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Remote patient monitoring acceptance trends among older adults residing in a frontier state

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ABSTRACT

This pilot study aims to present a methodological approach for investigating remote patient monitoring system acceptance trends for older adults residing in a frontier state. For this purpose, extended Technology Acceptance Model (TAM) variables, which included *subjective norm*, *perceived usefulness*, *perceived ease of use*, and *behavioral intention* were investigated using growth curve methods and modern resampling techniques. Results revealed our methodological and analytical approach shows promise for investigating technology acceptance over time on subjects where little literature exists and where recruiting adequate sample sizes for statistical power purposes may be challenging. Results of the data analysis showed there was a significant and reliable linear trend on subjective norm. Time did not predict perceived usefulness, perceived ease of use, or behavioral intention, indicating the levels of these factors were high and stable over the course of the study. Older adults accepted remote patient monitoring, and family and friends may influence technology acceptance promoting behaviors. The longer participants used the technology, the more they perceived those important to them would want them to use it. Attention to social influence to optimize the implementation of in-home health monitoring among this population is warranted. Recommendations for future research are provided.

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1. Introduction

Approximately 22% of U.S. older adults reside in rural regions. A commonly accepted definition of rural is an area with a population of <50,000 (U.S. Census Bureau, 2011). Frontier states are a particular strata of rural regions. The Patient Protection and Affordable Care Act of 2010's (ACA, 2010) defines a 'frontier state' as a state with at least 50% of the counties that have an average population density of six or fewer people per square mile. These states include South Dakota, North Dakota, Montana, Wyoming, and Nevada. Data indicates older adults residing in four of the five frontier states are approximately two times more likely to live in a rural region than the national average. The exception to this trend is Nevada, where only 8.2% of older adults reside in rural regions (U.S. Census Bureau, 2011).

Rural areas have a greatest proportion of adults over the age of 85, and compared with urban older adults, rural elderly individuals engage in preventative medical care less often and have an increased likelihood of multiple chronic conditions (Hutchison, Hawes, & Williams, 2005). Prevalence of chronic diseases such as diabetes, cancers, arthritis, and heart disease is higher among rural residents than among other segments of the population (Murray et al., 2006; Wingo et al., 2008). Factors that are highly correlated with poor health outcomes such as lower educational attainment and lower incomes are also more widespread in rural areas of the U.S. (Behringer & Friedell, 2006). Additional burdens for rural older adults living with chronic conditions include decreased access to physicians, hospitals and routine medical care.

Just 10% of physicians in America practice in rural areas even though 25% of the U.S. population lives in these regions (Barley, Reeves, & O-Brien-Gonzales, 2001). Those living in rural communities are often geographically isolated, lack public transportation options, and have to travel long distances to access health and social services (Hartley, 2004; Krout, 1998). In the Rural Healthy

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People 2010 survey, access to quality health services (including access to primary care) was ranked as the top rural health priority with about 75% of respondents naming access as a priority (Gamm, Hutchinson, Bellamy, & Dabney, 2002). Social isolation and financial constraints further complicate rural older adults' health (Goins, Williams, Carter, Spencer, & Solovieva, 2005).

Remote patient monitoring (RPM) (Field & Grigsby, 2002) has been proposed as a creative option to increase access to rural areas (Nelson & Gingerich, 2010). Remote patient monitoring (RPM) has been defined as the use of information technology and electronic communication to allow interaction between patients and health care providers located in different geographical locations ([ATA]; American Telemedicine Association, 2013). RPM interactions can include two-way video consultations with a physician or health care provider, constant remote measurement of vital signs or automated or phone-based check-ups of mental and physical well-being. Health monitoring is a promising approach for improving access to care and improving health outcomes by making it possible to monitor patients remotely so health care providers can intervene promptly if there is evidence of health status deterioration (Chaudhry et al., 2010; Wang et al., 2009; Zhou et al., 2009).

Given the geographic isolation and health care disparities older adults residing in rural and frontier areas encounter, there is a critical need to put forth a methodology for investigating remote patient monitoring acceptance trends for geographically isolated older adult populations where recruiting adequate sample size for statistical power purposes may be difficult. For this purpose, a methodological model is presented which reflects the Technology Acceptance Model (TAM; Davis, 1986) and modern, robust statistical methods used to maximize the accuracy and power of imperfect sample sizes (Erceg-Hurn & Mirosevich, 2008).

2. Calculation

2.1. Limited data on frontier health monitoring acceptance

The use of telemedicine to provide care for rural patients is expected to increase given that physicians are generally concentrated in large metropolitan regions (American Medical Association, 2012). Prior studies have explored and reported positive health outcomes related to remote monitoring (ATA, 2013; Chaudhry et al., 2010; Varma, Michalski, Stambler, & Pavri, 2014) and reported older adults' perspectives on in-home health monitoring technology (Demiris, Oliver, Giger, Skubic, & Rantz, 2009; Demiris et al., 2004; Mann, Marchant, Tomita, Fraas, & Stanton, 2000; Wild, Boise, Lundell, & Foucek, 2008). Results from these studies have been positive and suggest older adults are willing to accept technology. Yet, there is no known research specifically investigating rural older adult acceptance of in-home health monitoring technology, let alone frontier older adult acceptance. This gap in literature is problematic as technology adoption rates among rural citizens in the U.S. are lower when compared to national averages (U.S. Department of Commerce, 2011).

2.2. Technology Acceptance Model

A theoretical extension of the Technology Acceptance Model (TAM) provided the conceptual framework for this study (Venkatesh & Davis, 2000). The original TAM (Davis, 1986, 1989) was adapted from the theory of reasoned action (Fishbein & Ajzen, 1975) and predicts why end-users accept or reject a technology innovation. The TAM is empirically supported by meta-analytical studies (King & He, 2006) and typically explains around 40% of the variance in technology usage intentions and behavior (Venkatesh & Davis, 2000).

The original model consisted of perceived usefulness (PU), perceived ease of use (PE), attitude toward using (ATT), behavioral intention (BI), and actual technology use (Davis, Bagozzi, & Warshaw, 1989). TAM theorizes a person's behavioral intention to use a technology is determined by two key beliefs, perceived usefulness and perceived ease of use. Building on the theoretical support for the TAM (Davis, Bagozzi, & Warshaw, 1992; Lee, Kozar, & Larsen, 2003), others have reported that subjective influences such as an individual's belief that those important to them or those influencing their behavior would want them to use a technology should be a focus of technology adoption (Taylor & Todd, 1995). More recently researchers found social influences improved the predictive ability of the TAM (Schepers & Wetzels, 2007; Venkatesh & Davis, 2000). Based on these findings, TAM was re-conceptualized as TAM2 (Wu, Chou, Weng, & Huang, 2008).

2.3. Hypotheses

Researchers have recently focused on factors that influence older adult adoption of technology (Braun, 2013; Lian & Yen, 2014; Pan & Jordan-Marsh, 2010; Ryu, Kim, & Lee, 2009). More specifically, they have been interested in assessing ephemeral states of subjective norm, usefulness, ease of use, and behavioral intention (see Chung, Park, Wang, Fulk, & McLaughlin, 2010). Since cross-sectional acceptance may not necessarily lead to acceptance over time (Lee et al., 2003), this study seeks to investigate the influence time has on acceptance. This study draws on both TAM as our theoretical framework and previous research which found older adults accept in-home monitoring technology and they tend to become more familiar with and confident using home health technology after prolonged participation with a technology (Demiris, Speedie, & Finkelstein, 2001; Veerle, Els, Joz, & Koen's, 2014). Therefore, we anticipate technology acceptance among our participants will increase in a linear trend over time. Extending the prior literature, we proposed the following hypotheses:

H1. There is a linear trend of subjective norm among older adults residing in a frontier state.

H2. There is a linear trend of perceived usefulness among older adults residing in a frontier state.

H3. There is a linear trend of perceived ease of use among older adults residing in a frontier state.

H4. There is a linear trend of behavioral intention among older adults residing in a frontier state.

3. Methods and materials

3.1. Procedure

Obstacles exist when using technology to collect patient health data (Haigh & Yanco, 2002). Due to the lack of research and the absence of a known methodological framework guiding researchers investigating frontier older adult acceptance trends, we were concerned our study approach might be perceived by community and organizational leaders and staff as too complex and risky. Our concern related to the contribution complexity and risk play in the diffusion of innovations in service organizations (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004). Additionally, we were sensitive of the existing research that suggests a prevailing "rural culture", characterized by a strong sense of independence and suspicion of change, particularly from an outside source, may affect health care technology usage (Bull, Krout, Rathbone-McCuan, & Shreffler, 2001; Goins et al., 2005). To minimize possible study implementation obstacles, we infused community-based participatory research (CBPR) principles in our design (Hacker, 2013).

3.2. Community-based participatory research

Our CBPR strategy was established based on our desire to not only include the organization in the research design but also to build their capacity to design, lead, and contribute to future research projects. This strategy was consistent Hacker's (2013) core CBPR tenets which highlight the importance of trust building and bridging community and academic barriers. We reviewed our acceptance measures and study design with administration and staff of a not-for-profit provider (NFPP) of older adult care. There were no questions or concerns reported following the review. Administration and staff identified a support staff-member as a key informant. The principal investigator approached the staff member and discussed the project and methodology. The staff member agreed to assist in the study and serve as project manager. To reduce measurement error, a research team member piloted the survey with the program manager to increase his comfort-level with our methodology and to reinforce our commitment to study and data fidelity. There were no study questions or concerns before or after data collection suggesting our pre-data collection methodology was well tolerated.

3.3. Data collection

Data were collected from July 2013 to September 2013. The program manager met with the participants in their home and participants completed survey questions on their level of acceptance before they received the technology and training and then again after they received the technology at two-week intervals. This study involved six time measurements (T) taken before and after participants received their remote patient monitoring technology (X).

$$T_1 \quad X \quad T_2 \quad T_3 \quad T_4 \quad T_5 \quad T_6$$

The dependent variables used in our analyses were subjective norm, perceived usefulness, perceived ease of use, and behavioral intention, which yielded continuous scores for extended TAM variables. The Institutional Review Board of the principal investigator's institution approved the study.

3.4. Remote patient monitoring apparatus

Participants were provided a commercially available remote patient monitoring technology system suite (Honeywell International Inc., 2013) at no cost for one year. The suite included: (1) a Honeywell HomMed Genesis Touch Samsung tablet, (2) an A&D Bluetooth Blood Pressure Monitor, (3) a Bluetooth Oximeter, and (4) a Honeywell Wireless Scale. The HomMed system and the above peripherals are part of a remote patient monitoring technology (RPMT) suite that collects biometric information and addresses health topics such as nutrition, diabetes, cardiac care, and medication compliance.

3.5. Participants

Older adults residing in frontier states by definition are isolated. Cognizant of this reality, we used purposeful sampling due to the exploratory and methodological nature of our study. It should be noted the focus of this pilot study was to test our methodology for investigating technology acceptance trends in a real-world residential independent living community rather than testing a specific mode of technology education or developing an intervention protocol specific to in-home health monitoring.

Fourteen participants residing in an income-subsidized housing complex (ISHC; $N = 56$) at a NFPP of older adult care located in a frontier state were recruited for the project. Participants were briefed on the remote patient monitoring technology (RPMT) and the study eligibility criteria. Eligibility criteria included having residential status at the ISHC and being their own legal guardians. After agreeing to participate in the project, the study project manager once more reviewed and described the project and technology system to the residents, and pretest (baseline) sociodemographic, health concern, and technology acceptance data were obtained. Upon completion of the pretest survey, the project manager coordinated and arranged for technology installation and hands-on training with the participants. Training occurred in the participant's home by the project manager. Further augmenting the technology, the NFFP provided centralizing monitoring participant health data and coaching and wellness support by a registered nurse (RN). The RN addressed health concerns and referred residents to higher-level care if warranted (e.g., primary care physician or emergency room).

3.6. Measurements

3.6.1. Sociodemographic and health characteristics

No known data exists on frontier older adults, a strata of rural older adults. As such we collected sociodemographic and health questions on age, gender, marital status, race/ethnicity, education, height and weight, body mass index (BMI), and number and type of health concerns (e.g., diabetes and hypertension) to establish preliminary baseline data. BMI was calculated using the Centers for Disease Control and Prevention adult algorithm (CDC, 2014a).

3.6.2. Subjective norm

Subjective norm was examined using a valid 2-item measure (Venkatesh & Davis, 2000). Items were measured on a 7-point Likert scale, where 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral, 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree. Measure items included: "People who are important to me think that I should use the system" and "People who influence my behavior think that I should use the system." Higher scores mean more positive subjective norms with regard to remote patient monitoring use.

3.6.3. Perceived usefulness

Perceived usefulness was measured using a valid 4-item measure and a 7-point Likert scale ranging from "strongly disagree" to "strongly agree" (Venkatesh & Davis, 2000). Higher usefulness scores mean an individual perceives remote patient monitoring to be more useful as compared to person with a lower score. A sample item is as follows: "I find the system to be useful in improving my health outcome(s)."

3.6.4. Perceived ease of use

Ease of use was also measured using a valid 4-item measure and a 7-point Likert scale (Venkatesh & Davis, 2000), where 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral, 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree. Higher ease of use scores mean an individual perceives remote patient monitoring to be easy to use. A sample item is as follows: "I find it easy to get the system to do what I want it to do."

3.6.5. Behavioral intention

The study also investigated remote patient monitoring system acceptance among older adults residing in frontier state. In Venkatesh and Davis's (2000) research, participants were asked the extent to which they agree with the following two items: "Assuming I have access to the system, I intend to use it" and "Given that I have access to the system, I predict that I would use it." Since participants in our study knew they were receiving a remote patient monitoring system, we utilized a single item: "Given that I have access to the system, I predict that I would use it." Consistent with our previous measures, responses were obtained on a 7-point Likert scale ranging from "strongly disagree" to "strongly agree." Higher intention scores indicate a person has more intent to use remote patient monitoring in the future.

3.7. Analytical approach

Remote health monitoring technology has the potential to improve rural residents' access to services and improve quality and cost-efficiency of health care (Buckwalter, Davis, Wakefield, Kienzle, & Murray, 2002). International studies having demonstrated the utility of remote monitoring of health status (Celler et al., 1995). Yet, no known acceptance studies have been conducted in frontier, older adult living environments in the United States. Thus, there is an absence of data for researchers to explore and test hypotheses related to frontier older adults. The aim of this study was to test our methodological approach for investigating remote patient monitoring acceptance change over time (repeated measures) among frontier older adults and report our findings. To accomplish this goal, we applied growth curve methods (Field, 2013) and bootstrap resampling procedures, a modern robust statistical method (Erceg-Hurn & Mirosevich, 2008), to our data to derive reliable, preliminary outcome estimates from available data.

3.7.1. Growth curve modeling

We initially considered applying a one-way repeated measures ANOVA to our outcome data to test whether the means for each time point differ and whether the change was linear. However, there were two reasons why we avoided a simple one-way AVONA test (Weinfurt, 2000). First, one-way AVONA assumes measurements are independent. Our repeated measures would violate this assumption because each participant in the study contributes multiple scores to the data set. Second, and the most compelling reason, one-way ANOVA would ignore useful information in our data set, such as individual differences between our participants; the differences between individuals in their average acceptance score would be treated as error in the one-way ANOVA. We assumed that these differences in scores are related to individual differences among participants, not simply random error. As such, we applied growth models to our data by treating each subject as a random effect and time as fixed effect. The 10 participants represent each of the 10 levels of a random effect, the individual, and time was considered fixed since we chose six time points.

Repeated measures designs such as growth models are commonly used by researchers interested in change across time (Francis, Fletcher, Stuebing, Davidson, & Thompson, 1991; Francis, Schatschneider, & Carlson, 2000) and more importantly as it relates to this study, repeated measures tend to produce higher statistical power (Guo, Logan, Glueck, & Muller, 2013). Individual growth curve (IGC) analysis is a popular method for investigating within-subject change and represents a powerful way to assess change in a continuous dimension over time within subjects. IGC is also known as latent growth curve analysis, hierarchical linear modeling, mixed-effect modeling, random effects modeling, and multilevel modeling (Kozlowski, Pretz, Dams-O'Connor, Kreider, & Whiteneck, 2013). The IGC analysis postulates that, for each individual, or subject, the continuous dependent variable is a specified function of time. This function is called the individual growth trajectory (Lenzenweger, Johnson, & Willett, 2004). In this pilot study, growth curve parameters were used to test linear change at the aggregate level only due to our small, purposeful sample. Prior research provides readers with additional examples, discussion, and theory supporting our repeated measures approach (Hoyt, Massman, Schatschneider, Cooke, & Doody, 2005; Shek & Ma, 2011; Singer & Willett, 2003; West, 2009).

3.7.2. Bootstrap resampling

Since we are aware of no known study examining frontier technology acceptance over time, we wanted to further strengthen our study and illustrate the robustness of our small sample approach. To provide more precise estimates and to illustrate the benefit of bootstrapping confidence intervals (DiCiccio & Efron, 1996), we report 95% bias corrected and accelerated confidence intervals (BCa CIs) and parametric 95% confidence intervals (95% CI). Bootstrap resampling allowed us to overcome the limitations of our small sample size by providing the research community with preliminary model estimates. Leveraging the computation power of modern computers, bootstrapping provided us a way to account for error in our specific sample that may not reflect the population by simulating thousands of datasets. Previous research found that resampling calculates a robust distribution of a statistic of interest and is remarkably accurate when a sample is a reasonable approximation of a larger population (Efron & Tibshirani, 1993). Researchers are encouraged to use bootstrap procedures when: (1) a theoretical distribution of a statistic is unknown, (2) a sample size is insufficient or large samples are hard to obtain, and (3) the goal is to obtain the impression of population variance of statistic from a small sample (Ader, 2008). This study met all three considerations. A more comprehensive discussion on robust analysis and resampling applications is beyond the scope of this article (for reviews, see Hoaglin et al., 1983; Lunneborg, 2000; Mooney & Duval, 1993). For an exhaustive review on bootstrap resampling, readers are directed to Efron and Tibshirani's (1993) seminal text, *An Introduction to the Bootstrap*.

All bootstrap procedures used in this study simulated 10,000 resamples with replacement to obtain BCa CIs. Since the NFFP program manager deemed the sample a reasonable approximation of the larger income-subsidized housing complex, this resampling procedure simulated 10,000 datasets that we could have theoretically obtained. SPSS for Windows version 21 software (Armonk, NY) was used for all analysis.

4. Results

4.1. Study characteristics

Fourteen community-dwelling older adults residing at an ISHC in a frontier state enrolled in the study. Of the 14 participants, four residents enrolled late and only completed pretest and two subsequent bi-weekly measurements. The remaining ten participants completed pretest measurements and five subsequent bi-weekly measurements. We initially considered using two follow up observations instead of five in order to increase our pilot sample size from 10 to 14. Given that our primary aim was longitudinal analysis, we ultimately decided a moderated sample with additional observations would provide richer preliminary data on our analyses. Our pilot ($n = 10$) accounted for approximately 18% of the ISHC population, whereas the recruited sample accounted for approximately 25%. We deemed this sample size difference acceptable since the NFFP program manager reported the reduced data remained a reasonably accurate representation of the larger population ($N = 56$) and we employed resampling techniques to increase the power and reliability of our study.

Robust statistics describing participant sociodemographics and health concerns are provided in Table 1. Participants were primarily adult women with an average age of 76 years. Over half of the participants reported some post high school education and all participants reporting race/ethnicity were white. The most common reported health concerns were hypertension (43%), rheumatoid arthritis (21%), eye problems (21%), diabetes mellitus (14%), and chronic obstructive pulmonary disease (14%). The average BMI score was over 30.0, indicating obese status (CDC, 2014a). Bootstrap CIs on age, BMI, and number of health concern variables were comparable to parameter confidence intervals but ultimately more precise.

4.2. TAM descriptive data

Table 2 provides robust TAM parameters derived from 10,000 resamples with replacement. Acceptance variables showed participants had a high level of acceptance toward the remote patient monitoring. Participants' levels of subjective norm, perceived usefulness, ease of use, and behavioral intention levels were collectively elevated over the course of the study. Subjective norm variance was relatively large when compared to usefulness, ease of use, and intention estimates. Bootstrap CIs on TAM variables were similar to parametric CIs but ultimately more exact. Pooled psychometric analyses revealed TAM scales had satisfactory internal validity ($\alpha \geqslant 0.8$).

4.3. Hypotheses

Growth curve analyses using maximum likelihood methods and bootstrap resampling were performed separately for the outcome variables of technology acceptance. Since we obtained repeated measures, we specified an autoregressive, and heterogeneous covariance structure, ARH1, as recommended by Field (2013). It was hypothesized that there would be significant linear trends on subjective norm, perceived usefulness, perceived ease of use, and behavioral intention variables. Only *subjective norm* was significantly predicted by time. Table 3 provides growth curve analysis parameters for time on study technology acceptance variables. Time significantly predicted subjective norm over the course of the study, $F(1,39.02) = 3.15$, $p = .003$. This trend was positive, and linear, $b = .25$, $t(39.02) = 3.15$, 95% CI = [.09, .41], $p = .003$, and bootstrap resampling confirmed the reliability of the model BCa 95% CI = [.11, .35]. The longer the participant's used the system, the more they believed the people important to them or those that influence their behavior would want them to use the system. Time did not significantly predict *usefulness*, $F(1,10.00) = .97$, $p = .349$, BCa 95% CI = [−.19, .02], *ease of use*, $F(1,10.00) = .000$, $p = .984$, BCa 95% CI = [−.08, .09], or *behavioral intention*, $F(1,4.54) = -1.39$, $p = .229$, BCa 95% CI = [−.18, .04].

Table 2
Aggregate means with robust and Parametric Confidence Intervals and standard deviations of TAM variables ($n = 10$).

Variable	*M*	95% CI	BCa 95% CI	*SD*	Theoretical range
SN	6.06	[5.70, 6.42]	[5.70, 6.39]	.63	1–7
PU	6.11	[5.81, 6.42]	[5.81, 6.39]	.22	1–7
PE	6.63	[6.45, 6.80]	[6.44, 6.79]	.11	1–7
BI	6.68	[6.48 6.88]	[6.47, 6.86]	.32	1–7

Note: Higher the TAM scores indicate stronger perceptions. Bootstrap procedures simulated 10,000 datasets with replacement. 95% CI = Parametric Confidence Intervals. BCa 95% CI = Bias Corrected and Accelerated Bootstrap Confidence Interval. BI = behavioral intention; PU = perceived usefulness; PE = perceived ease of use; SN = subjective norm.

5. Discussion

The average population density of a frontier state is six or fewer people per square mile. In terms of remote patient monitoring technology acceptance, and general health characteristics for that matter, little is known about older adults residing in a frontier state. Research obstacles are likely related to geographic isolation and difficulties recruiting acceptable numbers of participant's to adequately power a study. To address this gap in the literature,

Table 1
Robust characteristics and estimates of the pilot ($n = 14$).

Characteristic	*n*	%	*M*	95% CI	BCa 95% CI	*SD*	Range
Age	14	100	75.93	[71.76, 80.10]	[72.29, 79.50]	7.23	61–90
BMI	13	93	30.97	[24.81, 37.13]	[25.24, 37.11]	10.19	19.3–51.2
# of health concerns	10	71	2.60	[1.57, 3.62]	[1.80, 3.40]	1.43	1–5
Most common health concerns							
Hypertension	6	43					
Rheumatoid arthritis	3	21					
Eye sight	3	21					
Diabetes	2	14					
COPD	2	14					
Gender (%)							
Male	3	21					
Female	11	79					
Relationship (%)							
Widowed	4	29					
Married	3	21					
Divorced	7	50					
Race/ethnicity (%)							
White	12	86					
Refused	2	14					
Education (%)							
<High school degree	2	14					
High school/GED	3	21					
Post high school	9	64					

Note: Percentages may not equal 100 due to rounding and "declined to answer" responses. Bootstrap procedures simulated 10,000 datasets. 95% CI = Parametric Confidence Interval. BCa 95% CI = Bias Corrected and Accelerated Bootstrap Confidence Interval. One participant refused to discuss her/his health concerns. BMI = body mass index; COPD = chronic obstructive pulmonary disease.

Table 3
Results of growth curve analysis for time and technology acceptance measures.

Measure and parameter	*M* (*SE*)	95% CI	BCa 95% CI
SN			
Intercept	5.43 (.47)	[4.38, 6.48]	[4.87, 6.17]
Time	.25 (.08)	[.09, .41]	[.11, .35]**
PU			
Intercept	6.31 (.23)	[5.81, 6.81]	[5.82, 6.72]
Time	−.08 (.08)	[−.26, .10]	[−.19, .02]ns
PE			
Intercept	6.62 (.17)	[6.24, 7.00]	[6.22, 6.85]
Time	.00 (.06)	[−.13, .13]	[−.08, .09]ns
BI			
Intercept	6.88 (.15)	[6.58, 7.18]	[6.43, 7.06]
Time	−.08 (.06)	[−.23, .07]	[−.18, .04]ns

Note: ns = not significant. Bootstrap procedures simulated 10,000 datasets with replacement. 95% CI = Parametric Confidence Interval. BCa 95% CI = Bias Corrected and Accelerated Bootstrap Confidence Interval. SN = subjective norm. PU = perceived usefulness. PE = perceived ease of use. BI = behavioral intention.
** $p < .01$.

the goal of our study was to test a robust methodology aimed at investigating remote patient monitoring system acceptance trends among older adults residing in a frontier state. Rather than examining technology acceptance in a cross-sectional manner, this research focused on older adult acceptance trends on theoretically grounded predictors of technology acceptance usage. To this end, our methodological and theoretical interest in bootstrapped linear growth trends provided encouraging preliminary findings and generated future hypotheses for testing.

5.1. TAM trends

We rejected the null hypothesis that there was no linear subjective norm trend. Data showed a significant linear trend on *subjective norm* and the trend was reliable using bootstrap resampling. This finding suggests the longer the residents used the technology, the more social factors influence technology-adoption behavior. The significant trend implies individuals became more sensitive to the potential of the technology over time. One possible explanation for this finding is that older adults experienced increased appreciation of the technology as a result of conversations with those important to them or conversations with persons that influence their behavior. Perhaps these conversations translated into fresh insight that monitoring systems, moderated by positive family and friend influences and professional caregivers, could result in improved levels of health and well-being (Seeman, 2000). Upon this background, research examining informal and formal caregivers' perspectives on technology is warranted (Giger & Markward, 2011).

Regarding the three hypotheses we failed to reject, participants' levels of *perceived usefulness*, *perceived ease of use*, and *behavioral intention* were high and stable but did not reveal significant linear trends. Of particular interest, when we forecasted TAM variables out 4 weeks, ease of use remained high and stable and usefulness and behavioral intention showed slight, downward linear trends. Figs. 1–4 show acceptance trend forecasts if we extended our study by two data collection periods. When considering our projections, data showed non-significant TAM variables were either largely stable or slightly trending down. Had we collected four or more additional weeks of data, time may have resulted in significant linear trends on usefulness and intention. It is possible that older adults residing in rural and frontier states require at least 14 weeks of remote patient monitoring technology exposure before trends emerge. Further, it is possible that over time older adults are less concerned with the monitoring technology usefulness, ease of

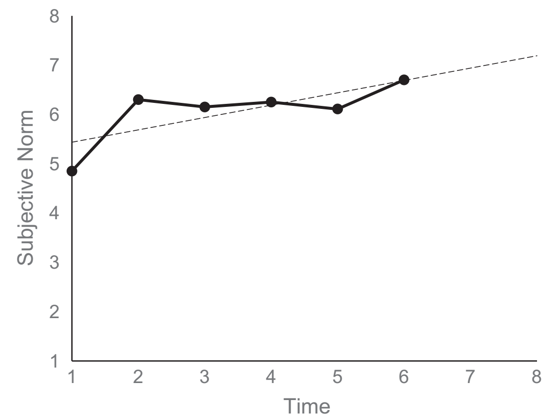

Fig. 1. Forecasting subjective norm by two data collection periods. Linear trend had we collected four more weeks of data. Time interval is two weeks.

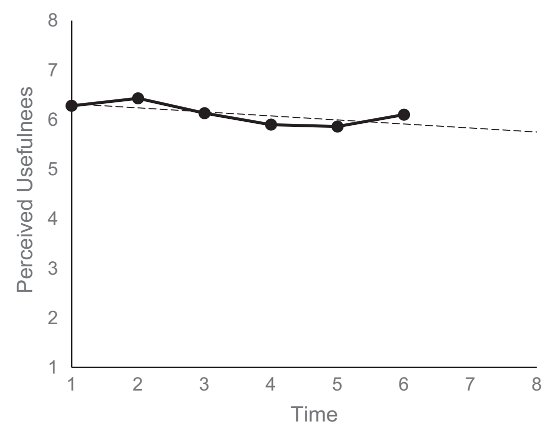

Fig. 2. Forecasting perceived usefulness by two data collection periods. Linear trend had we collected four more weeks of data. Time interval is two weeks.

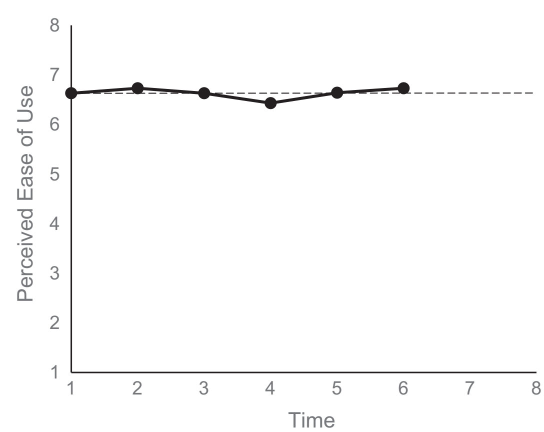

Fig. 3. Forecasting perceived ease of use by two data collection periods. Linear trend had we collected four more weeks of data. Time interval is two weeks.

use, and intention and largely compelled by social influences. Our forecasts signal future research should examine this line of inquiry.

5.2. Generating hypotheses

Medical co-morbidities were common in our sample. High blood pressure and high blood glucose were among the most

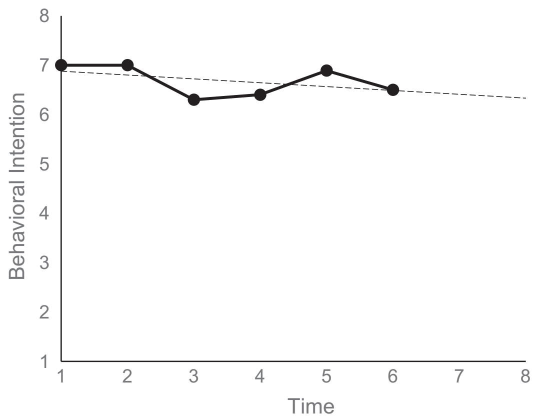

Fig. 4. Forecasting behavioral intention by two data collection periods. Linear trend had we collected four more weeks of data. Time interval is two weeks.

commonly reported health concerns and BMI was high. The health profile of our small study is generally consistent with Danaei et al.'s (2009) research investigating mortality effects of modifiable dietary, lifestyle, and metabolic risk factors in the United States. Our results signal that major health risk factors, otherwise considered preventable causes of death, could be quite common among low income community dwelling rural and frontier older adults. If future research confirms our findings, investigators should systematically compare and contrast frontier older adult health profiles, a strata of rural older adults, with urban and non-frontier rural older adult health profiles.

The overall health profile of the sample is concerning when using sterile, clinical language (i.e., "...preventable causes of death..."). However, effective interventions exist for individual health risk behaviors and the associated chronic health conditions of obesity, diabetes, and poor nutrition (Nichols, Ussery-Hall, Griffin-Blake, & Easton, 2012). The high levels of technology acceptance over time in our sample preliminarily support the use of remote patient monitoring and perhaps empirically supported interventions with this age and geographic cohort. Conceivably, participant health risks could be reduced by complementing in home health monitoring with a community based, integrated approach to chronic disease prevention such as the Centers for Disease Control and Prevention Healthy Communities Program (CDC, 2014b).

5.2.1. Strengths

Our study has several strengths. This is the first known study to examine remote patient monitoring system acceptance trends among older adults residing in a frontier state. Though there are findings on technology acceptance among broad populations of older adults including U.S. non rural (Veerle et al., 2014), Chinese (Pan & Jordan-Marsh, 2010), and the citizens of the UK (Nayak, Priest, & White, 2010), these findings may not be generalizable to U.S. residents living in frontier states. Our findings provide the scientific community with a reference point from which more rigorous prospective rural and frontier patient health monitoring research can extend. This line of inquiry is critical as over 20% of U.S. older adults reside in rural regions (Hutchison et al., 2005). A second strength of this study is the inclusion of valid technology acceptance measures for predicting whether frontier older adults will adopt new technology. The use of validated TAM scales lends credibility to our exploratory findings. The strong, positive acceptance estimates indicate older adults in our sample are willing to adopt monitoring technology. This finding is vital as understanding older adults' levels of technology acceptance is key to an organization's successful rollout of a technology (Wilkowska & Ziefle, 2009). Additionally, the "greying" of the U.S. population (Vincent & Velkoff, 2010) and the interest in maintaining older adults in their communities (Alley, Liebig, Pynoos, Banerjee, & Choi, 2007) make this study that much more valuable. Finally, we implemented modern statistical analysis methods. Since little is known about frontier older adult adoption of health monitoring technology, or health profiles for that matter, bootstrap procedures allowed us to provide researchers and other interested stake holders (e.g., policy makers) with robust preliminary estimates from which others can compare and contrast with other older adult technology acceptance findings.

5.2.2. Limitations

The present study has several limitations. First, the study sample was small. Though our sample provides strong exploratory data, the sample size limits the generalizability of the findings to other frontier older adults. While modern resampling methods were implemented, a large, probability sample is required to reproduce and bolster our findings. A second limitation is that the sample was predominantly white, and female, thus precluding race/ethnicity and gender comparisons. Third, the study lacked comparison groups or a control group. Biweekly assessment contacts by the program manager and the centralized monitoring and coaching and wellness support by an RN are likely confounding variables. Temporal effects may have been influenced by these confounds instead of the technology. Likewise, the technology was provided to participants for one year at no cost. It is unclear what effect cost has on acceptance trends, particularly with low income, community dwelling older adults in frontier communities. The use of randomization and control or waitlist group(s) in future research would allow for comparative analysis related to health outcomes, acceptance, and/or sociodemographic variables such as age, socioeconomic status, race ethnicity, gender, and education. Finally, our data were self report, which can be unreliable (Kuczmarski, Kuczmarski, & Najjar, 2001) and subject to social desirability bias (Hebert, Clemow, Pbert, Ockene, & Ockene, 1995). Utilizing health and technology *ground truth* data (Pickles, 1995) via objective measures, such as whole body air displacement plethysmography (Fields, Hunter, & Goran, 2000) for BMI, and in home sensor (Wang et al., 2009; Zhou et al., 2009) and technology metadata (Harris et al., 2009) to measure and manage activity levels and clinical data, would further add confidence to our findings.

6. Conclusions

Although we acknowledge the limitations of our study and that our findings need to be interpreted judiciously, we believe our methodological approach and results show considerable promise related to investigating technology acceptance trends in frontier older adults, and feasibly other strata of 'hard-to-reach populations' (Muhib et al., 2001). Small samples of understudied populations and bootstrap resampling procedures can provide noteworthy findings that generate hypotheses for future testing. Our findings provide researchers with a resource to utilize in future studies aimed at addressing the health needs of rural and frontier, low income older adults.

6.1. Implications

The findings have implications for policy makers, medical and allied health practitioners, and higher education. Policy makers, practitioners, and educators would be well advised to (1) foster environments that support and facilitate RPM use by frontier, older adults, and their providers of care, and (2) systematically educate the existing and future rural medical and allied health workforce to the potential of RPM. As the diffusion of technology continues to extend to rural and frontier areas (Giger, Newland, Lawler, Roh, & Carr, 2014), older adult and health professional technical support and training on remote patient monitoring systems and other technologies, should be explored as creative approaches to addressing the distinctive health obstacles people residing in geographically isolated states or regions encounter.

The implications of this study in human computer interaction, rural and frontier healthcare, and patient centered outcomes research could be wide ranging. Findings revealed in home health monitoring was well tolerated and could translate into higher levels of patient engagement, improved access to care, and improvements in service delivery and patient centered health outcomes for Americans residing in rural and frontier states. In fact, a recent study comparing in-person medical assessment and remote technology found that patient retention and treatment adherence improved through the use of remote monitoring (Varma et al., 2014). Acceptance of this technology by this age group and topographical cohort opens the door for eventual widespread deployment of in home health monitoring technology not only in independent, community living environments, but also in assisted living and individuals' homes. This adoption may lead to reduced health care costs and lower burdens on long-term care facilities by allowing people to live independently in their homes later in life, remaining active with regular or semi-regular monitoring by qualified health care professionals, or perhaps even by regular or semi-regular monitoring by lay family and friends. The results from future studies could also lay the groundwork for interventions such as remote peer and family support groups for older adults in rural and frontier communities and health community programs aimed at reducing or slowing health risks including but not limited to obesity, diabetes, and hypertension.

The current study supports the use of remote patient monitoring with lower income older adults living in a frontier state in the U.S. and supports our methodological approach to investigate technology accept change over time for geographically isolated rural and frontier populations. The longer older adults in our study used the technology, the more they believed those important to them would want them to use the monitoring technology. This crucial finding suggests social forces may influence technology acceptance behavior in frontier older adults, and perhaps other populations residing in isolated environments. Attention to social influences, such as subjective norm, to optimize the implementation of in home health monitoring among this population is warranted. Finally, our pilot demonstrated that growth curve modeling with a small sample, coupled with modern resampling techniques to increase the power and accuracy of available data, can produce strong, preliminary evidence where none currently exists and generate future hypotheses for testing.

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