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# Mobile technology adoption across the lifespan: A mixed methods investigation to clarify adoption stages, and the influence of diffusion attributes

Kate Magsamen-Conrad<sup>a,\*</sup>, Jeanette Muhleman Dillon<sup>b</sup>

<sup>a</sup> The University of Iowa, Department of Communication Studies, 257 Becker Communication Studies Building, USA

<sup>b</sup> Western Governors University, Department of General Education, Course Instructor, USA

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## ABSTRACT

We conducted a multi-study, mixed-methods, longitudinal investigation to examine how mobile technology diffuses across the lifespan, in real time, within a multi-generational population, while seeking local knowledge through community-based participatory research. Using qualitative methods (QUAL), we examined technology adoption within and across three iterations (16 weeks) of a nine-wave longitudinal community technology-training workshop, situated within a 15-wave study. In parallel, we interrogated existing conceptualization and operationalization of diffusion of technology variables, then deductively evaluated the dominant DOI-related variables re-conceptualized through the community study in a large cross-sectional quantitative (QUAN) investigation. We interpreted our results consistently and iteratively with a mixed-methods approach that included conceptualization, operationalization, and empirical testing. We discovered that oft-conflated concepts of knowledge, use, and ownership represent distinct stages of adoption. Our findings suggest constant feedback/permeable boundaries between these stages, and that DOI attributes may influence mobile technology adoption stages differentially. We suggest that innovators seeking to facilitate mobile technology adoption should focus on reducing complexity, and establishing calibration of complexity perceptions. We propose a lifespan mobile technology diffusion model, and call to question the language used in investigations related to the digital divide. We strive to clarify labels that may stereotype vulnerable populations, such as older adults. Our research contributes to theories of technology adoption – particularly after the introduction of digital communication – the diffusion of innovations in the community over time, and technology adoption process as affected by interpersonal communication and relationships, including among the technologically undercapitalized and the digitally privileged.

## 1. Introduction

Technology use and adoption has become increasingly compulsory in personal, professional, and social situations. Even before the 2019–2020 global lockdown in response to COVID-19 (World Health Organization, 2020) that forced people to transition to technologically mediated spaces rather than face-to-face contexts, people were being asked or required to use mobile technology to be eligible for “benefits” (e.g., medical record access, reduced wait time), to access information (e.g., newspapers reducing the frequency of print content), and to plan and execute travel (e.g., online check-in). Although some of these examples were avoidable before the global pandemic, technology was also

manifesting in more difficult to circumvent contexts, for example, at doctors’ appointments (e.g., tablets to record medical information, touchpads as part of the check-in process), restaurants (e.g., iPad menus), and even when parking a vehicle (e.g., digital or “smart” parking meters). Scholars have argued that over time, differences just in Internet use among various populations could exacerbate societal disparities and inequalities (Van Deursen & van Dijk, 2014). The COVID-19 lockdown that forced most individuals to adopt technology in order to work, maintain relationships, participate in education, and receive telehealth medical care, for instance, underscores the necessity of better understanding when and where the disparities occur and updating our theoretical understanding of those processes in order to mitigate

\* Corresponding author.

E-mail addresses: [kate-c-magsamen@uiowa.edu](mailto:kate-c-magsamen@uiowa.edu) (K. Magsamen-Conrad), [jeanette.dillon@wgu.edu](mailto:jeanette.dillon@wgu.edu) (J.M. Dillon).

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inequalities.

In this project, we utilize mixed methods to cultivate a deeper understanding of the diffusion and technology adoption processes across the lifespan. The experience of acclimating to technology can be arduous for certain segments of the population, for example “digital immigrants” (Magsamen-Conrad, Dillon, Billotte Verhoff, & Joa, 2020), which likely contributes to the lower rates of use and adoption among older adults (Jiang, 2018), and subsequent societal disparities and inequalities. Insights generated through nearly six years of observation of a community-based multi-generational intervention (QUAL), confirmed in a large cross-sectional survey (QUANT), and interpreted through ethnographic understanding, offers a thick description (Geertz, 1973) to further our understanding of diffusion and adoption at a time when technology reliance is escalating. Lauerman (2020) and others estimate that we will be battling waves of COVID-19 beyond 2022. Two years of forced technological interaction might so significantly exacerbate inequities that some populations will never recover. We argue scholarship, and particularly findings from this study, may offer guidance for helping vulnerable populations navigate an ever-changing technology-based landscape.

## 2. Theoretical background

### 2.1. Diffusion of innovations

Diffusion of innovations theory describes a social process of learning about new innovations through communicative processes among network actors (Rogers, 2003). Mediated and interpersonal communication both have important roles in the diffusion process (Rice, 2017). Mediated messages are often viewed as innovation dissemination, while the diffusion process occurs through interpersonal communication about a specific innovation (Dearing & Kreuter, 2010). Acceleration in the rate of innovation diffusion is typically the result of opinion leaders within a social network making the decision to adopt an intended behavior and communicating such decisions to others within that network, who in turn follow adoption behavior (DeWalt & DeWalt, 2002).

Diffusion of innovations (DOI) theory is useful for explaining why and how certain innovations spread among individuals (e.g., health innovations, Dearing & Cox, 2018). Conceptually, an innovation is not limited to just technological adoption of new hardware or software, but also includes the adoption of new ideas, new processes, and/or new services (Rice, 2017). Over more than six decades, Rogers' (2003) DOI theoretical framework has undergone many modifications, influenced by scholars calling for better recognition of interpersonal communication in the theory, as well as more ethnographic and mixed methods approaches to understanding the application of DOI theory.

Traditionally, much of DOI research has been quantitative (Melkote, 2002; Meyer, 2004; Rogers, 2003), and “rooted in the postulates and implicit assumptions of exogenous change theory” (Melkote, 2002, p. 425). Rogers, Singhal, and Quinlan (1996) acknowledged that the diffusion paradigm has been rightfully “criticized for reifying expert-driven, top-down approaches to address problems” (p. 428) rather than allowing local knowledge and expertise to inform solutions as often as it should have. Thus, critics advocated for diffusion models that recognized more efficient, community-appropriate innovations.

Another criticism of DOI is that previous research has primarily investigated innovativeness as the main dependent variable of the study using survey interview methods for quantitative analysis (Rogers et al., 1996). When participants are interviewed, they are asked to “retrospect about their time of adoption, the sources or channels of communication that they used in the innovation-decision process, to report their network links with others” (p. 426). Rogers and others have noted that this adherence to a paradigm established long ago has produced an overabundance of research focusing on individual decision-making and actions, and underemphasized investigations into interpersonal

influences. They argue that alternative qualitative methods, such as rich descriptions gathered via ethnographic methods, have been underutilized even as supplemental elements to the usual quantitative approach. For example, Freese, Rivas, and Hargittai (2006) took a quantitative approach as they investigated older adults' cognitive abilities and Internet use. Zhou (2008) also employed quantitative methods while working to integrate elements of DOI and the technology acceptance model. Increasingly, technology-adoption researchers more broadly are employing more qualitative methods to probe a particular population oft cited as a victim of the digital divide, “older” adults. Examples of these methodological applications include, by conducting focus groups to better understand attitudes older adults hold about technology (Mitzner et al., 2010), attitudes they may have towards smart home technologies (Demiris et al., 2004), and what motivates older adults to choose one form of technology over another (Melenhorst, Rogers, & Bouwhuis, 2006).

#### 2.1.1. Mobile technology adoption across the lifespan and in vulnerable populations

One area suitable for investigation of DOI is the diffusion process of mobile technology adoption across the lifespan, especially among historically technologically undercapitalized populations, such as older adults in the United States. Older adults comprise the fastest growing portion of Western society (U.S. Department of Health and Human Services, 2011; He, Goodkind, & Kowal, 2016). By the year 2030, nearly one in five US residents will be 65 and older (National Institute on Aging, 2006), and by 2026, we will “witness an increase of about 236 million people aged 65 and older throughout the world” (He et al., 2016, p. 1). Older and middle-aged adults from later generations such as The Greatest Generation (born 1901–1927), The Silent Generation (1928–1945), and the latter part of The Baby Boom generation (1946–1964), are thought to be “digital immigrants” (people born between 1936 and 1977; Chelsey & Johnson, 2014). Digital immigrants lag behind in terms of mobile technology use and adoption (Jiang, 2018), and tend to evaluate technology significantly less positively in terms of ease of use and efficacy (Magsamen-Conrad, Dillon, Billotte Verhoff, & Faulkner, 2019; Venkatesh, Morris, Davis, & Davis, 2003). In contrast, individuals born after 1980 (e.g., Millennials) are thought to be naturally fluent in using digital devices having “grown up” with digital technology (Jones, Ramanau, Cross, & Healing, 2010), and may be considered “digital natives” (see Chesley & Johnson, 2014). Although there are flaws in adoption arguments related solely to age (see Magsamen-Conrad et al., 2020), documented differences between cohorts across the lifespan, especially from emerging adult to old age, still serve to emphasize disparities between the technologically “literate” and the technologically “illiterate” (Bickmore & Paasche-Orlow, 2012). These disparities have implications for innovation adoption and use, as well as access, health, social integration, and quality of life, making diffusion of mobile technology adoption across the lifespan an important area of inquisition.

#### 2.1.2. The present study

In this project, we answer the call for understanding the application of DOI theory in several ways. Our research responds to the call for more community involvement and qualitative analysis in diffusion research, while also responding to Meyer's (2004) suggestion that “the integration of qualitative methods hold much promise for advancing the state of knowledge in diffusion literature” (p. 68). We employed a mixed methods approach combining ethnographic research within a longitudinal, multi-year community intervention with a large cross-sectional QUAN survey. Both studies represent individuals across the lifespan from emerging adults to old age. During the community intervention, twice per year across several weeks each bi-annual iteration, emerging adult “digital natives” taught workshops in the community for middle-aged and older adult “digital immigrants.” The community intervention provided an opportunity to study how mobile technology -

as a representation of innovation including programs and devices, hardware and/or software, new ideas, new processes, and/or new services-diffuses in real time (vs. retrospective accounts) within a community and among age-diverse groups, all while highlighting local knowledge. Instead of relying on expert-driven top-down knowledge, we employed a mixed-methods research design to identify relevant aspects of DOI in mobile technology diffusion and adoption across the lifespan. Finally, we answer the call for mixed methods research by examining the DOI concepts that emerged in the QUAL ethnographic investigation (innovation attributes and stages of innovation decision, described next) in a large cross-sectional QUAN investigation.

### 2.1.3. Innovation attributes in mobile technology adoption across the lifespan

DOI theory posits that an innovation has attributes that affect the rate of adoption. Generally, these attributes relate in some way to the potential adopter, that is, what one person considers an important attribute and whether the innovation has enough of the attributes most important to the potential adopter is a personal decision. According to Rogers (2003), perceptions of an innovation's attributes can be classified into five categories. *Relative advantage* describes whether the innovation is a good value in terms of price, whether it will enhance the adopter's social status (labeled *image* in subsequent research, see Moore & Benbasat, 1991), or whether it will be better than an existing innovation. *Compatibility* is related to relative advantage in that the potential adopter desires an understanding of how the innovation compares to previous innovations in how it fits individuals' needs, especially in terms of values and beliefs. *Complexity* relates to the innovation's ease of use. *Trialability* recognizes that potential adopters may want to "try out" an innovation before they commit to adoption. Finally, *observability* involves the visibility of the innovation, particularly within the potential adopters' interpersonal network. Other researchers added to the idea of observability by separating the idea of visibility, and adding the concept of result demonstrability (witnessing the results of an innovation; see Moore & Benbasat, 1991). Despite difficulty in consistent operationalization of some concepts (e.g., observability), in general, the rate of adoption increases if the innovation seems to have a relative advantage, is compatible with a person's belief system, is not too difficult to use, is available to "try out," and has been adopted by others in the potential adopter's social system. We seek to explore these concepts as they apply to mobile technology adoption across the lifespan. However, first we explore what it means to "adopt" an innovation.

### 2.1.4. The intersection of DOI attribute influence and adoption stage

The diffusion-adoption process describes stages that people experience as they decide whether to adopt or reject an innovation (Rogers, 2003): *knowledge*, *persuasion*, *decision*, *implementation*, and *confirmation* (p. 426). Rogers describes the *knowledge* stage as the time at which people are made aware of an innovation and perhaps its suggested use. The *persuasion* stage is when a person begins developing a positive or negative attitude about the innovation. A person in the *decision* stage starts doing things to either continue or reject the adoption process, whereas a person in the *implementation* stage actually utilizes the innovation. *Confirmation* is the final stage when the innovation is adopted, but the adopter always has the right to change his or her mind about continuing to use the innovation if new information arises suggesting a different decision. All stage patterns generally suggest movement from an innovation to adoption, with newer iterations of the DOI model allowing for more adopter feedback, recognition that an innovation may be adopted then rejected, or that an innovation may be re-invented before it is adopted (Rogers, 2003). However, "adoption" is often referenced in mobile technology research as a single point in time. We seek to explore stages of mobile technology adoption and provide rich description for how these stages manifest when studies across time, examining the intersection of DOI attribute influence and adoption stage. We used mixed methods strategies (QUAL then QUAN) in a

*sequential design* (Schoonenboom & Johnson, 2017) to answer the following questions:

**RQ1:** How does mobile technology adoption diffuse across the lifespan?

**RQ2:** Are existing conceptualizations of diffusion of technology variables, created before the introduction of digital communication, able to capture nuances of present-day mobile technology adoption across diverse user groups, in community settings?

**RQ3:** How may diffusion of technology variables be operationalized to better understand mobile technology use and adoption in a multi-generational population?

**RQ4:** How do diffusion attributes, as informed by conceptualization and operationalization in RQ2 and RQ3, affect the mobile technology adoption process across the lifespan between various stages of innovation decision.

## 3. Mixed method overview

Recognizing the five purposes for mixing identified by Greene, Caracelli, and Graham (1989; triangulation, complementarity, development, initiation, and expansion), in the following sections, we describe the methods separately, but present QUAL findings and QUAN discussion as a *joint display* (Schoonenboom & Johnson, 2017), using the "discussion" section as the *point of interface* (Guest, 2013). Study flow details are incorporated in Table 1, which is presented mostly sequentially but our mixed methods research design was also parallel in that QUAL/QUAN preparation and interpretation stages were consistent and iterative. For instance, researchers (including community participants) were disciplined note-takers who informed QUAL interviews and QUAN surveys that were updated periodically to survey developing research questions.

We use DOI theory as a framework to bind the data, analysis, and implications (Creswell & Plano Clark, 2011). We strive for transparency and clarity in describing not only our methods, but also our results, and interpretations, and hope we struck an appropriate balance. With that intention, first in this methods section, we describe the ethnography (QUAL) we conducted of the community intervention devoted to increasing mobile technology literacy, use, and comfort (Magsamen-Conrad, Dillon, Hanasono, & Valdez, 2016; Magsamen-Conrad, Hanasono, & Billotte Verhoff, 2013). Our method also includes tenets posited by Kramer (2004): Researcher access, collecting and analyzing data, and involving participants in the verification of findings. Further explanation of our method follows in subsequent sections and can be found in Magsamen-Conrad et al. (2020).

### 3.1. Qualitative study (ethnography)

#### 3.1.1. Community intervention setting (QUAL)

The first author developed the Intergroup Communication Intervention (ICI), (see (Magsamen-Conrad et al., 2013, 2016, 2020) for a description of the community project) with representatives from the Wood County Committee on Aging (a.k.a. senior center). The ICI is grounded in Intergroup Contact Theory (Allport, 1954; Pettigrew, 1998; Pettigrew & Tropp, 2006) and technology adoption theory (e.g., Venkatesh et al., 2003; Wang & Wang, 2010) and principles of community based participatory research (Israel, Eng, Schulz, & Parker, 2013). The ICI utilizes systematic, supported intergroup contact to foster technological skills acquisition and positive attitude change between multi-generational groups of community members.

#### 3.1.2. Participants (QUAL)

Our qualitative research phase included studying the adoption process in real time in a four to six-week technology training workshop offered in the community among 128 middle-aged and older-adult participants who participated, and their 63 emerging adult trainers (see Table 1 for detailed demographic information). Most (72%) individuals

**Table 1**

Detailed demographic information and study flow.

Study in chronological order	Participant n, (% male), and age/Generation		Participants' )/Educational background	Participant race	Additional Notes
	Trainer	Community	Community	Community	
Focus Community Study 1 (Wave 5): 4 weeks in intervention	22 Trainers (59%), ages 20-27/emerging adult, millennials	57 (26%) 58-83/ middle-aged and older adults representing baby boomers, the silent generation	self-reported educational background ranged from completing the 9 <sup>th</sup> grade to PhD	100% white non-Hispanic	<b>Study Flow:</b> The project began in 2012, with research focus on interpersonal communication variables in Waves 1 & 2 of ICI. Technology adoption questions were incorporated after emerging from the 2013 studies. We began to probe general technology adoption, health, and stigma in Wave 3 with structured open-ended interviews. These interviews included probes related to dominant technology adoption theories (e.g., UTAUT) but not DOI. We then followed up with a large cross-sectional survey testing the same variables. Focus community study 1, where we start our analysis for this paper, was in Wave 5 of the larger project. <b>Intervention:</b> Although the classes were divided into "iPad" and "Kindle Fire" classes based on participant disclosure of their tablet type, three of four groups had at least one community participant who had a tablet different from the main lesson (e.g., one participant indicated s/he had an "iPad", but actually had a Galaxy).
Focus Community Study 2 (Wave 6): 5–6 weeks in intervention	25 (36%) 19-26/ emerging adult, millennials	39 (34%) 59-86/ older adults representing baby boomers, the silent generation,	ranged from completing the 10th grade to PhD.	90% white non-Hispanic, 5% African American/Black American 3% Latino-Hispanic, 1 person did not report race (2%)	<b>Study Flow:</b> We started to see DOI adoption emerge in Wave 5, and incorporated open-ended questions in the intake ICI questionnaires. We began cross-sectional survey development in Wave 6. <b>Intervention:</b> In Study 2 we instituted a "Try It Out" class specifically designed for individuals who did not own a tablet but were interested in learning about the technology. The trainers teaching the "Try" class felt that the community participants needed one additional class, thus, the "Try" class was six weeks instead of five.
Cross-sectional study Wave 10)	634 (38%), Participants were born between 1926 and 1998 ( $M = 1969$ , $SD = 17.53$ )/ representing the greatest and silent generation, baby boomers, generation x, millennials, generation Z or "zoomers",.			84% Caucasian, 11% African American, 3% Hispanic/Latino. Asian/Pacific Islander, bi-racial/ multiracial, and Native American participants each representing less than 1% of the total sample.	<b>Study Flow:</b> Waves 7–9 were primarily replication. In Wave 9 we continued intake and outtake questionnaires with the ICI, but they were significantly shorter, as we instituted behavioral observation assessment surveys. Wave 10 included cross-sectional surveys in 2016.
	Trainer	Community	Community		
Focus Community Study 3 (Wave 12): 6 weeks in intervention	16 (75%) 19-33/ emerging adult, millennials, zoomers	32 (22%) 44-88, middle-aged and older adults representing generation x, baby boomers, and the silent generation	ranged from completing the 9th grade to Masters.	Participants were 96% white non-Hispanic, 3% "Mexican", 3% American Indian	<b>Study Flow:</b> We conducted another set of structured open-ended interviews in Wave 11. These interviews included probes related to multiple technology adoption theories (e.g., UTAUT, TAM, Coolness) as well as DOI. Wave 12 included mixed methods of observation (ICI) intake/outtake surveys. Behavioral assessment observation interviews continued. <b>Intervention:</b> Additionally, Study 3 introduced an "iPad advanced" workshop

NOTE: All trainers were current undergraduate university students.



owned their mobile device. Participants used a variety of mobile technology platforms including Apple, Android, Kindle Fire, and occasionally, Chrome. The Galaxy was the Android platform most frequently used. Participants entered the program in diverse stages of mobile technology “adoption”, some prior to device acquisition; others who owned devices, often for some time, but had not removed these devices from their packaging; and still others who used their devices regularly and confidently.

### 3.1.3. Procedure (QUAL)

O’Cathain (2010) argues that when mixed method researchers are explicit about key factors including their planning, design, data, inference, and reporting quality, the validity of their work is more transparent and more easily judged. The first author gained access in 2012 and used a community-based participatory research (CBPR) approach to design both the research study and the intervention itself. The planning is described in detail in other publications (e.g., Magsamen-Conrad et al., 2016, 2020) and omitted in this article. The senior center advertised the workshops in various internal and external publications, including the Center’s newsletter and flyers, in the local newspaper, on their website and Facebook pages, and via word-of-mouth through senior center employees. Community member participation in the program by older adults was voluntary.

Under the direction of the first author, trainers who were enrolled in a credit-bearing elective course at a mid-sized Midwestern university prepared 1–1.5 h weekly educational workshops for interested community members. The first author described the project on the first day of class, emphasizing details in the informed consent that explained that although elements of the project were required for the course (e.g., giving training workshops), agreement to allow data to be used for research was voluntary. Before the ICI began, senior center representatives provided a 50-min training detailing content the CBPR team deemed important, including the mission of the senior center, and how to adapt training to aging-related physiological changes and diverse learning styles.

The first author collected students’ schedules to determine overlapping free time, and students were grouped according to time available. The senior center initially advertised the general content of the ICI, but not the times of classes. The CBPR team worked together to group participants by mobile device ownership, then by brand/operating system. Center representatives then contacted participants who had registered for the ICI to inform them of the workshop time for their device. All participants completed pre- (T1) and post- (T2) test survey measures that informed workshop design and assessment. The content/focus of the ICI was driven by information provided by community participants through the T1 survey, however, the measures included in the surveys did not assess DOI, and results from these surveys are not included in the current study.

The CBPR team worked together to gain informed consent and survey data from participants, refining these procedures between Studies 1 & 3. For example, Study 1 included 34 participants, all of whom completed informed consent, but only 26 completed T1 surveys. Study 3 included 66 participants, all of whom completed both informed consent and the T1 surveys. The first author introduced herself to the community participants at the start of the ICI, explained the role of the trainers, answered questions, and then sat in the back of the room making observations. The first author gave both written and verbal feedback to trainers about workshop delivery, and trainers had approximately 50 min weekly (S1 n = 4 days, S2 n = 5, S3 n = 6) during the ICI duration (S1 4 weeks, S2 5 weeks, S3 6 weeks) to develop, discuss, and troubleshoot the ICI with CBPR team oversight.

Community participants attended workshops with the intention of receiving help with mobile technology, and the content of communication was primarily task-based (e.g., learning how to use a tablet or smartphone, including using various applications). Elements of interpersonal and relational communication emerged during the interaction,

similar to what one would expect in a physician-patient context (Venetis, Robinson, & Kearney, 2013) that is, primarily task-based but with emergent interpersonal themes.

After introducing all participants, the first author allowed the ICI to unfold with minimal intervention but constant observation. This action categorizes the role of the first author as *observer-as-participant* (Lindlof & Taylor, 2011), recognizing that although she participated in ICI communication and activities, she was more of an observer than a participant during the weekly sessions.

The initial goal of the ICI was to respond to a community need of offering mobile technology training classes to older adults connected to the community senior center. Additionally, the intention was to further the education of college students in a group communication course - in vivo - to perhaps facilitate positive intergroup contact. We were not sponsored by mobile technology companies, nor was technology adoption a goal of ICI. Our interests were always based in education and research. Over time, we understood that we were also learning under what conditions mobile technology adoption occurred, and began questioning the meaning (RQ2), and measurement (RQ3), of adoption. We also began seeing some disparities in technology use in groups of varying ages, that might better be articulated as being technologically undercapitalized (see (Glowacki, Zhu, Bernhardt, & Magsamen-Conrad, 2020), and digitally privileged.

### 3.1.4. Data sources and analysis (QUAL)

A focused ethnographic approach (Chambers, 2000) informed data collection and analysis. Data gathered included fieldnotes kept during observation of the ICI across three implementations, trainers’ exit interviews, educational materials produced (e.g., device operation manuals, tutorials, handouts, and PowerPoint presentations created during the semester), and weekly trainer journal entries (added in Study 2). Data included informal interviews with key informants that also acted as member checks. We talked frequently with the program and technology specialist for the senior center (age 35) who, emerged as a key informant for the community population (through her membership with the senior center) and a trainer who had participated in Study 1, and stayed with the project through Studies 2 & 3 as a mentor (age 23). Finally, we conducted a formal, semi-structured interview with a participant, an 80 year old retired teacher from a small community in the Midwest who the senior center key informant had identified as a key informant and opinion leader for the older adult population.

We employed the constant comparative method proffered by Glaser and Strauss (1967), which suggests identifying concepts as they emerge and probing further to see if the concepts are salient as categories or properties. Although our analysis was informed by DOI theory, codes and interpretations emerged naturally from the data. Themes related to multigenerational mobile technology adoption emerged as we analyzed notes completed during the ICI. We related those themes to innovation attributes and the innovation decision process when possible to add to a thick description. The community intervention brought to light concepts that we were able to capture and explore deductively in a large, cross-sectional (QUAN) study, described next.

## 3.2. Quantitative study (cross-sectional survey)

### 3.2.1. Participants (QUAN)

We surveyed 634 participants including 240 males, 393 females, and one individual who did not identify sex. We screened data for normality and multivariate outliers, and no transformations were needed. Participants were born between 1926 and 1998 ( $M = 1969$ ,  $SD = 17.53$ ), representing The Greatest Generation and The Silent Generation (born 1901–1945; 8%; The Greatest Generation was born 1901–1927, The Silent Generation, 1928–1945, due to smaller sample sizes and similarity between groups, we collapsed these two groups for analyses), Boomers (1946–1964; 38%), Generation X (Gen X; 1965–1980; 26%), and millennials (1981–1996; 28%, we collapsed this group with

participants born up to 1998 because of smaller sample sizes and similarity between groups) (these groupings are used by PEW; see Fry, 2018). The sample was predominantly Caucasian (84%), African Americans (11%), and Hispanic/Latino (3%) with Asian/Pacific Islander, bi-racial/multiracial, and Native American participants each representing less than 1% of the total sample.

### 3.2.2. Procedure (QUAN)

Human-subjects certified student researchers recruited individuals from their social networks, and snowballing from their networks' networks, as a component of a communication research methods course in a Midwestern public university. Participants completed the surveys in a private location with the certified researcher present and available to answer questions. Surveys were screened for authenticity using multiple strategies, including callbacks with all of the participants to verify participation and age. Surveys that did not meet authenticity standards were excluded from the data for analysis.

### 3.2.3. Measures (QUAN)

We wanted to capture diffusion of mobile technology adoption, and asked people to think about mobile technology broadly before answering a series of questions. About half of our sample indicated that they were thinking about a smartphone (52%), followed by those thinking about smartphones and tablets interchangeably (30%). We focused on key DOI concepts that emerged from the ethnography and, guided by RQ2, adapted items from previously psychometrically validated scales (Moore & Benbasat, 1991). We substituted "handheld device" for "PWS"-personal work station-rather than "mobile technology" because our QUAL study revealed that digital immigrants do not share terminology with digital natives. The term "mobile technology" was problematic in our sample (e.g., mobile technology made some people think of satellites). The decision to use the term "handheld devices" in the QUAN study stemmed from the QUAL investigation.

We measured DOI concepts with 7-point Likert-type items where 1 indicated "Extremely Disagree" and 7 indicated "Extremely Agree." For each variable, we conducted principal components analysis to evaluate the dimensionality of all measures. We created composite scores by averaging responses to individual items (where a higher number indicates greater perceptions of the concept measured) and estimated reliability by Cronbach's alphas. Factor analysis indicated a single factor solution for each scale with good reliability. See Table 4.

We measured **relative advantage** with seven items. A sample item includes "Using a handheld device gives me greater control" (eigenvalue = 4.15; var. = 82.92%;  $\alpha = 0.94$ ;  $M = 5.22$ ;  $SD = 1.25$ ). We measured **complexity** with five items (eigenvalue = 4.15; var. = 82.92%;  $\alpha = 0.95$ ;  $M = 5.25$ ;  $SD = 1.29$ ). A sample item includes "I believe that it is easy to get a handheld device to do what I want it to do." Note that a higher number in this composite indicates perceptions that personal IT is "easier" to use, less complex, to be consistent with the coding of other determinants. We measured **compatibility** with two items. A sample item includes "Using a handheld device is compatible with all aspects of my life" (eigenvalue = 1.21; var. = 60.32%;  $r = 0.21$ ;  $M = 4.45$ ;  $SD = 1.25$ ). We measured **visibility/observability** with four items. A sample item includes "A handheld device stands apart from similar products" (eigenvalue = 2.76; var. = 69.07%;  $\alpha = 0.85$ ;  $M = 3.13$ ;  $SD = 1.42$ ). We measured **image** with three items. A sample item includes "Using a handheld device is a status symbol in my social network" (eigenvalue = 2.49; var. = 82.93%;  $\alpha = 0.90$ ;  $M = 3.07$ ;  $SD = 1.48$ ). We measured **result demonstrability** with three items. A sample item includes "I believe I could communicate the consequences of using a handheld device" (eigenvalue = 2.09; var. = 69.81%;  $\alpha = 0.78$ ;  $M = 4.78$ ;  $SD = 1.27$ ). We measured **trialability** with two items. A sample item includes "Before deciding whether to use a handheld device, I was able to properly try it out" (eigenvalue = 1.45; var. = 72.64%;  $r = 0.45$ ;  $M = 3.77$ ;  $SD = 1.41$ ).

Guided by an iterative, mixed methods process, we employed

multiple strategies to assess "adoption," recognizing the importance of Rogers' "stages of innovation decision." First, we included a one-page description of mobile technology with images of smartphones and tablets. We measured our primary outcome variable, **adoption intention** (modeled after measures employed in the behavior change literature, used as a proxy for **decision to adopt**) with four items (one recoded) (eigenvalue = 3.24; var. = 80.97%;  $\alpha = 0.91$ ;  $M = 6.28$ ;  $SD = 1.15$ ). A sample item includes "I intend to use a handheld device in the next 3 months." We used single item measures about handheld devices, smartphones, and tablets to assess other stages of innovation decision, recognizing that ownership and adoption are not interchangeable terms (RQ 2), especially when mobile technology is often gifted (Magsamen-Conrad, Dillon, Billotte Verhoff, & Faulkner, 2019). To assess **knowledge**, we asked people if they understood what a handheld device is (99.5% indicated yes), what a smartphone is (98% indicated yes), what a tablet is (98% indicated yes). Replicating large population studies, we also asked about use and ownership: 96% of our sample **owned** mobile technology (i.e., including both smartphone and tablet), 88% owned a smartphone, 65% owned a tablet. We asked people if they had ever **used** mobile technologies, with 98% having used mobile technology, 93% a smartphone, and 88% a tablet. We assessed **continued use** as a potential proxy for implementation or confirmation stages by asking people to report how many hours per day, on average, they used mobile technology ( $M = 5.32$ ;  $SD = 4.00$ ).

### 3.2.4. Data analysis (QUAN)

Table 2 presents zero-order bivariate correlations for all QUAN variables. First, we utilized a stepwise regression to determine if DOI attributes predict handheld device "adoption," measured as handheld device use intention (decision), and average reported handheld device use (implementation/confirmation). Second, we conducted a series of t-tests to examine the interaction between use, ownership, and understanding, and DOI attributes (see Table 3). Finally, we conducted a one-way ANOVA to evaluate the generational differences in DOI attributes (see Table 4). We set significance levels at  $p < .05$  for all analyses (Tabachnick & Fidell, 2007).

### 3.2.5. Results (QUAN)

This section first describes the results of the QUAN associations (RQ4), tested with measures that emerged from RQ2, then RQ3, and finally interpreted in the scope of the broader ethnography (QUAL), via points of interface and discussion, to answer RQ1. First, we examined, quantitatively, existing theoretical observations related to DOI that were informed by our ongoing qualitative information gathering (Moore & Benbasat, 1991) using a series of independent sample t-tests and stepwise regressions. Although hierarchical regression is often utilized in theory testing, our project looks to mixed methods to allow predictors to emerge more naturally from the data, and harkens more exploratory modeling benefits of using stepwise regressions (Field, 2013).

We used independent samples t-tests with single item measures about handheld devices, smartphones, and tablets as the independent variables to assess other stages of innovation decision, recognizing that ownership and adoption are not interchangeable terms (see Table 3). We measured our primary outcome variable, adoption intention (modeled after measures employed in the behavior change literature, used as a proxy for decision to adopt) with stepwise regressions. For each regression, relative advantage, complexity, compatibility, visibility, result demonstrability, and trialability were the predictors with a proxy for adoption stage (adoption intention and handheld device use) as the criteria. First, we examined the composite for adoption intention (decision stage). The first step was significant (Adj.  $R^2 = 0.181$ ,  $F(1,633) = 141.47$ ,  $p < .001$ ), complexity positively ( $\beta = 0.43$ ,  $t = 11.89$ ,  $p < .001$ ) predicted adoption intention. The second step produced a significant change,  $\Delta R^2 = 0.04$ ,  $\Delta F(1,632) = 33.63$ ,  $p < .001$ , with image negatively predicting adoption intention ( $\beta = -0.21$ ,  $t = -6.01$ ,  $p < .001$ ). The third step produced a significant change,  $\Delta R^2 = 0.03$ ,  $\Delta F(1,631) =$

**Table 2**  
Correlation matrix for study variables.

	1	2	3	4	5	6	7	8	9	10
1. Year Born (Age)	1.00									
2. Relative Advantage	.21***	1.00								
3. Complexity	.45***	.63***	1.00							
4. Compatibility	.12**	.39***	.41***	1.00						
5. Visibility	.05	.07	-.01	-.15***	1.00					
6. Image	.25***	.17***	.136***	.04	.35***	1.00				
7. Result Demonstrability	.28***	.42***	.66***	.35***	-.03	.12**	1.00			
8. Trialability	.15***	.16***	.23***	.12**	.20***	.26***	.20***	1.00		
9. Adoption Intention	.17***	.39***	.42***	.29***	-.20***	-.15***	.38***	-.01	1.00	
10. Continued Use	.38***	.19***	.30***	.16***	.12**	.20***	.22***	.13**	.10*	1.00

Note: Adoption Intention (“decision to adopt”); Continued use = average self-reported hours mobile technology use.

Note: \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$ .

**Table 3**  
Mean differences between “adopters” and “non adopters” on DOI attributes.

DOI Attribute (7 point scale)	Mobile Tech. Knowledge	Ever Used Mobile Technology	Own Mobile Technology	Smartphone Knowledge	Ever Used a Smartphone	Own Smartphone	Tablet Knowledge	Ever Used Tablet	Own Tablet
Relative Advantage	-2.47**	-1.49***	-1.12***	-1.66***	-1.05***	-1.22***	-1.10**	-.81***	-.45***
Complexity	-3.52***	-2.28***	-1.79***	-2.29***	-1.79***	-1.62***	-1.68**	-1.37***	-.49***
Compatibility	-.95 NS	-.83*	-.76**	-.83**	-.67***	-.75***	-.65 NS	-.63***	-.48***
Visibility	<b>1.69*</b>	<b>1.02**</b>	<b>.18 NS</b>	<b>1.31***</b>	<b>.79***</b>	<b>.39*</b>	<b>1.30***</b>	<b>.33*</b>	<b>.30*</b>
Image	<b>1.14 NS</b>	<b>.53 NS</b>	<b>.05 NS</b>	<b>.45 NS</b>	-.12 NS	-.20 NS	<b>.74 NS</b>	-.07 NS	<b>.24 NS</b>
Result Demonstrability	-1.06 NS	-1.62***	-1.31***	-1.83***	-1.40***	-1.22***	-1.32***	-1.08***	-.55***
Trialability	-1.46 NS	-.12 NS	-.27 NS	-.79*	.59 NS	-.07 NS	-.75 NS	-.49**	-.13 NS
Adoption Intent	-3.41***	-3.21***	-2.61***	-1.85**	-1.60***	-1.59***	-1.51	-1.01***	-.48***

Note. \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$ .

*Italicized* indicates that the mean for the “no” participants is *higher*, i.e., that people who do not use/own/understand mobile technology think mobile technology is *more* visible than people who do use it. **Bolded** indicates that results are counterpredictive.

25.72,  $p < .001$ , with relative advantage positively predicting adoption intention ( $\beta = 0.23$ ,  $t = 5.07$ ,  $p < .001$ ). The fourth step produced a significant change,  $\Delta R^2 = 0.02$ ,  $\Delta F(1,630) = 16.58$ ,  $p < .001$ , with visibility negatively predicting adoption intention ( $\beta = -0.15$ ,  $t = -4.07$ ,  $p < .001$ ). The final step produced a significant change,  $\Delta R^2 = 0.01$ ,  $\Delta F(1,629) = 12.51$ ,  $p < .001$ , with result demonstrability positively predicting adoption intention ( $\beta = 0.16$ ,  $t = 3.54$ ,  $p < .001$ ). Compatibility, trialability, and age were not significant in the final model. In the final model, feelings that handheld devices were less complex, contributing less to image, more “relatively” advantageous, less visible, and perceptions that “what the device does” is transparent (result demonstrability) predicted 29% of the variance handheld device adoption intention.

We also examined how DOI attributes predict participants’ reported average daily mobile technology use (implementation/confirmation). The first step was significant (Adj.  $R^2 = 0.137$ ,  $F(1,523) = 84.36$ ,  $p < .001$ ), age positively ( $\beta = 0.37$ ,  $t = 9.19$ ,  $p < .001$ ) predicted continued use. The second step produced a significant change,  $\Delta R^2 = 0.02$ ,  $\Delta F(1,522) = 49.62$ ,  $p < .001$ , with complexity positively predicting adoption intention ( $\beta = 0.16$ ,  $t = 3.60$ ,  $p < .001$ ). The third step produced a significant change,  $\Delta R^2 = 0.01$ ,  $\Delta F(1,521) = 34.90$ ,  $p < .001$ , with visibility positively predicting adoption intention ( $\beta = 0.09$ ,  $t = 2.18$ ,  $p < .030$ ). The final step produced a significant change,  $\Delta R^2 = 0.01$ ,  $\Delta F(1,520) = 27.53$ ,  $p < .001$ , with compatibility positively predicting adoption intention ( $\beta = 0.10$ ,  $t = 2.16$ ,  $p < .031$ ). Relative advantage, image, result demonstrability, and trialability were not significant in the final model. In the final model, being younger, feeling that handheld devices were less complex, more visible, and more compatible predicted 17% of the variance average continued use (reported average daily hours of use).

Finally, in order to deductively explore the lifespan component of our research question, we examined differences across all DOI variables across age cohorts. The one way ANOVA demonstrated statistical

significance of generational differences in DOI variables including relative advantage ( $F(3,641) = 13.75$ ,  $p < .001$ ), complexity ( $F(3,641) = 54.58$ ,  $p < .001$ ), compatibility ( $F(3,638) = 4.37$ ,  $p < .01$ ), visibility ( $F(3,639) = 18.02$ ,  $p < .001$ ), image ( $F(3,638) = 26.15$ ,  $p < .001$ ), result demonstrability ( $F(3,636) = 19.56$ ,  $p < .001$ ), trialability ( $F(3,633) = 7.68$ ,  $p < .001$ ), adoption intention ( $F(3,644) = 8.34$ ,  $p < .001$ ), and continued use ( $F(3,549) = 31.46$ ,  $p < .001$ ) (see Table 4 for post hoc analyses).

#### 4. Point of interface and discussion (QUAL and QUAN)

In this section, we integrate the rich ethnographic data of the QUAL investigation with the QUAN results, recognizing the strength in mixed-method research, as we examine and propose explanations for the diffusion of mobile technology and adoption across the lifespan (RQ1) (see Fig. 1). Our time in the community enabled constant consideration of technology diffusion variables (RQ2), which we harnessed to clarify the conceptualization, and measurement (RQ3) of these variables. We then examined the interaction between variables (RQ4), and interpreted those findings within the scope of the community studies. Next, we present a discussion of our multimethod findings regarding the diffusion and adoption of mobile technology within a community across both time and age-diverse groups.

##### 4.1. Are the current conceptualizations of diffusion of technology variables sufficient?

Technology adoption scholarship, both theoretical (e.g., UTAUT, Venkatesh et al., 2003) and atheoretical (PEW, Anderson & Perrin, 2017) strives to predict “adoption.” Rogers (2003) describes multiple stages of adoption, allowing for rejection or discontinued use. However, “adoption” is often measured in survey-driven research in ways that do not capture the nuances of innovation decision stage variation. The



**Table 4**  
One-way ANOVA for different generations.

Variable (# items) Generation	N	Mean (SD)	F	p
Scale psychometrics				
<b>Relative Advantage</b> (7)		5.22 (1.25)	13.75	.001
eigenvalue = 4.15 Silent <sup>234</sup>	53	4.32		
var. = 82.92% Boomers <sup>14</sup>	249	5.18		
$\alpha$ = .94 Gen-Xers <sup>1</sup>	170	5.22		
Millennials <sup>12</sup>	173	5.54		
<b>Complexity (less complex)</b> (5) eigenvalue = 4.15 Silent <sup>234</sup>	53	5.25 (1.29)	54.58	.001
var = 82.92% Boomers <sup>134</sup>	249	3.98	4.37	.005
$\alpha$ = .95 Gen-Xers <sup>124</sup>	170	4.91	18.02	.001
Millennials <sup>123</sup>	173	5.36	26.15	.001
<b>Compatibility</b> (2) eigenvalue = 1.21 Silent <sup>34</sup>	53	6.02	19.56	.001
var. = 60.32% Boomers	247	4.45 (1.25)		
$r$ = .21 Gen-Xers <sup>1</sup>	170	3.92		
Millennials <sup>7</sup>	172	4.41		
<b>Visibility</b> (4) eigenvalue = 2.76 Silent <sup>23</sup>	53	4.51		
var. = 69.07% Boomers <sup>14</sup>	248	4.61		
$\alpha$ = .85 Gen-Xers <sup>14</sup>	170	3.13 (1.42)		
Millennials <sup>23</sup>	172	4.05		
<b>Image</b> (3) eigenvalue = 2.49 Silent <sup>4</sup>	53	2.83		
var. = 82.93% Boomers <sup>4</sup>	247	2.89		
$\alpha$ = .90 Gen-Xers <sup>4</sup>	170	3.51		
Millennials <sup>123</sup>	172	3.07 (1.48)		
<b>Result Demonstrability</b> (3) eigenvalue = 2.09 Silent <sup>234</sup>	53	3.03		
var. = 69.81% Boomers <sup>134</sup>	248	2.83		
$\alpha$ = .78 Gen-Xers <sup>12</sup>	170	2.64		
Millennials <sup>12</sup>	169	3.86		
		4.78 (1.27)		
		3.92		
		4.58		
		4.92		
<b>Trialability</b> (2) eigenvalue = 1.45 Silent	52	3.77 (1.41)	7.68	.001
var. = 72.64% Boomers <sup>4</sup>	247	3.68		
$r$ = .45 Gen-Xers <sup>4</sup>	170	3.52		
Millennials <sup>23</sup>	168	3.74		
		4.19 (1.15)		
<b>Adoption Intention</b> (4)		6.28	8.34	.001
eigenvalue = 3.24 Silent <sup>234</sup>	52	5.64		
var. = 80.97% Boomers <sup>7</sup>	246	6.23		
$\alpha$ = .91 Gen-Xers <sup>1</sup>	170	6.48		
Millennials <sup>1</sup>	170	6.39		
<b>Average Daily Hours Mobile Technology Use</b>	35	5.32 (4.00)	31.46	.001
Silent <sup>234</sup>	195	1.77		
Boomers <sup>7</sup>	141	3.92		
Gen-Xers <sup>1</sup>	182	5.40		
Millennials <sup>1</sup>		7.44		

Note. 1 = Silent; 2 = Boomers; 3 = Gen-Xers; 4 = Millennials; Post Hoc analysis (Scheffe) illustrated by underlining ( $p < .05$ ), italicizing ( $p < .01$ ), or bolding ( $p < .001$ ) superscripts. All composite scales for attributes ranged from 1(Strongly Disagree) to 7(Strongly Agree), and were coded such that a higher number meant more, or a more “positive” appraisal of the attribute (e.g., greater intent; more relative advantage, etc.).

community ethnography (QUAL) allowed us to observe the adoption process over many months among multiple generational groups, giving us a rich view of the mobile technology innovation decision and adoption process as articulated by DOI theory. The clarity we gleaned from considering existing knowledge about innovation decision stages allowed us to enact variation in stage operationalization in the QUAN study, in order to investigate how diffusion attributes affect the mobile technology adoption process across the lifespan. We begin by describing stages of innovation decision as they manifested in the QUAL study

across multiple generations.

Our time spent in the community examining mobile technology adoption revealed variability in progression through decision stages, especially as relevant to adoption practices of technologically under-capitalized populations, such as many digital immigrants. Contrary to expectations, individuals entered the community workshop from multiple stages. As expected, some community participants had limited knowledge of mobile technology prior to the ICI, especially those in the class designed for people who wanted to “try out” mobile technology, and those who accompanied friends. Other community participants entered the training from a later adoption stage, having progressed through the knowledge and/or persuasion stages of the decision process before attending the training workshops. These individuals were aware of the innovation (or had received it as a gift), and had developed initial attitudes related to their mobile technology, often expressing *both* positive and negative attitudes. “I have a love/hate relationship with my iPad” one participant explained to his trainers during the first week of the ICI. We also witnessed individuals who transitioned between multiple stages throughout the duration of the workshop iteration. For example, some individuals were in the decision and implementation stages before they started the training workshops, but reentered persuasion while in the workshops, forming new valenced attitudes. Conversely, many of the community participants in our sample ( $N = 117$  across three studies) had not fully formed attitudes about the innovation before they reached implementation and confirmation stages. This fluidity in decision making is reflected in Fig. 1 by including the stages in boxes within a larger box, a double headed arrow representing movement between stages. However, other metaphors may better represent this process, for example, a staircase (see Transtheoretical Model, (Prochaska, Redding, & Evers, 2002), and should be explored in future research. Our visual representation of fluidity in stages of innovation decision also facilitated directional paths that begin and/or end at the level of the box (adoption broadly), rather than at the individual stage level, depicting how diffusion attribute may intersect with stage progression, and, specific to the community study itself, how the training workshops affect DOI attributes and stages of innovation decision.

Examining how innovation decision stages manifested in the community study informed our conceptualization and operationalization of “adoption” in our QUAN study, particularly not conflating “ownership” or “having used” mobile technology with “adoption.” We assessed stages of “knowledge” and “persuasion” with several nominal items about use and ownership. We assessed “decision to adopt” by measuring adoption intention with an interval scale. Recognizing that we could not fully distinguish between the nuances of “decision” and “initial use” without a longitudinal study, we also assessed “continued use” (implementation/confirmation) by asking participants to report average daily use in hours.

In reconsidering existing knowledge about innovation decision stages and probing ideas in our QUAL research (RQ2, RQ3) we provided clarity to continue with our QUAN approach to investigate our fourth research question, which asked how diffusion attributes affect the mobile technology progression across various stages of innovation decision across the lifespan. These processes/questions all served to answer our primary research question (RQ1): How does mobile technology adoption diffuse across the lifespan? Broadly, we found that DOI attributes predicted “adoption” in different ways depending on adoption stage. Our QUAN analyses revealed that perceptions that mobile technology was less complex (complexity), contributed less to status/social approval (image), was more “relatively” advantageous (relative advantage), less visible (visibility), and perceptions that “what the device does” was transparent (result demonstrability) predicted 29% of the variance mobile technology adoption intention (decision). Age (being younger), feeling that handheld devices were less complex, more visible, and more compatible predicted 17% of the variance average continued use (reported average daily hours of use; implementation/confirmation). Diffusion attributes, therefore, do play an important role in the adoption

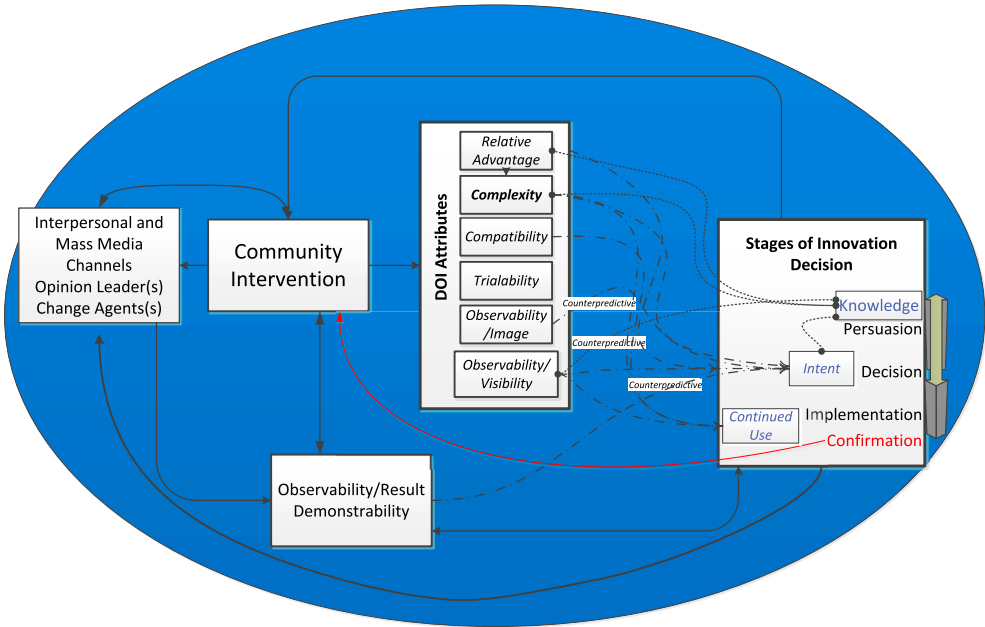


Fig. 1. Preliminary lifespan mobile technology diffusion model.

process, however, our results suggest that diffusion attributes affect the mobile technology adoption process differentially, depending on adoption stage. For example, visibility contributed negatively to the decision to adopt (as measured by adoption intention) but positively to continued use. Image (social acceptance), relative advantage, and result demonstrability contributed to adoption intentions, but not continued use. Age and compatibility contributed to continued use, but not adoption intention.

Our findings suggest that understanding how adoption-decision stages manifest in mobile technology adoption is necessary to

understanding both how diffusion attributes affect mobile technology adoption across the lifespan and, more broadly, how mobile technology diffuses within a community. This is an important finding as we consider how knowledge about innovation use and adoption is exhibited and diffused. For example, the Pew Research and American Life Project proclaims that “adoption” is rising among “older adults,” with adoption indicated by “smartphone ownership” and “going online” (Anderson & Perrin, 2017). While useful in establishing “ownership,” both our time in the community and the results of the large cross-sectional (QUAN) survey that compared decision and initial and continued use, suggest

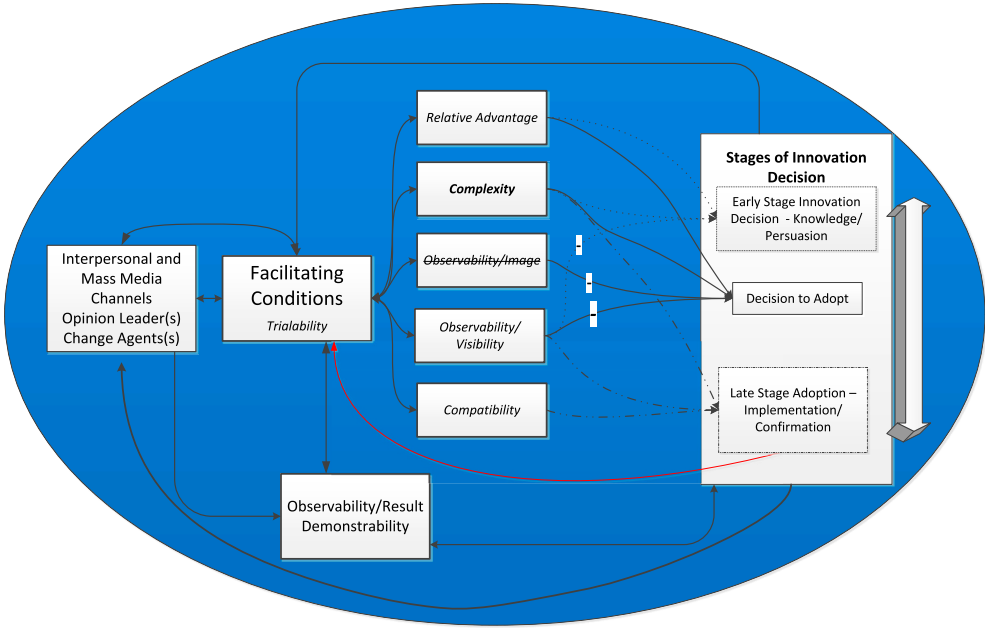


Fig. 2. Final lifespan mobile technology diffusion model.

that the concept of ownership may not truly represent “adoption.” During our years in the community we talked to many participants who “own” but do not “use” mobile technology, and for whom “going online” means text messaging. In Fig. 2 we proffer a more parsimonious version of our Fig. 1, and turn now to discuss the associations between attributes and stages in depth in the following paragraphs.

The mixed methods approach allowed us to understand, identify, and test relationships between DOI concepts. First, we propose that the DOI attribute of *complexity* (bolded in Figs. 1 and 2) is paramount in the mobile technology diffusion process across stages of innovation decision. QUAN analyses revealed that individuals who did not understand what mobile technologies were, had not ever used them, and did not own them perceived mobile technologies, smartphones, and tablets as significantly more complex than participants who did report understanding and use (see Table 3). These analyses provide insight into knowledge and persuasion stages. Complexity also emerged as a primary predictor for both proxies we used to assess “adoption,” possibly representing decision, implementation, and confirmation. Further, complexity is the only DOI attribute for which we found significant differences across all generations (see Table 4), with the oldest generation (silent) assessing mobile technology a full two (of seven potential) points higher in complexity than the youngest generation.

The intersection of the salience of complexity and lifespan differences in how mobile-technology complexity is experienced and understood was cultivated and reinforced in the community ethnography. Emerging adult trainers frequently described a number of processes and features of mobile technology that they would not have considered complex before working with community participants in the ICI. For example, one trainer noted that a community participant struggled with using mobile technology for something the trainer would have expected to be a common act and transferable skill: “We started out by having them take a picture of themselves or their belonging which was a really good exercise. I was surprised to see that some members actually ... don’t know how to use the camera.” Digital immigrants have likely taken photos with cameras throughout their lives, but the camera of some mobile devices was innovative enough to some individuals to add an element of complexity, and underscoring Rice’s (2017) expanded conceptualization of “innovation.” Multigenerational interaction with passwords provides another example of the intersection of complexity and lifespan stage. Community participants often did not know a password necessary for a particular program on their mobile device. One trainer explained in a journal entry,

I did a lot of resetting passwords this class. It seemed as if all but maybe one or two had Apple IDs already, which is great. Half of those who did, didn’t remember their password! It was such a frustrating process because I know I can remember mine and if not, it takes me less than two minutes to retrieve it.

Best practices for safely adopting mobile technology advise against reusing passwords, which may contribute to feelings of complexity for some potential adopters (e.g., digital immigrants). Further, coordinating passwords can be particularly difficult if passwords are created by others. Some community participants, for instance, contended that they had received help from a friend or family member when they initially set-up their device, and surmised that their helpers must have established passwords “without telling them.” In another instance, a community participant became very frustrated with a trainer who was unable to reset a password that was not designed to be reset, underscoring the intersection of complexity and interpersonal communication. Potential mobile-technology adopters may lose confidence in an innovation, and a change agent (a person who brings new innovations into a community, see Rogers, 2003), without mindful trainer interpersonal communication that understands and respects others’ conceptualization of complexity.

Our research suggests lifespan differences across individuals’

assessment of what is (or could be) complex. Complexity may be particularly salient in the adoption process among digital immigrants, and incongruent understanding of complexity may compound skill-acquisition experiences, particularly if trainers are digital natives and potential adopters are digital immigrants. Understanding potential intergroup differences in complexity appraisal is particularly important in contexts where individuals want to positively affect mobile technology innovation acceptance in order to improve quality of life (e.g., tailored online health interventions) or because quality of life depends on acceptance and use. Our findings suggest that innovators should focus on reducing complexity, but equally important, should conduct pilot research that enables calibration of complexity perceptions, and train educators in related interpersonal communication strategies that are at the core of much multi-group interaction.

Rogers (2003) original work describes four additional areas into which perceptions of an innovation’s attributes can be categorized: relative advantage, compatibility, trialability, and observability. Image, visibility, and result demonstrability were constructs developed from Rogers’ original (2003) conceptualization of observability and operationalized in the Moore and Benbasat (1991) study we adapted in our large cross-sectional study. After complexity, relative advantage predicted adoption most consistently across stages, predicting knowledge and decision (but not continued use/implementation/confirmation; see Fig. 1). Relative advantage and result demonstrability were significant predictors of handheld device adoption intention (but not continued use, which we will address later) in QUAN analyses (see Fig. 1). These attributes were also notable in how adoption unfolded in real time in the community intervention, and this QUAL research deepened our understanding of how relative advantage and result demonstrability manifest in the adoption process. The ICI exposed many community participants to numerous potential uses of mobile technology previously unknown, enhancing perceptions of relative advantage. This was especially true among community participants who received mobile technology as a gift from loved ones and were skeptical about the advantages of this technology over existing innovations. As one trainer noted in her journal, “I was also happy that everyone seemed really excited and proud of themselves when they realized they could download apps all on their own and that there are apps for literally any interest or hobby imaginable.” Another trainer’s journal revealed a similar sentiment,

I play a game called dots, which is a simple game and the goal is to connect as many as the same color dots as possible before the time is up, doesn’t take much to understand and almost anyone could play. I showed a woman who mentioned to us that she loves playing games the app and I helped her download it on her tablet, let’s just say within 5 minutes of playing she was already asking me what my high score was, safe to say she liked it. I was helping out another lady who wasn’t here the first week, after Connecting to the internet she had questions about an app for weather, I showed her the weather channel APP and she went right ahead and downloaded it. She was surprised with how quickly and easily she could find out information using this app and loved the idea of how many things you could look up and do.

Thus, we suggest that the relative advantage of mobile technology is important to innovation decision during early stages of knowledge, persuasion, and intention, but less important during later stages of implementation and confirmation (see Fig. 2).

Our research suggests that image, visibility, result demonstrability, and observability are particular concepts that require continued attention to best understand their role in the context of mobile-technology adoption. These variables presented psychometric issues in past studies, resulting in Moore and Benbasat’s (1991) separation of the Rogers’ (2003) original concept of observability into three constructs, image, visibility, and result demonstrability, which we recognize in Figs. 1 and 2 by labeling concepts observability/image,

observability/visibility, and observability/result demonstrability.

The image construct describes “the degree to which use of an innovation is perceived to enhance one’s image or status in one’s social system” or social approval (Moore & Benbasat, 1991, p. 195) and authors acknowledge that Rogers and other researchers perceive image as an aspect of a completely separate attribute, relative advantage. In our QUAN study, both image and relative advantage significantly predicted adoption intentions (decision), but not continued use (implementation/confirmation) (see Fig. 1). However, what is atypical is that image contributed to the decision stage in ways that are counterpredictive, that is, less social approval predicted adoption. In contrast, relative advantage predicted adoption decisions in ways that are expected, that is, perceptions that mobile technology is more advantageous than an existing innovation predicted adoption intentions (see Fig. 1). Further, individuals who understood and had used mobile technology perceived it as more relatively advantageous, where we found no significant differences for knowledge or persuasion proxies and image (see Table 3). Therefore, we propose that relative advantage and image are distinct concepts that affect the adoption process in different ways. However, we question the utility of continuing to investigate the role of image attributes in mobile-technology adoption without consideration of lifespan influence, especially considering that Moore and Benbasat (1991) also found that image was a weak predictor of adoption of personal work stations.

As scholars continue to explore how to operationalize concepts and interpret implications related to technology adoption in an ever-changing, rapidly-developing, and inequality-inducing technological landscape, we must seek macrotheoretical explanations for changes in innovation adoption and appraisal. The shift in how image affects technological innovation adoption might be related to a lifespan stage (see Table 4). Although there are consistent differences between the silent generation and all/most other generations for the other five DOI attributes, image is the only construct where there are significant differences between (and only between) millennials and all other generational groups (albeit with similar results for trialability). Millennials, at least those who participated in the large cross-sectional study, report significantly higher means for the importance of social status, a perspective that Johnson, Tariq, and Baker (2018) noticed, too, as they researched how undergraduates consumed pro-social products to make visible their commitment to the environment, or other social issues. Image’s instability as a construct may be explained within the context of how it is potentially fractured across lifespan stages, an idea worth continued attention in future research. Next, we turn to examine the observability attribute of visibility.

Moore and Benbasat (1991) describe visibility as “the actual visibility of the PWS” (personal work station), and determined that it was a weak predictor of PWS adoption. Visibility predicted all measured stages of innovation decision, but again in fundamentally different ways; less visibility was related to mobile technology knowledge, and decision, whereas more visibility predicted continued use (implementation/confirmation). Further, instead of being juxtaposed against other generational groups, millennials and the silent generation aligned for visibility, each with significantly higher means than boomers or gen-xers, but not each other. Our results suggest that future research should cultivate a more nuanced understanding of the role of visibility in innovation adoption decision-making. We propose that visibility may play a more salient role for older and younger potential adopters, but not for middle-aged adopters. Additionally, less visibility may be salient in early stages of adoption (knowledge, persuasion, and decision), but heightened visibility in later stages (implementation and confirmation; see Fig. 2). Finally, visibility, and more broadly, observability, may interact with other attributes and channels when it manifests in the context of group exposure and training.

The final variable in the trio that originally stemmed from the concept of observability is result demonstrability. Result demonstrability was central in the adoption process in both QUAL and QUAN data,

but examining the adoption process as it unfolded in real time suggests a more indirect relationship between the attribute and adoption stages. Our time in the community suggests that the attribute of observability may positively affect innovation adoption, but through the mechanism of group learning and relational influence instead of the more direct route of the other attributes.

First, the group-learning nature of the ICI facilitated participants’ abilities to measure, observe, and communicate the “results” of using mobile technology, enhancing result demonstrability. For example, one older adult indicated she appreciated being helped by another community participant, suggesting a path from result demonstrability to complexity (a phenomenon Moore & Benbasat, 1991 suggested as well) through the community intervention by highlighting the intersection of observing the results of a peer’s successful innovation use.

Further, the experience of mobile technology adoption is constructed within interpersonal relationships (discussed in detail in Author, under review, and depicted as the blue background in Figs. 1 and 2). For example, our opinion leader told the authors that part of the reason she liked the ICI was,

the camaraderie of the people and like, you know, the [trainer] beside me today, she was helping me a lot, also. And another thing that’s really given me confidence, I now recognize that no one person knows everything about a computer.

Members of the social system can influence each other as detailed in DOI theory. Unlike other aspects of the innovation that are more clearly unidirectionally influenced by the intervention itself, observability/result demonstrability affects more nuanced adoption processes that are encapsulated in the community workshop environment and/or via relational influence, more so than the other DOI attributes. Thus, it has been separated in our models. Both Figs. 1 and 2 reflect our finding that observability/result demonstrability both affects and is affected by the community intervention. Observability/result demonstrability is also directly influenced by interpersonal channels, opinion leader(s), and change agents(s), as compared to other attributes where the path filters through the community intervention.

The final DOI attribute we examined is trialability. According to DOI theory, when individuals have a chance to try out or audition an innovation to see how it works for them (e.g., trialability), the adoption process is sped up (Rogers, 2003). The first author repeatedly witnessed how community participants built efficacy through continual trial, error, and success in the ICI during the QUAL investigation of DOI. However, while replicating Moore and Benbasat’s (1991) finding that trialability was a weak predictor of PWS adoption, trialability did not enter into either regression model in our cross-sectional study, and perceptions of trialability were only significantly different (see Table 3) for proxies of smartphone knowledge (knowing what a smartphone was) and having ever used a tablet, instead of factoring into knowledge/persuasion, decision, or implementation/confirmation stages for mobile technology broadly.

Our complementarity mixed methods approach meant to enhance strengths and minimize weaknesses of monomethod approaches (Greene et al., 1989) may help explain the discrepancy between our QUAL and QUAN findings for trialability. In the QUAN research, millennials had a significantly higher mean for trialability than both boomers and gen-xers, but not the silent generation, which may explain the disconnect between the lack of importance of the trialability attribute in the large multi-generational cross-sectional study as compared to our observed importance of trialability for community participants in the longitudinal community study. Trialability was particularly important for earlier rather than later adopters in the community sample. It is also possible that older potential adopters do not have a frame of reference for the opportunity to “try out” mobile technology before adopting outside of programs that introduce facilitating conditions into the system, as programs like the ICI are the exception rather than the norm.



Alternatively, we propose that observability and trialability intersect. Indeed, some older studies found that trialability and observability did not emerge as separate attributes (Hurt & Hubbard, 1987). Borrowing from other technology adoption theories, there is conceptual overlap between both variables of complexity and perceived ease of use (TAM, Davis, 1989; UTAUT, Venkatesh et al., 2003), and relative advantage and perceived usefulness, as well evidence that supports the prominence of these variables in mobile technology adoption (e.g., ease of use most important variable in tablet adoption, see Magsamen-Conrad, Upadhyaya, Joa, & Dowd, 2015). We propose that the ICI and other programs that endeavor to affect mobile-technology adoption create what are described as “facilitating conditions” in UTAUT. Facilitating conditions are important to tablet adoption (Magsamen-Conrad et al., 2015, Magsamen-Conrad, Dillon, Billotte Verhoff, & Joa, 2020). As the ICI in particular fosters these facilitating conditions, and recognizing that the group learning and relational influence enhance all DOI attributes, we propose that the ICI fundamentally shifts the nature of the adoption process. We propose that trialability may only be relevant in certain contexts, for example, trialability may only be relevant in the presence of facilitating conditions. We reflect these propositions in Fig. 2 by replacing “community intervention” with “facilitating conditions.”

We suggest that interpersonal channels are influential in connecting potential adopters to an innovation (see Authors, under review for more details). Our results suggest that observability/result demonstrability may be more important than other innovation attributes within some social networks. This relationship is recognized in DOI theory and noted in Figs. 1 and 2, particularly by the feedback loops linking stages to the community intervention (both during the six-week duration and after the conclusion of the ICI series) and to facilitating conditions more broadly. In fact, several community participants reached the confirmation stage of adoption before and after the ICI series conclusion, yet they continued to cycle through the ICI. We propose that this is due to relational influences, rather than continued lack of technological capital or confirmation indecision. Our results also link the stages of decision-making back to the persuasive potential of the interpersonal channels, and that association is noted by a feedback loop in both Figures. Observability/result demonstrability is directly influenced by interpersonal channels, opinion leader(s), and change agents(s), and this intersection may be a factor in whether a community participant may repeat the ICI in particular, or a training program more broadly. The older adult we have designated as an opinion leader herself had repeated the workshop series, which may have influenced other community participants to repeat the ICI.

We posit that the relational link of observability-result demonstrability to innovation adoption deserves future exploration, as does the relational aspect that links the stages of innovation decision-making to the influence of opinion leaders and change agents. It is also important to recognize that family members often act as facilitating conditions support for mobile technology adoption (Magsamen-Conrad, Dillon, Billotte Verhoff, & Joa, 2020) and may influence decision-making as they offer this support throughout the entire adoption process. Thus, knowledge and persuasion are not always separate stages for digital immigrants as they contemplate use, ownership, and/or adoption. Moreover, they may re-cycle through those stages more than once in mobile technology adoption contexts even after seemingly “adopting” the technology in some fashion.

## 5. Limitations

This study had limitations, including the overrepresentation of white people in our community sample, although these demographics are consistent with the county in which the ICI was implemented. Additionally, community participants may overrepresent those of a socioeconomic status that allowed for transportation to the senior center on a regular basis, and therefore do not necessarily represent the portions of society more powerfully affected by disparities, those with multiple

layers of insufficient technological capital. The QUAN study was limited in ways noted by Johnson and Onwuegbuzie (2004), who stated that “many human (i.e., subjective) decisions are made throughout the research process and that researchers are members of various social groups” (p. 15). Our observations and quantitative findings could be understood as subjective and yet, also part of the strength of the mixed method research approach (Johnson & Onwuegbuzie, 2004).

### 5.1. Threats to reliability, validity, and inference quality

The framework of DOI theory was useful in understanding our findings, but it may be necessary to use other theoretical frames instead of, or in conjunction with DOI in future research to more fully comprehend mobile technology adoption across the lifespan. DOI, TAM, and UTAUT share overlap among some central concepts, not surprising as TAM and DOI were examined in the development of UTAUT. However, scholars have not yet (to our knowledge) systematically re-examined the conceptualization and operationalization of major adoption theories’ core concepts as they relate to mobile technology adoption in an approach similar to that employed by Venkatesh et al. (2003). Further, uses and gratifications theory (Katz, Blumler, & Gurevitch, 1973) is often applied to mobile technology contexts, and may have offered explanation for some adoption choices. We stand to gain understanding by also examining notable perspectives developed since the UTAUT’s initial inception, for example, Sundar, Tamul, & Wu’s (2014) concept of “coolness” may add insight into the role of image in mobile technology adoption. Future researchers might consider those theories in future studies of mobile technology adoption.

Worth noting, mixed methods research quality is not always described in terms of validity or reliability, but rather inference quality (Teddle & Tashakkori, 2009), or legitimization (Onwuegbuzie & Johnson, 2006). Generally, terminology debates regarding quality issues are meant to offer transparency about when one research method or paradigm is dominant over another in any stages of the mixed methods research. The threats to quality research when employing mixed methods, according to Collins, Onwuegbuzie, and Johnson (2012) include holistic and synergistic components such as the inclusion of researchers with different paradigms, allowing research questions to inform when and what QUAL or QUAN methods are used, and allowing input from participants and stakeholders. To the best of our abilities we have mitigated threats to research, but recognize inferences might be singular to our community of study, and further exploration is needed.

## 6. Further implications

Our extended time in the community allowed for a rich understanding of the conceptualization and operationalization of diffusion attributes in a new context, the stages of the innovation decision process described by Rogers (2003), and how individuals enter into and leave these stages. Existing conceptualizations of DOI attributes shared by other diffusion models do not capture the nuances of technology adoption today, and falsely represent what we argue is happening in the community spaces we gather. An understanding of how technology diffuses, is adopted, and used, is important because we make decisions and appraisals from those understandings, regardless of their precision, which may exclude some vulnerable populations further exacerbating disparities.

Mobile technology “adoption,” for instance, is not a singular concept that can be assessed simplistically by asking if an individual owns a mobile device. Further, when clarifying and measuring nuanced definitions and processes of adoption, we discover that mobile technology, as an innovation, diffuses through different processes. Our findings suggest constant feedback/permeable boundaries between stages, and that DOI attributes influence adoption stages differentially. The inconsistency that manifested in the cross-sectional study when using different proxies for what adoption “means,” and our time spent in the



community, work together to urge us to call for more clarity and transparency in future research in conceptualization and operationalization of all diffusion of technology variables. For example, the way that the visibility attribute affects the mobile technology adoption process serves as an example of why future researchers should cultivate a more nuanced understanding these variables. We learned that visibility may play a more salient role for older and younger potential adopters, but not for middle-aged adopters. Additionally, less visibility may be salient in early stages of adoption (knowledge, persuasion, and decision), but heightened visibility is important in later stages (implementation and confirmation). Finally, visibility may interact with other attributes and channels in certain contexts such as in small group and training situations. Further, we suggest a focus on reducing perceptions of complexity, being especially mindful to calibrate complexity perceptions. Individuals or groups aiming to affect adoption in later stages may benefit from making connections between mobile technology and previously adopted innovations (compatibility), especially among older audiences. Recognizing these nuances is necessary for developing tailored approaches to mobile technology adoption, which should be the basis of any technology-based interventions for health promotion and disease prevention and treatment. More broadly, modifications in the DOI model suggested in this article (and Fig. 2) may add to researchers' abilities to address the divide in a way that adds to positive skill and attitude development useful to people of all ages, which is paramount in a society where technology adoption is increasingly compulsory in personal, professional, and social situations.

That a digital divide exists in our society is real and relevant. What is less well understood are the factors that sanction people on either side of the divide. Age is commonly articulated as one of these factors, and as such, we framed our analysis in similar ways. Consistent with previous research (e.g., Bickmore & Paasche-Orlow, 2012), we found differences between cohorts across the lifespan, especially from emerging to older adults, or between digital immigrants and digital natives, which serves to emphasize disparities between what is often described as the "technologically literate" and the "technologically illiterate," even in our own research. However, our extended time in the community leads us to examine the negative connotation these terms in and of themselves might hold as they suggest a failure with the individual instead of the system. Through this project we encourage reconceptualization of the terms we use to describe those across the digital divide, redirecting the focus to resources that individuals have available to them, instead of characteristics of individuals themselves. For example, thinking of the "illiterate" as technologically undercapitalized, underscores our findings that facilitating conditions, an example of technological capital, leading to real or full adoption could be seen as common for digital natives, but more difficult to access for digital immigrants. Thus, is the "illiteracy" explained by age, or by insufficient technological capital? Importantly, individuals who are "technologically literate" enjoy a significant degree of digital privilege. Digital privilege describes the societal privilege that benefits the technologically capitalized over the technologically undercapitalized. The digitally privileged, for instance, can use technology to work, maintain relationships, participate in education, and receive telehealth medical care. Probing a relationship between digital privilege and technological capital could help explain inequities and disparities in use and adoption across the lifespan, while refocusing the locus of control in the digital divide. Rice (2017) noted that the definition of innovation adoption is expanding beyond device use to include processes, services, and ideas. Our study has underscored that mobile technology is an excellent example of a multi-faceted device necessitating robust technological capital in the form of device ownership, broadband/Wi-Fi access, hardware and software knowledge - often specific to each app/process/program- and other interpersonal (e.g., family) or community (e.g., programs like the ICI) resources. We urge other researchers to consider not only the process of innovation diffusion, but also how terminology we use to describe non/adopters affects those individuals (see labeling theory, looking glass self, and in the case

of "digital immigrants" aging self-stereotyping), as we work in the context of the digital divide.

## 7. Conclusion

Our multi-study, mixed-methods, longitudinal investigation contributes to theories of technology adoption, particularly DOI theory, and the technology adoption process as affected by interpersonal communication, relationships, and mobile technology experiences across the lifespan. We offer points of intersection of various DOI propositions (e.g. Fig. 1), as well as a more parsimonious reflection of our propositions about DOI theory as it applies to mobile technology adoption (e.g., Fig. 2). With modifications to conceptualization and operationalization of variables we propose that DOI can be used to explain how mobile technology diffuses across the lifespan. We further propose that DOI is particularly relevant when viewed through a collective and intergroup communication lens (e.g., communication among generations across the lifespan), rather than an individualistic, often uni-generational perspective usually found in diffusion research. Given the rate with which technology is introduced within, and increasingly relied upon, in our society, we argue that our Lifespan Mobile Technology Diffusion Model (Fig. 2) is a useful framework for researchers trying to understand the intersection of mobile technology and communication in people's daily lives, across the lifespan, as it relates to privilege and intersectionality, and in places commonly found in American communities.

The ability to explain and intervene within the mobile technology diffusion timeline is essential, now more than ever. Ajit Pai, chairman of the FCC, launched the Keep Americans Connected Act in March of 2020 saying "As the coronavirus outbreak spreads and causes a series of disruptions to the economic, educational, medical, and civic life of our country, it is imperative that Americans stay connected. Broadband will enable them to communicate with their loved ones and doctors, telework, ensure their children can engage in remote learning, and—importantly—take part in the 'social distancing' that will be so critical to limiting the spread of this novel coronavirus" (Federal Communications Commission, 2020; para. 4). Clearly, continued technology innovation will enable communication, education, and connection for current and future generations. But only for those digitally privileged individuals with the technological capital to adopt these innovations.

## CRedit authorship contribution statement

**Kate Magsamen-Conrad:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Jeanette Muhleman Dillon:** Conceptualization, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing.

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Kate Magsamen-Conrad is an intervention scientist with a research agenda that prioritizes partnering with communities to solve problems. Her research focuses on improving health for individuals across the lifespan through building and testing theoretical

understanding of the role of interpersonal communication processes (e.g., information management, privacy) and mobile technology use (e.g., for health-information seeking, eHealth literacy), particularly within vulnerable populations.

**Jeanette Muhleman Dillon** is a critical cultural scholar specializing in organizational and health communication who is also a 25-year media veteran. Her most recent research

investigates how Millennials engage with social enterprises in general and the TOMS shoe company in particular. Other research involves examining the best ways to reduce negative ageist attitudes as Millennials teach tablet skills to older adults within two nonprofit organizations, and active research while developing an anti-sexual assault health campaign to affect positive change on a college campus.