. Sets of factors (i.e., individual characteristics, social roles, and personality traits) predicted each class membership differently. Multi-users were more likely to be women, younger, married, in families with higher household income, in better subjective health, more education, and higher openness than non-users. Selective users were more likely to be employed, married, in better subjective health, more education, and have higher agreeableness and openness than non-users.

In the third study, I examined associations between patterns of technology usage and multidimensional psychological well-being of older adults. Results from ordinary least squares regression (OLS) models showed selective users, but not non-users, had lower levels of depressive symptoms compared to multi-users. Non-users reported lower levels of psychological well-being compared to multi-users in all six subdomains (i.e., autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, and self-acceptance) of Ryff's psychological well-being scales. Also, selective users showed a lower level of personal growth compared to multi-users.

Taken together, the findings from this dissertation contribute to the literature examining technology use of older adults and its antecedents and outcomes. In particular, refined technology constructs demonstrate diverse aspects of technology use in older populations, and the explored typology provides a framework to translate findings into intervention programs that will consider multidimensionality of older populations in technology use.

## CHAPTER 1. GENERAL INTRODUCTION

Ever since the powerful tide of *the third wave* hit the world, technology development has affected how humans work, learn, entertain, and communicate in the information-oriented society (Toffler, 1980). The dissemination of technology in various formats and devices enabled affordable and even cost-free technology to the general public. Of particular interest to scholars is the potential benefit that may be provided by these technologies to older populations. Not only can older adults adopt specific types of technology to fit their interests and needs, but they can also achieve independence through adopting various forms of assistive technology or health technology, which in turn, can have further ramifications for lessening burdens of caregivers (Mitzner et al., 2010). Despite the fact that older adults' technology use is on the rise, the age-related digital divide continues to impede some older adults from benefiting from technology (Czaja & Lee, 2012; Fisk, Rogers, Charness, Czaja, & Sharit, 2009). Previous studies on older adults' technology use do not fully explain differences among the users and non-users, and the lack of understanding on this issue could hinder development and diffusion of user-oriented technology among older adults (Czaja & Lee, 2012).

Older adults' technology use has been examined by researchers across various disciplines, but no consensus exists among researchers on how to define key concepts in this topic (Lee & Coughlin, 2015; Wagner, Hassanein, & Head, 2010). This lack of consensus on the definition and measurement of technology use may account for some of the discrepancies in the literature (Elliot, Mooney, Douthit, & Lynch, 2014). Defining technology can be challenging for most researchers because of its multiple functions. Further, there is a lack of attention regarding the necessity of differentiating technology types (Heinz, 2013).

Researchers have studied older adults' technology use with several different national studies and datasets (e.g., the Health and Retirement Study [HRS], the National Health and Aging Trends Study [NHATS], the WLS, the Longitudinal Study of Generations, the Midlife in the U.S. study [MIDUS]). They have been widely successful in providing invaluable data on older Americans' lives over time, with each dataset having distinctive strengths. Various investigations have been made on the associations of older adults' technology use and related variables using these datasets.

The HRS has multiple waves of biennial data of older adults (Sonnegg et al., 2014). Older adults' technology use was measured using a single item of "Do you regularly use the World Wide Web, or the Internet, for sending and receiving e-mail or for any other purpose, such as making purchases, searching for information, or making travel reservations?," which does not address the purposes of the Internet use. The Midlife in the U.S. study (MIDUS) is a longitudinal study that collected data in 1995-96, 2005-06, and 2013-2014 from a large number ( $n = 1,176$ ) of adults aged 60 and over (Bae, Suh, Ryu, & Heo, 2017). Older adults' technology use was assessed in the second and third waves with a single item of how often participants used a computer for purposes of e-mail, Internet searching, etc. (Tun & Lachman, 2010). Recent waves of the Longitudinal Study of Generations had the following two items of measuring technology use of older adults: "During the past year, how often have you had contact with this child by e-mail?," and "During the past year, how often have you had contact with this child by texting?" These items were focused on the use of technology for communicating with children. The NHATS is a dataset collected annually since 2011, which has a large sample of U.S. Medicare beneficiaries aged 65 and older (Kasper & Freedman, 2017). The NHATS has several different measurements of technology use in each

wave. The measurements in this dataset differentiate older adults' technology use by its purpose, whether communicational, health-related, commercial, or financial. However, the NHATS is primarily focused on the health-related Internet activities of older adults and relatively less on measurements of psychological well-being compared to other datasets. The NHATS does not contain items regarding older adults' Internet use for recreational purposes or work-related purposes, which also were research interests of this dissertation.

The WLS has various measurements of technology use in older adults asking about different purposes of Internet use at home and the frequency of the usage, which are described in each study of this dissertation. Specifically, the WLS had items asking participants if their interest in using the Internet for work-related, communicational or recreational purposes has led them to obtain Internet access at home in two recent waves. However, the item for measuring the use of the Internet for health-related purposes was inconsistent across the years studied in WLS. For example, in the 2004 wave, it was "Have you ever used the Internet to look for advice or information about your health or health care?" In the 2011 wave, a different question was asked for health-related IT use: "In the past year, have you used the Internet to look for advice or information about your health and healthcare?"

There were two main difficulties in the operationalization of technology use types in this dissertation: (a) the uniform questions stem across WIT and CT, and ET was missing for HIT, and (b) the question was limited to acquiring Internet access only, not to measure the actual usage in the past year. First, in WLS, the prevailing questions stem of "For you, was using technology for WIT/CT/ET among the most important reasons why your household first obtained Internet access?" was not available for HIT. To incorporate a HIT item with

other technology use items, I conducted various descriptive analyses on these items across two waves.

In the process of operationalizing each type of technology use, the results from descriptive analyses on the health-related IT use item from both waves, 2004 and 2011, showed increased use of IT for health-related purpose in 2011. In the 2004 wave, when asked if they have ever used HIT, 34.6% of participants answered yes. In comparison, when asked if they have used the Internet for a health-related information search during the last 12 months in the 2011 wave, 43.1% of participants reported their experiences.

The second limitation was that all types of technology use, except HIT, were measured based on retrospective answers to the “reasons why older adults chose to obtain the Internet access” question and the assumption that older adults are active technology users, instead of being based the actual use of technology for each purpose. In the WLS, there were items such as “Number of minutes participant spends per week using the Internet from home, including using e-mail, the Internet, chat rooms, and any instant messaging.” The results showed 82% ( $n = 3,903$ ) of the study sample in 2011 were using the Internet at home. Further, among 2,584 participants who have answered in both waves, approximately 75% to 80% of participants reported the same answer, and changes from use to non-use and non-use to use (20% to 25%) show these items reflect participants’ actual use of the technology for listed purposes. When 82% of the study sample were active users of technology, more than 75% of consistent responses and a quarter of changes between use and non-use show these items would indicate older adults’ purposes of technology use. Thus, I applied these items to the refined definition of each type of technology use. Understanding the various types of technology use is important because they serve different needs of individuals, which can be

used to match the types of individuals to the types of technology. The technology acceptance model (TAM) has been used widely to explain why people use technology (Davis, Bagozzi, & Warshaw, 1989). TAM highlights perceived usefulness and ease of use as two main antecedents of technology acceptance (Davis et al., 1989). However, TAM has been criticized for being overly simplistic (Arning & Zeifler, 2009; Heinz, 2013; Hossain & de Silva, 2009; Kim, Chan, & Gupta, 2007). To overcome this limitation, Venkatesh and Davis (2000) have expanded TAM to include both cognitive instrumental processes and social influence processes. Moreover, the growing body of literature in this field has been contributing new factors that predict technology acceptance using various modifications of TAM (Marangunić & Granić, 2015). Researchers have expanded TAM by introducing factors such as personality traits (Devaraj, Easley, & Crant, 2008; Heinz, 2013), technology-specific patterns (Arning & Zeifler, 2009), social ties (Hossain & de Silva, 2009), and consumable values (Kim et al., 2007), etc. However, most studies that have used TAM have not differentiated between different types of technology, choosing to focus on a single type of technology and its use instead. Thus, limited attention has been paid to differentiating between various types of technology.

### **Predictors of Technology Use**

There is a volume of literature on investigating various antecedents (i.e., individual characteristics, social roles, and personality traits) of older adults' technology use. Literature focusing on individual characteristics of technology users has indicated individuals who are male, white, healthier, younger, and more educated, are more likely to use technology than their counterparts (Carpenter & Buday, 2007; Czaja et al., 2006; Elliot et al., 2014; Fazeli, Ross, Vance, & Ball, 2013; Koopman-Boyden & Reid, 2009; Wagner et al., 2010). Other

factors merit consideration, such as social roles and personality traits (Heinz, 2013; Selwyn, Gorard, Furlong, & Madden, 2003). The degree of how social roles such as employment status and marital status affect technology use also varies by the types of technology older adults use. For example, remaining in the workforce longer increases the likelihood of learning to use technology among older adults (Mitzner et al., 2010). Support availability is an important factor for older adults to use technology, as families and colleagues are their main sources of support in technology use (Wang, Bennett, & Probst, 2011). Compared to those who never married, older adults who have ever married or are in a marital relationship may be more likely to use technology. Older adults not only learn how to use technology from their offspring (Selwyn, 2004; Wang et al., 2011) but also use CT to maintain contact with their children (Gubernskaya & Treas, 2016). Some literature focusing on personality traits of technology users has indicated individuals with greater openness and agreeableness were more likely to use technology (Correa, Hinsley, & Gil de Zúñiga, 2010; Heinz, 2013). However, previous studies about antecedents of older adults' technology use have mixed findings. For example, findings on personality traits were inconsistent based on the types of technology in the studies, and personality traits affecting technology use were different between adults and older adults (Correa et al., 2010; Moorehead et al., 2013).

The inconsistencies in the predictors of older adults' technology use may be partly explained by the fact that most researchers have focused on one type of technology use—Internet use (Gatto & Tak, 2008; Zickuhr & Madden, 2012). Some older adults may be interested in the use of technology for a single purpose, but others may be interested in the use of technology for multiple purposes. The diffusion of innovations theory may be useful to explain older adults' technology use (Rogers, 2003). The theory describes the process of

diffusion of innovations as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 2003, p. 5). The theory not only explains how modern technology spreads in diffusion processes but also illustrates how groups of individuals in the system fall into five different user categories and spread accordingly. The five adopter categories Rogers (2003) developed on the innovativeness dimension were (a) innovators, (b) early adopters, (c) early majority, (d) late majority, and (e) laggards. Rogers was interested in the timing of adoption. However, in this study, I primarily examined the types of adoption, considering the various types of users and non-users in particular. I anticipated some older adults would embrace multiple types of technology use, whereas other older adults might be more selective about which types of technology they adopt. Further, some older adults might avoid technology use altogether.

### **Outcomes of Technology Use**

Research findings on consequences of technology use remain largely equivocal. The psychological impact of technology use on older adults has been investigated, but the mechanisms linking technology use to psychological well-being are less clear (Cotten, Ford, Ford, & Hale, 2014; Dickinson & Gregor, 2006). For example, research has shown technology use sometimes results in improvements in health and well-being (Cotten et al., 2014; Freese, Rivas, & Hargittai, 2006), whereas other researchers have found no meaningful health outcomes of technology use (Slegers, van Boxtel, & Jolles, 2008; White et al., 2002). However, a review study on the association between technology use and psychological well-being of older adults has indicated various shortcomings in the extant literature (Dickinson & Gregor, 2006). They suggested the following reasons for the failure of the research in the field: misattribution of causality, misinterpretation of training/support effect, and



inappropriate generalization of results (Dickinson & Gregor, 2006). Hence, it is possible that the mixed findings in the literature regarding the consequences of technology use are also attributed to limitations in research, such as the failure to consider multiple types of technology use.

This dissertation attempted to overcome some of these shortcomings in the previous literature by examining the relationship between various types of technology use and psychological well-being of older adults by using a typological approach. To clarify the existing confusion and misinterpretation over findings of previous literature, I intended to provide a rationale of refining definitions of various types of technology and to further examine antecedents and outcomes of older adults' technology use based on various types of technology and user groups. This dissertation is comprised of three quantitative studies that center around the topic of older adults' technology use.

The first study sought to differentiate between different types of technology, focusing on antecedents of each type. Specifically, I conceptualized the construct of "technology" as having four different subtypes: HIT, WIT, CT, and ET. With this refined conceptualization, I intended to examine how individual characteristics, social roles, and personality traits predict each type of technology use, respectively.

The second study was designed to examine the typological structure underlying older adults' technology use behaviors. Analyzing multidimensional combinations of technology use patterns yielded different class memberships, and I examined how factors such as individual characteristics, personality traits, and social roles predicted the classes. This typology approach helped to better understand patterns of older adults' technology selection and diverse characteristics associated with each class.

The objective of the third study was to investigate the association between the identified class memberships and psychological well-being. Based on a conceptual distinction put forth by Ryff and Keyes (1995), psychological well-being was assessed based on multidimensional constructs of psychological well-being.

In sum, the objectives of this dissertation were as follows: (1) to refine the conceptualization of technology by making the distinction between different types and examine predictors for each technology type; (2) to explore the typological structure underlying patterns of older adults' technology use and to examine factors that predict different class memberships; and (3) to examine the associations between technology use patterns and psychological well-being. The most recent wave (2011) of the WLS was used to address these study objectives.

I closed by providing a general discussion of the three studies in the final chapter, where the primary results from each study were summarized. In addition, I discussed the limitations of each study and provided recommendations for future research.

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## CHAPTER 2. DEFINING TECHNOLOGY OLDER ADULTS USE AND PREDICTORS OF TECHNOLOGY TYPES: HIT, WIT, CT, AND ET

A paper to be submitted to Research on Aging

Sangbo Nam

Human Development and Family Studies, Iowa State University

Address correspondence to Sangbo Nam, Human Development, and Family Studies, Iowa State University, 0084 LeBaron Hall, Ames, Iowa 50011. E-mail: sbnam@iastate.edu

### Abstract

Although researchers from various disciplines have examined the topic of technology use among older adults, findings from these studies are inconsistent, in part due to a lack of consensus on the definition and measurement of technology. I conceptualized the construct of technology as having three different subtypes of information technology (IT), CT and ET, and separated the IT subtype into two additional subtypes—health-related and work-related. Women were more likely than men to use health-related IT and CT, but less likely to use work-related IT. For ET use, there were no gender differences. The findings suggested men and women tended to use different types of technology for different purposes. I also found openness, among the big-five personality traits, was the strongest predictors of all types of technology use. Higher agreeableness was associated with less prevalent use of both health-related IT and work-related IT, and older adults with less conscientiousness were less likely to use ET. These findings are not consistent with findings from earlier studies on personality traits and technology use among the younger population, thereby suggesting how age may moderate the association between personality traits and technology use.

Keywords: *older adults, technology use, individual characteristics, social roles, personality traits*

## Introduction

The modernization theory of aging is grounded in functionalist sociology, tracing back to Durkheim's work in the 1890s, which suggested modernization degraded the status of older adults within the family (Marshall, 1999). In the 1960s, Ernest Burgess put forth the idea that modernization would lead to role losses among older adults and influence their functional survival in society (Marshall, 1999). In the 1970s, the prominent social gerontologist Cowgill (1974; Cowgill & Holmes, 1972) proposed a modernization theory of aging, which predicted modernization would weaken the extended family system and lead to a status decline of older adults. Subsequently, Silverstein and colleagues developed the idea that older adults were in danger of losing control and power over their lives because they could not keep up with technological progress (Silverstein, Burholt, Wenger, & Bengtson, 1998). Throughout the decades, studies based on the modernization theory of aging examined the status of older adults across different cultures and showed how societal changes associated with modernization and technology development contributed to the disadvantaged position of older adults (Settersten & Angel, 2011).

Relatedly, Coughlin (2017) addressed a misperception about technology and aging, where he emphasized the importance of recognizing the older population as viable buyers of the market and the need to develop technology exclusively for older adults. Reasons for the digital divide not only come from difficulties in older adults adopting technology, but also from failures of technology in meeting their needs. Older adults are known to purchase certain types of technology, such as quality of life technologies (QoLTs; e.g., health technology, assistive technology) that support house maintenance (Mitzner et al., 2010; Schulz et al., 2014). However, older adults often decide not to use other forms of technology,

in part due to high prices (Schulz et al., 2014) and the failure of the product to meet design needs and guidelines for older adults (Fisk, Rogers, Charness, Czaja, & Sharit, 2009). Other factors that could influence older adults' technology use include demographic characteristics (Elliot, Mooney, Douthit, & Lynch, 2014; Gell, Rosenberg, Demiris, LaCroix, & Patel, 2015) and personality traits (Barnett, Pearson, Pearson, & Kellermanns, 2015; Devaraj, Easley, & Crant, 2008).

Despite the digital divide, a recent report showed technology use among older adults was on the rise. During the 5 years from 2010 to 2015, older adults have substantially increased their use of mobile devices, such that the use of smartphones increased by 30% and e-books and tablets by 50% (Anderson, 2015). However, the questions regarding how frequently they are using these devices, and for what specific purposes, remain to be answered. For example, some of these devices may be used several times per day whereas others may be used only once or twice per week. As well, while some devices may facilitate communication with friends and family, other devices may serve the purposes of entertainment or information.

### **Literature Review**

Older adults' technology use has been examined by researchers across various disciplines, such as gerontology, IT, consumer studies, human factors, behavioral sciences, design, computer sciences, human behaviors, and medicine (Lee & Coughlin, 2015). However, no consensus exists among researchers on how to define or measure the key technology concepts (Wagner, Hassanein, & Head, 2010). Most research to date on technology use conceptualizes information and CT (ICT) as a single construct, either as "ICT" or "technology" (Elliot et al., 2014; Gell et al., 2015; Schulz et al., 2014). It is



important to note, however, while a comprehensive and inclusive definition of technology can be useful to describe trends in technology use, it can also hinder the understanding of differential characteristics associated with using distinct forms of technology.

### **Conceptualization of Technology Use**

The various ways in which older adults use different types of technology are related to how difficult it is to define technology use among this population. Terms such as IT, CT, ICT, and technology tend to be used broadly without distinction. For example, Selwyn (2003, p. 108) defined technology as “medium of human action-facilitating (and sometimes constraining) human actions.” Therefore, technology use should be seen as “human agents appropriate[ing] technology by assigning shared meanings to it, which influence their appropriation of the interpretative schemes, facilities and norms designed into the technology, thus allowing those elements to influence their task execution.” March and Smith (1995, p. 252) defined IT as the means “to acquire and process information in support of human purposes.” CT is defined as “connection by way of radio, television, wire, satellite, or cable” (Federal Communications Commission, n.d.). In a review study, ICT was defined as “a broad concept which enables people to communicate, gather information and interact with distant services, faster, easier and without limits of time and space” (Magnusson, Hanson, & Borg, 2004, p. 224).

Reflective of such broad definitions, researchers to date have tended to use the term ICT loosely to include almost all types of technology usage. Consequently, technology or ICT has been widely used to represent any of the following: (a) the Internet, (b) e-mail, (c) chat rooms and discussion groups, (d) the Internet and telephone-based support groups, (e) voice technology, webcams, video telephones and video conferencing, and (f) stand-alone

and online computer games (Blaschke, Freddolino, & Mullen, 2009). To be familiar with IT, the National Research Council Committee on Information Technology Literacy (1999) suggested one acquire major components of ICT skills, concepts, and application, implying that ICT skills are a subdomain of IT. As such, definitions and guidelines are often too comprehensive to describe a specific occasion, and others are somewhat outdated to be used in the current environment. Further, most studies rarely consider purposes and reasons underlying a specific type of technology use (March & Smith, 1995).

Such varied definitions and measurements of IT and CT in the social sciences may account for some of the inconsistencies in research findings. A number of studies on older adults' technology use showed that computer use was associated with enhanced cognitive ability, psychological well-being, and reduced depressive symptoms (Choi, Kong, & Jung, 2012; Cotten, Ford, Ford, & Hale, 2014; Freese, Rivas, & Hargittai, 2006; Tun & Lachman, 2010). As well, ET use such as video games resulted in improvements in cognitive control among older adults (Anguera et al., 2013). However, other studies have shown computer use and Internet training had no meaningful effects on older adults' mental health and well-being (Slegers et al., 2008; White et al., 2002). By redefining technology use types, one can better understand the positive and negative association with each form of technology use.

In this dissertation, I classified technology into four distinctive subtypes: HIT, WIT, CT, and ET. HIT is defined as technological invention or services involving advice or information about health or healthcare. WIT is defined as technological invention supports performing tasks related job. CT is defined as technological invention or services enabling communications with others. ET is defined as technological invention or services intended to fulfill entertainment purposes.

## Predictors of Technology Use

Previous research on antecedents of older adults' technology use was mainly focused on individual characteristics (Elliot et al., 2014; Werner, Carlson, Jordan-Marsh, & Clark, 2011). In addition to these individual characteristics, however, other factors merit consideration, such as personality traits and social roles (Selwyn, Gorard, Furlong, & Madden, 2003).

**Individual characteristics.** The literature on technology use indicates several individual characteristics that may influence technology use. In particular, people who are younger, healthier, non-Hispanic white, more educated, and have higher household income are more likely to use technology than their counterparts (Carpenter & Buday, 2007; Czaja et al., 2006; Elliot et al., 2014; Fazeli, Ross, Vance, & Ball, 2013; Koopman-Boyden & Reid, 2009; Wagner et al., 2010; Werner et al., 2011). Also, research has indicated individuals with better cognitive health and active behavioral coping styles are more likely to use technology (Werner et al., 2011). However, findings remain somewhat ambiguous. For example, Elliot and colleagues (2014) found no significant relationships between ICT use and physical health. Similarly, research findings on income (Carpenter & Buday, 2007; Elliot et al., 2014; Gell et al., 2015; Karavidas, Lim, & Katsikas, 2005; Werner et al., 2011) also remain inconsistent. The gender differences tend to change depending on what types of technology are included in the definition (Selwyn et al., 2003; Werner et al., 2011). A more refined definition may yield different results. Specifically, because men and women may use technology for different purposes, measuring technology using discrete categories may reveal gender differences that are specific to each type of technology.

As for IT use, gender differences inherent in social roles and technological knowledge may play an important role. Among working older adults, men were 1.5 times more likely to use IT than women (Werner et al., 2011). Among retired older adults, men and women have shown no differences with regard to how much they used technology, but women tended to report more anxiety and less knowledge upon using IT (Karavidas et al., 2005).

With regard to CT use, previous studies found discrepancies between older women's needs and actual CT use. Fallows (2005) reported there were no differences between men and women in time spent online, but women used technology more for social interaction while men were more focused on task-oriented activities. Similarly, Gefen and Straub (1997) reported gender differences in terms of attitude and use of e-mail, such that women had a more positive view on using emails and wrote emails more often than men did. Alternatively, older employed men were twice as likely to use CT as their female counterparts (Werner et al., 2011) while younger women utilized all forms of CT more frequently than younger men (Kimbrough, Guadagno, Muscanell, & Dill, 2013). Further, there is a limited but small body of evidence indicating women tend to adopt CT more comfortably than men do (Gerling, Livingston, Nacke, & Mandryk, 2012; Marston, Greenlay, & van Hoof, 2013).

Studies on ET use primarily have been focused on the younger population. On average, boys played video games more frequently than girls from 3 to 12 years, and the same tendency was observed among young adults over 20 (Ogletree & Drake, 2007; Wright et al., 2001). Despite the scarcity of evidence, there are reasons to assume ET use among older adults may also be gendered. Reading is one of the most common recreational activities, and older adults' usage of e-book devices has been on the rise (Smith, 2014).

Although women read more books than men regardless of age, (Bureau of Labor Statistics, 2018), research on older adults' e-book use largely neglected to examine potential gender differences. Further, older women were more like to search hobby-related topics on the Internet (Karavidas et al., 2005). Men were more likely to watch TV, play games, and enjoy sports compared to women, but how these activities translated into technology use is largely unknown.

Based on the discussion and existing evidence, I hypothesized women would be less likely to use WIT, but more likely to use HIT and CT compared to men. Given the insufficiency of evidence on ET use among older adults, no hypothesis was provided on gender differences on ET use; this part of the study was exploratory.

**Personality traits.** Big-five personality traits (e.g., openness, conscientiousness, extraversion, agreeableness, neuroticism) have been shown to influence older adults' use of technology (Costa & McCrae, 1992; Heinz, 2013). The literature also indicates how the personality traits may be associated with specific types of technology use behaviors. For example, Flynn and colleagues (2006) found individuals who were more open were more likely to use the Internet to look up health information. Correa and colleagues (2010) found individuals with higher levels of openness and extraversion were more likely to use CT. Similarly, individuals with high levels of neuroticism have been found to prefer to interact via CT versus face-to-face contact (Amichai-Hamburger, Wainapel, & Fox, 2002). In a student sample, Teng (2008) found players of online games had higher openness, conscientiousness, and extraversion. Internet use in older adults showed seemingly higher mean scores than for non-users in extraversion and openness (Chen & Persson, 2002).

Therefore, I expected older adults with higher openness, extraversion, conscientiousness, and neuroticism would be more likely to use HIT, and CT.

**Social roles.** Social roles, including roles within the family, also merit consideration in relation to technology use. First, one's familial role is often considered as a critical factor predicting use of CT. For example, older mothers' kin-keeping role makes them more likely to contact their adult children than fathers (Greenwell & Bengtson, 1997; Peng et al., in press). Relatedly, parental status can also play an important role in older adults' technology use, as older adults' technology adoption is predominantly initiated by their adult children (Selwyn, 2004). Second, employment status and history are also relevant factors in technology use, as older adults with experience of technology use at work tended to have a favorable attitude toward technology (Mitzner et al., 2010). Exposure to technology in their work environment might cause disparity among older adults. Working older men were more likely to use a computer than working older women (Werner et al., 2011). Alternatively, more women used ICT than men after they were no longer working, whereas there was no gender difference in ICT use when older adults were employed (Koopman-Boyden & Reid, 2009). These findings notwithstanding, more studies are needed to clarify how social roles influence technology use. Each social role may be related to the use of a particular type of technology more closely than others, but previous research has not adequately considered those differences. Based on the above findings, I expected employed older adults would be more likely to use IT and married and retired older adults would be more likely to use CT. I also expected older adults who were not married would be more likely to use ET.

## **The Present Study**

Based on the empirical evidence and discussion provided thus far, I conceptualized technology as having three different subtypes of IT, CT, and ET, where IT was further separated into WIT and HIT. Based on the refined conceptualization, antecedents of each type of technology use were examined with a focus on gender, personality traits, and social roles.

## **Hypotheses**

1. For individual characteristics, I hypothesized older women would be more likely to use HIT and CT, and older men will be more likely to use WIT. I also hypothesized older adults with lower subjective health would be more likely to use HIT, and less likely to use WIT and ET.
2. For social roles, I hypothesized employed older adults would be more likely to use WIT, and older adults who were not employed would be more likely to use HIT, CT, and ET. I also hypothesized older adults who were not married would be more likely to use HIT, ET, and CT.
3. For personality traits, I hypothesized older adults with higher neuroticism would be more likely to use HIT, whereas older adults with higher agreeableness and openness would be more likely to use WIT, CT, and ET.

## **Method**

### **Data and Sample**

The data for this study came from wave six of the WLS (2015), which were collected in 2011. The project has been one of the most extensive longitudinal studies of American who were born primarily in 1939. The WLS consists of a random sample of 10,317 women

and men who were in their final year of high school in Wisconsin State in 1957. Survey data were collected in 1957, 1964, 1975, 1993, 2004, and 2011.

All the participants in the WLS had completed a state-sponsored questionnaire intended to examine their plans for post-high school education, at a time when approximately 75% of students in the state were graduating from high school (Herd, Carr, & Roan, 2014; WLS, 2015). The WLS is a one-third random sample of all high school graduates in Wisconsin in 1957 ( $n = 10,307$ ) who were born between 1938 and 1941. The WLS sample is widely representative of white, non-Hispanic American women and men who have completed at least a high school level of education. Thus, some arrays of American society may not be well represented. However, WLS still includes substantial heterogeneity in the sample because the U.S. Census reported at least 76.9% of the sample cohort in the WLS had graduated high school or higher nationwide (Stoops, 2004). Despite the limitations of educational selectivity and small numbers of ethnic minorities in the sample, the WLS is a valuable source of information about non-Hispanic White cohorts born in the 1930s and 1940s with high heterogeneity in socioeconomic status (Herd et al., 2014).

The first wave of the WLS was collected by an in-person questionnaire in 1957, and it was followed by a mailed survey of parents in 1965, a telephone survey in 1975, telephone and mail surveys in 1993 and 2004, and an in-person survey and a mail survey in 2011 (Herd et al., 2014). This study uses the most recent wave of the WLS, and the simple retention rate for the 2011 wave was 59.6%, but it went up to 86.8% when deaths and non-contact were ruled out. The response rate was relatively high considering the long duration of the panel, and the primary reason for attrition has been mortality (Herd et al., 2014).



In the 2011 wave, of the initial 10,317 study participants, 6,152 respondents returned for a follow-up survey. Among 4,165 non-responsive individuals, 940 refused to participate, 2,049 were known deceased, and 96 were unavailable to contact. The simple retention rate was 59.6%, but it went up to 86.8% when accounting for deaths and non-contact. The study sample for the current study included 4,882 participants between the ages of 71 to 74 in 2011 ( $M$  age = 72.13,  $SD$  = .50, 54% women), who completed a self-administered questionnaire and provided valid information for all study variables.

## Measures

### Technology Use

HIT use was assessed with the following item: “In the past year, have you used the Internet to look for advice or information about your health or healthcare?” The item had two response options of 1 = yes and 0 = no. WIT use was assessed with the following item: “For you, was ‘doing tasks related to your job’ among the most important reasons why your household first obtained Internet access?” CT use was assessed with four questions with the same question stem of “For you, was ‘using e-mail to communicate with this person’ among the most important reasons why your household first obtained Internet access?” In each of the four questions, “this person” was replaced by “friends,” “one of your siblings,” “one of your children,” and “other relatives,” respectively. ET use was assessed with the following item: “For you, was ‘interested in using Web for recreation’ among the most important reasons why your household first obtained Internet access?” Responses for WIT use, CT use, and ET use had nine categories of 1 = yes for respondent, spouse, and someone else, 2 = yes for respondent and spouse, not for else, 3 = yes for respondent and else, not for spouse, 4 = yes for respondent, not for spouse and else, 5 = not for respondent, yes for spouse and else, 6

= not for respondent and else, yes for spouse, 7 = not for respondent and spouse, yes for else, 8 = not for any household members, and 9 = not ascertained for respondent, spouse, or else. I recoded these items into 1 = yes for respondent and 0 = not for respondent. For communication technology use, responding yes to any of four questions about CT use was recoded as 1 = use, and responding zero to all four questions were recoded as 0 = no use.

### **Individual Characteristics**

For gender, female was coded as 1, and male was coded as 0. Participants' birth years were provided, and they were recoded as their ages in 2011. Total household income was transformed by the natural log. Subjective health was asked as "How do you rate your health at the present time?" on a 5-point Likert scale ranging from 1 = very poor, 2 = poor, 3 = fair, 4 = good, to 5 = excellent. The degrees of education were dummy coded as high school graduate, college graduate (or associated), and beyond college-level.

### **Social Roles**

Employment status was coded as 1 = employed, and 0 = retired. Marital statuses were dummy coded as married, separated/divorced, widowed, and never married (Ha & Pai, 2012).

### **Personality Traits**

Extraversion, agreeableness, conscientiousness, neuroticism, and openness were assessed with the Big Five Personality scales (Costa & McCrae, 1992) at wave six (2011). Personality traits were assessed with the following question stem of "To what extent do you agree that you see yourself as a following self-descriptive statements," with response options ranging from 1 = agree strongly, 2 = agree moderately, 3 = agree slightly, 4 = disagree slightly, 5 = disagree moderately, to 6 = disagree strongly. Extraversion was assessed with

the following statements: someone who (a) is talkative, (b) is reserved, (c) is full of energy, (d) tends to be quiet, (e) is sometimes shy or inhibited, and (f) generates a lot of enthusiasm. Items (a), (c), and (f) were reverse coded. Agreeableness was assessed with the following statements: someone who (a) tends to find fault with others, (b) is sometimes rude to others, (c) is generally trusting, (d) can be cold and aloof, (e) is considerate to almost everyone, and (f) likes to cooperate with others. Items (a), (b), and (d) were reverse coded.

Conscientiousness was assessed with the following statements: someone who (a) does a thorough job, (b) is a reliable worker, (c) tends to be disorganized, (d) is lazy at times, (e) does things efficiently, and (f) is easily distracted. Items (c), (d), and (f) were reverse coded. Neuroticism was assessed with the following statements: someone who (a) can be tense, (b) emotionally stable and not easily upset, (c) worries a lot, (d) remains calm in tense situations, and (e) gets nervous easily. Items (b) and (d) were reverse coded. Openness was assessed with the following statements: someone who (a) prefers the conventional and traditional, (b) prefers work that is routine and simple, (c) values artistic, aesthetic experiences, (d) has an active imagination, (e) wants things to be simple and clear-cut, and (f) is sophisticated in art, music, or literature. Items (a), (b), and (e) were reverse coded. The sum scores of these subscales were calculated by summing whether at least three of its six items (three of five for neuroticism) had a valid response, and missing responses were imputed as the mean of the valid items prior to summing (Ha & Pai, 2012). Listwise deletion was used to handle missing values on the independent variables, which did not have any valid response to at least one of the scales because there were fewer than 1.2% missing (Allison, 2010). Higher scores on each subscale indicated higher levels of given personality traits.

## Analytic Plan

Sample characteristics were first examined (Table 1). Prevalence of technology use for each subtype was also presented (Table 2). The research questions are addressed using a series of logistic regression models predicting each type of technology use (Table 3). All analyses were conducted using the IBM SPSS Statistics 23.

## Treatment of Missing Data

Missing data analysis was performed using SPSS 23, and Little's (1988) missing completely at random (MCAR) test was conducted. The result for technology use was  $\chi^2(3) = 74.036, p < .001$ , and for personality variables was  $\chi^2(28) = 648.806, p < .001$ , indicating the null hypothesis that data were MCAR should be rejected. Hence, the four binary logistic regression analyses were performed using data with full information on all four technology use variables.

## Results

Results for the logistic regression models predicting each domain of technology use are presented in Table 3. As shown in model 1, individual characteristics, personality, and social roles were associated with HIT. Older women were more likely than men to use the Internet for health-related purposes ( $OR = 1.39, p < .01$ ). Also, characteristics such as being younger, and wealthier, and more educated were associated with a greater likelihood of using HIT. Compared to married older adults, widowed ( $OR = .78, p < .01$ ) and never married ( $OR = .57, p < .01$ ) older adults were associated with a lesser likelihood of this type of IT use. Among five personality traits, older adults with higher openness ( $OR = 1.08, p < .01$ ) was associated with a higher likelihood of HIT use, whereas higher agreeableness was associated with a ( $OR = .98, p < .05$ ) lesser likelihood of the use of this type of technology.

In model 2, older women were less likely than their male counterparts to use the Internet for work-related purposes ( $OR = .82, p < .05$ ), and characteristics such as being younger, wealthier, feeling healthier, and more educated were associated with a higher likelihood of using this type of IT. Compared to married older adults, only never married ( $OR = .65, p < .05$ ) older adults were associated with a lesser likelihood of WIT use. Among five personality traits, older adults with higher openness ( $OR = 1.10, p < .01$ ) was associated with a higher likelihood of WIT use at home, whereas higher agreeableness was associated with a ( $OR = .97, p < .01$ ) lesser likelihood of the use of this type of technology.

Conversely, in model 3, older women were much more likely than men to use CT ( $OR = 1.53, p < .01$ ). Also, characteristics such as being younger, wealthier, feeling healthier, and more educated were associated with a greater likelihood of using CT at home. Compared to married older adults, widowed ( $OR = .83, p < .05$ ) and never married ( $OR = .54, p < .01$ ) older adults were associated with a lesser likelihood of CT use. Among five personality traits, older adults with higher openness ( $OR = 1.06, p < .01$ ) was only associated with a higher likelihood of CT use.

In model 4, there were no gender differences of ET use at home whereas characteristics such as being younger, wealthier, feeling healthier, and more educated were associated with a greater likelihood of using this type of technology. Marital status was not a significant predictor of ET use. Among five personality traits, older adults with higher openness ( $OR = 1.04, p < .01$ ) was associated with a higher likelihood of WET use at home, whereas higher conscientiousness was associated with a ( $OR = .98, p < .01$ ) lesser likelihood of the use of this type of technology.

## Discussion

The purpose of this study was to examine the antecedents of older adults' technology use, as defined by four specific subtypes, namely, WIT, WIT, CT, and ET. Findings indicated the associations between technology use and the set of predictors were different for each type of technology examined.

Among individual characteristics, given the age homogeneity of the WLS sample, I did not expect age would predict the use of any type of technology in the same cohort. However, age did, in fact, predict a lower rate of technology use of all four subtypes. In later life, older adults' technology uses for communication purposes decreases loneliness and increases their social contact (Cotten, Anderson, & McCullough, 2013). However, age effects should be interpreted with caution because the age range of the sample in this study is narrow.

Previous studies have consistently found healthier older adults were more likely to use technology (Elliot et al., 2014; Gell et al., 2015), and findings from this study partially supported this. Older adults with higher subjective health were more likely to use WIT, CT, and ET, but there was no significant difference in the use of HIT. I interpreted this finding as implying older adults were interested and motivated to use HIT regardless of their level of subjective health. Proportionally, approximately 46.4% of the total sample have used the Internet to search health-related information, and this reflects the high interests of this population in health-related information in general. In particular, because almost half of the sample used HIT, health-related technology might be the type that older adults with poor health are equally motivated to benefit from; this supports previous research that health-

related technology is one of the most significant interests of this population (Coughlin, 2017; Fisk et al., 2009).

The literature indicates higher household income predicts older adults' technology use (Werner et al., 2011). Similarly, in this study, household income was a significant predictor of all four types of technology use. The minimum level of educational attainment in the WLS is high school graduate, which is an overall higher level of education than older populations in the United States. Nonetheless, the degree of education positively predicted all four types of technology use. Older adults with college-level education were more likely to use technology than the high school graduated, and older adults with higher degrees were more likely to use technology than older adults with college degrees. However, the proportional increase in the likelihood of usage across different types of technology use varied, as it was smallest in ET use and largest in WIT use.

Previous research has reported inconsistent findings regarding the role of gender in older adults' technology use. Some studies have shown older men use the Internet more than older women (Czaja et al., 2006), and were more likely to use the Internet for information seeking, compared to women who were more interested in communication using the Internet (Jackson, Ervin, Gardner, & Schmitt, 2001). However, Karavidas and colleagues (2005) specified women were more interested in using the Internet to seek health-related information than men. Taken together, these mixed findings suggested the role of gender as a predictor of technology could differ by the type of technology use. By differentiating subtypes of technology use, this study has shown men use IT more than women for work-related purposes, whereas women are more likely to use IT for health information seeking and communicating with others; this supported previous research (Karavidas et al., 2005).

However, although 35% of older adults in the sample used ET, there were no gender differences in ET use, which indicates similar interests in using technology for recreational purpose regardless of gender. The finding also supports what Heinz and colleagues (2013) reported on older adults' common interest in using technology for entertainment.

For social roles, there are a higher proportion of married individuals in the WLS compared to samples in other national data (Gell et al., 2015). In contrast to their married peers, divorced or separated older adults showed no differences in the use of all four types of technology. However, the widowed were less likely to use HIT and CT than the married. Moreover, the finding implies widowed individuals may suffer from another type of digital divide in later life caused by bereavement, and even suggests potential gender effects. Specifically, older women were significantly more likely to use HIT and CT than older men; as a result, widowed men might be more disadvantaged than widowed women. Further, given that CT is an effective source of emotional support and HIT is the use of technology for their own health, the bereaved men might be experiencing consequential disadvantages from their behavioral patterns of technology use. Of the marital status groups of older adults, those who were the least likely to use technology, in general, was the never married group. Compared to married older adults, they were significantly less likely to use HIT, WIT, and CT. One of the primary sources of learning how to use technology for older adults is their family members including spouses, children, and grandchildren (Gatto & Tak, 2008; Kuerbis, Mulliken, Muench, Moore, & Gardner, 2017). Never married older adults might be more disadvantaged from using technology. Not only might they have a smaller number of networks to communicate with or without technology, but they might also have fewer opportunities to get instrumental support, and fewer personal relations to engage with technology.



Being employed significantly predicted WIT use as hypothesized, but employment status did not predict the use of CT and ET. An interesting finding was that employed older adults were less likely to use HIT. Given the cross-sectional characteristics of this study, drawing inferences from this finding is impossible, but several hypotheses can be made to explain it. First, a lower tendency to use HIT by employed older adults could be associated with their better access to medical care, which implies retired older adults may need to search for health-related information on the Internet. Despite the higher necessities of medical assistance, older adults' access to medical services in the United States was limited (Andersen, Davidson, & Baumeister, 2013), so retired older adults might need to use HIT more than others with more resources. Third, Kim and Moen (2002) reported being employed in later life could have dynamic influences on older adults' well-being, so reasons for being employed over 70 ( $M = 72.1$ ) could be associated with their health-related feelings and behaviors.

Most investigations on the association between personality traits and technology use were focused on testing models and frameworks such as the TAM and its various modifications, including the unified theory of acceptance and use of technology (Barnett et al., 2015; Davis et al., 1989; Devaraj et al., 2008; Heinz, 2013; Rockmann & Gewald, 2015). Different personality factors were reported as having relationships with technology acceptance. Higher agreeableness (Heinz, 2013), and higher conscientiousness and extraversion (Barnett et al., 2015), were associated with higher acceptance, and higher neuroticism with less acceptance (Barnett et al., 2015). In this study, I tested the association between each personality trait and each type of technology. Regarding the association between personality traits and technology use, the results of this study partially supported my

hypothesis. Openness predicted the use of all four technology types. In contrast to my hypothesis, agreeableness predicted less HIT and WIT. Neuroticism did not predict any type of technology use. In this study, however, the magnitude of predictors of personality traits was not significant. Openness was most associated with all types of technology; older adults with more openness may be less resistant and reluctant to try technology. However, given the large sample size of the study, the influences of personality traits on technology use should be interpreted with caution.

Finally, this study contributed to a large body of literature from various disciplines that attempts to understand older adults' technology use. In particular, this study extended previous work by providing a detailed conceptualization and operationalization of four different types of technology use and allowing individual characteristics, social roles, and personality traits to predict each technology type differently. For example, predictors such as gender, employment status, subjective health, marital status, and personality traits showed different associations with the use of each type. To be specific, the big five personality traits as predictors of older adults' technology use partially supported previous findings in the literature (Chen & Persson, 2002; Flynn et al., 2006, Teng, 2008), but also contradicted some findings (Chen & Persson, 2002; Correa et al., 2010; Heinz, 2013). More importantly, personality traits in this study showed relatively low magnitude as predictors. Similarly, Ross and colleagues (2009) reported personality traits were not as influential as previous research suggested.

Although my work makes contributions, the study also had limitations. The first limitation was the generalizability of the findings. Every participant in the WLS study had at least graduated from high school, is mostly non-Hispanic Whites, and married. Despite the

degree of homogeneity in this sample, it was largely representative of married older Americans in that age cohort, and their educational attainment and racial distribution (Moorman & Carr, 2008). The second limitation was the cross-sectional design of this study which did not allow drawing inferences from the causal relationship. Given the importance of period effects in this specific topic, findings from this study could be affected by the time when data was collected. Despite such limitations, this study provided partial explanations for existing inconsistent findings in this topic. By introducing refined definitions of technology, the results also provide useful insights for the significance of the distinction among technology types not only in research design but also in planning training programs and intervention for older adults.

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Table 1. *Sample characteristics*

Older Adults	Total (N = 4,882)
Individual characteristics	
Sex female	54.0%
Age (M, SD)	72.1 (.49)
Household income (M, SD)	\$49,783 (\$66,056)
Subjective health (M, SD)	4.0 (.67)
Education (in %)	
High school graduate	66.4
Some college	20.4
Beyond college-level	13.2
Social roles	
Marital status (in %)	
Married	73.3
Divorced/separated	10.3
Widowed	13.0
Never married	3.4
Employment status (in %)	
Employed	27.6
Personality traits (M, SD)	
Extraversion	22.3 (5.39)
Agreeableness	28.4 (4.57)
Conscientiousness	28.1 (4.58)
Neuroticism	14.8 (4.70)
Openness	20.4 (4.83)

Table 2. *Ratio of each type of technology use*

Use (in %)	HIT	WIT	CT	ET
Men	44.1	32.1	53.9	35.0
Women	48.3	23.7	61.3	35.1
Total	46.4	27.6	57.9	35.0

Table 3. *Logistic Regression results predicting the use of Health-related IT, Work-related IT, CT, and ET use in 2011*

	Model 1 (HIT)		Model 2 (WIT)		Model 3 (CT)		Model 4 (ET)	
	OR	SE	OR	SE	OR	SE	OR	SE
Individual characteristics								
Female	1.39**	.07	.82*	.08	1.53**	.07	1.02	.07
Age	.81**	.06	.78**	.08	.80**	.06	.84**	.07
Household income	1.05**	.01	1.05**	.02	1.05**	.01	1.04**	.01
Subjective health	.96	.05	1.21**	.06	1.33**	.05	1.15**	.05
Education (ref = high school diploma)								
Some college	1.78**	.08	2.13**	.09	2.18**	.09	1.25**	.08
Beyond college	2.25**	.10	3.98**	.11	2.67**	.11	1.38**	.10
Social roles								
Employed	.87*	.07	2.61**	.08	.99	.07	.91	.07
Marital status (ref = married)								
Divorced/separated	.78**	.09	.86	.12	.83*	.10	1.13	.10
Widowed	.57**	.18	.65*	.21	.54**	.18	.98	.17
Never married								
Personality traits								
Extraversion	.99	.01	1.01	.01	1.01	.01	1.00	.01
Agreeableness	.98*	.01	.97**	.01	1.01	.01	.99	.01
Conscientiousness	1.01	.01	1.00	.01	1.00	.01	.98**	.01
Neuroticism	.99	.01	.99	.01	1.00	.01	1.00	.01
Openness	1.08**	.01	1.01**	.01	1.06**	.01	1.04**	.01
-2 log likelihood	6183.42		4958.31		6320.05		6335.99	
X <sup>2</sup>	421.07**		912.90**		518.05**		117.59**	

Notes.  $N = 4,882$ . \*\* $p < .01$ ; \* $p < .05$

### CHAPTER 3. EXPLORATION OF LATENT CLASSES ON OLDER ADULTS' TECHNOLOGY USE PATTERNS AND PREDICTING CLASSES

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Social Sciences

Sangbo Nam

Human Development and Family Studies, Iowa State University

Address correspondence to Sangbo Nam, Human Development and Family Studies, Iowa  
State University, 0084 LeBaron Hall, Ames, Iowa 50011. E-mail: sbnam@iastate.edu

#### **Abstract**

Based on the understanding that older adults are heterogenous in terms of individual characteristics, social roles, as well as personality, this study used a multidimensional approach to understand older adults' technology use behaviors. I applied latent class analysis to data from the Wisconsin Longitudinal Study ( $n = 4,882$ ) to capture older adults' technology use patterns. The best fitting model consisted of three latent classes identified as multi-users, selective users, and non-users. Multi-users were more likely to be women, younger, had higher household income, better subjective health, more education, higher openness, and were more likely to be married than non-users. Selective users were better in subjective health, had more education, were more likely to be employed, married, and showed higher agreeableness and openness than non-users. I discuss characteristics of each category in relation to Rogers's adopter categories. Findings from this study add to our understanding of older adults' technology use and have implications for practice in terms of designing intervention programs that meet older adults' distinctive characteristics and diverse needs.

Keywords: *technology use patterns, latent class analysis, individual characteristics, social roles, personality traits*

## **Introduction**

Previous works on the antecedents of technology use among older adults have primarily examined technology as a single construct measured by global use of the Internet. However, antecedents and outcomes of technology use may vary by the specific types of technology use. For example, although previous literature has indicated men are more likely to use the Internet than women (Czaja et al., 2006; Karavidas et al., 2005; Kim, Lee, Christensen, & Merighi, 2017; Werner et al., 2011), Study 1 in this dissertation demonstrated women were more likely to use the Internet to seek health-related information and for communication purposes, although they were less likely to use the Internet for work-related purposes. Despite increasing number of studies on predictors of older adults' technology use, potential linkages among technology types have been overlooked.

Although findings from previous studies have improved the understanding of older adults' technology use for each type, it may not capture the diversity of older adults' technology use patterns. For example, among older technology users, some may use all types of technology that were previously identified, whereas others may not use any of them. Further, there may be a group of older adults who use a combination of some types. Thus, a unidimensional approach to older individuals' technology use may fail to capture the variations in its usage in older populations and the unique characteristics of older individuals' technology use in later life. Instead of using a single-dimensional approach, exploring typologies allowed capturing the underlying technology use patterns of older adults.

The previous chapter of this dissertation (Study 1) extended the existing literature by considering four different types of technology use: health-related information, work-related information, communication, and entertainment. This chapter took these efforts a step further by considering patterns in these four types of technology use to construct typologies of older adults' technology use. In particular, I distinguished between users and non-users as well as older adults who used multiple types of technology.

### **Literature Review**

Many intervention programs focus on reducing the age-related digital divide by providing training in the basic skills of using PCs, tablets, and smartphone applications (Chan, Haber, Drew, & Park, 2016; Czaja et al., 2015; Delello & McWhorter, 2015; Slegers, van Boxtel, & Jolles, 2008). Interventions and programs intend to improve a variety of outcomes in older adults' lives, including: psychological well-being, preventive health behaviors, cognitive functioning, digital literacy, and self-efficacy (Chan et al., 2016; Tsai, Shillair, Cotten, Winstead, & Yost, 2015; Yuan, Hussain, Hales, & Cotten, 2015; Widmer et al., 2015). However, these programs rarely consider the individual needs of older adults (Silveira, van het Reve, Daniel, Casati, & de Bruin, 2013; Werner et al., 2011). As a result, there are insufficient findings in literature to tailor programs in ways to fit the needs of diverse older adults. The diffusion of innovations theory may be useful in explaining how technology has spread in society. The theory describes the process of diffusion of innovations as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 2003, p. 5). Rogers (2003) highlighted the temporal pattern in how people react to and adopt technology, suggesting five adopter categories based on the timing of adoption: (a) innovators, (b) early adopters, (c) early

majority, (d) late majority, and (e) laggards. However, Rogers and other researchers were more focused on the trend of the diffusion process itself than on the individual users (Tatnall & Lepa, 2003). Older adults are likely to use technology for a variety of purposes including work-related information seeking, health-related information seeking, communication, and entertainment (Billipp, 2001; Gell, Rosenberg, Demiris, LaCroix, & Patel, 2015; Schulz et al., 2014). In previous literature, technology use mostly referred to the use of electronic devices for information and communication purposes. However, the use of technology for entertainment purposes among older adults has shown strong growth in recent years (Heinz et al., 2013). The rising number of intervention programs also use ET, such as video gaming and social media uses on PCs and tablet computers (Anguera et al., 2013; Leung, 2013; Tsai, Shillair, & Cotten, 2017). Further, frequent changes in U.S. health care reform expanded health-related information on the Internet (Buntin, Jain, & Blumenthal, 2010). The gap between people who search health-related information and those who do not is referred to as the digital health divide (Kane, Alavi, Labianca, & Borgatti, 2014). The digital health divide is another type of age-related digital divide easily observed among older populations (Olson, O'Brien, Rogers, & Charness, 2011). The latent class structures of older technology user groups regarding HIT use provide some implications for the understanding of the digital health divide among older adults.

Not only it is important to know who uses technology but knowing how users and non-users of various types of technology are distributed is also crucial in understanding older adults' technology use. In the previous study (Study 1), I investigated four different types of technology use and found variation in the predictors of each type. For example, older women may use HIT and CT more than their counterparts, whereas older men use WIT more (Study

1). In this chapter, I extended this work by considering the patterns in the use of these four different types of technology, as well as the predictors of these patterns. Based on the categorization strategy in the theory of diffusion of innovations (Rogers, 2003), I hypothesized there would be at least three different types of user categories. Older adults who are open to using any type of new technology were categorized as “multi-users”; those who used at least one type of new technology were categorized as “selective users”; and as a referent group, those who did not use any type of technology were categorized as “non-users.”

### **Predicting Multi-purpose Technology Use**

Past research has reported some factors predicting technology use of older adults, but some findings have been inconsistent. To reduce the inconsistency, a previous study in this dissertation investigated antecedents of technology use of older adults with refined definitions. Findings showed while there were factors predicting all types of technology use, others predicted each type of technology use differently (Study 1). Do older adults use multiple types of technology? What factors predict the different classes of technology use? As discussed in the previous study, factors such as individual characteristics, personality traits, and social roles have been associated with older adults’ personal choice to adopt a certain type of technology. The factors may also predict older adults’ patterns of technology use.

**Multi-users.** The literature on technology use indicated several factors; including individual characteristics, social roles, and personality traits; predicted various types of technology use. In particular, the previous study in this dissertation showed all four subtypes (Study 1) of older adults with more household income, more education, higher openness, and



who were relatively younger in their sample group, were more likely to use technology. The findings were consistent with past literature that older adults who are younger than their peers are non-Hispanic white, with more education, more household income, and better health, are more likely to use technology than their counterparts (Carpenter & Buday, 2007; Czaja et al., 2006; Elliot et al., 2014; Fazeli et al., 2013; Koopman-Boyden & Reid, 2009; Wagner et al., 2010; Werner et al., 2011). Thus, based on existing evidence, I hypothesized older adults with more income, more education, who are relatively younger in their group, and have higher openness would be associated with older adults who use multiple types of technology categorized as multi-users.

**Selective users.** The TAM indicates perceived usefulness, which is one of the two significant factors affecting technology acceptance (Davis, Bagozzi, & Warshaw, 1989). People perceive different values as useful. Thus, they try to adopt different types of technology based on their own sets of motivations. For example, older adults occasionally used computers and regularly used the Internet for information searching and communication purposes (Olson et al., 2011). In the meantime, some people used social media for information and entertainment while others used them for social interaction and communication purposes (Shao, 2009). There is a possibility that new groups of older adults emerge based on the combinations of technology types they use more than others.

Previous research predicting technology use of older adults has some inconsistent findings regarding the role of gender, subjective health, employment status, marital status, and personality traits (Czaja et al., 2006; Karavidas et al., 2005; Marston et al., 2013; Study 1; Werner et al., 2011). Although gender is a factor that has been given adequate attention in the technology literature, findings on gender differences in technology use are unclear. In

part, such inconsistencies are attributable to the broad definitions of technology used in earlier studies, leading to biased estimates of technology (i.e., higher use of WIT among men compared to women). For example, Study 1 found women were more likely to use HIT and CT while men were more likely to use WIT. Similarly, Elliot et al. (2014) found there was no significant association between ICT use and physical health, whereas Study 1 indicated older adults with better subjective health were more likely to use WIT, CT, and ET. Also, being employed was strongly associated with the use of IT (Werner et al., 2011), but unemployed older adults were more likely to use HIT than the employed (Study 1). Remaining in marriage in later life was associated with greater use of technology (Selwyn, 2004; Wang, Bennett, & Probst, 2011), but divorced older adults were not significantly different in comparison in the use of technology (Study 1). Widowed older adults were less likely to use HIT and CT, and never married older adults were less likely to use HIT, WIT, and CT (Study 1). Previous findings on the effects of personality traits on technology use were inconsistent in terms of the types of technology used. Individuals with greater openness and agreeableness were more likely to use technology (Correa, Hinsley, & de Zúñiga, 2010; Devaraj, Easley, & Crant, 2008; Heinz, 2013), whereas older adults with higher agreeableness were less likely to use WIT and HIT, and higher conscientiousness was associated with less use of ET (Study 1).

Based on the discussion and existing evidence, I hypothesized the combination of being older women, unemployed, and having better subjective health would predict a technology use pattern of some combinations of HIT, CT, and ET. I also hypothesized older adults who are employed, married, and with better subjective health would predict a pattern

of combinations of WIT and other types of technology. This part of the study was exploratory because I could not hypothesize in detail before yielding class memberships.

**Non-users.** As a reference group to other patterns of technology use, older adults who were older in their group, had less household income, less education, lower openness, who were never married, and were known to be less likely to use technology were categorized as non-users (Elliot et al., 2014; Fazeli, Ross, Vance, & Ball, 2013; Gell et al., 2015; Kim et al., 2017; Study 1).

Thus, the objective of this study was to identify patterns of older adults' technology use based on four distinct types of technology (i.e., health-related information, work-related information, communication, and entertainment). Exploring specific patterns of technology use by different combinations of technology types may show behavioral patterns in technology use among older adults and what factors predict those patterns. Thus, I examined the associations between technology use patterns and factors such as individual characteristics, personality traits, and social roles of older adults.

## Method

### Data and Sample

The Wisconsin Longitudinal Study is a random sample survey, which initially consists of 10,317 women and men who graduated from high schools in Wisconsin State in 1957. The data for this study were collected as part of the WLS in 1957, 1964, 1975, 1993, 2004, and 2011, and I used wave six of the data, which were collected in 2011. The project is one of the first large longitudinal studies of American adolescents who were born primarily in 1939.

In the 2011 wave, of the initial 10,317 participants, 6,152 respondents provided data. Among 4,165 non-responsive people, 940 refused to participate, 2,049 were known to be deceased, and 96 were unavailable to contact. The simple retention rate was 59.6%, but it increased to 86.8% when ruling out deaths and participants who were not available to contact. The current sample included 4,882 participants between the ages of 71 to 74 at 2011 ( $M = 72.13$ ,  $SD = .50$ , 54% women). This sample was selected from the whole sample based on their responses to the measures. Regarding marital status, 73.3% of the participants were married, 10.3% were divorced or separated, 13% were widowed, and 3.4% indicated they were never married. In 2011, 27.6% of participants reported they were still employed. In terms of household income, 25% of participants reported an income less than \$20,372 per year, 50% of participants made between \$20,400 and \$55,600 per year, and 25% of participants reported a household income of more than \$55,600 per year, with the median of \$33,420 per year. Regarding education level, 66.5% of participants reported high school was their highest educational achievement, 20.4% reported themselves as college graduates, and 13.2% reported having a master's degree or higher. Participants' demographic characteristics are presented in Table 1, and the ratios of each type of technology use are presented in Table 2.

### **Procedure**

The WLS was a state-sponsored questionnaire intended to examine participants' plans for post-high school education when the graduation rate was approximately 75% (Herd, Carr, & Roan, 2014). The WLS used a one-third random sample of all high school graduates in Wisconsin in 1957 ( $n = 10,307$ ) who were born between 1938 and 1941. The WLS sample is widely representative of white, non-Hispanic American women and men who have

completed at least a high school level of education. Therefore, some arrays of American society may not be well represented. Nevertheless, the 2003 U.S. Census reported that at least 76.9% of the population in the age group to which WLS cohort belongs were high school graduates, revealing the WLS cohort was reasonably representative of the nation in terms of educational attainment (Stoops, 2004). Despite the limitations of educational selectivity and small numbers of ethnic minorities in the sample, the WLS is a valuable source of information about non-Hispanic White cohorts born in the 1930s and 1940s containing a wide variety of heterogeneity in socioeconomic status (Herd et al., 2014).

The first wave of the WLS was collected by an in-person questionnaire in 1957, and it was followed by a mail survey of parents in 1965, a telephone survey in 1975, telephone and mail surveys in 1993 and 2004, and an in-person survey and a mail survey in 2011 (Herd et al., 2014). This study used the 2011 wave, the most recent of the WLS. The simple retention rate was 59.6%, but it increased to 86.8% when ruling out deaths and non-contact/not-fielded. The response rate is relatively high considering the long duration of the panel, and the main reason for attrition has been mortality (Herd et al., 2014).

## Measures

### Technology Use

HIT use was assessed with the following item: “In the past year, have you used the Internet to look for advice or information about your health or healthcare?” The item had two response options of 1 = *yes* and 0 = *no*. WIT use was assessed with the following item: “For you, was ‘doing tasks related to your job’ among the most important reasons why your household first obtained Internet access?” CT use was assessed with following four questions with the same question stem of “For you, was ‘using e-mail to communicate with this person’

among the most important reasons why your household first obtained Internet access?” In the four questions, “this person” was each replaced by friends, one of your siblings, one of your children, and other relatives. ET use was assessed with the following item: “For you, was ‘interested in using Web for recreation’ among the most important reasons why your household first obtained Internet access?” Responses for WIT use, CT use, and ET use had nine categories of 1 = *yes for respondent, spouse, and someone else*, 2 = *yes for respondent & spouse, not for else*, 3 = *yes for respondent & else, not for spouse*, 4 = *yes for respondent, not for spouse & else*, 5 = *not for respondent, yes for spouse & else*, 6 = *not for respondent & else, yes for spouse*, 7 = *not for respondent & spouse, yes for else*, 8 = *not for any household members*, and 9 = *not ascertained for respondent, spouse, or else*. I recoded them into 1 = *yes for respondent* and 0 = *not for respondent*. For communication technology use, responding yes to any of four questions about CT use was recoded as 1 = *use*, and responding zero to all four questions was recoded as 0 = *no use*.

### **Individual Characteristics**

For gender, female was coded as 1, and male was coded as 0. Participants’ birth years were provided, and they were recoded as their ages in 2011. Total household income was transformed by the natural log. Subjective health was asked as “How do you rate your health at the present time?” on a five-point Likert scale ranging from 1 = *very poor*, 2 = *poor*, 3 = *fair*, 4 = *good*, to 5 = *excellent*. The degrees of education were dummy coded as high school graduate, graduates from a college or associated, and beyond college-level.

## Social Roles

Employment status was coded as 1 = *employed*, and 0 = *retired*. Marital statuses were dummy coded as married, separated/divorced, widowed, and never married (Ha & Pai, 2012).

## Personality Traits

Extraversion, agreeableness, conscientiousness, neuroticism, and openness were assessed with the Big Five Personality scales (Costa & McCrae, 1992) at wave 6 (2011). Personality traits were assessed with the following question stem of “To what extent do you agree that you see yourself as a following self-descriptive statements,” with response options ranging from 1 = *agree strongly*, 2 = *agree moderately*, 3 = *agree slightly*, 4 = *disagree slightly*, 5 = *disagree moderately*, to 6 = *disagree strongly*. Extraversion was assessed with the following statements: someone who (a) is talkative, (b) is reserved, (c) is full of energy, (d) tends to be quiet, (e) is sometimes shy or inhibited, and (f) generates a lot of enthusiasm. Items (a), (c), and (f) were reverse coded. Agreeableness was assessed with the following statements: someone who (a) tends to find fault with others, (b) is sometimes rude to others, (c) is generally trusting, (d) can be cold and aloof, (e) is considerate to almost everyone, and (f) likes to cooperate with others. Items (a), (b), and (d) were reverse coded. Conscientiousness was assessed with the following statements: someone who (a) does a thorough job, (b) is a reliable worker, (c) tends to be disorganized, (d) is lazy at times, (e) does things efficiently, and (f) is easily distracted. Items (c), (d), and (f) were reverse coded. Neuroticism was assessed with the following statements: someone who (a) can be tense, (b) emotionally stable and not easily upset, (c) worries a lot, (d) remains calm in tense situations, and (e) gets nervous easily. Items (b) and (d) were reverse coded. Openness was assessed

with the following statements: someone who (a) prefers the conventional and traditional, (b) prefers work that is routine and simple, (c) values artistic, aesthetic experiences, (d) has an active imagination, (e) wants things to be simple and clear-cut, and (f) is sophisticated in art, music, or literature. Items (a), (b), and (e) were reverse coded. The sum scores of these subscales were calculated by summing whether at least three of its six items (three of five for neuroticism) had a valid response, and missing responses were imputed as the mean of the valid items prior to summing (Ha & Pai, 2012). Listwise deletion was used to handle missing data related to the independent variables that did not have any valid response to at least one of the scales because there were fewer than 1.2% of missing (Allison, 2010). Higher scores on each subscale indicated higher levels of given personality traits.

### **Analytic Plan**

Latent class analysis (LCA) was used to identify distinct groups of respondents based on their subtypes of technology use. An approach in which the latent variables is categorical is referred to as LCA (Collins & Lanza, 2010). I used MPlus 7.0 to conduct LCA and multinomial logistic regression. Sample characteristics were first examined (Table 1) (Muthén & Muthén, 2012). Prevalence of technology use for each subtype is also presented (Table 2). Model fit indices from the LCA are presented (Table 3). Explored classes are presented (Table 4), and latent class probabilities are also presented (Table 5). The three explored classes are presented (Figure 1). The probability scale from LCA is presented (Table 6). The research questions were addressed using a set of multinomial logistic regression models predicting class memberships (Table 7).



### Treatment of Missing Data

To test the nature of missing four technology use variables and five personality trait variables, Little's MCAR test (Little, 1988) was performed in SPSS 23 (Study 1). The result for technology use variables was  $\chi^2(3) = 74.036, p < .001$ , and for personality variables was  $\chi^2(28) = 648.806, p < .001$ , indicating the null hypothesis that data were missing completely at random should be rejected. Hence, the following LCA was performed using data with complete information on all four technology use variables.

### Results

Starting from a single latent class model, and then increased the number of classes by one each time, in that process, LCA has estimated various models with the number of latent classes ranging from 1 to 4. I compared the models to identify the optimal number of classes for the data. Table 3 showed the fit statistics for the four LCA models with the various numbers of latent classes. As shown in the table, both BIC and adjusted BIC stopped decreasing for the three-class LCA model, and the  $p$ -values for both LMR-LRT and BLRT were significant, indicating the three-class model had a significantly better fit for the data than the two-class model. Alternatively, the four-class LCA model showed poor fit on all the fit statistics. Hence, I chose the three-class model as the preferred one.

Table 4 showed the class counts and corresponding proportions for each of three classes based on the most likely posterior class. Based on the previously discussed classification strategy, class one was referred to as multi-users, class two was referred to as selective users, and class three was referred to as non-users.

Compared to non-users, multi-users were more likely to be female ( $OR = 1.48, p < .01$ ), with higher household income ( $OR = 1.06, p < .01$ ), with higher self-rated health ( $OR$

= 1.24,  $p < .01$ ), and with higher education (some college:  $OR = 2.29$ ,  $p < .01$ , college and above:  $OR = 3.57$ ,  $p < .01$ ). Alternatively, respondents who were older ( $OR = .73$ ,  $p < .01$ ), divorced or separated with spouse ( $OR = .73$ ,  $p < .01$ ), widowed ( $OR = .78$ ,  $p < .01$ ), and never married ( $OR = .46$ ,  $p < .01$ ) were less likely in multi-users. In terms of the personality difference of respondents in two classes, multi-users showed a significantly higher openness score.

Compared to non-users, selective users were more likely to be employed ( $OR = 1.23$ ,  $p < .01$ ), with higher self-rated health ( $OR = 1.60$ ,  $p < .01$ ), and with higher education (some college:  $OR = 1.88$ ,  $p < .01$ , college and above:  $OR = 2.41$ ,  $p < .01$ ). Alternatively, respondents who were separated or divorced ( $OR = .72$ ,  $p < .01$ ), or never married ( $OR = .51$ ,  $p < .01$ ) were less likely to be selective users. In terms of the personality difference of respondents in two classes, selective users showed a significantly higher score on agreeableness ( $OR = 1.02$ ,  $p < .01$ ) and openness ( $OR = 1.04$ ,  $p < .01$ ).

Compared to multi-users, selective users were more likely to be employed ( $OR = 1.21$ ,  $p < .01$ ), widowed ( $OR = 1.11$ ,  $p < .01$ ), and with higher self-rated health ( $OR = 1.29$ ,  $p < .01$ ). Alternatively, respondents who were female ( $OR = .72$ ,  $p < .01$ ), never married ( $OR = .54$ ,  $p < .01$ ), and with higher education (some college:  $OR = .82$ ,  $p < .01$ , college and above:  $OR = .67$ ,  $p < .01$ ) were less likely to be selective users. In terms of the personality difference of respondents in two classes, selective users showed a significantly higher score on agreeableness ( $OR = 1.03$ ,  $p < .01$ ) and a significantly lower score on conscientiousness ( $OR = .98$ ,  $p < .01$ ) and openness ( $OR = .95$ ,  $p < .01$ ).

## Discussion

The purpose of this study was to identify the latent classes of older technology users and non-users to investigate different qualitative aspects of those memberships and examine how factors such as individual characteristics, personality traits, and social roles predicted the explored memberships. The LCA of four subtypes of technology; WIT, HIT, CT, and ET; yielded three classes of technology use types, categorizing distinctive technology user models of older adults. The results demonstrated a three-class model; multi-users, selective users, and non-users; best described older adults' technology use patterns.

In the diffusion of innovations theory, Rogers (2003) subdivided adopters of innovations into five different categories—innovators, early adopters, early majority, late majority, and laggards—based on observations that served as a framework for subsequent research. I used a similar categorization system to identify different patterns of older adult's technology use. Rogers generalized that early adopters in his model were similar to later adopters in age, which was supported by the findings of this study: there was no difference in age between the two technology user groups—multi-users and selective users. However, multi-users were significantly younger than non-users. This finding is meaningful in that even among older adults in the same cohort, an age-related digital divide existed between the most benefited group and the least benefited group. However, findings of age differences should be interpreted with caution because of the narrow range of three years. The same trend was found when comparing income levels among the three groups. Household income of multi-users was only significantly higher than non-users, but income level was no different between multi-users and selective users, and between selective users and non-users.

Rogers (2003) indicated early adopters have more years of education than later adopters, and findings from this study supported this argument. Multi-users had more years of education than selective users, and selective users had more years of education than non-users, revealing higher education was positively associated with greater technology use. Thus, this finding suggests education is a significant factor affecting older adults' technology use as well as numbers of different technology use.

In the previous study (Study 1), older women were more likely to use HIT and CT, and older men were more likely to use WIT when there was no difference in ET use. In this study, older women were more likely to be multi-users. Although selective users were more likely to use CT than non-users, interestingly, there was no difference in gender between selective users and non-users. Personality traits were also found to predict different class memberships. Selective users showed higher openness than non-users, and openness of multi-users was both higher than that of selective users and non-users. Also, higher openness predicted membership in the high usage group, regardless of the type of technology used. Agreeableness was the highest in selective users, and multi-users and non-users were not significantly different in agreeableness.

In regard to social roles, multi-users were more likely to stay in their marriage than non-users, but there were no differences in their employment status. This may imply their employment status could be similar for involuntary reasons, but we cannot infer this from the current study. Selective users were more likely to be employed than both multi-users and non-users, more likely to be married than multi-users and non-users, and less likely to be divorced than non-users. Selective users had no significant differences in household income compared to other groups, but they were more likely to be working and married than other

groups. Further, older adults who have not been employed throughout their lives might not have chosen WIT. When it comes to current employment status, selective users were more likely to be employed than non-users, but there were no differences between multi-users and selective users. However, this limited effect of current employment status on the class memberships does not explain how overall work experiences in older adults' lives led them to different types of technology use behaviors.

Study 1 of this dissertation showed various sets of factors predicted different types of technology use. Findings from this study extended the understanding of older adults' technology use a step further by revealing there were different patterns of technology use, and factors predicting each pattern may also vary. Most studies regarding older adults' technology use examined the associations based on either the frequency of use or use/no use approach. Findings from this study showed various technology use patterns among older populations, and factors predicting those patterns. Applying these frameworks may help translational research efforts and development of programs and products that will well serve older adults' needs for technological advancements.

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Table 1. *Sample characteristics*

Older Adults	Total (N = 4,882)
Age (M, SD)	72.1 (.49)
Sex female	54.0%
Marital status	
Married	73.3%
Divorced/Separated	10.3%
Widowed	13.0%
Never Married	3.4%
Subjective health (M, SD)	4.0 (.67)
Employment status	
Employed	27.6%
Household income (M, SD)	\$49,783 (\$66,056)
Education	
High school graduate	66.4%
Some college	20.4%
Beyond college-level	13.2%
Personality traits (M, SD)	
Extraversion	22.3 (5.39)
Agreeableness	28.4 (4.57)
Conscientiousness	28.1 (4.58)
Neuroticism	14.8 (4.70)
Openness	20.4 (4.83)

Table 2. *Ratio of each type of technology use (N = 4,882)*

Use	HIT	WIT	Communication Technology	ET
Men	44.1%	32.1%	53.9%	35.0%
Women	48.3%	23.7%	61.3%	35.1%
Total	46.4%	27.6%	57.9%	35.0%

Table 3. *Comparison of fitting indexes of models with different number of classes*

	BIC	Adjusted BIC	LMR-LRT P-value	BLRT P-value	Entropy
One-class model	26350.022	26337.312	na	na	na
Two-class model	22915.266	22886.667	< .001	< .001	0.792
Three-class model	22908.003	22863.516	< .001	< .001	0.922
Four-class model	22934.119	22873.743	0.0067	< .001	0.525

Notes. na = Not applicable, (N = 5,053).

Table 4. *Class Counts and Proportions for 3-class model*

	Counts	Proportion (%)
Latent class one	2,034	40.3
Latent class two	1,098	21.7
Latent class three	1,921	38.0

Note. (N = 5,053)

Table 5. *Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)*

Class membership	1	2	3
1	0.995	0.000	0.005
2	0.000	0.993	0.007
3	0.022	0.038	0.940

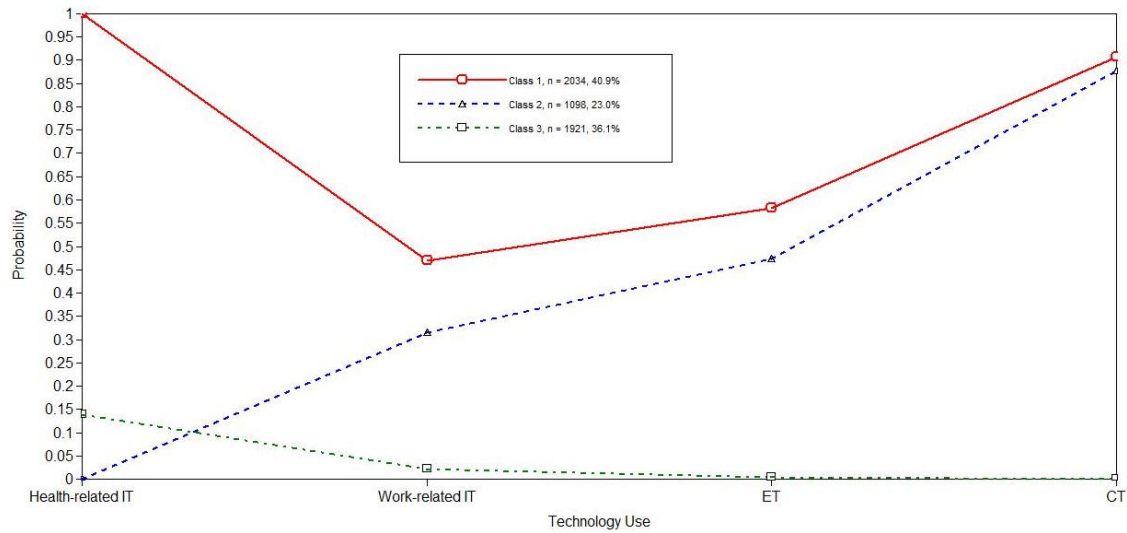
Figure 1. *Profiles for three-class LCA model of technology use.*

Table 6. 3-Class LCA Results in Probability Scale

	Latent Class		
	Class 1 = Multi-users (n = 2,034)	Class 2 = Selective users (n = 1,098)	Class 3 = Non-users (n = 1,921)
HIT use			
No	0.00	1.00	0.86
Yes	1.00	0.11	0.14
WIT use			
No	0.53	0.69	0.98
Yes	0.47	0.31	0.02
ET use			
No	0.42	0.53	1.00
Yes	0.58	0.47	0.00
CT use			
No	0.09	0.12	1.00
Yes	0.91	0.88	0.00

Note. (N = 5,053).

Table 7. Multinomial logistic regression models predicting the class membership of HIT, WIT, CT, and ET use in 2011

	(Multi-user vs. Non-users)		(Selective Users vs. Non-users)	
	OR	SE	OR	SE
<i>Individual characteristics</i>				
Female	1.48**	.08	1.07	.09
Age	.73**	.07	.86	.08
Household income	1.06**	.01	1.03	.02
Subjective health	1.24**	.06	1.60**	.07
Education ( <i>ref</i> = high school diploma)				
Some college	2.29**	.10	1.88**	.11
Beyond college	3.57**	.13	2.41**	.15
<i>Social roles</i>				
Employed	.98	.08	1.21*	.09
Marital status ( <i>ref</i> = married)				
Divorced/separated	.73**	.12	.72*	.14
Widowed	.78*	.11	.87	.12
Never married	.46**	.20	.51**	.23
<i>Personality traits</i>				
Extraversion	1.00	.01	1.00	.01
Agreeableness	.99	.01	1.02*	.01
Conscientiousness	1.00	.01	.98	.01
Neuroticism	.99	.01	.99	.01
Openness	1.09**	.01	1.04**	.01
-2 log likelihood			9464.168	
$\chi^2$			658.21**	

Notes. \* $p < .05$ ; \*\* $p < .01$ , ( $N = 4,882$ ).

## CHAPTER 4. OLDER ADULTS' TECHNOLOGY USE PATTERNS AND THEIR PSYCHOLOGICAL WELL-BEING: A TYPOLOGY APPROACH

A paper to be submitted to The Gerontologist

Sangbo Nam

Human Development and Family Studies, Iowa State University

Address correspondence to Sangbo Nam, Human Development, and Family Studies, Iowa State University, 0084 LeBaron Hall, Ames, Iowa 50011. E-mail: sbnam@iastate.edu

### Abstract

Despite numerous interventions and programs that have been designed and implemented to reduce the age-related digital divide and enhance older adults' quality of life, our understanding of the relationship between older adults' technology use and well-being remains unclear. The objective of this study was to examine the relationship between patterns of technology use and the multidimensional aspects of psychological well-being among older adults. Based on the results of the LCA model illustrated in Study 2, I examined how the three-category pattern identified as multi-users, selective users, and non-users were associated with psychological well-being. Data for this study came from the Wisconsin Longitudinal Study ( $n = 4,882$ ). Results from OLS models showed selective users, but not non-users, had lower levels of depressive symptoms compared to multi-users. Non-users reported lower levels of psychological well-being compared to multi-users in all six subdomains of Ryff's psychological well-being scales. Also, selective users showed a lower level of personal growth compared to multi-users. Findings from this study suggested psychological well-being outcomes of technology use among older adults were dependent on patterns of technology use and the subdomains of psychological well-being.

*Keywords:* technology use patterns, multidimensional psychological well-being, Ryff's scale

### **Introduction**

The psychological effects of technology use on older adults have been investigated, but the mechanisms linking technology use to psychological well-being are less clear (Cotten, Ford, Ford, & Hale, 2012; Dickinson & Gregor, 2006). Although modern technology has profoundly affected human lives, due to its relatively short history of development, most findings from previous research have been criticized for some common limitations, including methodological issues such as inconsistent conceptualization and measurement, small sample sizes, variation in targeted age populations, and different living conditions of older participants. As a result, findings were inconsistent (Chen & Persson, 2002; Cotten et al., 2012; Dickinson & Gregor, 2006; Slegers, van Boxtel, & Jolles, 2008; White et al., 2002). Despite a substantial body of qualitative research that indicates positive effects of technology use (Dickinson & Gregor, 2006; White et al., 2002), the literature still lacks consistent findings from quantitative research with large sample sizes with individuals from same cohort and refined conceptualization of technology use (Cotten, Ford, Ford, & Hale, 2014). A review study on the association between technology use and psychological well-being of older adults has indicated various types of mistakes in the previous literature (Dickinson & Gregor, 2006). They attributed the failure of past research in the field to: misattribution of causality, misinterpretation of training/support effect, and inappropriate generalization of results (Dickinson & Gregor, 2006). This study attempted to examine the relationship between various types of technology use and psychological well-being of older adults by applying a typology approach explored in the previous study of this dissertation (Study 2).

## Literature Review

The existing evidence on the psychological well-being outcomes of technology use has heavily relied on the data obtained from younger populations, most of which have focused on the negative consequences of heavy technology use on children and families (Chesley, 2005; Kuss, van Rooji, Shorter, Griffiths, & van de Mheen, 2013). A smaller body of literature that examined the association between older adults' technology use and psychological well-being has produced inconsistent findings (Chen & Persson, 2002; Cotten et al., 2012, 2014; Elliot, Mooney, Douthit, & Lynch, 2014). For example, previous studies on the associations between technology use and psychological well-being among older adults indicated technology use was associated with reduced depressive symptoms and better psychological well-being (Choi, Kong, & Jung, 2012; Cotten et al., 2012, 2014). However, other studies have shown no significant associations between technology use and older adults' mental health (Slegers et al., 2008; White et al., 2002).

Previous publications in this area often misinterpreted findings and inappropriately generalized results (Dickinson & Gregor, 2006). Literature often suggested technology use was "good" or "bad" for older adults' well-being, but the implications tended to be much more nuanced. For example, a meta-analysis study indicated intervention studies have had an effect on decreasing loneliness of older adults but were not effective in decreasing their depression (Choi et al., 2012), which implies the significance of accurate conceptualization of constructs. This study intended to examine the association between the technology use patterns identified in the previous study (Study 2) and psychological well-being. Further, multidimensional aspects of psychological well-being were assessed based on a conceptual distinction put forth by Ryff and Keyes (1995).



## **Multidimensional Psychological Well-being**

Research on the association between older adults' technology use and psychological well-being has primarily focused on reducing negative feelings and mood such as loneliness and depression (Choi et al., 2012; Cotten et al., 2012, 2014; Dickinson & Gregor, 2006). For example, older populations at risk of social isolation may experience more detrimental effects on their psychological well-being than the rest (Schnittker, 2007). Also, the effectiveness of technology as an intervention for psychological well-being is in question. In fact, CT use of older adults was associated with less social loneliness while CT use for personal networking purpose was associated with higher emotional loneliness (Sum, Mathews, Hughes, & Campbell, 2008). These findings suggest technology use may alleviate social isolation but also reduce older adults' psychological well-being; however, the link between technology use and negative psychological well-being is not unidimensional. In addition, current understanding of the consequences of technology use is somewhat limited because most of the studies to date have focused on IT while neglecting other forms of technology (Selwyn, Gorard, Furlong, & Madden, 2003). Thus, in this study, I examined the associations between technology use patterns and negative psychological well-being of older adults.

Previous studies on the associations between technology use and psychological well-being have focused on the link between technology use and negative psychological well-being. There is some evidence indicating how technology use can promote well-being among older populations. For example, a CT-based intervention program with older adults significantly improved people's quality of life (Bradley & Poppen, 2003). As well, several studies on Nintendo Wii, a form of ET, have shown improvements in older adults' physical

functioning due to its use, which also has implications for their psychological well-being (Graves et al., 2010; Laufer, Dar, & Kodesh, 2014), and increased socialization (Strand, Francis, Margrett, Franke, & Peterson, 2014). Older adults' Internet use was associated with higher perceived self-efficacy (Erickson & Johnson, 2011). In consideration of these benefits, researchers in human-computer interaction have suggested designing "positive technologies" to improve human lives and experiences (Riva, Baños, Botella, Wiederhold, & Gaggioli, 2012). They proposed building technology providing positive emotional, sensorial, and shared positive emotional experiences (Botella et al., 2012; Riva et al., 2012). Taken together, this literature indicates a positive association between patterns of technology use and various kinds of psychological well-being. Thus, in this study, I examined the associations between technology use patterns and multidimensional psychological well-being of older adults.

In sum, the objective of this study was to add to this small body of research by clarifying how different patterns of technology use are associated with multidimensional psychological well-being among the older population by examining the following hypotheses: (a) multi-users and selective users will be negatively associated with depressive symptoms, and positively associated with higher multidimensional psychological well-being (b) non-users will be associated with higher depressive symptoms, and lower multidimensional psychological well-being.

## **Method**

### **Data and Sample**

The data for this dissertation were collected as part of the Wisconsin Longitudinal Study, and I used the most recent wave of the study, collected in 2011. The project has been

one of the first large longitudinal studies of American adolescents who were born primarily in 1939. The WLS consists of a random sample of 10,317 women and men who graduated from high schools in Wisconsin State in 1957, and data were collected in 1957, 1964, 1975, 1993, 2004, and 2011.

In the 2011 wave, of the initial 10,317 participants, 6,152 respondents provided data. Among 4,165 non-responsive people, 940 refused to participate, 2,049 were known deceased, and 96 were unavailable to contact. The simple retention rate was 59.6%, but it increased to 86.8% when ruling out participants who died and those who were not able to be contacted. The current sample included 4,882 participants between the ages of 71 to 74 at 2011 ( $M = 72.13$ ,  $SD = .50$ , 54% women). This sample was selected from the whole sample based on their responses to the measures of interests. Regarding marital status, 73.3% of the participants were married, 10.3% were divorced or separated, 13% were widowed, and 3.4% indicated they were never married. In 2011, 27.6% of participants reported they were still employed. For the household income of participants, 25% reported an income less than \$20,372 per year, 50% of participants made between \$20,400 and \$55,600 per year, and the median was \$33,420 per year. Twenty-five percent of participants reported a household income of more than \$55,600 per year. Regarding education level, 66.5% of participants reported high school was their highest educational achievement, 20.4% reported themselves as college graduates, and 13.2% reported having a master's degree or higher. Participants' demographic characteristics are presented in Table 1, and the ratios of each type of technology use are presented in Table 2.

## Procedure

The Wisconsin longitudinal study (WLS) uses a state-sponsored questionnaire that began in 1957 to examine post-secondary education plans of students (Herd, Carr, & Roan, 2014; Wisconsin Longitudinal Study, 2015). It uses a one-third random sample of all high school graduates in Wisconsin in 1957 ( $n = 10,307$ ) who were born between 1938 and 1941. The cohort group widely represents white, non-Hispanic American women and men who have completed at least a high school level of education. As everyone in the primary WLS sample had finished a high school education, some arrays of American society may not be well represented. However, there is still a substantial heterogeneity in the WLS sample, as U.S. Census revealed at least 76.9% of the age group of the WLS sample cohort had attained high school education, which matches the high school graduation rate of 75% in Wisconsin in 1957 (Herd et al., 2014; Stoops, 2004). Despite the limitations of educational selectivity and small numbers of ethnic minorities in the sample, the WLS is a valuable source of information about non-Hispanic White cohorts born in the 1930s and 1940s containing a wide variety of heterogeneity in socioeconomic status (Herd et al., 2014). The first wave of the WLS was collected by an in-person questionnaire in 1957, and it was followed by a mail survey of parents in 1965, a telephone survey in 1975, telephone and mail surveys in 1993 and 2004, and an in-person survey and a mail survey in 2011 (Herd et al., 2014). This study uses the most recent wave of the WLS, and the simple retention rate for the 2011 wave was 59.6%, but it increased to 86.8% when deaths and non-contact were ruled out. The response rate was relatively high considering the long duration of the panel, and the main reason for attrition has been mortality (Herd et al., 2014).

## Measures

### Technology Use

HIT use was assessed with the following item: “In the past year, have you used the Internet to look for advice or information about your health or healthcare?” The item had two response options of 1 = *yes* and 0 = *no*. WIT use was assessed with a following item: “For you, was ‘doing tasks related to your job’ among the most important reasons why your household first obtained Internet access?” CT use was assessed with four questions with the same question stem of “For you, was ‘using e-mail to communicate with this person’ among the most important reasons why your household first obtained Internet access?” In each of the four questions, “this person” was replaced by friends, one of your siblings, one of your children, and other relatives, respectively. ET use was assessed with the following item: “For you, was ‘interested in using Web for recreation’ among the most important reasons why your household first obtained Internet access?” Responses for WIT use, CT use, and ET use had nine categories of 1 = *yes for respondent, spouse, and someone else*, 2 = *yes for respondent & spouse, not for else*, 3 = *yes for respondent & else, not for spouse*, 4 = *yes for respondent, not for spouse & else*, 5 = *not for respondent, yes for spouse & else*, 6 = *not for respondent & else, yes for spouse*, 7 = *not for respondent & spouse, yes for else*, 8 = *not for any household members*, and 9 = *not ascertained for respondent, spouse, or else*. I recoded them into 1 = *yes for respondent* and 0 = *not for respondent*. For communication technology use, responding yes to any of four questions about CT use was recoded as 1 = *use*, and responding zero to all four questions were recoded as 0 = *no use*. Using LCA, starting from a single latent class model, by increasing the number of classes by one each time, and in that process, LCA estimated various models with the number of latent classes ranging from one

to four. After compared models with each other to identify the optimal number of classes for the data, a three-class LCA model was chosen in the previous study (Study 2). Based on the previously discussed classification strategy, class one is referred to as multi-users, class two as selective users, and class three as non-users.

### **Well-being Outcomes**

**Depressive symptoms.** In this dissertation, depressive symptoms were used as a measurement of negative psychological well-being. In the WLS dataset, there were 20 items in the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977). Sixteen items were asked in negative ways, so higher score meant more depressive symptoms. Four items were asked positively, but the WLS reverse coded in the creation of those variables. Each item was assessed with the following question stem: “On how many days during the past week did you feel . . .” Responses for depressive symptoms had eight categories between 0 = none, to 7 = every day in the past week. Based on that, they provided a total CES-D score constructed by summing the valid values across the 20 items. The sum of the CES-D score was calculated when at least 10 of its 20 items had a valid response, and missing responses were imputed as the mean of the valid items prior to summing (Ha & Pai, 2012). Listwise deletion was used to handle missing data on the sum score, which did not have any valid response to less than half of the scales because there were fewer than 1.0% of missing (Allison, 2010). Coefficient alpha for those 20 items was .86.

**Ryff’s psychological well-being.** Multidimensional psychological well-being was operationalized with six scales: autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, and self-acceptance (Ryff & Keyes, 1995). Each item was assessed with the following question stem: “To what extent do you agree that you.”

Response for each item had six categories of 1 = *agree strongly*, 2 = *agree moderately*, 3 = *agree slightly*, 4 = *disagree slightly*, 5 = *disagree moderately*, and 6 = *disagree strongly*.

Items were both asked in positive and negative ways. To compute sum scores so that higher score indicates better psychological well-being, items were reverse coded. Autonomy was assessed with five items, and three items were reverse coded. Environmental mastery was assessed with five items, and three items were reverse coded. Personal growth was assessed with five items, and three items were reverse coded. Positive relations with others was assessed with six items, and four items were reverse coded. Purpose in life was assessed with six items, and four items were reverse coded. Self-acceptance was assessed with five items, and three items were reverse coded. The WLS included a version with 32 items of the scale in the data. Sum scores for six subscales were created. Coefficient alpha for autonomy was .61, environmental mastery was .72, personal growth was .68, positive relations with others was .78, purpose in life was .64, and self-acceptance was .74.

The sum scores of these subscales were calculated by summing whether at least three of its five items (three of six for ‘positive relations with others’ and ‘purpose in life’) had a valid response, and missing responses were imputed as the mean of the valid items prior to summing (Ha & Pai, 2012). Listwise deletion was used to handle missing values of the independent variables that did not have any valid response to at least one of the scales because there were fewer than 1.0% of missing (Allison, 2010). Higher scores on each subscale indicated higher levels of given multidimensional psychological well-being.

### **Control Variables**

Multiple sociodemographic variables were included. For gender, female was coded as 1, and male was coded as 0. Participants’ birth years were provided, and they were recoded

as their ages in 2011. Employment status was coded as 1 = *employed*, and 0 = *retired*. Total household income was transformed by the natural log. Marital statuses were dummy coded as married, separated/divorced, widowed, and never married (Ha & Pai, 2012). The degrees of education were dummy coded as high school graduated, graduated college or associated, and beyond college-level.

### **Analytic Plan**

Based on the results of the LCA in the previous chapter, this study examined the association between technology use types (i.e., multi-users, selective users, non-users) and psychological well-being. Sample characteristics are presented in Table 1. The research questions pertaining to the relationship between technology use types and psychological well-being are addressed using a series of OLS models, presented in Table 2. I used STATA 14.0 to conduct OLS regression analyses.

### **Treatment of Missing Data**

Missing data analysis was performed using SPSS 23, and Little's MCAR test (Little, 1988) was conducted. The result for technology use was  $\chi^2(3) = 74.036, p < .001$ , and for personality variable was  $\chi^2(28) = 648.806, p < .001$ , indicating the null hypothesis that data were missing completely at random should be rejected. Hence, the four binary logistic regression analyses were performed using data with full information on all four technology use variables. Listwise deletion was used to handle missing values of the dependent variables that did not have any valid response to at least one of the scales because there were fewer than 1.0% missing (Allison, 2010).



## Results

Table 2 presents results for the OLS regression models predicting negative and multidimensional psychological well-being by latent classes, which were explored in Study 2. Based on the previously discussed classification strategy, Class 1 is referred to as multi-users, class 2 is referred to as selective users, and class 3 is referred to as non-users.

As shown in model 1, depressive symptoms of selective users were significantly lower compared to multi-users ( $\beta = -1.99, p < .05$ ) after controlling for covariates.

In the following models, non-users consistently reported significantly lower levels of well-being compared to multi-users, as indicated by autonomy ( $\beta = -.45, p < .01$ ; model 2), environmental mastery ( $\beta = -.85, p < .001$ ; model 3), personal growth ( $\beta = -1.11, p < .001$ ; model 4), positive relations with others ( $\beta = -.74, p < .01$ ; model 5), purpose in life ( $\beta = -1.43, p < .001$ ; model 6), and self-acceptance ( $\beta = -.65, p < .01$ ; model 7) after controlling for covariates.

In model 4, selective users reported significantly lower levels of personal growth ( $\beta = -.41, p < .01$ ) compared to multi-users. Overall, selective users reported lower levels of negative psychological well-being than multi-users, whereas multi-users showed higher multidimensional psychological well-being compared to their multi-user counterparts.

## Discussion

The purpose of this study was to examine the associations between patterns of technology use among older adults and multidimensional psychological well-being, including depressive symptoms. Findings indicated the associations between older adults' patterns of technology use and psychological well-being were different for negative and multidimensional psychological well-being.

I expected older adults who used technology would be less likely associated with negative psychological well-being (Hypothesis 1). Results showed selective users reported lower depressive symptoms compared to multi-users. However, there were no differences in depressive symptoms between older adults in multi-users and non-users. Several reasons may account for these findings. Multi-users were likely to use all four types of technology.

However, selective users were more likely to use technology for purposes of entertainment and communication. Previous literature indicated older adults' CT use was associated with better quality of life and less social loneliness (Bradley & Poppen, 2003; Sum et al., 2008), but there were no significant differences between two groups in the likelihood of CT use. In addition, the most distinctive difference between the two groups of technology users is the use of HIT (Study 2). Multi-users were active users of HIT while selective users were not. Multi-users may use HIT because they are more interested in health-related information, and selective users may not be interested in HIT because they are less worried about their health. A previous study supported this finding that Internet use for health-related information is associated with increased depression (Bessi re, Pressman, Kiesler, & Kraut, 2010). As a result, selective users who use technology mainly for entertainment and communication purposes may be less likely to be depressed than older adults who use technology for all purposes or not using them at all.

Further, a notable finding was there was no significant difference between multi-users and non-users in negative psychological well-being. The finding did not support hypothesis one that technology users may be less likely to be associated with negative psychological well-being. Specifically, Study 2 of this dissertation demonstrated multi-users were associated with higher household income, better subjective health, younger, more education,

and in a marital relationship compared to non-users. Despite meaningful differences in their socioeconomic status between multi-users and non-users, there were no significant differences in negative psychological well-being in the two groups. One possible reason for this could be the gender composition of multi-users and non-users. Multi-users were more likely to be women than non-users, and it is widely known women report higher depressive symptoms than men throughout life (Nolen-Hoeksema & Aldao, 2011). Thus, gender may have worked as a confounder in the comparison between multi-users and non-users in negative psychological well-being. Another possible reason for this finding could be the differences in the use of HIT between the two groups. Non-users do not use technology for health-related information seeking while multi-users use IT for health-related purposes. Non-users' use of IT for health-related purpose may be associated with less negative psychological well-being (Bessièrè et al., 2010).

In contrast, the opposite trends were observed in the associations between technology use and multidimensional psychological well-being. I hypothesized technology user groups would be more likely to be associated with multidimensional psychological well-being (hypothesis 2). Findings from the comparison between multi-users and non-users supported the hypothesis. Non-users were significantly lower in all six subdomains of multidimensional psychological well-being (i.e., autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, and self-acceptance) compared to multi-users. These significant differences in multidimensional psychological well-being between multi-users and non-users imply that numerous interventions and programs educating technology use for older adults may improve not only their cognitive function and quality of life (Bradley &

Poppen, 2003; Tun & Lachman, 2010), but also impact multidimensional psychological well-being among older adults.

In comparison between multi-users and selective users in multidimensional psychological well-being, selective users reported lower personal growth only compared to multi-users. Among the covariates, being employed was associated with higher personal growth, and even after being controlled for the employment status, multi-users were associated with higher personal growth than non-users. Multi-users were more likely to use technology for work-related purposes than the other two groups, and the use of IT for job-related purposes may be associated with a higher degree of personal growth even in later life.

Taken together, findings from this study contribute to the literature in several ways. First, multidimensional aspects of technology use behaviors in later life could be examined by using a typology approach. Although older adults experience the age-related digital divide compared to younger populations, there was distinctive diversity among older adults depending on the patterns of technology use. Previous literature mostly focused on comparing technology users and non-users in relation to the disadvantages of the age-related digital divide (Mitzner et al., 2010; Schulz et al., 2014; Settersten & Angel, 2011). However, findings from this study strongly suggest older adults' technology use and its consequences on their well-being should consider not only the use of technology but also reasons for the use. Findings that demonstrated no significant differences in negative psychological well-being between active users and non-users across all types of technology might also account for some of the previous literature findings that technology use was not associated with better mental health (Choi et al., 2012).

Second, the findings provided a rationale of separately examining psychological well-being for multidimensional and depressive symptoms. Although there were no differences in depressive symptoms between multi-users and non-users, the degrees of multidimensional psychological well-being between the two groups were largely different. The finding implies learning technology use in later life may not help older adults to improve their negative psychological well-being, but that it could improve the multidimensional psychological well-being of older adults. Professionals in interventions and programs for older adults' technology use should consider this variability among older adults when they develop programs. Therefore, interventions and programs should be tailored to the varied psychological needs of older populations, which may produce positive outcomes on their multidimensional psychological well-being.

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Table 1. Sample characteristics

Older Adults	Total
<i>Individual Characteristics</i>	
Age ( <i>M, SD</i> )	72.1 (.49)
Sex (in %)	
Female	54.0
Household Income ( <i>M, SD</i> )	\$49,783 (\$66,056)
Subjective Health ( <i>M, SD</i> )	4.0 (.67)
Education (in %)	
High school graduate	66.4
Some college	20.4
Beyond college-level	13.2
<i>Social Roles</i>	
Marital Status (in %)	
Married	73.3
Divorced/Separated	10.3
Widowed	13.0
Never Married	3.4
Employment Status (in %)	
Employed	27.6

*Note.* ( $N = 4,882$ )

Table 2. OLS regression Models Predicting Depressive Symptoms and Psychological Well-being Scales

	Model 1 Depressive symptoms	Model 2 Autonomy	Model 3 Environmental Mastery	Model 4 Personal Growth	Model 5 Positive Relations	Model 6 Purpose in life	Model 7 Self- Acceptance
Class membership ( <i>ref</i> = multi-users)							
Selective users	-1.99* (0.94)	-0.08 (0.19)	0.14 (0.20)	-0.41* (0.20)	0.05 (0.22)	-0.31 (0.25)	-0.08 (0.21)
Non-users	-0.03 (0.84)	-0.45** (0.17)	-0.85*** (0.18)	-1.11*** (0.17)	-0.74*** (0.19)	-1.43*** (0.22)	-0.65*** (0.19)
Female	1.85* (0.75)	-0.49** (0.15)	0.52*** (0.16)	1.35*** (0.16)	2.34*** (0.17)	0.94*** (0.20)	0.55** (0.17)
Age	-0.30 (0.73)	-0.05 (0.15)	0.03 (0.15)	0.15 (0.15)	0.14 (0.17)	0.06 (0.19)	0.21 (0.16)
Marital status ( <i>ref</i> = Married)							
Divorced/separated	1.93 (1.18)	0.69** (0.24)	0.53* (0.25)	0.29 (0.25)	-0.89** (0.27)	-0.17 (0.31)	-0.34 (0.26)
Widowed	2.56* (1.09)	-0.10 (0.22)	0.07 (0.23)	-0.34 (0.23)	-0.43 (0.25)	-0.96*** (0.29)	-0.57* (0.24)
Never married	2.01 (1.99)	-0.52 (0.41)	-0.37 (0.42)	-1.10** (0.41)	-2.29*** (0.46)	-1.22* (0.52)	-0.51 (0.45)
Education ( <i>ref</i> = high school diploma)							
Some college	-1.73 (0.92)	0.83*** (0.19)	0.88*** (0.19)	1.22*** (0.19)	0.59** (0.21)	1.56*** (0.24)	0.61** (0.21)
College graduate	-4.58*** (1.12)	1.13*** (0.23)	1.50*** (0.24)	1.90*** (0.23)	0.77** (0.26)	2.11*** (0.29)	1.02*** (0.25)
Household income	0.30* (0.14)	0.06* (0.03)	0.05 (0.03)	0.04 (0.03)	0.05 (0.03)	0.11** (0.04)	0.06* (0.03)
Employed	-0.58 (0.80)	0.14 (0.16)	0.14 (0.17)	0.63*** (0.17)	0.33 (0.19)	0.35 (0.21)	0.08 (0.18)
Constant	30.63 (52.97)	25.13* (10.86)	21.10 (11.18)	11.62 (11.02)	17.05 (12.31)	21.15 (13.95)	8.13 (11.86)
<i>R</i> <sup>2</sup>	.039	.050	.049	.088	.088	.039	.044

Notes. Unstandardized coefficients and standard errors in parenthesis reported. \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$ . ( $N = 4,882$ ).

## CHAPTER 5. GENERAL DISCUSSION AND CONCLUSIONS

The goal of this dissertation was to develop frameworks for predicting technology use in both older individuals and groups of older adults using refined definitions of technology to examine the associations between the explored technology use types and psychological well-being. This dissertation contributes to a growing body of literature examining antecedents and psychological well-being outcomes of older adults' technology use by refining the conceptualization and operationalization of the construct of technology. Specifically, I refined the conceptualization of technology into four subtypes; HIT, WIT, CT, and ET; and examined how subsets of factors affect each type of technology use differently. Results from this study provided a rationale for refining technology use into four subtypes. Next, instead of a unidimensional approach to older adults' technology use by type, the second study explored typologies to capture the underlying patterns of technology use. Finally, using these typologies, I examined associations between technology use patterns and both multidimensional and negative psychological well-being. Taken together, the three studies in this dissertation provided a framework to refine the construct of technology use and contributes to our understanding of older adults' technology use patterns.

The findings presented in Chapter 2 revealed antecedents of technology use varied when four different technology use types were considered: HIT, WIT, CT, and ET. Using data from the most recent wave of the Wisconsin Longitudinal Study, I found older adults who were younger, more educated, with higher income, and higher openness were more likely to use technology regardless of technology type. However, other individual characteristics, such as social roles, and personality traits predicted technology use differently by technology type. Specifically, older women were less likely to use WIT, but

more likely to use HIT and CT, and there was no gender difference in ET use. The lack of gender difference in ET use was consistent with previous qualitative interviews with focus groups, which have shown men and women to be equally interested in technology use for entertainment purposes (Heinz et al., 2013). Further, previous research has reported mostly inconsistent findings regarding the role of gender in older adults' technology use (Gerling et al., 2012; Karavidas, Lim, & Katsikas, 2005; Marston et al., 2013; Werner et al., 2011), which is partially explained by findings from Chapter 2. For example, studies that used measurements of WIT might have shown prevalent use by older men, but other studies that measured the use of HIT and CT might have resulted in higher prevalence use among older women (Czaja et al., 2006; Karavidas et al., 2005).

The findings presented in Chapter 2 also revealed a significant role of marital status in older adults' technology use. Similar to the findings regarding gender, marital status was not associated with the use of ET. The finding suggests older adults, regardless of marital status, are equally interested in ET use. However, marital status was associated with other types of technology use: HIT, WIT, and CT. Widowed older adults were less likely to use HIT and CT compared to married, and never married older adults were less likely to use HIT, WIT, and CT compared to married older adults. These findings indicated older adults who are not in a marital relationship (i.e., widowed and never married) might benefit less from technological advancements compared to married older adults. As a result, widowed or never married older adults may become more disadvantaged in a technology-oriented society. In particular, older adults who were widowed or never married may be less knowledgeable in monitoring their health and more isolated in digital communication. In the development of programs and interventions to reduce the age-related digital divide, more attention to those

vulnerable populations is needed, and efforts to provide materials and contents on HIT and CT may be more resourceful for them.

Based on the refined conceptualization of technology presented in Study 1, I identified three categories of older adults' technology use patterns in Study 2. Findings revealed older populations could largely be grouped into three different types by their technology use patterns: multi-users, selective users, and non-users. Older adults in the multi-users category were most likely to use all four different types of technology, selective users were likely to use technology for communication and entertainment purposes, and non-users were not likely to use technology for any purpose. In Study 1, I explored the association between older adults' technology use and different sets of factors: individual characteristics, social roles, and personality traits.

Compared to non-users, older adults in the multi-user category were more likely to be women, younger, married, and have higher household income, higher subjective health, higher openness, and more education. However, there were no differences in gender, age, and household income between selective users of ET and CT and non-users. These differences among selective users and non-users of various technology types may account for substantially inconsistent findings in the previous literature (Czaja et al., 2006; Karavidas et al., 2005). Indeed, previous literature in related fields has not adequately considered the diversity among older populations in their technology use patterns (Dickinson & Gregor, 2006). The lack of attention to diversity among older populations may have led experts in interventions and programs to provide a bundle of education programs with similar content (Choi, Kong, & Jung, 2012).

I extended these frameworks to examine the associations between technology use patterns of older adults and psychological well-being outcomes in Study 3. Previous literature regarding these associations has resulted in inconsistent findings. For example, technology use was associated with decreased depressive symptoms (Cotten et al., 2012, 2014); however, a meta-analysis study reported technology use was not effective in reducing negative psychological well-being, but effective in attenuating loneliness of older adults (Choi et al., 2012). Intervention efforts to promote older adults' psychological well-being through technology use affected their life satisfaction and sense of self-control (Shapira, Barak, & Gal, 2007). In the investigation of the associations between technology use and multiple dimensions of psychological well-being, I employed both negative and multidimensional psychological well-being measurements.

Findings from Study 3 showed differences in depressive symptoms between multi-users and selective users, but no differences between multi-users and non-users. Although previous literature has highlighted that technology use was associated with lower negative psychological well-being, findings from Study 3 suggest types of technology older adults use matter more than their experience of technology use. As a result, the negative impact of technology use on psychological well-being of older adults was associated with patterns of technology use.

However, it is important to note that both multidimensional and negative psychological well-being were associated with technology use patterns differently. Particularly, when comparing the two well-being outcomes, the opposite trends were observed in the associations between technology use and psychological well-being.

Findings from study 2 identified that multi-users were more likely to be advantaged in the sets of factors (i.e., individual characteristics, social roles, and personality traits) than non-users. Despite those differences in socioeconomic status, there were no differences in negative psychological well-being between the two groups. However, multi-users were found to have a significantly higher association with multidimensional psychological well-being than non-users. These findings suggest education in technology on technologically inexperienced older adults may not improve their negative psychological well-being but may impact their multidimensional psychological well-being.

Taken together, this dissertation contributes to the literature in the consideration of technology use types of older adults is necessary to capture the diverse characteristics of older populations. Different findings were observed not only between technology users and non-users in later life but also among older technology users with different patterns of use. Further, associations between older adults' technology use and psychological well-being varied by dimensions of psychological well-being. Thus, the development of products and programs for older adults regarding technology use should consider multidimensionality of older populations, and possible different consequences of technology use for older adults with different profiles.

### **Overall Limitations**

There were several limitations to this dissertation. The first limitation was the generalizability of the findings. This dissertation could not capture the different characteristics of older adults among diverse racial/ethnic groups. The study sample had a minimum education level of high school diploma, and most of them were non-Hispanic Whites and married. To be specific, two-thirds of American older adults aged 70 to 74 in

2010 were Non-Hispanic Whites with at least a high school education, which implies the study still cannot represent one-third of the current U.S. older populations in that cohort (Herd, Carr, & Roan, 2014).

A second limitation is the cross-sectional design of this dissertation, which did not allow drawing inferences from the causal relationship. Most large datasets recently added technology-related variables in them. Datasets with multiple waves of data-containing technology constructs lack in the variability of technology construct, and the WLS, which contains diverse measurements of technology constructs still lacks accumulation of data over waves.

Although this dissertation contributes to the literature with the refined conceptualization and operationalization, at least two limitations remain regarding measurements. First is the lack of items with the same question stems on different purposes of technology use and the exact measurement of the actual use of technology for each purpose made it more difficult to interpret findings from the dissertation. For example, “do you regularly use the Internet for health-related purpose/work-related purposes /communicating purpose/entertaining purposes?” and asking the frequencies of the use would be one proper way of measuring technology use of older adults.

Last, this dissertation tried to suggest the necessity of refining technology constructs but could not include various features of modern technology such as smartphones and social media. As a result, given the importance of period effects in this specific topic, findings from this dissertation are affected by the time when data were collected.



### Future Directions

This dissertation refined the measures of technology use based on four reasons behind Internet usage. Although this dissertation used a sample from relatively recent data, frameworks provided in this dissertation may already be behind the current trend of technology use behaviors; thus, results from this study may not be directly applicable to today's older adults. Future studies should utilize the frameworks proposed in this study to understand older adults' use of more recent and popular technology (e.g., Facebook, smartphones, Facetime). When creating items asking older adults' technology use, (a) experience, (b) actual use, (c) purpose of use, and (d) degree of use may be considered. Currently, available datasets including older adults' technology use commonly lack at least one of those aspects, which limits the detailed understanding of older adults' technology use. Especially, the importance of surveying the purpose of the use must be highlighted. In terms of diffusion of technology, various technology advancements become popular, and most of them perform and satisfy multiple purposes. For example, Facebook not only allows people to learn and communicate but also entertains users. Thus, asking participants how much they use technology and for what purpose will allow better understanding and interpretation of older adults' technology use behaviors and consequences of technology use.

The findings from this dissertation suggest factors predicting technology use vary depending on what type of technology is under consideration. Further, findings showed there were three different patterns of technology use behaviors among older adults, and each pattern was predicted by different sets of individual characteristics, personality traits, and social roles. Future studies should examine the antecedents of other recent types of technology. As well, technology-education programs for older adults should consider

diversity within the older populations and address their different needs and interests, as suggested by findings of this study based on a typological approach.

Numerous interventions have applied technology-based programs to positively affect older adults' quality of life and to reduce negative psychological well-being such as loneliness and depression and enhancing multidimensional psychological well-being by empowering them with training and skills (Chan, Haber, Drew, & Park, 2016; Choi et al., 2012; Delello & McWhorter, 2015; Gatto & Tak, 2008; Slegers, van Boxtel, & Jolles, 2008). However, findings from this dissertation showed the associations between technology use and psychological well-being vary by both technology use groups and multidimensional /negative aspects of psychological well-being. Specifically, inexperienced older adults may improve their multidimensional psychological well-being by learning basic technology skills. However, programs intended to reduce older adults' negative psychological well-being by teaching them how to use technology may not be largely effective. Older adults who use the Internet to find social relationships showed higher levels of loneliness (Sum, Mathews, Hughes, & Campbell, 2008). Thus, future studies should identify vulnerable groups of older adults and examine effective ways to help them adopt technology in a way that increases human interaction based on local social networks.

### **Summary**

This dissertation contributes to our understanding of antecedents and outcomes of older adults' technology use at both the individual level and group level. In particular, the findings revealed different factors predict varied types of technology use among older adults. Further, the findings revealed patterns of older adults' technology use, as well as antecedents of such patterns, contribute to different multidimensional psychological well-being outcomes

including negative psychological well-being. As a result, this dissertation provides useful frameworks for understanding and supporting older adults' technology use. Taken together, the findings from this dissertation indicate older adults' technology use consists of multidimensional aspects and that both researchers and professionals adjacent to the field should be mindful of the diversity of older adults' technology use behaviors.

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## APPENDIX. INSTITUTIONAL REVIEW BOARD APPROVAL

**IOWA STATE UNIVERSITY**  
OF SCIENCE AND TECHNOLOGY

Institutional Review Board  
Office for Responsible Research  
Vice President for Research  
1138 Pearson Hall  
Ames, Iowa 50011-2207  
515-294-4566  
FAX 515-294-4207

**Date:** 11/5/2015

**To:** Sangbo Nam

**CC:** Dr. Megan Gilligan  
ner

**From:**

**Project Title:** Predictors and Outcomes of Older Adults' Information Technology (IT) and Communication Technology (CT) Use

The Co-Chair of the ISU Institutional Review Board (IRB) has reviewed the project noted above and determined that the project:

- Does not meet the definition of research according to federal regulations.
- Is research that does not involve human subjects according to federal regulations.

Accordingly, this project does not need IRB approval and you may proceed at any time. We do, however, urge you to protect the rights of your participants in the same ways you would if IRB approval were required. For example, best practices include informing participants that involvement in the project is voluntary and maintaining confidentiality as appropriate.

If you modify the project, we recommend communicating with the IRB staff to ensure that the modifications do not change this determination such that IRB approval is required.