Changes in Healthcare Utilization and Charges Among Supportive Housing Residents Enrolled in a Health Coaching Program

DISSERTATION

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Abstract

The effectiveness of self-management programs on healthcare use outcomes is an active area of research with inconsistent results. This study was the first to evaluate changes in healthcare utilization (including hospital encounters, inpatient visits, outpatient visits, and emergency visits) and charged amounts among supportive housing residents enrolled in a health coaching program. We utilized retrospective longitudinal medical claims data and a qualitative examination of participants' perceptions of the program's influence on their healthcare use. Zero-inflated negative binomial model and log-gamma models were used to assess change in count variables and charged amounts respectively. Although participants reported a positive impact of the program on their overall quality of life through improved health self-management strategies, the analysis of claims data showed no significant change in healthcare use and charged amounts in all analyses spanning 12 months prior to 24 months post enrollment. These findings may potentially demonstrate the success of health coaching programs in stabilizing healthcare utilization among individuals who otherwise might have increased their healthcare use over time. During interviews and focus groups, participants also shared personal and systems-level challenges that influenced their healthcare use. The inclusion of a control group in future analyses would help measure the actual impact of health coaching on healthcare utilization measures among supportive housing residents with high health needs.

Chapter 1: Introduction

1.1 Statement of the Problem

Homelessness is a complex public health concern in the United States. Although there was a 15% overall reduction in the last decade, addressing homelessness remains a challenge (National Alliance to End Homelessness, 2018b). On a single night in January of 2017 more than half a million individuals were experiencing homelessness (National Alliance to End Homelessness, 2018b).

Homeless individuals are among the most vulnerable members of our community with heightened healthcare needs. Homelessness and health are interconnected. Mental health and substance use problems are among key factors causing homelessness (Tessler, Rosenheck, & Gamache, 2001). Homeless individuals continue to report a high prevalence of mental, and physical health problems, and substance use disorders (Fazel, Khosla, Doll, & Geddes, 2008; Fischer & Breakey, 1991; Romanoski, 1989; Schanzer, Dominguez, Shrout, & Caton, 2007). People experiencing homelessness encounter numerous barriers to healthcare that further worsen their health (Baggett, O'connell, Singer, & Rigotti, 2010; Campbell, O'Neill, Gibson, & Thurston, 2015). Collectively, these factors result in higher premature mortality rates among this subgroup compared to the general population (Barrow, Herman, Cordova, & Struening, 1999; Hwang, 2000). Problems related to health are further intensified among people who experience homelessness for a prolonged period of time (referred to as chronic homelessness).

Chronically homeless individuals are those who have a disabling condition and experience continuous homelessness for a year or longer or experience four or more instances of homelessness in three years (U.S. Department of Housing and Urban Development, 2007). People experiencing chronic homelessness account for high rates of emergency health services use and face a trimorbid co-occurrence of mental health, substance abuse, and chronic health conditions (Chalmers McLaughlin, 2011; Cronley, Petrovich, Spence-Almaguer, & Preble, 2013; Larimer et al., 2009) Given the multitude of problems faced by this group, the needs of chronically homeless individuals are more complex compared to the nonchronically homeless population, and they are considered one of the most expensive groups for human service systems (including healthcare systems, criminal justice services, and emergency shelters) (Poulin, Maguire, Metraux, & Culhane, 2010).

Housing First (HF) is an evidence-based consumer-driven approach to placing people experiencing chronic homelessness into Permanent Supportive Housing (PSH) programs before connecting them with other additional services (Tsemberis, 2015). The HF model evolved as an improvement to traditional housing services. The traditional housing programs (also referred to as treatment as usual or continuum of care services) is described as a linear model (Tsemberis, 2010). According to this linear approach, “all housing options are available to clients only if they first demonstrate continued participation in psychiatric treatment and achieve a period of sobriety” (Tsemberis, 2010). On the contrary, the HF model is grounded in the idea that “housing is a basic human right rather than something people with mental health disorders have to earn or prove they deserve by being in treatment”(Tsemberis, 2010). Hence, HF participants are provided housing followed by treatment and supportive services for their substance use and/or mental health needs (Pathways Housing First, 2018). The array of supportive services includes case management, counseling, workforce development and advocacy (United States Interagency Council on Homelessness, 2014). By eliminating the conditionality in the linear model, the HF model has been successful in achieving higher housing retention rates compared to the traditional approach (Rog et al., 2014; Tsemberis, Gulcur, & Nakae, 2004).

Stable housing and supportive services have made some contribution to the health and healthcare use among people with a history of chronic homelessness (Culhane, Metraux, & Hadley, 2002; Sadowski, Kee, VanderWeele, & Buchanan, 2009; Gilmer, Manning, & Ettner, 2009). Supportive housing programs have demonstrated an increase in outpatient service use and reductions in emergency department (ED) admissions, preventable healthcare encounters, and the probability of hospital admissions compared to healthcare use when homeless (Rieke et al., 2015; Martinez & Burt, 2006). However, numerous factors continue to threaten the well-being of supportive housing residents (Henwood, Byrne, & Scriber, 2015; Wolf, Burnam, Koegel, Sullivan, & Morton, 2001). Even after being housed, the average resident lives near or below the poverty line and struggles to manage chronic disabling conditions and improve overall quality of life. The definition of quality of life incorporates a subjective component (understood through individuals' perceptions) and a multidimensional component (that includes emotional, physical, functional and social well-being) (Cella, 1994). Although becoming housed improves some aspects, it does not improve a person's overall quality of life in its entirety (Wolf et al., 2001). Furthermore, the overall premature mortality rates among HF residents is higher compared to the general population (Henwood et al., 2015). As a result, there is a need to understand ongoing health problems among supportive housing residents and provide additional services accordingly.

Emphasis on self-management techniques has shown promise with improving health and healthcare use among people living with chronic conditions (Jovicic, Holroyd-Leduc, & Straus, 2006; Lorig et al., 1999; Norris, Engelgau, & Narayan, 2001). Traditionally health interventions focused on one behavior at a time or a single health condition or disease state (e.g., overweight, hypertensive). However, there is some evidence that interventions targeting multiple behaviors are more impactful compared to traditional approaches (Prochaska, Spring, & Nigg, 2008). Health coaching is gaining momentum as a strategy to promoting such lifestyle changes and disease self-management (Huffman, 2007). No previous studies that have utilized health coaching to improve health among supportive housing residents were identified. This study was the first to explore the impact of a health coaching program on the health and healthcare use among supportive housing residents.

1.2 Health Coaching for Supportive Housing Residents

Mobile Community Health Assistance for Tenants (*m.chat)* was established as a supplemental program to improve the overall quality of life among supportive housing residents by providing services that are not covered through existing housing programs. *m.chat* utilized health coaching techniques to promote broader lifestyle changes and enhance health among program participants. Additionally, motivational interviewing and solution focused strategies, and wellness incentives were incorporated into the program (Walters, Spence-Almaguer, Hill, & Abraham, 2015). Coaches met with participants on a monthly basis to develop and work towards personalized health goals within six domains namely diet, exercise, substance use, social support, medication adherence, and recreation. In addition to improving participants' well-being, *m.chat* also hoped to reduce the burden of healthcare costs incurred by the target population.

Prior evaluation of *m.chat* data showed significant improvement in the overall quality of life, diet, physical activity, medication adherence and depression from baseline to 12 months follow up (Chhetri, Rohr, Spence-Almaguer, & Walters, 2017). The influence of *m.chat* on healthcare use is yet to be determined. This study aimed to explore changes in healthcare utilization patterns and the associated charged amounts among *m.chat* participants before and after their enrollment into the program. Utilization included total hospital encounters, emergency department visits, outpatient hospital visits and inpatient stays.

1.3 Study Rationale

Healthcare in the United States is complex, and expenditures are increasing. In the year 1970, the healthcare expenditures in the United States accounted for 6.2% of the gross domestic product (GDP) which has risen to 17.9% in 2016 (Centers for Medicare and Medicaid Services, 2017; Kaiser Family Foundation, 2017). Economists are concerned that the total cost of healthcare will soon exceed half of all economic transactions in the country (Rich & Barry, 2017). Despite these higher healthcare expenditures, people in the United States have relatively poorer health outcomes compared to other high-income countries (Squires & Anderson, 2015). Compared to 10 other developed nations, the United States has the highest infant mortality rates (5.8 deaths per 1000 live births compared to a mean of 3.6 deaths for all 11 countries) and lowest life expectancy (Papanicolas, Woskie, & Jha, 2018). It is argued that this is a result of fragmented healthcare systems that lack efficient coordination of care (Hicks, 2015).

The cost of healthcare in the United States is distributed disproportionately based on various population characteristics (Mitchell & Machlin, 2017). A small percentage of the population account for a significant portion of healthcare expenditures (Mitchell & Machlin, 2017). There is a growing interest in targeting high utilizers with cost-effective health promotion programs. Studies promoting self-management have shown encouraging results regarding self-reported and clinical health outcomes (Lorig et al., 1999; Warsi, Wang, LaValley, Avorn, & Solomon, 2004). A study evaluating the effectiveness of a self-management program designed for chronic disease patients showed improvement in self-reported health, and reduction in hospitalizations and inpatients stays (Lorig et al., 1999). However, there is mixed evidence in the literature regarding the effectiveness of self-management programs in changing healthcare use patterns and reducing costs (Burton et al., 2017; Fedder, Chang, Curry, & Nichols, 2003; Rettig, Shrauger, Recker, Gallagher, & Wiltse, 1986; Schmidt, Collinsworth, Barnes, & Brown, 2015; Sidorov et al., 2002). For example, an evaluation of a diabetes self-management education program showed no reduction in hospital utilization (including inpatient hospital visits, emergency visits and costs) (Burton et al., 2017).

There are several limitations to the existing body of literature regarding healthcare utilization. First, the recruitment strategies varied across studies. Some studies recruited participants from the community based on a health condition irrespective of their healthcare use status at baseline which could have impacted healthcare use outcomes (Burton et al., 2017; Rettig et al., 1986). For instance, studies enrolling individuals who were already engaged in their healthcare were less likely to see changes in the short-term compared to those who were not engaged at baseline. Studies also covered different timeframes (monthly change versus change over the course of a year versus change over the course of multiple years) which may have impacted results (Ofman et al., 2004). There were also variations in the sources of data. Some studies utilized comprehensive data from multiple hospitals to explore healthcare use; others included data from only one hospital underestimating the actual use (Schmidt et al., 2015; Wheeler, 2003). Moreover, the majority of studies focused on managing one disease condition at a time and excluded individuals experiencing pressing medical problems (terminal illness such as cancer), or co-morbid conditions (such as alcohol abuse, substance use, and mental health diagnosis) during their recruitment phase (Bourbeau et al., 2003; Cline, Israelsson, Willenheimer, Broms, & Erhardt, 1998; Fedder et al., 2003; Lorig et al., 2001; Wheeler, 2003).

This selection approach reduces applicability to people living with multiple chronic health conditions.

Several modifiable risk factors are associated with chronic health conditions. For example, both cardiovascular diseases and type 2 diabetes are associated with poor diet, lack of physical activity, smoking, and alcohol abuse (Centers for Disease Control and Prevention, 2015; Hu et al., 2001). Moreover, the majority of Americans engage in more than one risk behavior simultaneously (Fine, Philogene, Gramling, Coups, & Sinha, 2004). Studies have demonstrated a collective adverse effect of multiple risk factors on individual's long-term health (Prochaska & Prochaska, 2011). For example, a smoker is less likely to be physically active, and more likely to have poor appetite, and engage in high alcohol consumption compared to a non-smoker (Chiolero, Wietlisbach, Ruffieux, Paccaud, & Cornuz, 2006). This clustering of risk factors demand a health promotion approach targeting numerous behaviors (Noble, Paul, Turon, & Oldmeadow, 2015). Few studies have assessed the effectiveness of a lifestyle change approach on healthcare use among high-utilizers. This was the first study to look into changes in healthcare use patterns among supportive housing residents enrolled in a health coaching program aimed at making lifestyle changes to improve health.

Through a retrospective longitudinal study design, this study examined changes in healthcare utilization and charged amounts among supportive housing residents enrolled in a health coaching program. Quantitative medical claims data obtained from Dallas Fort Worth Hospital Council (DFWHC) was utilized to address Aim 1 and Aim 2. Due to limited resources, this study only included medical claims data over a 44-month period of time. Additionally, the DFWHC dataset does not differentiate between preventive visits and lacks data from preventive clinics. This study utilized a mixed method approach with the addition of qualitative focus groups and interviews to address Aim 3. The qualitative component of this study explored participants' perceptions of the impact of *m.chat* on their health and healthcare use. Results from this study will help inform future intervention studies targeted to improve health and healthcare use outcomes among high users.

1.4 Specific Aims

Aim 1: To describe patterns and assess changes in healthcare utilization measures, including total hospital encounters, inpatient stays, outpatient hospital visits, emergency department visits and charged amounts among *m.chat* participants 12-months pre and 12-months post enrollment into the program.

Aim 2: To compare changes in healthcare utilization measures, including total hospital encounters, inpatient stays, outpatient hospital visits, emergency department visits and charged amounts among *m.chat* participants at 12-months pre, 12-months post, and between 12 to 24-months post enrollment into the program.

Aim 3: To explore participants' perceptions about how *m.chat* influenced their health management and healthcare use through focus groups and interviews.

Chapter 2: Literature Review

2.1 Homelessness and Health

2.1.1 Introduction to homelessness in the United States

Homelessness is a complex public health concern in the United States. Although there was a 15% overall reduction in the last decade, addressing homelessness remains a challenge (National Alliance to End Homelessness, 2018b). On a single night in January of 2017 more than half a million individuals were experiencing homelessness (National Alliance to End Homelessness, 2018b). Historically homelessness has been viewed through two distinct lenses – an individual versus a structural problem. Researchers have attributed increasing homelessness to a rise in poverty and unemployment, and simultaneous reduction in the availability of low-income housing (Wright, 2017). Others have argued that homelessness is a result of personal factors, as 85% of American adults experiencing homelessness reported serious social isolation resulting from their mental illness, substance use, and criminal history (Baum & Burnes, 1993). However, contemporary researchers are claiming that both structural and individual factors collectively contribute towards homelessness (Main, 1998; Snow & Anderson, 1993). Furthermore, the likelihood of becoming homeless varies based on gender. Men are more likely to be homeless due to loss of employment, mental health and substance use problems, and challenges with community reentry upon being discharged from an institution (Tessler et al., 2001). In contrast, factors such as eviction, interpersonal violence, and lack of social support are more likely to lead women into homelessness (Tessler et al., 2001). It is essential to correctly identify factors causing homelessness to fully understand the complexity of the problem and design programs accordingly.

2.1.2 Health Status of People Experiencing Homelessness

Homelessness has a detrimental impact on individual health (Schanzer et al., 2007). People experiencing homelessness have a high prevalence of mental and physical health problems, and substance use disorders (Fazel et al., 2008; Fischer & Breakey, 1991; Romanoski, 1989; Schanzer et al., 2007). Mental health disorders and substance use problems are both causes and consequences of being homeless. The majority of individuals suffer from co-morbid health conditions, but only a small fraction receive any form of treatment for these conditions as necessities like housing, food, and clothing take precedence among homeless individuals (Gelberg, Gallagher, Andersen, & Koegel, 1997; Koegel, Sullivan, Burnam, Morton, & Wenzel, 1999). This population also demonstrates extremely low medication adherence for their existing medical conditions (Hunter et al., 2015; Kidder, Wolitski, Campsmith, & Nakamura, 2007).

Life on the street further exacerbates health problems. Due to the exposure to extreme climates, pollution, and communicable diseases, homeless individuals with pre-existing unmanaged chronic health conditions are prone to developing new diseases (Ramin & Svoboda, 2009). Additionally, homeless adults are more likely to be nutrient deficient which is associated with weakened health and higher healthcare needs (Baggett et al., 2011). Individuals are also susceptible to physical and sexual abuse during their time on the street (Kushel, Evans, Perry, Robertson, & Moss, 2003). These factors together result in higher premature mortality rates among this subgroup compared to the general population (Barrow et al., 1999; Hwang, 2000). Homeless people are among the most vulnerable members of the community with heightened healthcare needs.

People experiencing homelessness encounter numerous barriers to healthcare (lack of awareness and access to community resources) that worsens their health (Baggett et al., 2010;

Campbell et al., 2015). Homeless individuals episodically use acute-hospital based services which tend to create fragmented care and thereby, place an exponential burden on healthcare resources and overall healthcare costs (Kushel, Vittinghoff, & Haas, 2001; Nosyk, Li, Sun, & Anis, 2007). They also tend to use the ED for their psychological health needs rather than utilizing outpatient care (Folsom et al., 2005; Ku, Scott, Kertesz, & Pitts, 2010). Furthermore, hospitalization among this population is often related to substance use and mental illness and could be prevented through preemptive care (Ku et al., 2010; Salit, Kuhn, Hartz, Vu, & Mosso, 1998). Thus, the lack of access to preventive care and disease management, high healthcare needs, continually worsening health, and intermittent use of expensive healthcare services creates a vicious cycle for homeless individuals, making them one of the most costly subgroups to the healthcare systems (Bodenheimer, 2013).

Problems related to health are further intensified among people who experience homelessness for a prolonged period of time; health outcomes are worse for people who spend longer time on the street. After controlling for age and disability status, lengthy exposure to homelessness (also referred to as chronic homelessness) was demonstrated as a strong predictor of early mortality among men (Barrow et al., 1999). Prolonged experience of homelessness is a complex and pressing public health concern.

2.1.3 Characteristics and Needs among Chronically Homeless

According to the point-in-time count in 2017, 24% of individuals experiencing homelessness were categorized as chronically homeless (National Alliance to End Homelessness, 2018a). The US Department of Housing and Urban Development (HUD) defines chronically homeless individuals as those who have a disabling condition and experience continuous homelessness for a year or longer or experience four or more instances of homelessness in three years (HUD, September 2007). Homeless individuals with mental health and substance use co-morbidity are more likely to become chronically homeless (Tsemberis & Eisenberg, 2000; Tsemberis, Kent, & Respress, 2012). According to a survey conducted in 1999, 60% of chronically homeless experienced mental health problems and more than 80% experienced alcohol and/or drug use problems in their lifetime (Burt, Aron, Lee, & Valente, 2001). In addition, individuals experiencing such comorbidities are at a higher risk of developing physical health conditions such as heart diseases, gastrointestinal disorders, asthma, respiratory disorders and skin conditions (Dickey, Normand, Weiss, Drake, & Azeni, 2002). Given the multitude of problems faced by this subpopulation, needs of chronically homeless are more complicated compared to the nonchronically homeless population. They also constitute one of the most expensive groups to healthcare systems (Poulin et al., 2010).

2.1.4 Community Resources to End Chronic Homelessness

Historically, communities approached the problem of homelessness by mandating mental health and substance abuse stabilization services prior to offering connections to housing (Padgett, Stanhope, Henwood, & Stefancic, 2011). Under this model, housing is conditional on individual's readiness to comply with treatment conditions. However, this "treatment first" approach contradicts Maslow's hierarchy of needs; physiological needs such as food, air, water, safety take precedence over needs related to self-actualization (Maslow & Lewis, 1987). Contrary to the traditional treatment first approach, in 1992, Dr. Sam Tsemberis founded the Pathways' Housing First (HF) Model (Tsemberis, 2010). This is an evidence-based consumer-driven approach to placing people experiencing chronic homelessness into housing. Once placed into housing participants are offered an array of concurrent services (Tsemberis, 2015). The HF model is grounded on the idea that "housing is a basic human right rather than something people with mental health disorders have to earn or prove they deserve by being in treatment" (Tsemberis, 2010).

Many studies have attested to the success of the HF approach in housing chronically homeless individuals with substance use and mental health problems (Rog et al., 2014; Tsemberis et al., 2004). An exploratory study that tracked 80 PSH residents reported that 84% of participants remained housed at the end of a year (Pearson, Montgomery, & Locke, 2009). Similarly, in a randomized controlled trial, the HF group demonstrated higher housing retention at 6, 12, 18, and 24 months compared to the control group (continuum of care model) (Tsemberis et al., 2004). In another study conducted in five Canadian cities, the housing retention rate among HF participants was 73% compared to the 31% among treatment as-usual participants at a one-year follow-up (Aubry et al., 2015).

The HF model has been successful in improving healthcare use (promoting necessary outpatient visits and reducing use of emergency services for non-emergency purposes) and reducing criminal justice use among chronically homeless individuals. A study that explored the healthcare impacts of placing homeless individuals into a supportive housing program found an increase in outpatient service use and a reduction in ED admissions one year following their placement (Rieke et al., 2015). Another study echoed the finding that placement into supportive housing decreased the number of ED visits, the probability of hospital admission, and the average number of healthcare encounters per person (Martinez & Burt, 2006). Along with the reduction in hospital use and length of stay, PSH participants have also demonstrated a reduction in time spent in jail or prison (Culhane et al., 2002). Homelessness can be both a cause and a consequence of incarceration; about 10% of people in jail/prison report history of homlessness and a similar percent enter homelessness upon release (Roman, 2004). The HF model aims to break this vicious cycle and has shown success by significantly reducing recidivism (Somers, Rezansoff, Moniruzzaman, Palepu, & Patterson, 2013).

Due to policymakers' interest in cost containment, proponents of HF often use service costs (including emergency shelters, criminal justice services and healthcare use) as a proxy to illustrate the success of housing individuals into PSH programs. About two decades ago, the cost of serving a homeless individual with mental health problems (including health, emergency shelters and criminal justice services) was estimated to be $40,451 which was reduced by $12,146 per placement in the first year (Culhane et al., 2002). Another study that looked at the overall costs of alcohol-related ED use, jail use, and use of sobering centers found that at six months the average HF participant had a reduced cost of $2449 per month compared to wait-listed controls (Larimer et al., 2009). Similarly, another study comparing six months before and after housing individuals into PSH programs found a reduction in costs related to health care, mental health care, substance abuse treatment, ambulance use, police contact, jail use, shelter use, and ED use (McLaughlin, 2011). While these studies demonstrate positive results in favor of PSH programs, their success is relative to the costs of homelessness. Less is known about longer-term service costs including health care utilization following placement into housing.

2.1.5 Ongoing Health Needs among Individuals with a History of Chronic Homelessness

Even after being placed into housing, many HF residents continue to struggle with managing their health conditions. Early mortality rates are higher among HF residents compared to people in the general population (Henwood et al., 2015). In one study, the all-cause mortality among 45-64 year old male residents of a PSH program was found to be 4.7 times higher compared to that group in the general population (Henwood et al., 2015). On-going health needs further increase the chance of exit from supportive housing programs (Gabrielian et al., 2015).

Among other factors, supportive housing loss was found to be associated with lack of chronic pain management and poor adherence to outpatient care (Gabrielian et al., 2015).

Though stable housing and supportive services have made valuable contributions to the health of people with a history of chronic homelessness, even after being housed numerous barriers continue to threaten the well-being of these individuals (Culhane et al., 2002; Sadowski et al., 2009; Gilmer et al., 2009). Residents typically live near or below the poverty line and struggle to manage chronic disabling conditions. Although, being housed improves some aspects of quality of life (such as food, clothing, shelter and safety), becoming housed does not improve a person's overall quality of life in its entirety (Wolf et al., 2001).

Furthermore, there is a lack of evidence in the literature regarding changes in direct health outcomes after being placed into PSH (Kertesz, Baggett, O'Connell, Buck, & Kushel, 2016). Unlike some studies that found cost savings as described previously, other studies did not show any difference in the healthcare utilization patterns (particularly related to physical health and substance use treatment) of supportive housing residents, compared to those who are eligible but have not been placed (Kessell, Bhatia, Bamberger, & Kushel, 2006). Supportive housing may show success with reducing psychiatric hospitalizations but there is a lack of evidence that it improves healthcare use related to other chronic health problems (Culhane et al., 2002). These findings further highlight a need for additional services to better overall health among supportive housing residents.

2.2 Disease Self-Management and Health

In the past, healthcare systems primarily focused on providing treatment for acute health conditions and placed less emphasis on self-management (Nodhturft et al., 2000). In other words, people only interacted with healthcare systems when they got sick and needed medication/treatment but not for preventive purposes. This placed an inherent dependency on healthcare systems to manage overall health of the population (Nodhturft et al., 2000). In recent years, as the prevalence of chronic diseases has increased, more emphasis is being placed on preventive care and disease management (Anderson & Horvath, 2004). Programs emphasizing self-management to address chronic health conditions have gained popularity over the years (Lorig & Holman, 2003). Six self-management skills are involved in chronic disease management: decision making, problem solving, utilization of resources, establishing a relationship with the provider, planning actions, and tailoring (Lorig & Holman, 2003).

Research evidence shows the benefit of adopting self-management strategies for chronic disease management. In a four-year chronic arthritis self-management program, authors highlighted that pain level among participants decreased by an average of 20% and the number of doctor's visits decreased by 40% contrary to the comparison group that did not see change (Lorig, Mazonson, & Holman, 1993). Another systematic review of randomized controlled trials on the effectiveness of diabetes self-management programs demonstrated improvement in knowledge, diet, glycemic control, and monitoring of blood glucose (Norris et al., 2001). Similarly, in a systematic review of randomized controlled trials assessing the effectiveness of self-management interventions among heart failure patients, authors reported a reduction in hospitalization related to all-causes as well as heart-related (Jovicic et al., 2006).

Traditionally health interventions focused on one behavior at a time or a single health condition or disease state (e.g., overweight, hypertensive). However, there is some evidence that interventions targeting multiple behaviors are more impactful compared to traditional approaches (Prochaska et al., 2008). For example, in a study comparing DASH (Dietary Approaches to Stop Hypertension) to DASH along with exercise and weight management authors reported significant positive results for both groups but the magnitude of improvement was higher for the latter group (Blumenthal et al., 2010). Given this shift, interventions are now targeting chronic disease prevention by focusing on multiple lifestyle changes simultaneously. Health coaching is gaining momentum as a strategy to promoting such lifestyle changes and disease self-management (Huffman, 2007). Although, multiple definitions exist in the literature, health coaching is best described as, “a patient-centered process that is based upon behavior change theory and is delivered by health professionals with diverse backgrounds” (Wolever et al., 2013, p. 38). Based on the theory of self-determination, health coaching promotes intrinsic desire to change and encourages individuals to work towards self-identified health goals (Wolever & Eisenberg, 2011). Evaluation of a health coaching program that served residents affected by Hurricane Sandy showed significant improvements in self-reported health outcomes compared to baseline (Russell, Oberlink, Shah, Evans, & Bassuk, 2018). Case studies of homeless and low-income individuals demonstrated the usefulness of health coaching strategy in building rapport, empowering individuals, and accomplishing individualized goals (Jordan, 2013). No previous studies that utilized health coaching to improve health among supportive housing residents were identified.

2.3 Healthcare Costs in the United States

2.3.1 Healthcare Costs in the United States

Healthcare in the United States is complex, and expenditures are increasing. In the year 1970, the healthcare expenditures in the United States accounted for 6.2% of the gross domestic product (GDP) which has risen to 17.9% in 2016 (Centers for Medicare and Medicaid Services, 2017; Kaiser et al., 2017). The total healthcare expenditures in 2016 was $3.3 trillion or $10,348 per capita (Centers for Medicare and Medicaid Services, 2017). Healthcare expenditures in 2016 represented a 4.3% increase over the previous year (Centers for Medicare and Medicaid Services, 2017). Economists are concerned that the total cost of healthcare will soon exceed half of all economic transactions in the United States (Rich & Barry, 2017). Furthermore, America has the highest healthcare costs compared to other high-income countries listed under the Organization for Economic Cooperation and Development (OECD) (Squires & Anderson, 2015). In 2013, the amount of GDP assigned for healthcare expenditures in the United States was 16.4% in contrast to a mean of 8.9% among all other OECD members countries (OECD, 2015). Hence, the United States has the most expensive healthcare on a global scale in terms of GDP spent on healthcare expenditures.

2.3.2 Factors Driving Healthcare Costs

Multiple factors are associated with healthcare costs in the United States. First, healthcare resources and products are highly-priced. Between 2000 to 2010, 84% of the increase in healthcare costs was attributed to the rise in prices of drugs, medical technologies, and hospital services (Moses et al., 2013). Americans pay more on prescription drugs than other industrialized countries (Kesselheim, Avorn, & Sarpatwari, 2016). Similarly, the cost of the same technical procedures (such as a CT scan) is priced disproportionately higher in the American market compared to other countries (International Federation of Health Plans, 2012).

Second, wasteful spending that is categorized as costs of services that could be eliminated without affecting the quality of care is another key factor responsible for high healthcare costs in the United States (Lallemand, 2012). About $750 billion (30%) of healthcare expenditures in 2009 was unwarranted and wasted due to high administrative costs and avoidable services (McGinnis, Stuckhardt, Saunders, & Smith, 2013). This waste often results from fragmented healthcare systems that lack efficient coordination of care (Hicks, 2015). Additionally, part of the overuse stems from physicians' desire to practice caution. A large cohort study showed that many individuals visiting the ED with low-risk chest pain are often hospitalized for observation and more testing although chances of such symptoms leading to any cardiac event are meager (Weinstock et al., 2015). Another study highlighted that about 43% of doctors were likely to proceed with heart disease-related treatment plans even when evidence showed no benefits to their patients (Rothberg et al., 2010). Fear of malpractice, desire to be cautious, and monetary benefits among doctors results in added overuse of the healthcare system.

The rise in healthcare costs has resulted in a shift in the private insurance structure. Insurance providers have increased the insured consumer's share of the total cost as an approach to reduce healthcare spending (Brot-Goldberg, Chandra, Handel, & Kolstad, 2017). From 2006 to 2015 the percentage of individuals with employer-sponsored insurance paying an annual deductible of $1000 or more increased from 10% to 46% (Kaiser Family Foundation, 2015). There was more focus on the consumer-based payment mechanism after a randomized controlled trial (Rand Health Insurance Experiment) showed a reduction in utilization and overall expenditures as a result of the cost-sharing method (Newhouse, 1993). The cost-sharing approach shares responsibilities between individuals and their insurance providers towards total healthcare expenditures thereby reducing overuse. A recent study reiterated previous findings and projected that if the cost-sharing plans among non-elderly population continued to grow, America could save a total $57.1 billion annually (Haviland, Marquis, McDevitt, & Sood, 2012). Similarly, in another study, participants who switched from free healthcare to high-deductible insurance, healthcare expenditures were reduced 11.79% to 13.80% (Brot-Goldberg et al., 2017). However, the cost effectiveness of this approach is arguable. The reduction in cost alluded by abovementioned studies mostly reflects a drop in the total number of healthcare encounters including ones that are essential for maintaining overall well-being (Brot-Goldberg et al., 2017; Fisher & Lee, 2016; Haviland et al., 2012). Particularly among high-income individuals, the cost-sharing led to a 10% and 18% reduction in the use of preventive services and physician visits respectively (Brot-Goldberg et al., 2017). Therefore, while cost-sharing by increasing deductibles may show promise with a reduction in healthcare spending by controlling overuse in the short term; it can hinder access to necessary care.

Medicaid and Medicare are forms of public insurance designed to provide coverage to low-income or people with severe disabilities and seniors, respectively, and thus largely influence healthcare systems. Serving a total of 111 million beneficiaries, Medicaid and Medicare account for 43% of hospital revenues and 39% of total healthcare expenditures (Altman & Frist, 2015). Considering their large contribution towards overall healthcare costs, both Medicaid and Medicare are often subjected to polarized political debate in America (Cohen, Colby, Wailoo, & Zelizer, 2015). The changing political environment continues to influence the structure of Medicaid and Medicare programs by redefining eligible beneficiaries and reimbursement strategies, thereby affecting healthcare utilization and costs (Kandula, Grogan, Rathouz, & Lauderdale, 2004; Oberlander, 2003).

In summary, healthcare in the United States is complex and expensive. Furthermore, despite higher healthcare spending, people in America have relatively poorer health outcomes compared to other high-income countries (Squires & Anderson, 2015). Reducing cost, increasing access and improving the quality of care remains an utmost priority. To holistically address this issue, it is essential to restore a proper balance among population, enterprises (including pharmaceutical and insurance companies that control market value), and the government (Kaplan & Babad, 2011). The task of achieving this balance is further complicated by many factors such as the social, political, economic, professional, and historical environment (Kaplan & Babad, 2011). A drastic transformation to the current healthcare system, although not impossible, is going to require time. Consequently, it is vital that service providers explore cost-effective approaches to improving population health while planning for a fundamental change in the long run (Austin, Bentkover, & Chait, 2016).

2.3.3 Preventing Services as a Cost-Effective Approach

Failure to execute best practices related to patient safety and preventive services has been identified as a contributor to overall healthcare costs (Berwick & Hackbarth, 2012). There is a growing interest among both policy makers and service providers in promoting preventive services and managed care strategies at the population level to combat at least a fraction of healthcare costs.

2.4 High Utilizers of Healthcare

The total healthcare cost in the United States is distributed disproportionately based on population characteristics (Mitchell & Machlin, 2017). According to the national Medical Expenditure Panel Survey (MEPS) conducted among non-institutionalized individuals in 2015, 5% of high healthcare utilizers accounted for more than 50% of total expenditures (Mitchell & Machlin, 2017). These individuals are referred to as high utilizers. The definition of high utilizers varies in the literature. In general, high utilizers are those who are costly to the system or those who will become expensive in the future. Furthermore, there is a difference between episodic high-utilizers needing expensive care as a result of an adverse event versus regular high utilizers (Newton & Lefebvre, 2015). Designing specific interventions to meet the needs of high-users can help a fraction of healthcare cost (Emeche, 2015). However, it is crucial to recognize the fluidity in the definition and understand characteristics and needs of high utilizers when designing interventions.

There has been a substantial growth in the life expectancy in America giving rise to the number of people over the age of 65, and that number is expected to surge further as baby boomers continue to age (Yang, Norton, & Stearns, 2003). As an inevitable part of the aging process, people who are seniors experience multiple morbidities (Fried, 2012). Due to the complex health needs of older adults, they are often perceived as the primary high utilizers of the healthcare system (Getzen, 1992). Contrary to popular belief, MEPS data showed that 58% of the top 5% of high utilizers were composed of individuals under 65 years of age (Mitchell & Machlin, 2017). Research revealed that it is the proximity to death that predicts increased healthcare expenditure irrespective of the age (Yang et al., 2003). Therefore, focusing on the aging population alone will discount the health needs of other high utilizers.

While Medicare high utilizers are an aging population with multiple chronic health conditions, Medicaid high-utilizers are those experiencing a combination of problems related to their physical health, mental health, substance use, and housing insecurities (Bodenheimer, 2013). Across all age groups, the most common health conditions reported by high utilizers were hypertension, osteoarthritis/joint disorders, hyperlipidemia, mental disorder, heart disease, COPD/asthma, and diabetes (Mitchell & Machlin, 2017). Additionally, people with multiple health conditions continue with high healthcare use over time (Harris et al., 2016). High utilizers often experience delayed care due to lack of access to health care, low level of assistance with managing physical and mental health, and social isolation (Ryan, Abrams, Doty, Shah, & Schneider, 2016). Moreover, 15% of Americans reported no healthcare use in 2015 (Mitchell & Machlin, 2017). No use indicates a lack of recommended preventive care which could create potential high-users in the future (McGlynn et al., 2003). Recognizing these characteristics is a vital step towards designing impactful interventions targeted to address the needs of high utilizers.

2.5 Review of Existing Programs

There is a growing interest in reducing healthcare utilization and costs and improving overall health among high utilizers by implementing additional programs. This section summarizes the evaluation of various interventions and their effectiveness in achieving the goal. Programs included here vary regarding their model selection, target behavior, recruitment criteria, eligibility, doses of the intervention, and rigor of evaluation methods. Community based and hospital discharge approaches are among the two most frequently mentioned methods in the literature.

In a community based program, participants are recruited from the community and the intervention is delivered at the location that works for participants (Bodenheimer, 2013). This model often employs professional (case-managers) or semi-professional (lay community health workers or peer-leaders) health workers to deliver basic health services to the people (Urrutia-Rojas & Luna-Hollen, 2012). Widely utilized among low-income communities all over the world, the community-based approach focuses on primary prevention and health promotion (Edberg, 2012; Urrutia-Rojas & Luna-Hollen, 2012). Furthermore, this model optimizes the health worker's familiarity with the community and bridges access gaps by connecting people to necessary services. Given the lower implementation costs and potentially higher cost saving by reducing morbidity, the community-based strategy has been a popular approach to lowering overall hospital utilization costs (Levine, Becker, & Bone, 1992; Witmer, Seifer, Finocchio, Leslie, & O'neil, 1995). In programs implementing a hospital-discharge approach the focus is on providing care management to patients transitioning from hospital care to home (Bodenheimer, 2013). It is important to distinguish the difference between the target population served when comparing the effectiveness of the two models. While the former model includes individuals based on a health condition thought to be prevalent among high-utilizers, the latter includes direct recruitment of high utilizers. Results regarding cost-savings in particular have to be extrapolated with caution depending on the model used.

There are mixed results in the literature regarding the effectiveness of interventions in reducing overall healthcare spending. A systematic review of 34 studies explored the impact of community health worker interventions designed for individuals with chronic health conditions on their outcomes related to healthcare utilization (Jack, Arabadjis, Sun, Sullivan, & Phillips, 2017). Among 19 studies that looked into change in ED visits, authors discovered varying results; while 5 out of 8 pre-post studies and 2 out of 3 cohort studies showed a significant reduction in ED visits, only 3 out of the 5 randomized controlled trials (RCT) found the same results (Jack et al., 2017). Additionally, among the 17 studies that measured change in hospital use patterns and costs, 1 out of 7 RCTs and 5 of 7 pre-post tests showed significant reduction in hospitalization, and 2 of 3 cohort studies showed substantial decreases in hospitalization costs (Jack et al., 2017). While this systematic review provides a comprehensive overview of the effectiveness of a community-based approach in reducing healthcare use, it is difficult to draw conclusions based on their findings alone given the variability in intervention design and evaluation rigor among the studies included. However, it is clear that such approaches are not universally effective in mitigating costs.

Additionally, interventions varied based on the chronic health condition used as their respective recruitment criteria (Jack et al., 2017). While promoting self-management through health education improves outcomes for some chronic health conditions; it may not produce a desirable result for all depending on the nature and characteristics of the health condition (Warsi et al., 2004). Furthermore, success rates of community-based health promotion programs in influencing healthcare use vary based on the nature of the principal diagnosis (Basu, Jack, Arabadjis, & Phillips, 2017). In a review of RCTs designed to explore the effectiveness of self-management programs among people with diabetes, heart disease, asthma, and mental health, authors reported that the reduction in healthcare utilization was more robust among programs focusing on respiratory and cardiovascular disorders (Panagioti et al., 2014). The majority of the published studies focus on a single health condition. Therefore, for a thorough analysis, this paper categorizes evidence from the literature according to the targeted health condition.

Health promotion programs encouraging self-management have shown improvement in clinical outcomes among people with diabetes (Warsi et al., 2004). Thus, many studies have looked into the efficiency of diabetes management programs in reducing overall healthcare use and found mixed results. Contrary to the expectation, some of the diabetes self-management programs showed no change or increased healthcare use upon engagement in the program (Burton et al., 2017; Rettig et al., 1986). For example, a Diabetes Self-Management Education (DSME) program utilizing a peer-led 8-week diabetes education and nutrition curriculum examined the change in hospital utilization and healthcare costs among participants before and after their enrollment into the program (Burton et al., 2017). This study demonstrated an increase in inpatient stays and costs, but the rate of ED visits stayed the same. Furthermore, the authors looked at utilization based on participants' engagement – individuals who attended 6 or more sessions were considered engaged, and those who attended 5 or fewer sessions were considered unengaged. The unengaged group showed lower hospital costs and fewer admissions compared to the engaged group (Burton et al., 2017). Similarly, in a study that randomized diabetic individuals to an intervention group (who received personalized diabetes self-care education) and control (treatment as usual) found no difference in the hospitalization pattern including emergency visits, doctor's visits, and length of hospital stays between the groups at follow-up (Rettig et al., 1986).

In contrast, some diabetes management programs have seen success with changing healthcare utilization patterns (Fedder et al., 2003; Schmidt et al., 2015; Sidorov et al., 2002). A study that explored the change in healthcare use among African American diabetes patients enrolled in a community based peer-led program found a 38% reduction in the total ED visits and a 5% drop in the length of hospital stays before and after the intervention (Fedder et al., 2003). The study also showed a 27% reduction in mean healthcare expenditures (Fedder et al., 2003). Health workers involved in the program assisted participants with scheduling the recommended physician appointments, which could have contributed towards their successful outcomes. Similarly, another community-based diabetes education program reported a significant reduction in the length of hospital stays and inpatient costs in a pre-post analysis among participants (Schmidt et al., 2015). However, a control group recruited from the same clinic as the intervention group also showed a significant reduction in both categories (Schmidt et al., 2015). The observed changes cannot be attributed to the education program alone. Likewise, in another study comparing healthcare use among diabetic individuals enrolled in a disease management program to those not enrolled, researchers found a lower use of inpatient care and fewer ED visits, but higher number of primary care visits among program participants compared to nonparticipants (Sidorov et al., 2002).

Self-management interventions targeting older individuals with a heart condition showed promise in reducing healthcare use (Cline et al., 1998; Wheeler, 2003). In an RCT designed for women 60 years or older and diagnosed with a heart condition, the authors compared healthcare use and associated costs of the intervention group (peer-led disease self-management education program) to a control group (treatment as usual) (Wheeler, 2003). The intervention group demonstrated 46% fewer hospital inpatient days and 49% lower related charges compared to the control group. However, there were no significant findings related to ED visits or costs (Wheeler, 2003). Similarly, in another RCT, patients 65 or older were recruited at the hospital following an episode of heart failure and randomized into intervention (education on heart health and self-management strategies) and control (routine clinical practice) groups (Cline et al., 1998). The mean time for readmission was prolonged among the intervention group compared to the control group (Cline et al., 1998). Additionally, the intervention group experienced a reduction in their length of hospital stay.

On the contrary, some of the heart health self-management programs displayed no change in healthcare utilization (Galbreath et al., 2004; Smeulders et al., 2009). Individuals with congestive health failure receiving peer-led 6-week self-management sessions (intervention group) reported no significant difference in healthcare utilization including hospital admissions, inpatient days and ED use compared to the control group at follow-up (Smeulders et al., 2009). In another study, patients with experience of congestive heart failure were identified and provided disease management by telephone over the course of 18 months (Galbreath et al., 2004). Healthcare utilization measures in the study were performed using rigorous chart review accounting for all inpatient and outpatient encounters for the study period. Although the program showed improvement with clinical outcomes and survival rates compared to the control group, the program was unsuccessful in reducing hospital utilization including outpatient, inpatient, ED use, and costs (Galbreath et al., 2004).

Interventions focusing on respiratory health exhibited positive results (Bourbeau et al., 2003; Gadoury et al., 2005). Patients with advanced chronic obstructive pulmonary disease (COPD) with at least one hospitalization related to COPD in the previous year were randomly divided into a self-management program or care as usual (Bourbeau et al., 2003). Comprehensive education accompanied by weekly check-ins by trained healthcare specialists were provided to the intervention group for 2 months. As per the data collected at 12 months follow-up, authors found a significant reduction in COPD related hospitalization and other hospitalization by 39.8% and 57.1% respectively among the intervention group compared to the control group (Bourbeau et al., 2003). Additionally, the study also showed a substantial reduction in ED visits (by 41%) and unscheduled physician visits (58.9%) in the intervention group (Bourbeau et al., 2003). This study was followed-up by another group of researchers who examined the long-term outcomes of the program (Gadoury et al., 2005). Although lower in magnitude compared to short-term changes reported in the first paper, at 24-months, the intervention group maintained a significant reduction in hospitalization (26.9%) and ED visits (21.1%) compared to the control group (Gadoury et al., 2005). Despite the sustained positive outcomes, at the caseload of 14 individuals per case manager, the cost of providing this intervention was reported to be higher than the cost saved (Bourbeau et al., 2006). It was recommended to increase the case-load between 50 -70 individuals per case manager to make this program cost-effective as well (Bourbeau et al., 2006).

Few programs addressing self-management focused on more than one chronic health condition at a time (Baicker, Chernew, & Robbins, 2013; Lorig et al., 2001). The Chronic Disease Self-Management Program (CDSMP), a community-based peer-led program, was designed to help participants cultivate self-management skills regarding chronic conditions (Lorig et al., 2001). Individuals 40 years or older with lung disease, heart disease, stroke or arthritis were recruited for the program. Upon completing the program, authors reported a decline in healthcare utilization from baseline to 1 to 2 years among participants (Lorig et al., 2001). Although the results looked promising, one of the key limitations to this study is the manner in which healthcare utilization was operationalized. The physicians and ED visits were combined to calculate a healthcare outcome which could potentially overestimate the effectiveness of the program. Another managed care program with a focus on preventive care among Medicare-eligible seniors did not decrease the number of hospitalizations among participants, but it reduced the length of hospital stay and costs (Baicker et al., 2013).

Although individuals with substance use and mental health disorders have been identified as high utilizers of the system, fewer studies have explored the benefits of self-management programs on their healthcare use (Jack et al., 2017; Bodenheimer, 2013). Among the limited studies promoting substance use management, researchers have shown promising results with improving healthcare use outcomes (Fleming et al., 2000, 2002; Paltzer et al., 2017). In a substance use screening, intervention, and referral program designed for adult Medicaid patients, participants displayed an increase in outpatient days but decreased inpatient hospitalization compared to the treatment-as-usual group over the course of 24-months (Paltzer et al., 2017). While the study also saw a reduction in ED visits among the intervention group, this change was not statistically significant. The net annual Medicaid costs saved were reported to be $391 per adult beneficiary (Paltzer et al., 2017). Likewise, in another brief intervention designed for problem drinkers (defined as consuming more than 14 drinks per week for men and more than 11 drinks per week for women) participants in the intervention group (two 15 minutes brief intervention and reinforcement sessions with the family physician) reported significantly fewer days hospitalized during 12 months follow-up compared to the control group (Fleming et al., 2000). However, other healthcare measures were not significantly different between the two groups at 12 months (Fleming et al., 2000). The research group later published results from 48 months follow up for the same study group and found that the intervention group maintained fewer hospitalized days compared to the control (Fleming et al., 2002). Additionally, the intervention group also maintained fewer ED visits compared to the control at 48 months follow-up (Fleming et al., 2002).

Adhering to medication is vital for mental health patients. In a study that looked at the association between antipsychotic medication adherence and health expenditures among Medicaid beneficiaries, researchers found a lower rate of mental health-related hospitalization among those who adhered to medication compared to those who did not adhere (Gilmer et al., 2004). Promoting self-management among people with mental health problems is key to reducing healthcare use and costs. An observational study examined hospitalization data among adults with severe mental illness 2 years before and after their enrollment in the Assertive Community Treatment (ACT) program (Clausen et al., 2016). The authors found that although the number of hospital admissions stayed the same (average of 3 during each 2 year period), the inpatient days was reduced by 50% after their enrollment in the program (Clausen et al., 2016). The authors also compared the change between high utilizers (categorized as participants with 100 consecutive days of inpatient stay or more than 4 mental health-related hospitalizations during 2 years) at baseline and low utilizers (all others). While the reduction in inpatient days was obvious among high utilizers, low utilizers saw an initial increase followed by a reduction in that category (Clausen et al., 2016).

In summary, evidence on the effectiveness of self-management programs on healthcare use outcomes is inconsistent in the literature. Due to differences in recruitment strategies, study timeframes, data collection methods, targeted chronic health conditions and rigor of analyses, it is difficult to draw comparisons and assess the relative success of interventions. Furthermore, studies have demonstrated a collective adverse effect of multiple risk factors on individuals' long-term health (Prochaska & Prochaska, 2011). This clustering of risk factors demand a health promotion approach targeting numerous behaviors (Noble et al., 2015). We also know that the majority of Americans engage in more than one risk behavior (Fine et al., 2004). Although promising, few studies have evaluated interventions targeting holistic lifestyle change among high utilizers of human service systems and even fewer have assessed it's impact on healthcare use outcomes (Prochaska & Prochaska, 2011). This study was the first to look at the effectiveness of lifestyle change approaches on healthcare use outcomes for a supportive housing residents.

Chapter 3: Methods

This mixed method evaluation study of the *m.chat* program included a retrospective medical claims record review for participants enrolled in *m.chat*, as well as focus groups and interviews intended to elicit information about perceived health status, healthcare utilization, and programmatic impacts on health.

3.1 Mobile Community Health Assistance for Tenants (*m.chat)*

Funded through a Medicaid 1115 Waiver to the State of Texas, Mobile Community Health Assistance for Tenants (*m.chat)* was developed as a community-based research project to improve health and well-being among low-income supportive housing residents in the RHP 10 Region of North Texas. The RHP 10 Region includes nine counties: Tarrant, Wise, Parker, Erath, Hood, Somervell, Johnson, Ellis, and Navarro. The goal of *m.chat* was to improve health outcomes by providing supplemental services that were not already offered through participant's housing services (Walters, Spence-Almaguer, Hill, & Abraham, 2015).

3.1.1 Theoretical basis of *m.chat*

m.chat utilized technology-enhanced health coaching, motivational interviewing and brief solution-focused strategies, and wellness incentives. Health coaching for *m.chat* was defined as a client-centered process to promote behavior change delivered through one-on-one coaching over the course of the program (Wolever et al., 2013). Coaches utilized motivational interviewing to tap into an individual's intrinsic motivation to change (Miller & Rollnick, 2012). Additionally, the program used solution-focused therapy techniques founded by de Shazer and Berg and placed an emphasis on exploring solutions, community resources, and goal setting for health improvements instead of concentrating on participants' current and past problems (Iveson, 2002). The technological platform of the program provided customized reminders concerning participants' goals to increase motivation for change (Fogg, 2009). Furthermore, financial incentives were used to promote achievement of behavioral goals (Kane, Johnson, Town, & Butler, 2004).

3.1.2 *m.chat* screening criteria

Participants' eligibility in the program was determined based on three screening criteria: housing, insurance, and mental health status. Participants were required to be enrolled in a supportive housing program. As *m.chat* was funded through a Medicaid Waiver, participants were also required to be Medicaid recipients or Medicaid eligible (including Medicaid only recipients, Medicaid and Medicare recipients, and uninsured). Furthermore, *m.chat* was designed to serve people experiencing mental health symptoms as defined by a score of 9 or higher on the PHQ-9 scale or who answered "yes" to any one of the following questions: Do you receive a pension for a psychiatric disability? Have you experienced hallucinations-saw things/heard voices that others didn't see/hear? Have you been prescribed medication for psychological and emotional problems? Participants who met these criteria were eligible to be enrolled in *m.chat.*

3.1.3 *m.chat* program structure

Upon enrolling into the program, each participant was assigned a health coach. However, due to staff turnover, some participants may have worked with more than one health coach over the course of their time in *m.chat.* Participants met with their health coaches monthly to develop customized health goals within six domains: exercise, diet, social support, medication adherence, substance use, and recreation. Coaching software was utilized during health coaching sessions to record personalized goals, track goals progress, and store coaching notes. To monitor changes over time in the abovementioned domains, participants were assessed at baseline, 6 months, 12 months, and 18 months. Data from assessments and participant encounters were stored in a cloud-based system called Efforts to Outcomes (ETO).

3.1.4 Participant characteristics

From November 2014 to November 2017, a total of 653 participants enrolled in the program. Fifty six percent of *m.chat* participants were female and 44% were male. The majority of participants were black (57%), while 35% were white, and 8% identified as a race other than black or white. The average age of participants was 51 years and ranged from 20 to 80 years. The average time spent during monthly coaching sessions was 53 minutes. Participants could be enrolled for up to 18 months, but participants spent a varying amount of time engaged in the program. Additionally, the 18-month timeframe for the program was introduced later in the implementation of *m.chat*, therefore, a small portion of participants (n=36) engaged in the program for longer than 18 months. The table below shows the number of participants completing various milestones in the program.

Amount of time spent in the program	Number of participants
Enrolled	653
At least 6 months	461
At least 12 months	300
At least 18 months	252

3.2 Quantitative Study Design and Data Source

This component of the study involved a retrospective medical claims data review for *m.chat* participants to assess Aim 1 and Aim 2. At the time of enrollment all *m.chat* participants provided written consent granting *m.chat* permission to collect additional data regarding their healthcare utilization to assess the effectiveness of the program under the IRB protocol approved by the University of North Texas Health Science Center. In the Spring of 2017, we commenced a data request process with the Dallas Fort Worth Hospital Council (DFWHC).

3.2.1 Dallas Fort Worth Hospital Council (DFWHC)

Established in 1968, DFWHC Foundation is a non-profit organization that aims to improve community health by promoting accessible, equitable, affordable, safe and high-quality healthcare (Dallas Fort Worth Hospital Council, 2018). DFWHC aspires to "enhance hospital value by continually promoting patient safety and cost effective, quality healthcare in the region" (Dallas Fort Worth Hospital Council, 2016). Currently there are 90 member hospitals in partnership with DFWHC (Dallas Fort Worth Hospital Council, 2016).

In 1999, North Texas Hospital Systems developed a data warehouse as a centralized location to store individual level medical claims data (Mendoza et al., 2014). The DFWHC Research Foundation is in charge of securely housing and managing the data warehouse also known as the Information and Quality Service Center (IQSC) (Mendoza et al., 2014). The IQSC gathers healthcare data from 95% of hospitals (DFWHC partners) in the North Texas area which includes over 35 million hospital encounters for over 9.5 million patients (Mendoza et al., 2014).

Member hospitals send identifiable patient level medical claims data to IQSC on a quarterly basis. Data sent by member hospitals include outpatient hospital visits (including surgical procedures and advanced imaging) but does not include office based/clinic visits. IQSC assigns a unique ID to each patient and consolidates data at individual level. Hence, IQSC has the ability to track an individual patient by their number of encounters, hospitals they visited, and by payers over time (Mendoza et al., 2014). The IQSC dataset includes variables such as demographic (age, race, gender), hospital name, hospital system, admission type (outpatient, inpatient, emergency visits), date of admission and discharge, up to 25 diagnostic categories and procedural codes, charged amounts (total, ancillary charges and accommodation charges), and bill type for every single encounter (defined as each distinct visit to the hospital for any purpose).

Given the geographic coverage of the data warehouse and the residential location of *m.chat* participants, UNTHSC contracted with DFWHC to purchase retrospective medical claims data. The following maps highlight geographical coverage of *m.chat* participants and DWFHC member hospitals.

Figure 1: *m.chat* participants' housing locations by zip code

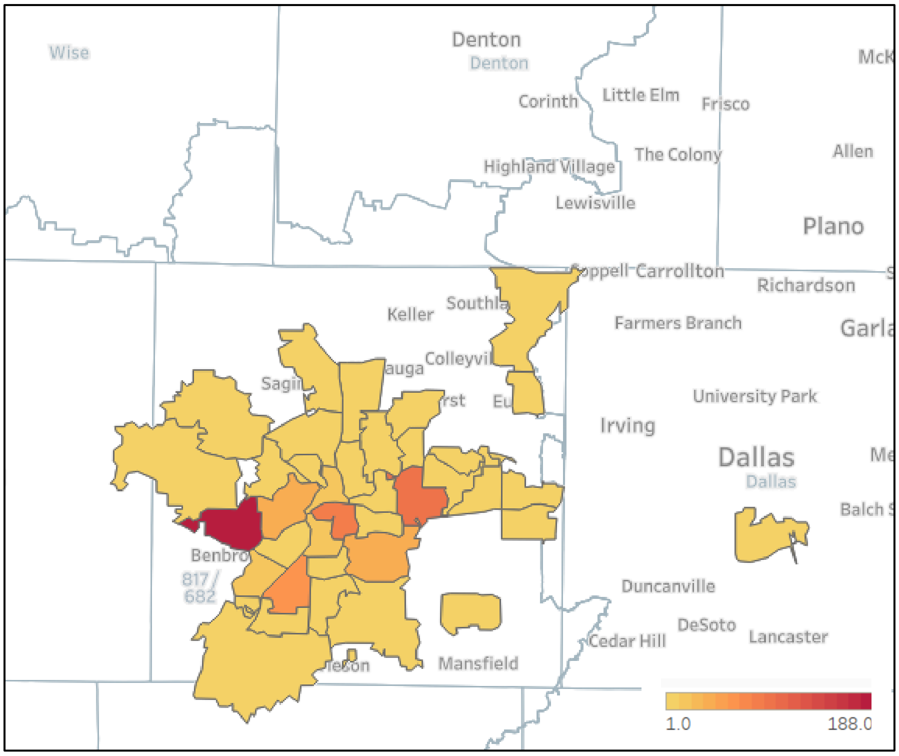
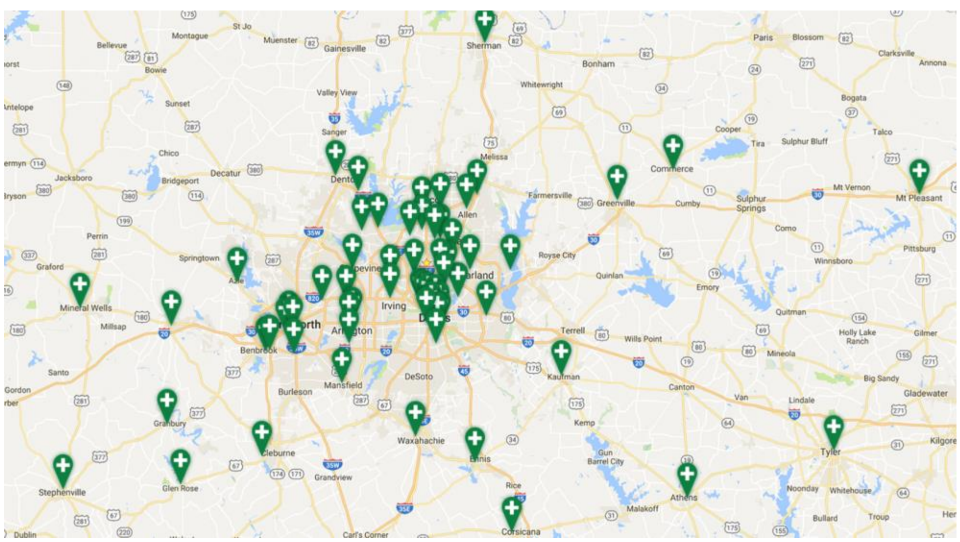


Figure 2: DFWHC member hospitals



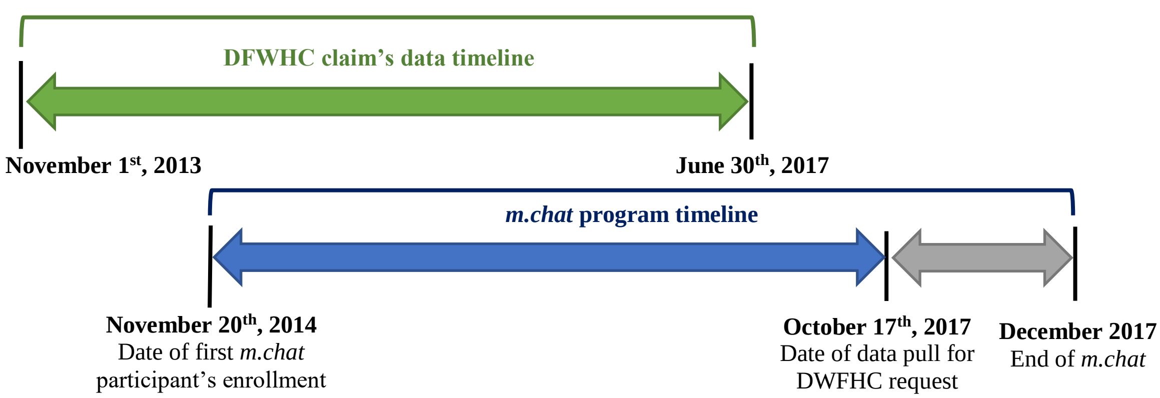
Picture Source: DFWHC website

3.2.2 Quantitative Data Request

Upon approval of the data request made to the DFWHC, a list of 650 *m.chat* participants (who had been screened and had successfully completed baseline at the time of data pull) was created on October 17th, 2017. The list was downloaded from the *m.chat* database (ETO) and included variables such as full name, date of birth, gender, race, all recorded addresses with zip codes, and all recorded phone numbers for the participants. The list was sent to DFWHC via a secure data share portal. DFWHC staff used the provided identifiers to flag *m.chat* participants in their system.

The very first *m.chat* participant was enrolled in the program in November 2014. To ensure the availability of medical claims data for at least one year before enrollment for all *m.chat* participants, the first enrollment data was utilized as an anchor and healthcare use data was requested from November 1st, 2013. At the time of data request in October of 2017, DFWHC's databased contained complete data through June 30th, 2017; the lag between this date and the data request date is due to the time it takes for hospitals to generate medical claims and send data to DFWHC, as well as the time needed for DFWHC to upload the data. Hence, for all the matched *m.chat* participants, medical claims data was requested for the period of November 1, 2013 to June 30, 2017. The figure below demonstrates data timeline.

Figure 3: Timeline for *m.chat* and DFWHC data pull



3.2.3 Quantitative Data Source

The DFWHC team were able to match identifiers for 566 out of 650 (87%) *m.chat* participants in their system. The compiled medical claims data from November 1st, 2013 to June 30th, 2017 for all matched participants were sent to the UNTHSC research team via a secure file transfer method. The dataset includes a total of 55,257 records for 566 people for the 44-month time period.

Data pertaining to each encounter was linked to DFWHCID (an encounter specific unique ID assigned by DFWHC). A unique patient identifier (REMPID) was assigned to each individual. Key variables in the DFWHC dataset included demographic (age, race, gender), hospital name, hospital system, admission type (outpatient, inpatient), date of admission and discharge, up to 25 diagnostic categories and procedural codes, charged amount (total, ancillary charges and accommodation charges), and bill type. In the event of an inpatient stay that resulted in a transfer to another DFWHC partner hospital, the transfer was recorded as a separate encounter. However, a transfer to a non-partner healthcare facility is not included in DFWHC data and therefore, was not included in analysis for this study.

Data regarding participants' dates of enrollment into *m.chat*, number of heath coaching sessions completed, time spent per coaching session, and number of assessments completed along with the date of completion for the matched participants were extracted from the ETO database and merged with the DFWHC medical claims data.

3.2.4 Descriptive Statistics on participants characteristics

Given the timeframe included in DFWHC dataset and the varying dates of enrollment of *m.chat* participants, a separate subgroup of participants was created for the analysis for Aim 1 and Aim 2. A total of 244 *m.chat* participants had 12-months pre enrollment and 12-month post enrollment medical claims data according to their date of enrollment into *m.chat* and date cut-offs for DFWHC data and were included in Aim 1. However, only 131 matched *m.chat* participants with 12-24 months post enrollment claims data in the dataset were included in analysis for Aim 2. Descriptive statistics were performed on both subgroups to assess participant characteristics.

3.2.5 Quantitative Outcome Assessment and Statistical Considerations

Aim 1: To describe patterns and assess changes in healthcare utilization measures, including total hospital encounters, inpatient stays, outpatient hospital visits, emergency department visits and charged amounst among m.chat participants 12-months pre and 12-months post enrollment into the program.

To explore the patterns of hospital use, data for variables such as total hospital encounters, inpatient stays, outpatient visits, emergency room visits, and charged amount was plotted using a spaghetti plot. This helped to visualize change over time.

Prior to analysis, each encounter was coded as 12-months pre *m.chat* enrollment encounter and 12-months post *m.chat* enrollment encounter using participant specific *m.chat* baseline dates and hospital discharge dates (from DFWHC). The table below shows variables of interest and the statistical approaches used for analyses.

Table 1: Quantitative variables and statistical approach included in Aim 1 and Aim 2 analysis

Variable	Type	Statistical approach
Total hospital encounters	Count	Zero-inflated negative binomial regression
Inpatient stays	Count	Zero-inflated negative binomial regression
Outpatient visits	Count	Zero-inflated negative binomial regression
Emergency department visits	Count	Zero-inflated negative binomial regression
Emergency department visits classification	Count	Descriptive
Charged amount	Continuous	Log-gamma model

Preliminary data exploration using the latest version of SPSS (version 24), showed that the means and variance were different for count variables, therefore Poisson regression could not be used for analysis. To address the excessive number of zeros in the count variables, zero-inflated negative binomial regression was used for analysis. Similarly, the charged amount variable was skewed, as a small portion of the sample tend to be responsible for a large portion of the overall charged amounts. The variable violated the assumption of homoscedasticity given the variability in the data (Blough & Ramsey, 2000). Therefore, to account for both skewedness and heteroscedasticity a log-gamma model was used. The participant ID variable was incorporated into both analyses to account for correlation among repeated measures within a participant. The statistical significance of the results from the analysis was determined using a type I error less than or equal to 0.05.

DFWHC file also included variables classifying the nature of ED visits based on an algorithm developed by New York University (Ballard et al., 2010). This NYU algorithm was created to help improve healthcare efficiency by distinguishing necessary ED visits from those that can be treated in a non-emergency setting (Ballard et al., 2010). Utilizing retrospective administrative data, the NYU algorithm calculates the probability that an ED visit was non-emergent, emergent-primary care treatable, emergent-preventable, or emergent-not-preventable (Johnston, Allen, Melanson, & Pitts, 2017). These variables were used to explore the nature of ED visits and their relationship to program participation. Furthermore, to assess condition-specific changes in heathcare use, the Clinical Classification Software (CCS) categories were also explored descriptively. Developed by the Agency for Healthcare Research and Quality, CCS categories represent a smaller number of clinically meaningful groups created based on various diagnosis and procedure codes (Agency for Healthcare Research and Quality, 2017). Given the timeframe covered, our dataset included CCS categories representing both ICD-9 and ICD-10 codes. However, CCS categories from ICD-10 codes are yet to be finalized so our results must be extrapolated with caution (Agency for Healthcare Research and Quality, 2018).

Aim 2: To compare changes in healthcare utilization measures, including total hospital encounters, inpatient stays, outpatient hospital visits, emergency department visits and charged amounts among m.chat participants at 12-months pre, 12-months post their enrollment, and between 12 to 24-months post enrollment into the program.

Statistical processes for Aim 1 were repeated for Aim 2 with a smaller sample size.

3.3 Qualitative Study Design and Data Source

This component of the study explored participants' perceptions about *m.chat* and ways in which the program influenced their health and healthcare utilization. This method involved non-probability purposive sampling; eligible participants (eligibility criterion described below) who were available and willing to participate at the time of recruitment were invited for focus group/interview sessions (Onwuegbuzie & Leech, 2007). It can also be coined homogeneous sampling (sampling of people with similar characteristics and experiences) as it involved recruitment of participants who have all been through the *m.chat* program and possess similar characteristics (Onwuegbuzie & Leech, 2007).

Aim 3: To explore participants' perceptions about how m.chat influenced their healthcare use through focus groups and interviews.

3.3.1 Qualitative Data Source

Throughout the course of the program, *m.chat* participants were also asked to complete monthly assessments where they were asked about their interest in being contacted for any future research activities. Complying with the research protocol approved by the Institutional Review Board (IRB) at UNTHSC, a list of participants who had answered "Yes" to the qualifying question in their most recent monthly assessment prior to the program end date was extracted from ETO where data from all monthly assessments were stored. A total of 181 participants out of the total 653 had answered "Yes" to the qualifying question.

The first phase of recruitment invited participants who completed at least 12 months with the program (52 out of the 181 eligible participants). As *m.chat* program ended as of Dec 2017, participants eligible for focus groups and interviews were no longer in contact with *m.chat* program staff. For some of the participants, the list of phone numbers available were no longer viable. Therefore, recruitment proved to be challenging. Unable to reach our target number we then opened recruitment to eligible participants who completed at least 6 months with *m.chat* program in the second phase.

We conducted 4 focus groups and 2 interviews with a total of 21 participants. While the recommended sample size for focus groups to reach theoretical saturation varies in the literature, some researchers indicate that 3-5 focus groups will generate reasonable amount of data to draw conclusions about sample population (Morgan, 1997). Additionally, it is possible to reach theoretical saturation with a homogeneous sample even with a smaller number of focus groups (Kuzel, 1992).

3.3.2 Coding

All focus groups/interviews were audio recorded. Recordings were then transcribed into an Excel file. Questions, participant numbers (assigned by the person transcribing to de-identify the data) and qualitative data were transcribed into separate columns in Excel. Each distinct thought that emerged from the transcript was recorded in respective rows. We used the grounded theory approach to coding and analysis of data. Founded by Glaser and Strauss, grounded theory is an inductive process of coding data and integrating categories (Charmaz & Belgrave, 2007). Over the years, grounded theory has evolved in its analytic approach. This study used the grounded theory open, axial and selective approach to coding (Walker & Myrick, 2006).

In the first phase of coding, each distinct idea within the transcript was coded into open codes using key phrases or basic descriptors from the data. Open coding captured the observed description of each thought from the data and assigned a label to the passage (Moghaddam, 2006). Open codes were then bundled into axial codes based on common characteristics and relationships generated by open codes. Axial codes represent a systematic classification of open codes based on themes generated through the first layer of coding process (Moghaddam, 2006). As a final stage of coding, axial codes were then categorized into fewer selective codes which signified core themes that helped explain the overarching phenomena (Moghaddam, 2006). We then ran a frequency count on the final list of selective and axial codes which were included in the results section to demonstrate concepts generated through qualitative process. Selected quotes from participants were used as examples to provide context in addition to frequencies.

Chapter 4: Results

4.1 Quantitative Results:

The DFWHC team were able to match identifiers for 566 out of 650 (87%) *m.chat* participants in their system. The dataset included 55,257 records associated with 5929 unduplicated encounters for 566 people over the course of the 44-month period.

4.1.1 Participant Characteristics:

Table 2 below highlights the demographic information for all matched participants included in DFWHC file. The majority of participants were female, Black/African American, divorced or separated, and with a high school level education. Table 3 shows hospital systems where 5929 unduplicated hospital services were received for 566 participants over the course of the requested time period.

Table 2: Demographic information on all matched participants (n=566)

		Frequency	Percentage
Gender			
	Female	319	56.4%
	Male	247	43.6%
Race			
	Black/African American	326	57.6%
	White	198	35.0%
	Other	33	5.8%
	White/Indian (Native American)	5	0.9%
	Refused to answer/Don’t know	4	0.7%
Age			
	Mean (min-max; SD)	53 (22–77, 9.8)	
Marital Status			
	Divorced/Separated	269	47.6%
	Never married	213	37.7%
	Widowed	41	7.3%
	Married/Remarried	41	7.3%
	Refused to answer	1	0.2%

Education Status			
	High school	249	44.1%
	Less than high school	184	32.6%
	More than high school	132	23.4%

Table 3: Hospital systems represented in the dataset (n=5929)		
	Frequency	Percentage
Tarrant County Hospital District	2610	44%
Texas Health Resources	2105	36%
Baylor Scott & White Health & Tenet	524	9%
HCA Healthcare	489	8%
Parkland Health & Hospital Systems	108	2%
Methodist Health System	51	1%
UTSW Medical Center University	19	0%
Wise Regional Health System	16	0%
Others	7	0%

4.1.2 Results for Aim 1:

Given the timeframe included in DFWHC dataset and the varying dates of enrollment of respective *m.chat* participants, a separate subgroup of participants was created for the analysis for Aim 1. A total of 244 matched *m.chat* participants had 12-months pre enrollment and 12-month post enrollment medical claims data included in the file.

Aim 1: To describe patterns and assess changes in healthcare utilization measures, including total hospital encounters, inpatient stays, outpatient hospital visits, emergency department visits and charged amounts among m.chat participants 12-months pre and 12-months post enrollment into the program.

Table 4 below highlights the demographic information for all participants included in the analysis of Aim 1. The majority of participants were female, Black/African American, divorced or separated, and with a high school level education. Table 5 shows hospital systems where 1187 unduplicated hospital services were received for 244 participants over the course of 2 years included in this analysis.

Table 4: Demographic information on participants included in 12-months pre and 12-months post analysis (n=244)

		Frequency	Percentage
Gender			
	Female	130	53.3%
	Male	114	46.7%
Race			
	Black/African American	124	50.8%
	White	104	42.6%
	Other	15	6.1%
	Refused to answer	1	0.4%
Age			
	Mean (min-max; SD)	55 (27–72, 8.4)	
Education Level			
	High school	102	41.8%
	Less than high school	78	32.0%
	More than high school	64	26.2%
Marital Status			
	Divorced/Separated	121	49.6%
	Never married	95	38.9%
	Married/Remarried	16	6.6%
	Widowed	12	4.9%
m.chat Health Coaching Attendance			
	10 or more sessions in year 1	127	52%
	6 to 9 sessions in year 1	94	39.0%
	Less than 6 sessions in year 1	23	9.0%

Table 5: Hospital Systems represented in 12-months pre and 12-months post analysis (n=1187)

Hospital	Frequency	Percentage
Tarrant County Hospital District	571	48%
Texas Health Resources	424	36%
Baylor Scott & White Health	109	9%
HCA Healthcare	68	6%
Methodist Health System	5	0%
UTSW Medical Center University	5	0%
Wise Regional Health System	4	0%
Parkland Health & Hospital Systems	1	0%

4.1.2.1 Total encounters

The total number of hospital encounters increased slightly from 589 to 598 from 12-months pre enrollment to 12-months post enrollment into *m.chat* for 244 participants. The mean number of encounters also showed a slight increase from 2.41 to 2.45. The number of encounters for 12-months pre enrollment period ranged from 0 to 29 which widened for 12-months post enrollment period ranging from 0 to 39. Figure 4 below shows the distribution of total encounters for the two time periods. Table 6 displays the breakdown of encounters pre and post based on demographic characteristics.

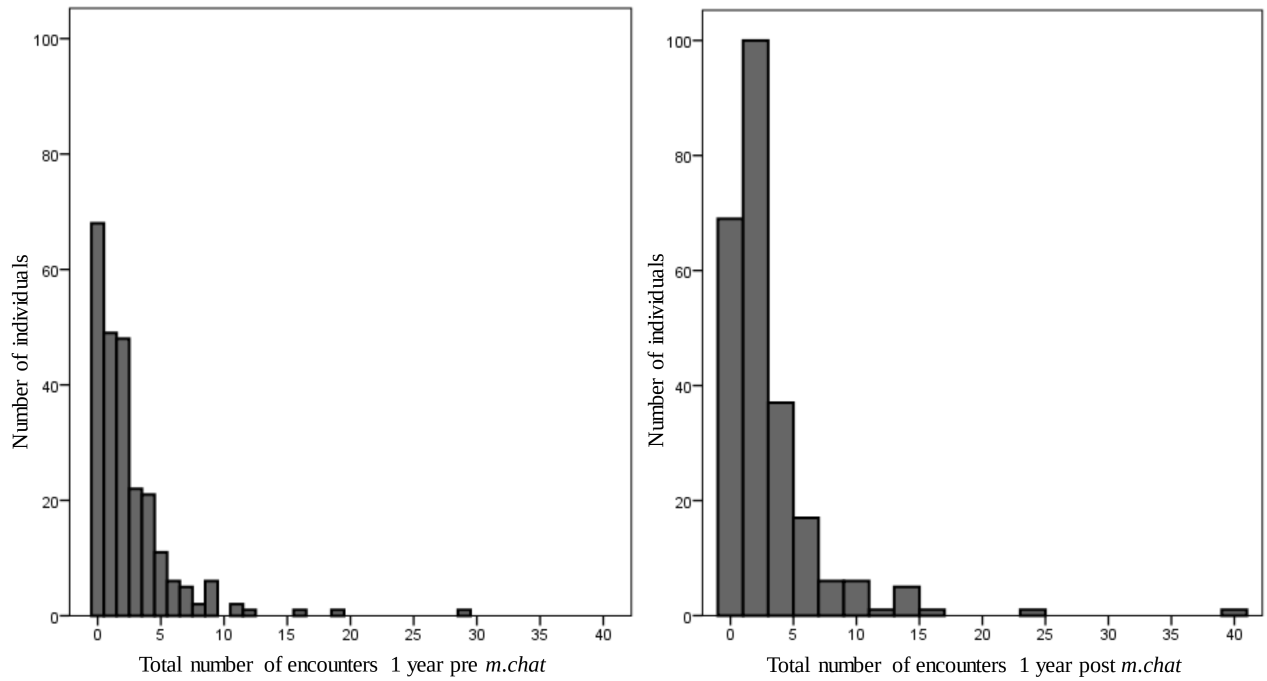


Figure 4: Distribution of total pre and post 1-year hospital encounters count per individual

Table 6: Total hospital encounters 12-months pre and 12-months post enrollment to *m.chat* broken down by demographic characteristics (N=1187)

			1-year pre *m.chat*				1-year post *m.chat*			
		N	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D
Gender										
	Female	130	322	2.48	0-19	2.84	373	2.87	0-39	4.26
	Male	114	267	2.34	0-29	3.65	225	1.97	0-23	3.50
	Total	244	589	2.41	0-29	3.24	598	2.45	0-39	3.94
Race										
	Black/African American	124	256	2.06	0-9	2.21	272	2.19	0-15	2.88
	White	104	295	2.84	0-29	4.20	288	2.77	0-39	5.07
	Other	15	32	2.13	0-9	2.39	29	1.93	0-7	1.87
	Total	243	583	2.41	0-29	3.24	589	2.42	0-39	3.93
Education Level										
	Less than high school	78	176	2.26	0-11	2.50	205	2.63	0-14	3.50
	High school	102	256	2.51	0-19	3.16	243	2.38	0-39	4.35
	More than high school	64	157	2.45	0-29	4.09	150	2.34	0-23	3.82
	Total	244	589	2.41	0-29	3.24	598	2.45	0-39	3.94
Marital Status										
	Divorced/ Separated	121	241	1.99	0-19	2.53	271	2.24	0-39	4.34
	Never married	95	258	2.72	0-29	3.89	230	2.42	0-23	3.44
	Married/ Remarried	16	56	3.50	0-16	3.97	52	3.25	0-10	3.53
	Widowed	12	34	2.83	0-7	2.48	45	3.75	0-15	4.09
	Total	244	589	2.41	0-29	3.24	598	2.45	0-39	3.94
Age										
	25-39 years	17	46	2.71	0-9	2.54	42	2.47	0-9	2.70
	40-59 years	155	387	2.50	0-29	3.72	374	2.41	0-39	4.42
	Above 60 years	72	156	2.17	0-11	2.09	182	2.53	0-15	3.04
	Total	244	589	2.41	0-29	3.24	598	2.45	0-39	3.94

4.1.2.2 Inpatient visits

The total number of inpatient visits decreased slightly from 45 to 43 from 12-months pre enrollment to 12-months post enrollment for 244 participants. The mean number of inpatient visits stayed the same at 0.18. The range of inpatient visits for 12-months pre enrollment period was 0 to 5 which decreased slightly for 12-months post enrollment period ranging from 0 to 4. Figure 5 below shows the distribution of inpatient visits for the two time periods. Table 7 displays the breakdown of inpatient visits pre and post based on demographic characteristics.

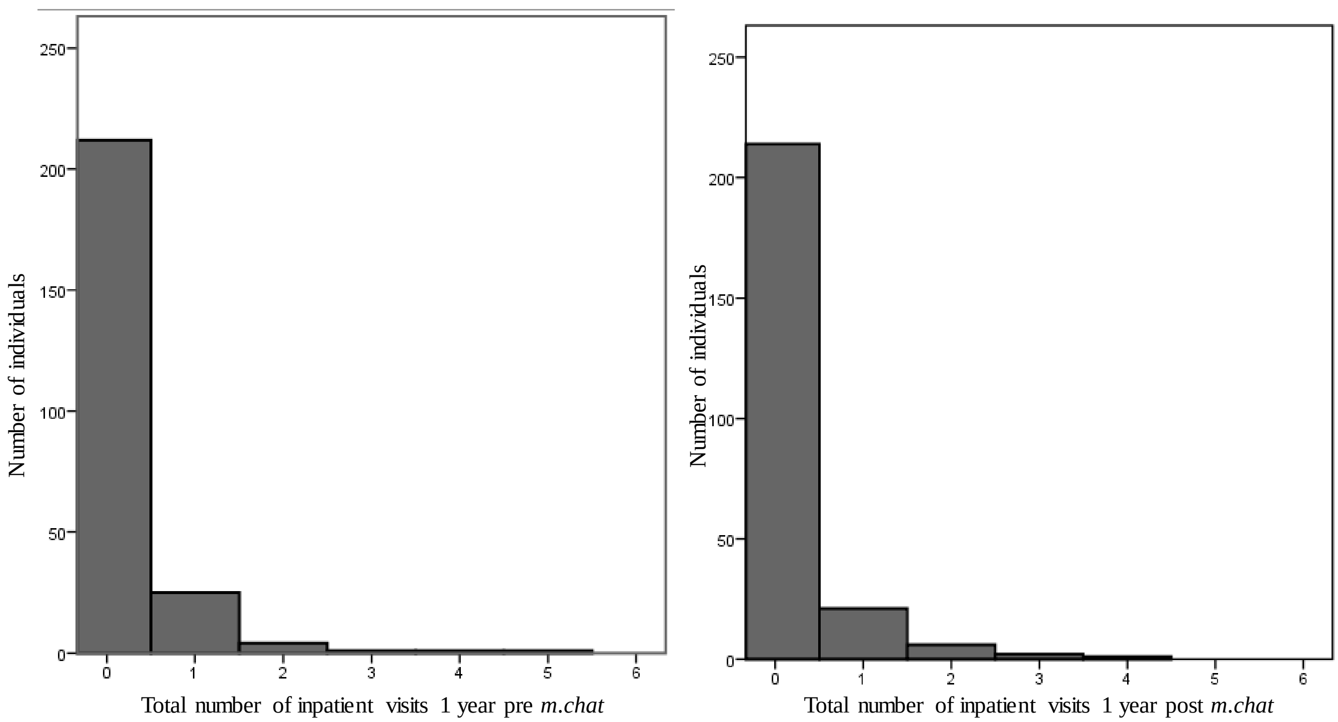


Figure 5: Distribution of total pre and post 1-year inpatient visits count per individual

Table 7: Total inpatient visits 12-months pre and 12-months post enrollment to *m.chat* broken down by demographic characteristics (N=1187)

			1-year pre *m.chat*				1-year post *m.chat*			
		N	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D
Gender										
	Female	130	25	0.19	0-3	0.48	24	0.18	0-4	0.55
	Male	114	20	0.18	0-5	0.68	19	0.17	0-3	0.53
	Total	244	45	0.18	0-5	0.58	43	0.18	0-4	0.54
Race										
	Black/African American	124	24	0.19	0-3	0.5	23	0.19	0-3	0.55
	White	104	19	0.18	0-5	0.69	17	0.16	0-4	0.54
	Other	15	2	0.13	0-1	0.35	1	0.07	0-1	0.26
	Total	243	45	0.19	0-5	0.58	41	0.17	0-4	0.53
Education Level										
	Less than high school	78	13	0.17	0-2	0.41	14	0.18	0-3	0.55
	high school	102	16	0.16	0-3	0.48	15	0.15	0-4	0.53
	More than high school	64	16	0.25	0-5	0.85	14	0.22	0-3	0.55
	Total	244	45	0.18	0-5	0.58	43	0.18	0-4	0.54
Marital Status										
	Divorced/ Separated	121	13	0.11	0-2	0.34	21	0.17	0-4	0.59
	Never married	95	24	0.25	0-5	0.77	16	0.17	0-2	0.45
	Married/ Remarried	16	2	0.13	0-2	0.50	5	0.31	0-3	0.79
	Widowed	12	6	0.50	0-2	0.80	1	0.08	0-1	0.29
	Total	244	45	0.18	0-5	0.58	43	0.18	0-4	0.54
Age										
	25-39 years	17	4	0.24	0-1	0.44	3	0.18	0-2	0.53
	40-59 years	155	29	0.19	0-5	0.65	23	0.15	0-4	0.52
	Above 60 years	72	12	0.17	0-2	0.44	17	0.24	0-3	0.59
	Total	244	45	0.18	0-5	0.58	43	0.18	0-4	0.54

4.1.2.3 Outpatient visits

The total number of outpatient visits increased slightly from 544 to 555 from 12-months pre enrollment to 12-months post enrollment for 244 participants. The mean number of outpatient visits also increased slightly from 2.23 to 2.27. The range of outpatient visits for 12-months pre enrollment period was 0 to 29 which widened for 12-months post enrollment period ranging from 0 to 35. Figure 6 below shows the distribution of outpatient visits for the two time periods. Table 8 displays the breakdown of outpatient visits pre and post based on demographic characteristics.

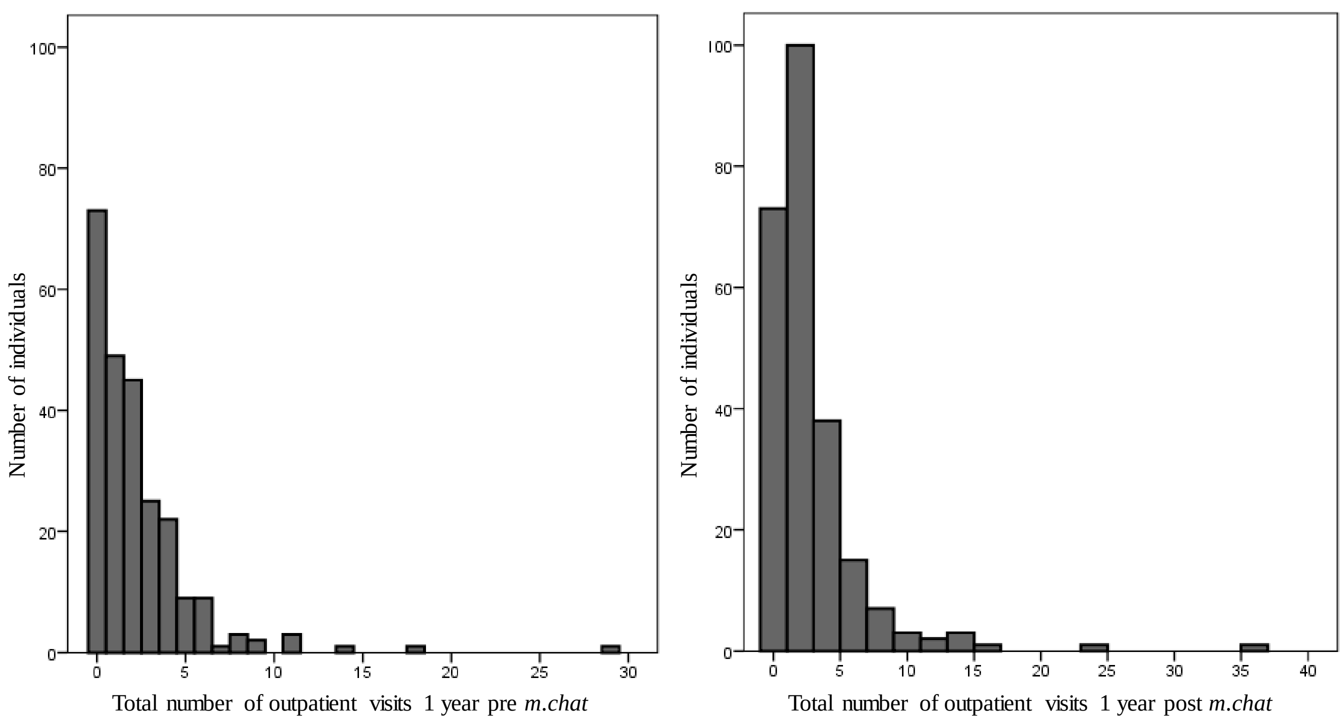


Figure 6: Distribution of total pre and post 1-year outpatient visits count per individual

Table 8: Total outpatient visits 12-months pre and 12-months post enrollment to *m.chat* broken down by demographic characteristics (N=1187)

			1-year pre *m.chat*				1-year post *m.chat*			
		N	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D
Gender										
	Female	130	297	2.28	0-18	2.66	349	2.68	0-35	3.89
	Male	114	247	2.17	0-29	3.46	206	1.81	0-23	3.35
	Total	244	544	2.23	0-29	3.06	555	2.27	0-35	3.67
Race										
	Black/African American	124	232	1.87	0-9	1.98	249	2.01	0-15	2.58
	White	104	276	2.65	0-29	4.03	271	2.61	0-35	4.77
	Other	15	30	2.00	0-8	2.20	28	1.87	0-7	1.92
	Total	243	538	2.21	0-29	3.05	548	2.26	0-35	3.66
Education Level										
	Less than high school	78	163	2.09	0-11	2.35	191	2.45	0-14	3.26
	high school	102	240	2.35	0-18	2.92	228	2.24	0-35	3.95
	More than high school	64	141	2.20	0-29	3.94	136	2.13	0-23	3.72
	Total	244	544	2.23	0-19	3.06	555	2.27	0-35	3.67
Marital Status										
	Divorced/ Separated	121	228	1.88	0-18	2.43	250	2.07	0-35	3.98
	Never married	95	234	2.46	0-29	3.71	214	2.25	0-23	3.27
	Married/ Remarried	16	54	3.38	0-14	3.56	47	2.94	0-9	3.04
	Widowed	12	28	2.33	0-5	1.87	44	3.67	0-15	4.08
	Total	244	544	2.23	0-29	3.06	555	2.27	0-35	3.67
Age										
	25-39 years	17	42	2.47	0-9	2.55	39	2.29	0-7	2.34
	40-59 years	155	358	2.31	0-29	3.51	351	2.26	0-35	4.13
	Above 60 years	72	144	2.00	0-11	1.93	165	2.29	0-15	2.79
	Total	244	544	2.23	0-29	3.06	555	2.27	0-35	3.67

4.1.2.4 Emergency visits

The total number of emergency visits increased from 434 to 454 from 12-months pre to 12-months post enrollment for 244 participants. The mean number of emergency visits also increased slightly from 1.78 to 1.86. The range of emergency visits for 12-months pre enrollment period was 0 to 28 which widened for 12-months post enrollment period ranging from 0 to 39. Figure 7 below shows the distribution of emergency visits for the two time periods. Table 9 displays the breakdown of emergency visits pre and post based on demographic characteristics.

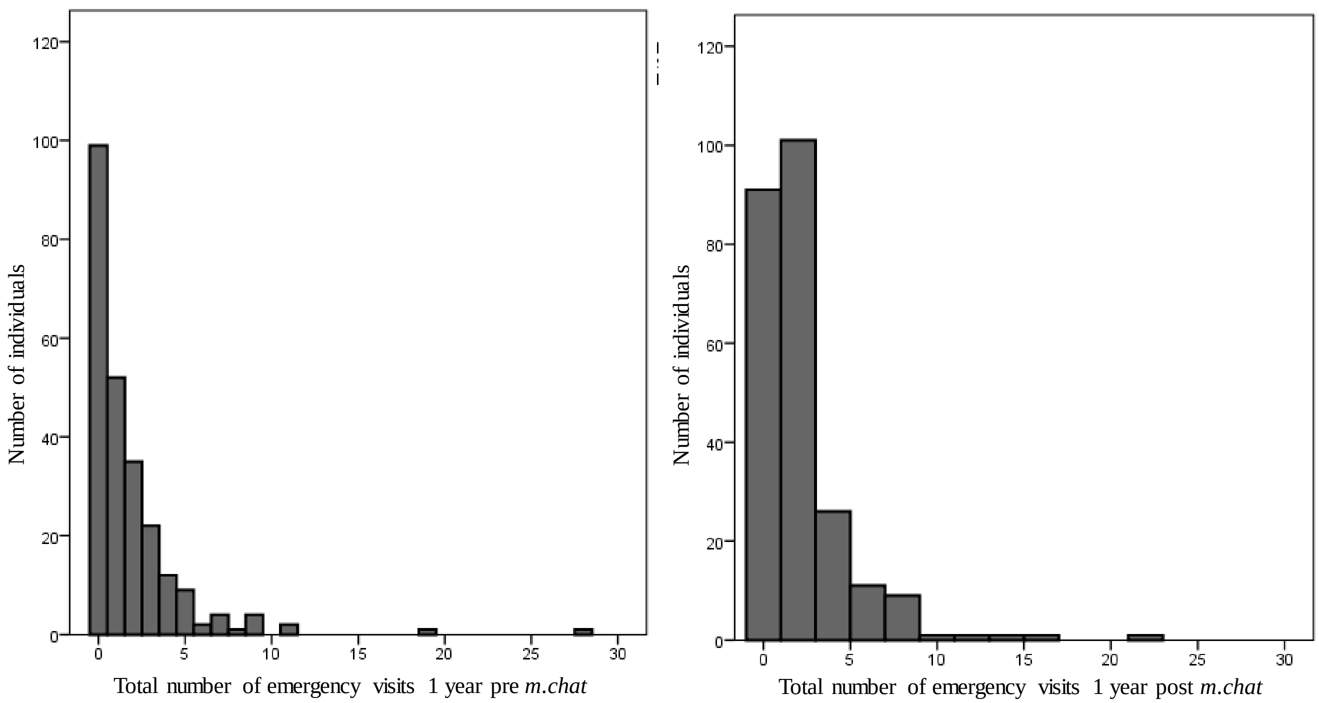


Figure 7: Distribution of total pre and post 1-year emergency visits count per individual

Table 9: Total emergency visits 12-months pre and 12-months post enrollment to *m.chat* broken down by demographic characteristics (N=1187)

			1-year pre *m.chat*				1-year post *m.chat*			
		N	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D
Gender										
	Female	130	236	1.82	0-19	2.61	285	2.19	0-39	3.93
	Male	114	198	1.74	0-28	3.25	169	1.48	0-22	3.10
	Total	244	434	1.78	0-28	2.92	454	1.86	0-39	3.58
Race										
	Black/African American	124	205	1.65	0-9	2.07	212	1.71	0-15	2.38
	White	104	203	1.95	0-28	3.78	216	2.08	0-39	4.78
	Other	15	20	1.33	0-7	1.95	19	1.27	0-4	1.16
	Total	243	428	1.76	0-28	2.92	447	1.84	0-39	3.57
Education Level										
	Less than high school	78	142	1.82	0-11	2.37	147	1.88	0-14	2.73
	high school	102	191	1.87	0-19	2.81	188	1.84	0-39	4.12
	More than high school	64	101	1.58	0-28	3.66	119	1.86	0-22	3.61
	Total	244	434	1.78	0-28	2.92	454	1.86	0-39	3.58
Marital Status										
	Divorced/ Separated	121	180	1.49	0-19	2.43	206	1.70	0-39	4.00
	Never married	95	199	2.09	0-28	3.63	177	1.86	0-22	3.06
	Married/ Remarried	16	30	1.88	0-5	1.96	34	2.13	0-8	2.66
	Widowed	12	25	2.08	0-5	2.15	37	3.08	0-15	4.03
	Total	244	434	1.78	0-28	2.92	454	1.86	0-39	3.58
Age										
	25-39 years	17	38	2.24	0-9	2.07	35	2.06	0-7	2.41
	40-59 years	155	293	1.89	0-28	3.30	286	1.85	0-39	4.10
	Above 60 years	72	103	1.43	0-11	1.95	133	1.85	0-15	2.47
	Total	244	434	1.78	0-28	2.92	454	1.86	0-39	3.58

4.1.2.5 Change in healthcare utilization

Figure 8 below displays patterns of total encounters, inpatient visits, outpatient visits and emergency visits over time in a spaghetti plot.

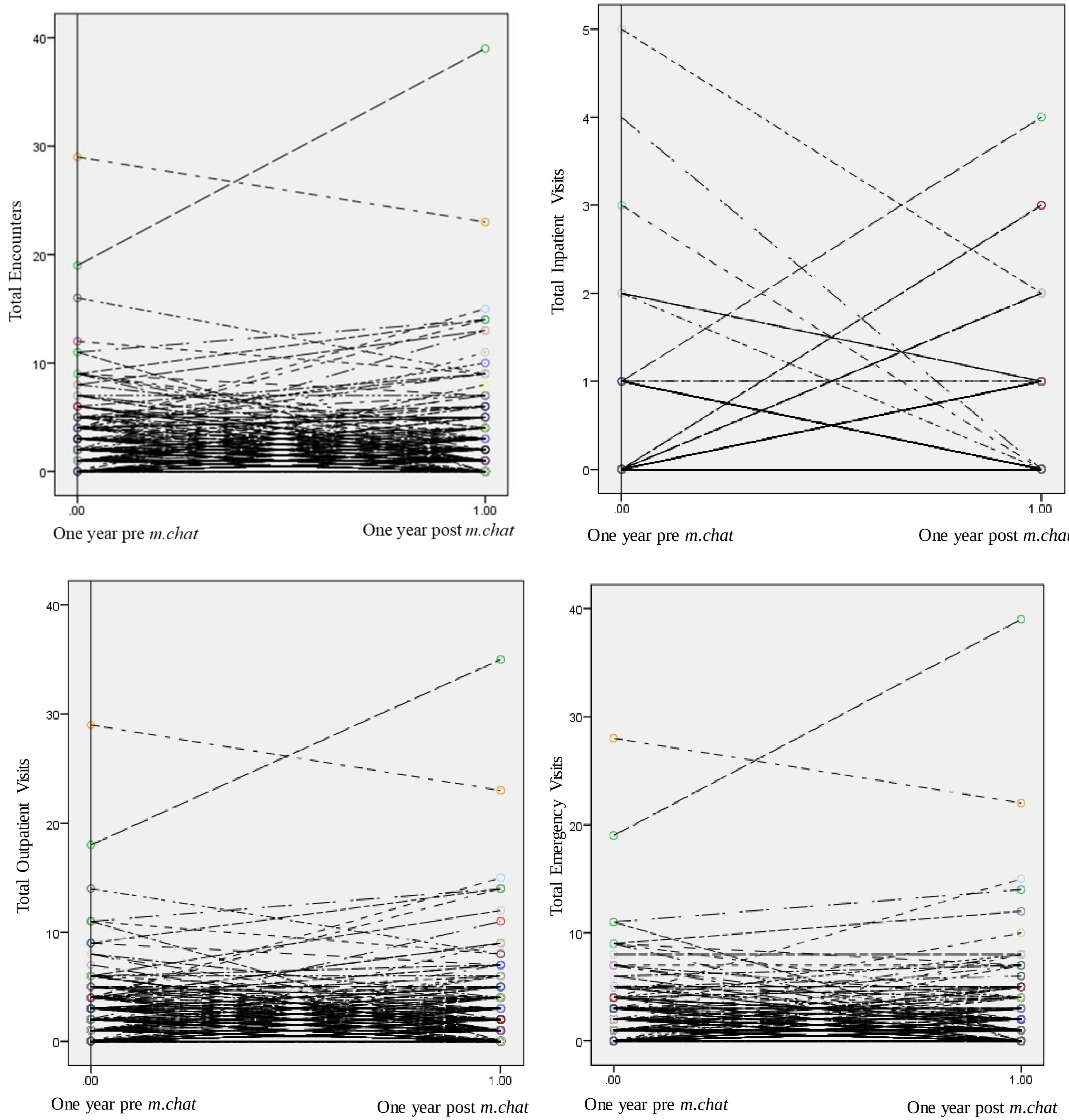


Figure 8: Change in healthcare utilization over time

Table 10 below shows changes in healthcare utilization over time. Twenty-seven out of 244 individuals had no hospital encounters over the course of 2 years. Fifty-one participants did not use the emergency department over the course of 2 years. While 32.4% of participants increased their use of the emergency department, 33.6% reduced their emergency department use from 12 months pre to post enrollment.

Table 10: Change in total encounters, inpatient visits, outpatient visits and emergency visits over time (n=244)

	Total Encounters		Inpatient Visits		Outpatient Visits		Emergency Visits	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
No utilization	27	11.1%	189	77.5%	28	11.5%	51	20.9%
No change	28	11.5%	2	0.8%	26	10.7%	32	13.1%
Decreased	101	41.4%	29	11.9%	101	41.4%	82	33.6%
Increased	88	36.1%	24	9.8%	89	36.5%	79	32.4%

Tables 11, 12, 13 display reasons for inpatient visits, outpatient visits, and emergency visits respectively for 12-month pre and post enrollment into *m.chat* based on CCS primary diagnosis categories. Table 14 shows the emergency visits categorized based of NYU algorithm for the two time periods.

Table 11: Count of primary diagnosis (based on CCS Category) for inpatient visits 12 months pre and post enrollment into *m.chat.*

	1-year pre *m.chat*	1-year post *m.chat*
Complications of pregnancy; childbirth; and the puerperium	3	2
Diseases of the blood and blood-forming organs	2	1
Diseases of the circulatory system	8	3
Diseases of the digestive system	3	4
Diseases of the genitourinary system	2	1
Diseases of the musculoskeletal system and connective tissue	4	3
Diseases of the nervous system and sense organs	0	1
Diseases of the respiratory system	4	4
Diseases of the skin and subcutaneous tissue	1	2
Endocrine; nutritional; and metabolic diseases and immunity disorders	2	4
Infectious and parasitic diseases	4	3
Injury and poisoning	3	6
Mental Illness	4	3
Neoplasms	4	5
Symptoms; signs; and ill-defined conditions and factors influencing health status	1	1
Total	45	43

Table 12: Count of primary diagnosis (based on CCS Category) for outpatient visits 12 months pre and post enrollment into *m.chat.*

	1-year pre *m.chat*	1-year post *m.chat*
Complications of pregnancy; childbirth; and the puerperium	4	10
Congenital anomalies	1	1
Diseases of the blood and blood-forming organs	2	0
Diseases of the circulatory system	54	57
Diseases of the digestive system	45	42
Diseases of the genitourinary system	34	35
Diseases of the musculoskeletal system and connective tissue	86	70
Diseases of the nervous system and sense organs	47	43
Diseases of the respiratory system	56	67
Diseases of the skin and subcutaneous tissue	15	15
Endocrine; nutritional; and metabolic diseases and immunity disorders	16	17
Infectious and parasitic diseases	14	10
Injury and poisoning	53	57
Mental Illness	28	37
Neoplasms	11	13
Residual codes; unclassified; all E codes [259. and 260.]	9	10

Symptoms; signs; and ill-defined conditions and factors influencing health status	69	71
Total	544	555

Table 13: Count of primary diagnosis (based on CCS Category) for emergency visits 12 months pre and post enrollment into *m.chat.*

	1-year pre *m.chat*	1-year post *m.chat*
Complications of pregnancy; childbirth; and the puerperium	2	8
Congenital anomalies	0	1
Diseases of the blood and blood-forming organs	4	1
Diseases of the circulatory system	48	41
Diseases of the digestive system	31	36
Diseases of the genitourinary system	29	28
Diseases of the musculoskeletal system and connective tissue	52	40
Diseases of the nervous system and sense organs	41	33
Diseases of the respiratory system	53	65
Diseases of the skin and subcutaneous tissue	14	15
Endocrine; nutritional; and metabolic diseases and immunity disorders	14	18
Infectious and parasitic diseases	10	11
Injury and poisoning	48	59
Mental Illness	30	38
Neoplasms	2	4
Residual codes; unclassified; all E codes [259. and 260.]	7	8
Symptoms; signs; and ill-defined conditions and factors influencing health status	49	48
Total	434	454

Table 14: Emergency visits 12 months pre and post enrollment into *m.chat* categorized based on NYU algorithm

	1-year pre *m.chat*		1-year post *m.chat*	
	Frequency	Percentage	Frequency	Percentage
Emergent (preventable/avoidable + not preventable/avoidable >50%)	146	36.2%	155	36.6%
Indeterminate (non-emergent + primary care treatable = 50% & preventable/avoidable + not preventable/avoidable = 50%)	79	19.6%	72	17.0%
Non-emergent (non-emergent + primary care treatable >50%)	41	10.2%	39	9.2%
Injury	45	11.2%	48	11.3%
Mental Health	15	3.7%	18	4.3%
Alcohol	9	2.2%	14	3.3%
Substance Abuse	2	0.5%	0	0.0%
Unclassified	66	16.4%	77	18.2%
Total	403	100.0%	423	100.0%

4.1.2.6 Change in healthcare utilization based on zero-inflated negative binomial count model

There was no significant change in total hospital encounters, inpatient visits, outpatient visits as well as emergency visits 12 months pre and post enrollment in *m.chat.*

Table 16: Change in hospital utilization measures from 12-months pre to 12-months post enrollment using zero-inflated negative binomial model

Total hospital encounters				
	Estimate	Std. Error	z Value	Significance
Post	-1.986	95.913	-0.021	0.983
Inpatient visits				
Post	4.066	53.366	0.076	0.939
Outpatient visits				
Post	-2.014	385.930	-0.005	0.996
Emergency visits				
Post	-2.944	199.738	-0.015	0.988

4.1.2.7 Charged amount

Table 17: Total charged amounts 12-months pre and 12-months post enrollment

	Total charged amount 12-months pre	Total charged amount 12-months post
Total Encounters	3.7 million	4.7 million
Inpatient Visits	1.7 million	2.2 million
Outpatient Visits	2.0 million	2.5 million
Emergency Visits	477,463	561,409

The median charged amount decreased from $3,463.26 to $2,872.68 from 12-months pre enrollment to 12-months post enrollment. The cost ranged from $0 to $266,099.83 (mean 15,292.31, SD 33146.8) at 12-months pre enrollment and from $0 to $552,888.47 (mean 19,274.18, SD 49207.65)12-months post enrollment. Figure 6 below shows the distribution of charged amount pre and post enrollment into *m.chat.* Table 18 displays the breakdown of charged amount pre and post based on demographic characteristics.

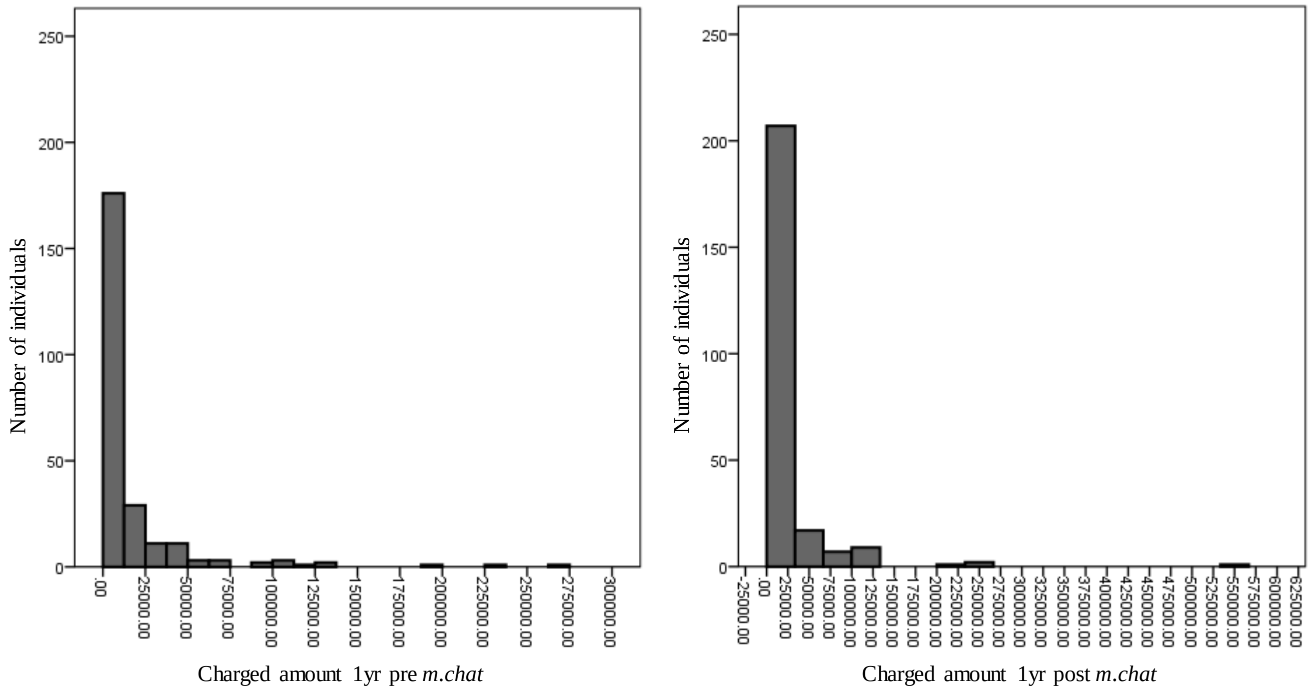


Figure 9: Distribution of charged amount 12-months pre and post enrollment into *m.chat.*

Table 18: Charged amount 12-months pre and 12-months post enrollment to *m.chat* broken down by demographic characteristics (N=1187)

			1-year pre *m.chat*				1-year post *m.chat*			
		N	Median	Mean	Min-Max	St. D	Median	Mean	Min-Max	St. D
Gender										
	Female	130	4052.34	15780.74	0-190524.01	30166.67	6105.5	19173.74	0-253799.7	37785.49
	Male	114	2456.26	14735.32	0-266099.83	36376.43	1574.68	19388.72	0-552888.47	59809.20
Race										
	Black/African American	124	2372.46	12692.64	0-190524.01	27467.55	2209.25	20130.81	0-552888.47	58858.28
	White	104	4574.00	18392.12	0-266099.83	39442.07	3675.94	18918.23	0-253799.70	39173.1
	Other	15	4225.00	15364.44	0-111743.0	29415.67	4353.00	13440.78	0-40071.01	15315.51
Education Level										
	Less than high school	78	3371.88	14274.75	0-111743.0	24492.09	4390.0	25232.91	0-552888.47	70360.06
	high school	102	2606.4	13401.37	0-190524.01	29248.58	2669.2	14706.24	0-253799.70	37479.09
	More than high school	64	3980.03	19546.14	0-266099.83	45910.59	3115.50	19292.14	0-129169.02	30972.67
Marital Status										
	Divorced/ Separated	121	2488.0	10898.41	0-125082.7	20044.6	1972.0	21295.31	0-552888.47	63457.79
	Never married	95	4225.0	18754.93	0-266099.83	43129.45	4229.0	16134.5	0-122786.36	27616.88
	Married/ Remarried	16	10000.93	15143.46	0-70446.0	19684.86	1763.12	22470.64	0-129169.02	39316.73
	Widowed	12	15208.61	32383.53	0-190524.01	53193.53	7622.15	19488.36	0-100378.61	28117.85
Age										
	25-39 years	17	7519.01	15159.1	0-125374.9	29550.27	2277.5	8032.32	0-37572.21	10205.28
	40-59 years	155	2424.51	14399.3	0-266099.83	34470.33	2373.25	15376.89	0-233598.16	30820.34
	Above 60 years	72	4288.0	17246.21	0-190524.01	31316.88	4620.0	30318.5	0-552888.47	77565.38

4.1.2.8 Changes in charged amounts

Figure 10 below displays patterns of charged amounts over time in a spaghetti plot.

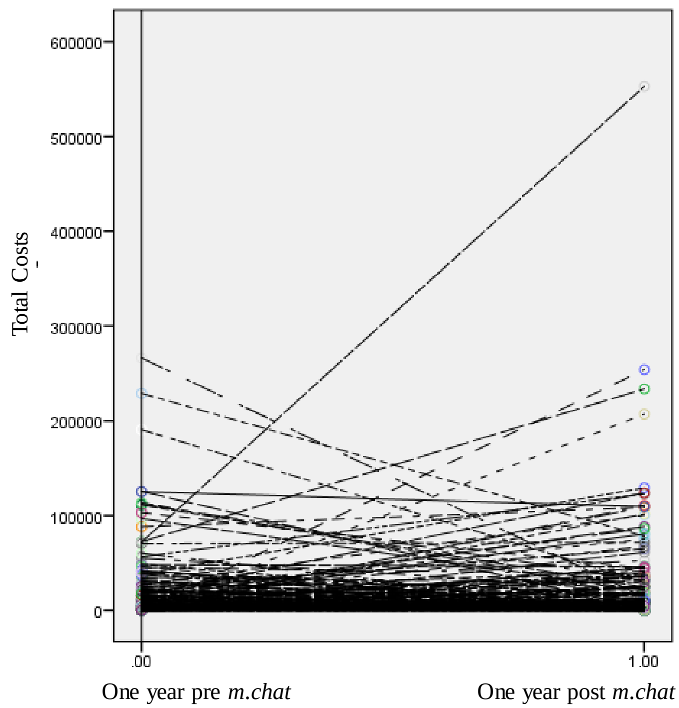


Figure 10: Change in charged amount pre and post enrollment into *m.chat.*

4.1.2.9 Changes in charged amounts based on log-gamma model analysis

There was no significant change in the charged amounts between 12-months pre and post enrollment into *m.chat.*

Table 19. Parameter estimates for charged amounts 12-months pre and 12-months post enrollment using log-gamma model

Parameter	B	Std. Error	Hypothesis Test		
			Wald Chi-Square	df	Sig.
Post	0.237	0.1851	1.641	1	0.200

4.1.3 Results for Aim 2

Given the timeframe included in DFWHC dataset and the varying date of enrollment of respective *m.chat* participants, a separate subgroup of participants was created for the analysis for Aim 2. A total of 131 matched *m.chat* participants had 12-months pre enrollment, 12-month post enrollment and 12-24 months post enrollment medical claims data included in the file.

Aim 2: To compare changes in healthcare utilization measures, including total hospital encounters, inpatient stays, outpatient hospital visits, emergency department visits and charged amounts among m.chat participants at 12-months pre, 12-months post their enrollment, and between 12 to 24-months post enrollment into the program.

Table 20: Demographic information on participants included in 12-months pre and 12 to 24 months post analysis (n=131)

		Frequency	Percentage
Gender			
	Female	72	55%
	Male	59	45%
Race			
	Black/African American	60	45.8%
	White	64	48.9%
	Other	7	5.3%
Age			
	Mean (Min-Max; SD)	55 (34-72;7.72)	
Education Level			
	Less than High School	44	33.6%
	High School	52	39.7%
	More than High School	35	26.7%
Marital Status			
	Never Married	50	38.2%
	Married/Remarried	8	6.1%
	Divorced/Separated	69	52.7%
	Widowed	4	3.1%

4.1.3.1 Total Encounters

The total hospital encounters increased from 318 to 341 to 354 from 12-months pre enrollment to 12 months post enrollment to 12-24 months post enrollment respectively for 131 participants. The average encounter also slightly increased from 2.4 (SD 3.79) to 2.6 (SD 4.5) to 2.7 (SD 5.15) for the respective time periods. While the minimum number of encounters remained 0 for all three time periods the maximum number of encounters increased from 29 to 39 to 40. Figure 11 below shows the distribution of total encounters for the three time periods. Table 21 displays the breakdown of encounters pre and post based on demographic characteristics.

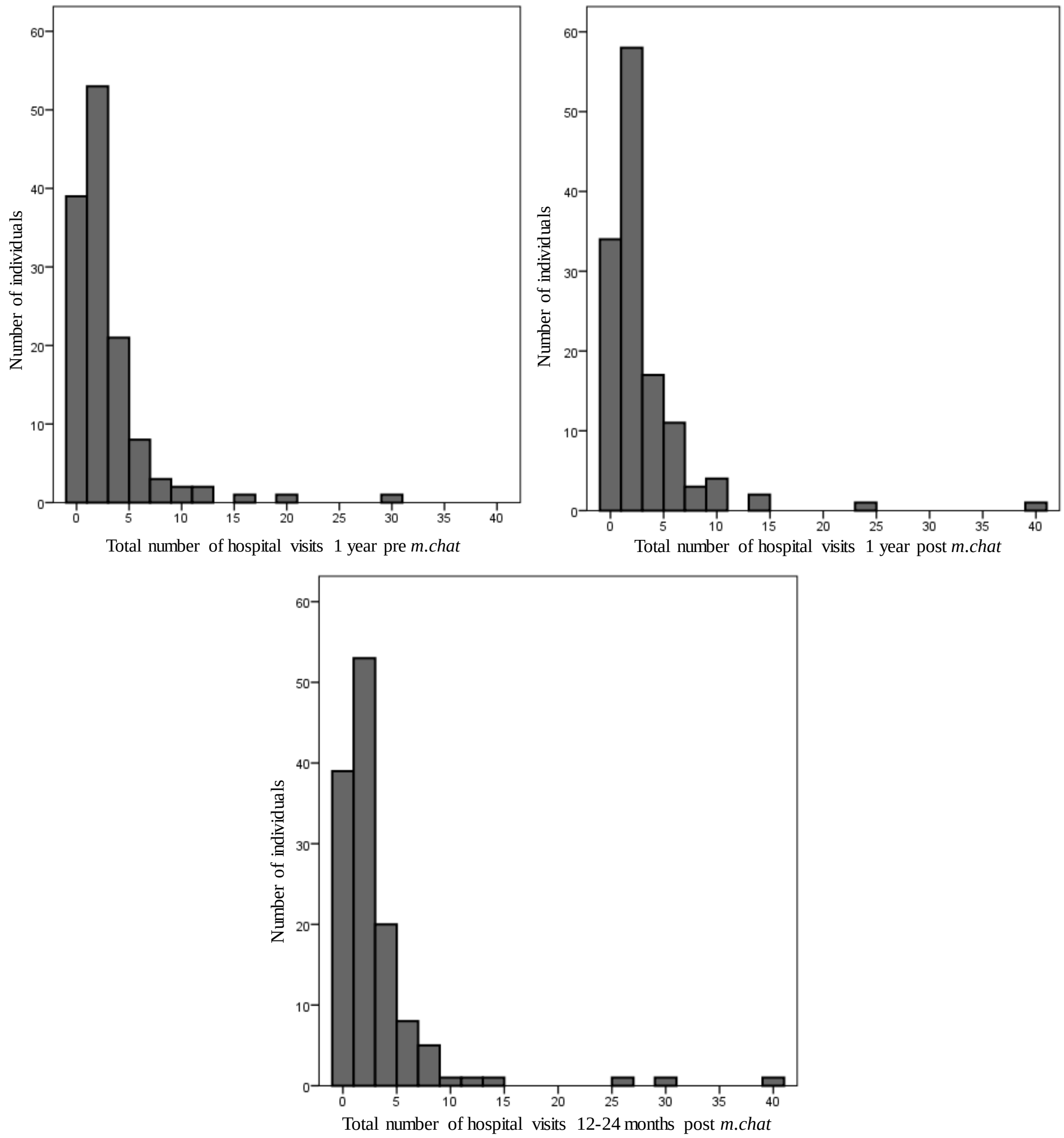


Figure 11: Distribution of total 1-year pre, 1-year post, and 12-24 months post hospital encounters count per individual

Table 21: Total hospital encounters 12-months pre, 12-months post, and 12-24 months post enrollment to *m.chat* broken down by demographic characteristics (N=1013)

			12-months pre *m.chat*				12-months post *m.chat*				12-24 months post *m.chat*			
		N	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Range	St. D	Total Encounters	Mean	Min-Max	St. D
Gender														
	Female	72	168	2.33	0-19	3.05	233	3.24	0-39	5.19	224	3.11	0-40	5.95
	Male	59	150	2.54	0-29	4.56	108	1.83	0-23	3.42	130	2.20	0-26	3.95
	Total	131	318	2.43	0-29	3.79	341	2.60	0-39	4.52	354	2.70	0-40	5.15
Race														
	Black/African American	60	103	1.72	0-7	1.74	115	1.92	0-13	2.52	124	2.07	0-13	2.45
	White	64	206	3.22	0-29	5.04	207	3.23	0-39	5.91	220	3.44	0-40	6.91
	Other	7	9	1.29	0-3	1.25	19	2.71	1-7	2.21	10	1.43	0-3	1.13
	Total	131	318	2.43	0-29	3.79	341	2.60	0-39	4.52	354	2.70	0-40	5.15
Education Level														
	Less than high school	44	74	1.68	0-9	2.08	107	2.43	0-14	3.32	98	2.23	0-13	2.57
	High school	52	138	2.65	0-19	3.69	141	2.71	0-39	5.55	136	2.62	0-40	5.80
	More than high school	35	106	3.03	0-29	5.29	93	2.66	0-23	4.23	120	3.43	0-29	6.45
	Total	131	318	2.43	0-29	3.79	341	2.60	0-39	4.52	354	2.70	0-40	5.15
Marital Status														
	Divorced/ Separated	69	138	2.0	0-19	2.99	160	2.32	0-39	5.11	156	2.26	0-40	5.28
	Never married	50	140	2.80	0-29	4.55	132	2.64	0-23	3.93	166	3.32	0-29	5.48
	Married/ Remarried	8	33	4.13	0-16	5.17	37	4.63	0-9	3.34	22	2.75	0-6	2.38
	Widowed	4	7	1.75	0-5	2.36	12	3.0	1-5	1.63	10	2.50	1-4	1.29
	Total	131	318	2.43	0-29	3.79	341	2.60	0-39	4.52	354	2.70	0-40	5.15
Age														
	25-39 years	5	14	2.80	0-7	3.03	11	2.20	0-6	2.39	9	1.80	0-5	2.17
	40-59 years	86	239	2.78	0-29	4.41	245	2.85	0-39	5.38	258	3.0	0-40	5.97
	Above 60 years	40	65	1.63	0-11	1.90	85	2.13	0-8	2.00	87	2.18	0-13	3.09
	Total	131	318	2.43	0-29	3.79	341	2.60	0-39	4.52	354	2.70	0-40	5.15

4.1.3.2 Inpatient visits

Inpatient visits increased from 24 to 26 to 34 from 12-months pre enrollment to 12 months post enrollment to 12-24 months post enrollment into *m.chat* respectively for 131 participants. The average inpatient visits also increased from one time point to another. Figure 12 below shows the distribution of inpatient visits for the three time periods. Table 22 displays the breakdown of encounters pre and post based on demographic characteristics.

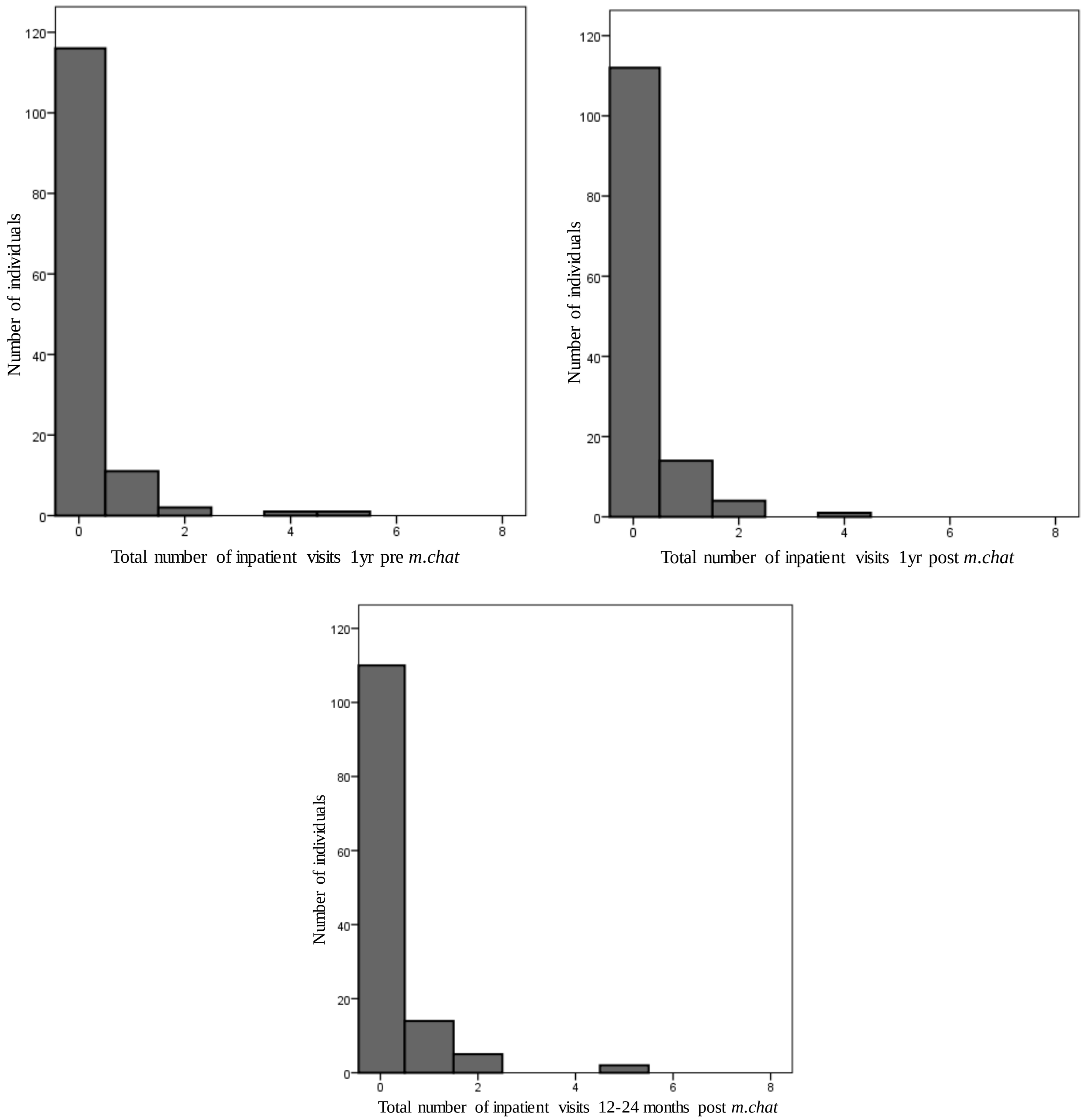


Figure 12: Distribution of total 1-year pre, 1-year post, and 12-24 months inpatient visits count per individual

Table 22: Inpatient visits 12-months pre, 12-months, 12-24 months post enrollment to *m.chat* broken down by demographic characteristics (N=1013)

			12-months pre *m.chat*				12-months post *m.chat*				12-24 months post *m.chat*			
		N	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D
Gender														
	Female	72	9	0.13	0-2	0.37	19	0.26	0-4	0.67	25	0.35	0-5	0.94
	Male	59	15	0.25	0-5	0.88	7	0.12	0-2	0.38	9	0.15	0-2	0.45
	Total	131	24	0.18	0-5	0.65	26	0.2	0-4	0.56	34	0.26	0-5	0.76
Race														
	Black/African American	60	8	0.13	0-2	0.39	10	0.17	0-2	0.46	13	0.22	0-5	0.74
	White	64	15	0.23	0-5	0.85	15	0.23	0-4	0.66	19	0.30	0-5	0.8
	Other	7	1	0.14	0-1	0.38	1	0.14	0-1	0.38	2	0.29	0-1	0.49
	Total	131	24	0.18	0-5	0.65	26	0.2	0-4	0.56	34	0.26	0-5	0.76
Education Level														
	Less than high school	44	6	0.14	0-1	0.35	6	0.14	0-2	0.46	12	0.27	0-5	0.85
	High school	52	4	0.08	0-2	0.33	11	0.21	0-4	0.67	8	0.15	0-2	0.41
	More than high school	35	14	0.4	0-5	1.12	9	0.26	0-2	0.50	14	0.4	0-5	1.01
	Total	131	24	0.18	0-5	0.65	26	0.2	0-4	0.56	34	0.26	0-5	0.76
Marital Status														
	Divorced/ Separated	69	5	0.07	0-1	0.26	13	0.19	0-4	0.62	11	0.16	0-2	0.47
	Never married	50	15	0.30	0-5	0.93	10	0.20	0-2	0.49	21	0.42	0-5	1.07
	Married/ Remarried	8	2	0.25	0-2	0.71	2	0.25	0-1	0.46	1	0.13	0-1	0.35
	Widowed	4	2	0.50	0-2	1.00	1	0.25	0-1	0.50	1	0.25	0-1	0.50
	Total	131	24	0.18	0-5	0.65	26	0.2	0-4	0.56	34	0.26	0-5	0.76
Age														
	25-39 years	5	2	0.4	0-1	0.55	1	0.2	0-1	0.45	0	0.0	0-0	0.00
	40-59 years	86	19	0.22	0-5	0.77	17	0.20	0-4	0.59	29	0.34	0-5	0.90
	Above 60 years	40	3	0.08	0-1	0.27	8	0.2	0-2	0.52	5	0.13	0-1	0.33
	Total	131	24	0.18	0-5	0.65	26	0.2	0-4	0.56	34	0.26	0-5	0.76

4.1.3.3 Outpatient visits

Outpatient visits increased from 294 to 315 to 320 from 12-months pre enrollment to 12 months post enrollment to 12-24 months post enrollment respectively for 131 participants. The average encounter also slightly increased from 2.24 to 2.40 to 2.44 for the respective time periods. While the minimum number of outpatient visits remained 0 for all three time periods the maximum number of encounters increased from 29 to 35 to 38. Figure 13 below shows the distribution of total encounters for the three time periods. Table 23 displays the breakdown of encounters pre and post based on demographic characteristics.

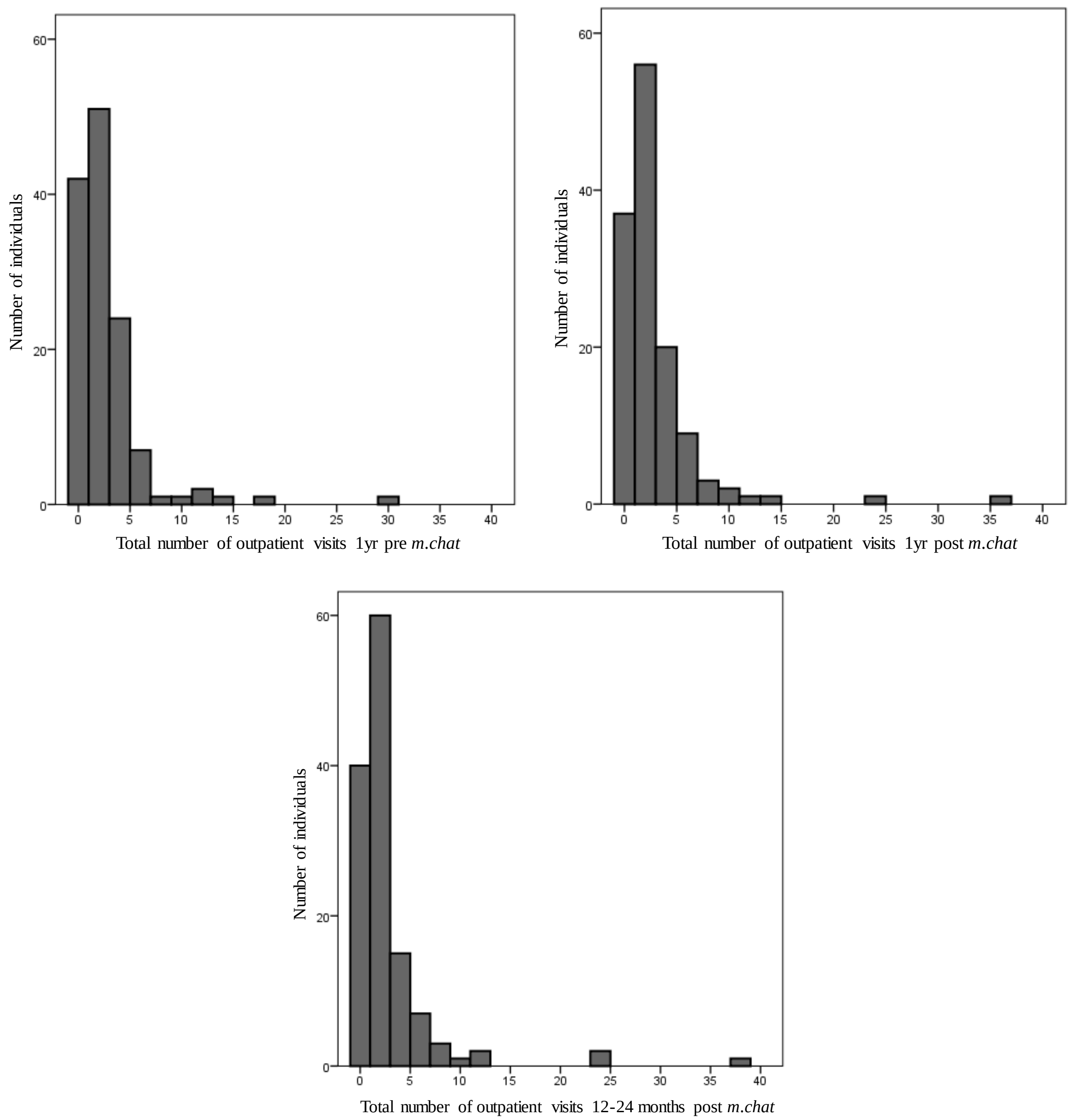


Figure 13: Distribution of total 1-year pre, 1-year post, and 12-24 months outpatient visits count per individual

Table 23: Outpatient visits 12-months pre, 12-months, and 12-24 months post enrollment to *m.chat* broken down by demographic characteristics (N=1013)

			12-months pre *m.chat*				12-months post *m.chat*				12-24 months post *m.chat*			
		N	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D
Gender														
	Female	72	159	2.21	0-18	2.93	214	2.97	0-35	4.69	199	2.76	0-38	5.42
	Male	59	135	2.29	0-29	4.33	101	1.71	0-23	3.38	121	2.05	0-24	3.72
	Total	131	294	2.24	0-29	3.61	315	2.40	0-35	4.19	320	2.44	0-38	4.73
Race														
	Black/African American	60	95	1.58	0-6	1.65	105	1.75	0-11	2.19	111	1.85	0-12	2.22
	White	64	191	2.98	0-29	4.81	192	3.0	0-35	5.51	201	3.14	0-38	6.36
	Other	7	8	1.14	0-3	1.21	18	2.57	0-7	2.37	8	1.14	0-2	0.89
	Total	131	294	2.24	0-29	3.61	315	2.40	0-35	4.19	320	2.44	0-38	4.73
Education Level														
	Less than high school	44	68	1.55	0-9	1.99	101	2.29	0-14	3.11	86	1.95	0-12	2.22
	High school	52	134	2.58	0-18	3.46	130	2.50	0-35	4.97	128	2.46	0-38	5.56
	More than high school	35	92	2.63	0-29	5.09	84	2.40	0-23	4.21	106	3.03	0-24	5.68
	Total	131	294	2.24	0-29	3.61	315	2.40	0-35	4.19	320	2.44	0-38	4.73
Marital Status														
	Divorced/ Separated	69	133	1.93	0-18	2.89	147	2.13	0-35	4.66	145	2.10	0-38	5.03
	Never married	50	125	2.50	0-29	4.39	122	2.44	0-23	3.76	145	2.90	0-24	4.80
	Married/ Remarried	8	31	3.88	0-14	4.52	35	4.38	0-9	3.11	21	2.63	0-6	2.33
	Widowed	4	5	1.25	0-3	1.50	11	2.75	1-4	1.26	9	2.25	1-4	1.26
	Total	131	294	2.24	0-29	3.61	315	2.40	0-35	4.19	320	2.44	0-38	4.73
Age														
	25-39 years	5	12	2.4	0-6	2.88	10	2.0	0-5	2.0	9	1.8	0-5	2.17
	40-59 years	86	220	2.56	0-29	4.20	228	2.65	0-35	4.99	229	2.66	0-38	5.45
	Above 60 years	40	62	1.55	0-11	1.89	77	1.93	0-7	1.8	82	2.05	0-12	2.99
	Total	131	294	2.24	0-29	3.61	315	2.40	0-35	4.19	320	2.44	0-38	4.73

4.1.3.4 Emergency visits

Emergency visits increased slightly from 234 to 250 to 284 from 12-months pre enrollment to 12 months post enrollment to 12-24 months post enrollment respectively for 131 participants. The average emergency visits also slightly increased from 1.79 to 1.91 to 2.17 for the respective time periods. While the minimum number of emergency visits remained 0 for all three time periods the maximum number of visits increased from 28 to 39 to 40. Figure 14 below shows the distribution of total encounters for the three time periods. Table 24 displays the breakdown of encounters pre and post based on demographic characteristics.

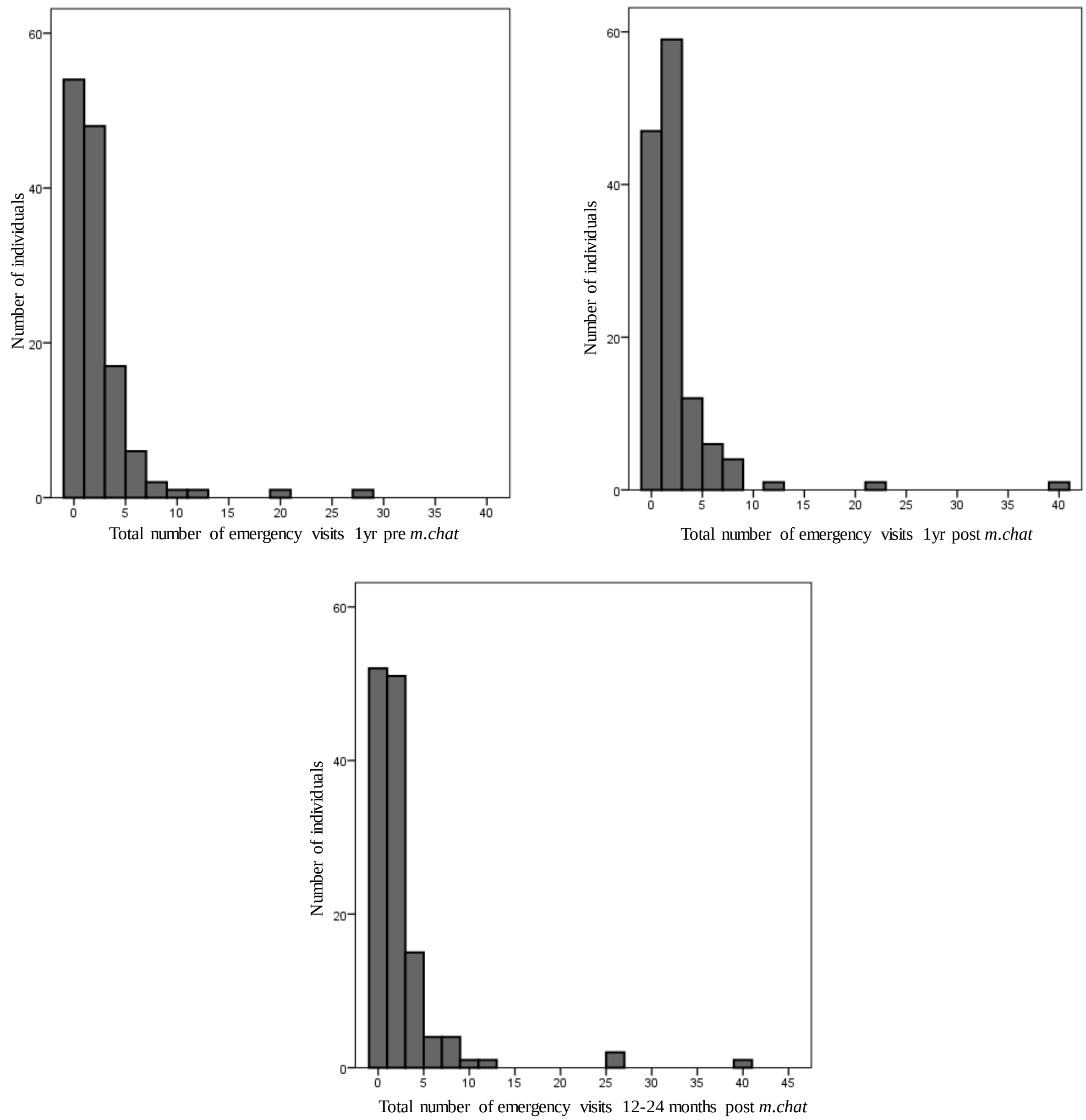


Figure 14: Distribution of total 1-year pre, 1-year post, and 12-24 months emergency visits count per individual

Table 24: Emergency visits 12 months pre, 12 months, and 12-24 months post enrollment to *m.chat* broken down by demographic characteristics (N=1013)

			12-months pre *m.chat*				12-months post *m.chat*				12-24 months post *m.chat*			
		N	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D	Total Encounters	Mean	Min-Max	St. D
Gender														
	Female	72	126	1.75	0-19	2.81	177	2.46	0-39	4.93	185	2.57	0-40	5.68
	Male	59	108	1.83	0-28	3.98	73	1.24	0-22	3.00	99	1.68	0-25	3.72
	Total	131	234	1.79	0-28	3.38	250	1.91	0-39	4.20	284	2.17	0-40	4.90
Race														
	Black/African American	60	87	1.45	0-6	1.62	85	1.42	0-8	1.92	93	1.55	0-9	1.95
	White	64	142	2.22	0-28	4.53	154	2.41	0-39	5.69	184	2.88	0-40	6.70
	Other	7	5	0.71	0-2	0.95	11	1.57	1-4	1.13	7	1.0	0-2	1.0
	Total	131	234	1.79	2-28	3.38	250	1.91	0-39	4.20	284	2.17	0-40	4.90
Education Level														
	Less than high school	44	56	1.27	0-9	1.88	70	1.59	0-12	2.44	70	1.59	0-8	1.96
	High school	52	105	2.02	0-19	3.22	106	2.04	0-39	5.42	112	2.15	0-40	5.77
	More than high school	35	73	2.09	0-28	4.80	74	2.11	0-22	3.97	102	2.91	0-26	5.99
	Total	131	234	1.79	0-28	3.38	250	1.91	0-39	4.20	284	2.17	0-40	4.90
Marital Status														
	Divorced/ Separated	69	104	1.51	0-19	2.93	123	1.78	0-39	4.94	120	1.74	0-40	5.09
	Never married	50	109	2.18	0-28	4.12	95	1.9	0-22	3.42	141	2.82	0-26	5.13
	Married/ Remarried	8	16	2.0	0-5	2.14	23	2.88	0-7	2.53	14	1.75	0-6	2.19
	Widowed	4	5	1.25	0-5	2.5	9	2.25	1-4	1.5	9	2.25	1-4	1.26
	Total	131	234	1.79	0-28	3.38	250	1.91	0-39	4.20	284	2.17	0-40	4.90
Age														
	25-39 years	5	12	2.4	0-6	2.88	10	2.0	0-5	2.0	8	1.60	0-5	2.07
	40-59 years	86	178	2.07	0-28	3.89	184	2.14	0-39	5.06	222	2.58	0-40	5.79
	Above 60 years	40	44	1.1	0-11	1.86	56	1.40	0-7	1.52	54	1.35	0-11	2.30
	Total	131	234	1.79	0-28	3.38	250	1.91	0-39	4.20	284	2.17	0-40	4.90

4.1.3.5 Changes in healthcare utilization

Figure 15 below displays patterns of total encounters, inpatient visits, outpatient visits and emergency visits over time in spaghetti plots.

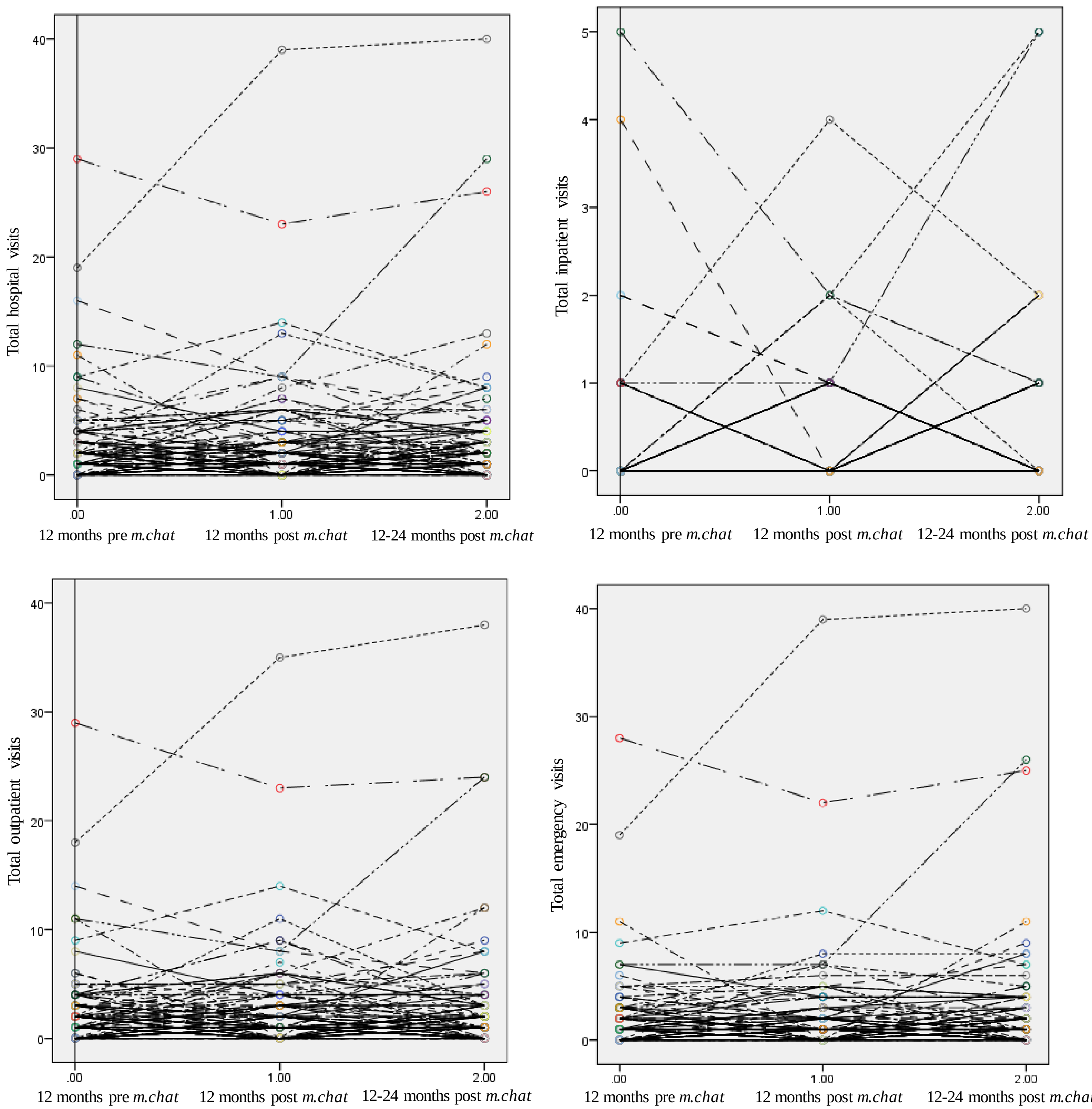


Figure 15: Change in healthcare utilization over time

Tables 25, 26 and 27 display reasons for inpatient visits, outpatient visits, and emergency visits respectively for 12 months pre, 12 months post, and 12-24 months post enrollment based on CCS primary diagnosis categories. Table 28 shows the emergency visits categorized based on the NYU algorithm for the three time periods.

Table 25: Count of primary diagnosis (based on CCS Category) for inpatient visits 12 months pre, 12 months post, and 12-24 months post enrollment.

	12-months before *m.chat*	12-months after *m.chat*	12-24 months after *m.chat*
Complications of pregnancy; childbirth; and the puerperium	1	1	0
Diseases of the blood and blood-forming organs	1	1	0
Diseases of the circulatory system	5	2	5
Diseases of the digestive system	3	3	4
Diseases of the genitourinary system	1	0	1
Diseases of the musculoskeletal system and connective tissue	2	3	0
Diseases of the nervous system and sense organs	0	0	3
Diseases of the respiratory system	2	1	6
Diseases of the skin and subcutaneous tissue	1	2	1
Endocrine; nutritional; and metabolic diseases and immunity disorders	1	4	0
Infectious and parasitic diseases	0	1	1
Injury and poisoning	1	2	1
Mental Illness	2	2	9
Neoplasms	4	3	3
Symptoms; signs; and ill-defined conditions and factors influencing health status	0	1	0
Total	24	26	34

Table 26: Count of primary diagnosis (based on CCS Category) for outpatient visits 12-months pre, 12-months post, and 12-24 months post enrollment.

	12-months before *m.chat*	12-months after *m.chat*	12-24 months after *m.chat*
Complications of pregnancy; childbirth; and the puerperium	2	4	0
Congenital anomalies	0	1	0
Diseases of the blood and blood-forming organs	1	0	0
Diseases of the circulatory system	29	27	25
Diseases of the digestive system	25	23	23
Diseases of the genitourinary system	17	21	10
Diseases of the musculoskeletal system and connective tissue	47	38	38
Diseases of the nervous system and sense organs	17	24	19
Diseases of the respiratory system	29	30	32
Diseases of the skin and subcutaneous tissue	8	10	18
Endocrine; nutritional; and metabolic diseases and immunity disorders	8	12	17
Infectious and parasitic diseases	4	8	5
Injury and poisoning	32	25	32
Mental Illness	18	30	44
Neoplasms	5	11	9
Residual codes; unclassified; all E codes [259. and 260.]	4	6	3
Symptoms; signs; and ill-defined conditions and factors influencing health status	48	45	45
Total	294	315	320

Table 27: Count of primary diagnosis (based on CCS Category) for emergency visits 12-months pre, 12-months post, and 12-24 months post enrollment.

	12-months before *m.chat*	12-months after *m.chat*	12-24 months after *m.chat*
Complications of pregnancy; childbirth; and the puerperium	2	4	0
Congenital anomalies	0	1	0
Diseases of the blood and blood-forming organs	2	1	0
Diseases of the circulatory system	23	21	23
Diseases of the digestive system	19	19	17
Diseases of the genitourinary system	15	15	9
Diseases of the musculoskeletal system and connective tissue	28	17	23
Diseases of the nervous system and sense organs	14	22	18
Diseases of the respiratory system	28	26	37
Diseases of the skin and subcutaneous tissue	8	10	18
Endocrine; nutritional; and metabolic diseases and immunity disorders	7	15	17
Infectious and parasitic diseases	2	8	6
Injury and poisoning	31	26	31
Mental Illness	19	30	48
Neoplasms	0	3	6
Residual codes; unclassified; all E codes [259. and 260.]	3	5	2
Symptoms; signs; and ill-defined conditions and factors influencing health status	33	27	29
Total	234	250	284

Table 28: Emergency visits 12-months pre, 12-months post, and 12-24 months post enrollment into *m.chat.*categorized based on the NYU algorithm

	12-months before *m.chat*		12-months after *m.chat*		12-24 months after *m.chat*	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Emergent (preventable/avoidable + not preventable/avoidable >50%)	84	38.0%	76	32.6%	92	35.8%
Indeterminate (non-emergent + primary care treatable = 50% & preventable/avoidable + not preventable/avoidable = 50%)	39	17.6%	41	17.6%	51	19.8%
Non-emergent (non-emergent + primary care treatable >50%)	21	9.5%	21	9.0%	12	4.7%
Injury	30	13.6%	24	10.3%	30	11.7%
Mental Health	10	4.5%	16	6.9%	18	7.0%
Substance Abuse	1	0.5%	0	0.0%	0	0.0%
Alcohol	6	2.7%	11	4.7%	23	8.9%
Unclassified	30	13.6%	44	18.9%	31	12.1%
Total	221	100.0%	233	100.0%	257	100.0%

4.1.3.6 Changes in healthcare utilization based on zero inflated negative binomial count model analysis

There were no significant changes in total hospital encounters, inpatient visits, outpatient visits as well as emergency visits 12-months pre, 12-months post and 12-24 months post enrollment in *m.chat.*

Table 29 Change in hospital utilization measures from 12-months pre, 12-months post, and 12-24 months post enrollment using zero-inflated negative binomial model

	Estimate	Std. Error	z Value	Significance
Total hospital encounters				
Post 1	-1.741	592.054	-0.003	0.998
Post 2	-1.703	927.268	-0.002	0.999
Inpatient visits				
Post 1	-7.612	82.605	-0.092	0.927
Post 2	-1.097	2.312	-0.475	0.635
Outpatient visits				
Post 1	-2.296	542.865	-0.004	0.997
Post 2	-2.130	643.873	-0.003	0.997
Emergency visits				
Post 1	-0.291	363.168	-0.001	0.999
Post 2	0.267	478.397	0.001	1.0

4.1.3.7 Charged amounts

Table 30 Total charged amounts over 12-months pre, 12-months post, and 12-24 months post enrollment

	Total Charged Amount 12-months pre	Total Charged Amount 12-months post	Total Charged Amount 12-24 months post
Total Encounters	2.0 million	2.4 million	3.0 million
Inpatient Visits	0.8 million	1.1 million	1.4 million
Outpatient Visits	1.2 million	1.3 million	1.6 million
Emergency Visits	271,623	311,947	416,400

The median charged amount changed from $2,488.0 to $3,464.0 to $3,657.19 from 12-months pre enrollment to 12 and 24 months post enrollment for 131 participants. The cost ranged from $0 to $266,099.83 (mean 15,628.69, SD 36600.92) at 12-months pre enrollment, $0 to $253,799.70 (mean 18,358.31, SD 37188.13) at 12 months post enrollment, and $0 to $394,155.30 (mean 22,962.12, SD 53160.94) at 12-24 months post enrollment. Figure 16 below shows the distribution of the charged amounts pre and post enrollment.

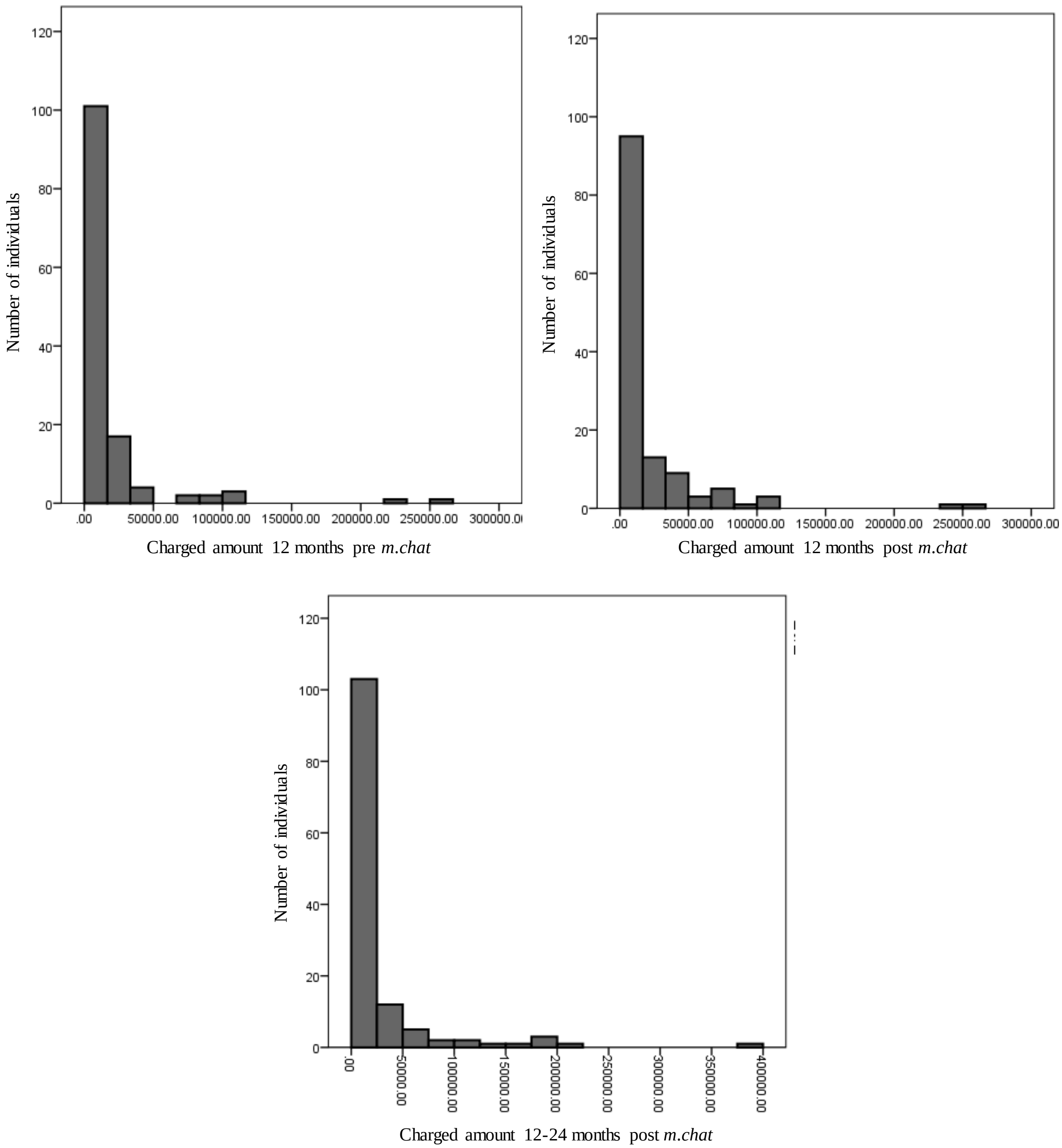


Figure 16: Distribution of charged amount over time

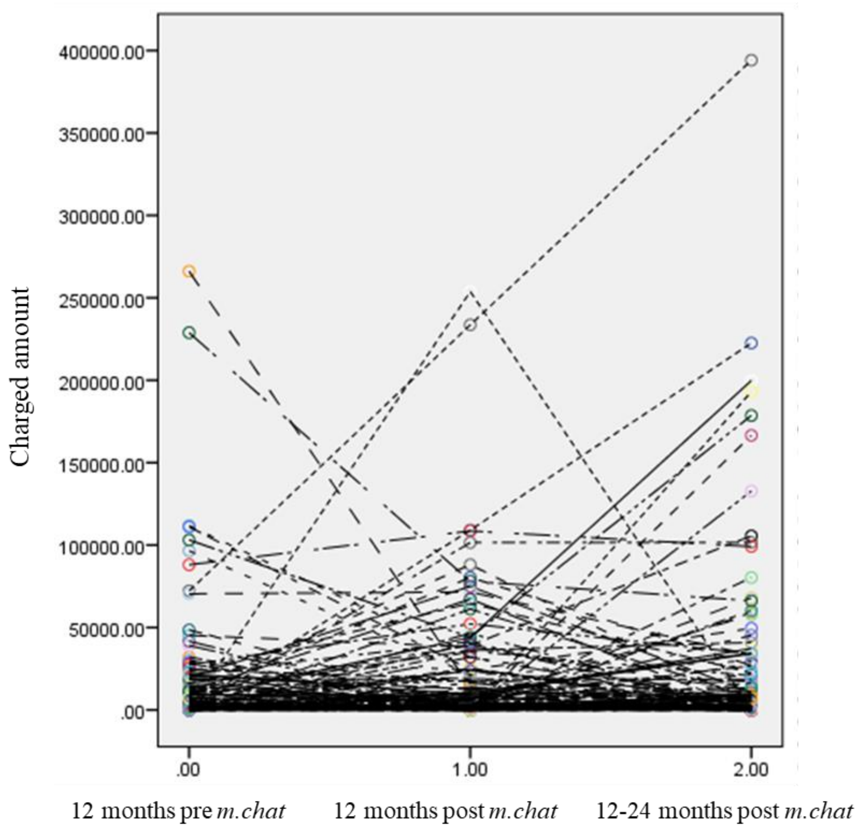


Figure 17: Changes in charged amount pre and post enrollment into *m.chat.*

4.1.3.9 Changes in charged amounts based on log-gamma model analysis

There were no significant changes in the charged amounts 12 months pre, 12 months post, and 12-24 months post enrollment into *m.chat.*

Table 31 Parameter estimates for charged amount 12-months pre and 12, 24 months post enrollment using log-gamma model

Parameter	B	Std. Error	Hypothesis Test		
			Wald Chi-Square	df	Sig.
Post 2	0.385	0.2520	2.330	1	0.127
Post 1	0.108	0.2357	0.210	1	0.647

4.2 Qualitative Results

We conducted 4 focus groups and 2 individual interviews with a total of 21 participants between March and December of 2018. The size of focus groups ranged from 3-9 people. Each session was facilitated by an interviewer and note taker and lasted between 30 minutes and an hour. Interview participants had been enrolled in *m.chat* for an average of 16 months, ranging from 6 to 24 months. On average interview participants worked with 2 health coaches over the course of the program. During the sessions, participants talked about their overall experience with *m.chat,* perceived benefits of health coaching, and perceived impact on their health and healthcare use. A total of 802 passages were coded into 589 open codes and 96 axial codes. This section highlights major themes highlighted by participants.

4.2.1 Experience with *m.chat*

Overall participants reported positive experience with *m.chat*. When asked about the difference *m.chat* made in their lives on a scale of 1 to 10 (where 1 is "not much is different" and 10 is "a lot changed"), the average score reported was 9.35 with the score ranging from 7 to 10. The group unanimously agreed on the helpfulness of *m.chat* and its influence on their overall life.

"It was pretty much a perfect program!"

"It changed me"

"What m.chat did was help me get back out of the ditch and stay out and stay afloat and stay you know, get back on living clean"

4.2.1.1 Positive aspects of *m.chat*

Participants identified health coaching (n=57), elements of the program including staff, reminders, assessments and tracking (n=31), and financial and household support (n=30) as the top three most helpful components of *m.chat.* The coaches' ability to listen without being overly intrusive, respect individual's autonomy, promote intrinsic motivation, and provide necessary resources was perceived as essential to help participants accomplish their respective health goals. The financial incentives and supply of household items helped address the basic necessities in life which in turn helped participants focus on their health goals. Participants also agreed that reminders and tracking nudged them to stay focused on their goals.

"They will encourage you to do better in your life."

"He was very open and he was somebody I felt like I could be totally honest with, he really worked with me."

"He was able to text me like somebody else said about, "it is time to walk" "it is time to stretch" and that helped."

"Seems like when you were getting things from m.chat, you didn't have to be constantly like broke now okay."

4.2.1.2 Challenges

Participants identified the time it took to get to know the program and their coach and build trust in the program as one of the primary reasons (n=22) that might have prevented them from getting more personal benefits from *m.chat.* Due to a lack of trust, the majority of participants agreed that they misinformed their coaches about their health and needs during the initial phase. They also mentioned that they were more comfortable answering personal questions during assessments than with their coach in the beginning. Even after building trust, a small proportion of participants indicated they continued to lie as they did not want to disappoint their coach by telling them about their relapse or for not accomplishing their goals. When asked what advice they would give to someone thinking about joining *m.chat,* all participants agreed that they would advise people to be open and honest with their coaches from the beginning so they can maximize their benefit from *m.chat.*

"Yeah when I first started out I lied to them like the back of my hand. Why would I tell a total stranger what I am doing drug habit wise for you to probably go back and report me to somebody that is with the program and get me into trouble? So I lied the first two months of the program and I finally got used to them and I just start telling them the truth."

"By the time I got the hang of it, it was over."

"Oh you know, open up and talk you know and be as open as you can be and honest as you can be to get you know the full benefits out of it. Because you all you all are more than willing to you know help and explore someone's problems and you know I really appreciated that."

A small proportion of participants also recognized staff turnover and discrepancy in the knowledge among coaches as challenges during the program.

"I hated having to switch up coaches cause mine left."

4.2.1.3 Transition after *m.chat*

Given the consistently positive responses to *m.chat*, participants mentioned being disappointed when the program ended. The majority of participants acknowledged that the program was too short (n=11) and requested we restart the program (n=15). While some participants mentioned maintaining health changes they made during *m.chat*, others struggled once the program ended. The struggles were related to their inability to finding a replacement for social and financial support provided by *m.chat*, continuing health needs, and chances of relapse. Moreover, participants echoed the important role *m.chat* played in improving their overall wellbeing and acknowledged that they would rejoin the program if given the opportunity.

"And then when m.chat was about to play out, I tried to find substitute. That was the hardest thing I ever try to get."

"I hope the program goes on. Cause sometimes if you are if you struggle with say a secondary you struggle with secondary issues beside addiction you know sometimes you know it is helpful to have the additional, the extra help so..."

"I have messed up with transition."

4.2.2 Perceived Improvement in Health

m.chat's influence in improving participants' perceptions of health was a major theme generated during the interviews and focus groups. Participants largely indicated that *m.chat* helped enhance one or more aspects of their health by promoting awareness and self-management strategies. Most participants acknowledged that they had health needs prior to enrolling into *m.chat* and the program helped them make important lifestyle changes.

"I don't have much because I had total hip replacement, back surgery and scoliosis..."

"I have a lot of chronic diseases like diabetes, hypertension and heart, congestive heart failure so I had to reach my goals…"

"I cannot live alone because if I live if I lived alone, I think I would have died."

4.2.2.1 Health awareness

Participants agreed that health coaches helped them be more aware of their health in general. Coaches encouraged participants to think about healthy eating, physical activity, medication management, the harmful effects of smoking, drinking and using substances. Although participants chose to set goals they wanted to work on, information and resources provided through the program helped increase awareness. Furthermore, text reminders helped participants keep their health goals in their awareness and strengthened their intentions to change.

"My health is impacted, my awareness about to take my medication on time and keep my doctor's appointment."

"But after I got my phone and you had to answer every morning, it made me very aware of how much fruits and vegetables I was eating and how I was talking care of my health and it changed me."

"It made me more aware of continuing to improve my health."

"They made me feel like to take inventory on myself."

4.2.2.2 Health self-management strategies

Improvement in self-management of health was one of the most prominent themes during interviews (n=137). All participants agreed that *m.chat* helped them cultivate one or more health management strategies. Participants credited *m.chat* for improvement in their overall health (physical, mental, and social health).

"I feel 100% better than what it was."

"I feel lot better about my health and everything."

Improvement in physical activity, diet, mental health, and medication management was among the top areas of progress. Along with the support from health coaches, increased access to healthy food and memberships at the YMCA through *m.chat* were among the factors that were perceived to enhance participant's self-management. Participants reported being more social and going out of their house more often after enrolling in *m.chat.* Losing weight (n=8), quitting smoking entirely (n=4), reducing smoking (n=3), maintaining abstinence from substances (n=3), and giving up drinking alcohol (n=1) were some of the most celebrated success stories during the sessions. Additionally, through financial incentives and household supplies *m.chat* helped improve personal hygiene. Some participants also mentioned that the financial incentives helped take care of their basic necessities which in turn helped them focus on other aspects of their health.

"At first, I didn't even eat no vegetables, I could not stand vegetables and now I am actually working in a vegetable garden [laughs]."

"And then I enjoy the YMCA and the bike riding. It was really helpful for exercise and strengthening and eating habits and I liked that …."

"I had the best coach. [name deleted] was the best coach. I stopped smoking within three months."

"…you know I lost like 30 pounds."

"m.chat released.. burden off me for buying household and hygiene stuff and I have extra money for my groceries and medications."

"I am a little calmer and I am clean you know I am sober."

Some participants reported working on their specific health needs such as pain and anxiety management. When asked if they were still maintaining changes they made during *m.chat,* some participants reported continuing with their health goals. Some, however mentioned having difficulty during the transition phase. Overall, participants reported improved self-management skills with regards to different aspects of their health.

4.2.3 Healthcare utilization

Participants were asked to reflect on their healthcare utilization and how *m.chat* might have influenced their use. While participants unanimously agreed on the positive impact of *m.chat* on their overall health, the topic of healthcare utilization was complex. Participants shared a wide range of experiences with healthcare systems and unique stories with regards to change after *m.chat.* First, participants reported varying types of healthcare needs prior to joining *m.chat* which might have influenced the impact of *m.chat* on their healthcare use. For example, individuals with prior conditions reflected on their healthcare use before and after *m.chat* differently than non-utilizers. Additionally, prior experiences with healthcare systems also influenced their perceptions of utilization.

"So many people when we have mental problems .. we are not diagnosed correctly but if we are diagnosed correctly, we are not treated correctly okay. And I have been going through that for a long long long long time.."

"I struggled..I stroked cause I didn't have no insurance. I needed a wheelchair real bad. I finally got John Peter Smith connection, they come and they take care of everything no co-pay or anything. Before I had John Peter Smith connection. Every time I run out, I would go and renew it." [incident took place right before joining *m.chat*].

Getting reminders and encouragement from health coaches to keep up with doctor's appointments was cited as one of the key factors that helped increase participants' interaction with the healthcare systems. Health coaches also helped participants develop communication skills when talking to their doctors to better understand and take charge of their health.

"Well with me, if I was feeling good, I was not going [laughs]. You know, after entering into the m.chat program I learned that whether you are feeling good or not, keep your appointment. Cause you are feeling good today doesn't mean you will feel good tomorrow if you don't keep that appointment. Just stay on top of it all the time."

"Another thing with me is..after I started with m.chat, I stopped relying on my memory for my appointments. I take my calendar and I write all my appointments down you know what day I got to go. That way when I put in the kitchen which I am going to go, it is facing me, it is staring me at my face you know. You got this appointment on this day you know. So that helps me keep up with my appointments."

Others shared that *m.chat* helped improved their healthcare use by promoting self-management strategies.

"Mine changed. Before m.chat, if I had any pain, I would just go to the emergency room. And [name deleted] taught me how to deal with my one doctor who knows me."

"Seems like I need less you know kind a interventions. Seems like I was going to the hospital a lot looking back so yeah I mean I am in somewhat better health. I have gained a lot of weight but … I don't go to the doctor a lot and it seems like I was going a lot at one time and I am not.."

"I used to have to go to the ER much more often but being with my health coach what it did - it has helped. The tips that was given to me it diminished my anxiety."

"I developed a really bad cough and I have never smoked. And so that led up to my surgery. I didn't have cancer but it was a really serious situation and that was all during the time. I talked to [health coach] about the cough cause I could not figure out why I had it so..." [During *m.chat*]

However other participants suggested that there was no change with healthcare use as a result of *m.chat.* Some non-utilizers remained non-utilizers throughout the program. Others pointed out that while *m.chat* improved their awareness of health, healthcare resources in the community did not change and hence was not conducive for healthcare use improvement. An individual without insurance, for example, continued to view the emergency department as a primary healthcare resource. Given available community resources, prior experiences, and familiarity with the healthcare systems, some participants also mentioned not changing their approach to healthcare utilization.

"I would just say that there was no change, same resources. I mean even if I didn't go to m.chat it was going to be the same." [community resources stayed the same]

"Okay, in extreme emergency, no I do not go to emergency room, I go to urgent care okay. Urgent care, they …okay this is the difference between emergency room and urgent care - urgent care you get to be seen quicker okay you are not sitting up in an emergency and you are deathly ill and you are sitting there for hours, I have sit up there for 15 and half hours, blood pressure sky high, sick, before I got to see a doctor. Urgent care, I go there, "look I am feeling bad, I checked my blood pressure at home, my blood pressure was high." They check my blood pressure and they send me into trauma automatically. Cause that stuff is dangerous. So they sent me to trauma and they worked on me to get my blood pressure down. Whereas if I was on emergency, I am just sitting there. So, that is why I say I got to urgent care."

Another individual mentioned that during the time they were uninsured and unable to utilize healthcare resources, they took advantage of their *m.chat*-sponsored YMCA membership to receive necessary services.

"At the time I didn't have my Medicare so because I I had my stroke in 2015, at the time my Medicare, I had to wait two years for Medicare to start. But I liked it where I could go use the..points for the YMCA to go to do therapy you know to help me to get my health right. And then, I ...used to.. So because there were a lot of things I could not do you know and when I had I had my stroke, I had to learn how to walk and do physical therapy and speech therapy and occupational therapy you know, so it helped me a lot but my Medicare kicked in and now I got a silver sneakers to go to the YMCA and still you know get these therapy."

Consequently, participants' experience with healthcare systems was unique based on their needs. While *m.chat* succeeded in improving healthcare use for some participants, there were factors such as community resources and insurance that were outside of the program's control that might have influenced participants healthcare utilization before and throughout the program.

4.2.4 Suggestions

Majority of suggestions were related to logistical aspects of the program. However, a few participants recommended incorporating healthcare providers into the program structure to better meet holistic health needs.

"Because most of the like the questionnaires .. those questionnaires are mostly in general for mostly all people. You see - you understand where I am coming from? So they will ask you only pin point everyone in general and you can only get so much done by doing that and a person can get a, they can be helped a lot more effectively if their mental problem is pin pointed specifically. But like I said it might cost much more money that you all are getting or much more professional people and much more professional people than you all have so...but it is just a thought."

"The thing I think would have made it better was little more on the health issues."

"Have health coach in one area and a medical coach on another area."

Chapter 5: Discussion

5.1 Overview of Findings

The purpose of this study was to assess changes in healthcare utilization and financial charges among supportive housing residents enrolled in a health coaching program. The study included medical claims data and a qualitative examination of participants' perceptions of the program's influence on their healthcare use. Participants reported a positive impact of *m.chat* on their overall quality of life through improved health self-management strategies. The analysis of claims data showed no significant change in healthcare use (including total hospital encounters, inpatient visits, outpatient visits, emergency visits, and charged amounts) in all analyses spanning 12 months prior to 24 months post enrollment.

The total number of hospital encounters 12 months pre and post enrollment slightly increased from 589 to 598 (n=244). When broken down by specific visits, the number of inpatient visits decreased from 45 to 43, outpatient visits increased from 544 to 555, and emergency visits increased from 434 to 454 for the two time-points, respectively. After controlling for excess zeros and variability within participants using a zero inflated negative binomial model for count variables, this study found no changes in healthcare utilization. Similarly, hospital encounters increased from 318 to 341 to 354 from 12-months pre enrollment to 12 and 24-months post enrollment respectively for 131 participants. Inpatient visits increased from 24 to 26 to 34, outpatient visits increased from 294 to 315 to 320, and emergency visits increased slightly from 234 to 250 to 284 for the three time periods respectively. There was no significant changes in healthcare utilization for the three time points.

The median charged amount decreased from \$3,463.26 to \$2,872.68 from 12-months pre to12-months post enrollment for 244 participants. On the contrary, the median charged amount increased from $2,488.0 to $3,464.0 to $3,657.19 from 12-months pre to 12-months post to 12-24 months post enrollment for 131 participants. The log-gamma model showed no significant change in charged amounts for the two-time point analysis as well as the three-time point analysis.

Analysis of healthcare utilization data is complicated given the multidirectional definition of desirable outcomes; the goal is to decrease the number of inpatient hospitalizations and emergency visits by increasing the number of outpatient visits related to preventive care. Additionally, when defining success of any self-management program (targeted to improve health outcomes) in changing healthcare use patterns and costs, it is crucial to acknowledge other factors such as insurance and available community healthcare resources that may influence results. Moreover, the goal should also be to aid early diagnosis of critical conditions such as cancer which will otherwise lead to costly treatment and high chances of mortality at a later stage. For example, the costs of treating oral and pharyngeal cancer at an early-stage is 36% lower compared to late-stage treatment costs (Epstein, Knight, Epstein, Bride, & Nichol, 2008).

5.2 Comparison to Past Research

Since *m.chat* was designed to provide health coaching specifically to supportive housing residents with history of homelessness and high health needs, our findings were compared to results of studies which examined changes in healthcare utilization among individuals with chronic health conditions who were enrolled in self-management interventions. As noted in the introduction, there was mixed evidence in the literature regarding the effectiveness of self-management programs in influencing healthcare services use. Our study concurred with some previous findings and showed no significant difference in healthcare use outcomes in pre-post analysis over the course of 24 months and 36 months (Burton et al., 2017; Rettig et al., 1986;

Schmidt et al., 2015). However, other studies found a significant change in healthcare utilization (Bourbeau et al., 2003; Cline et al., 1998; Fedder et al., 2003; Wheeler, 2003). Multiple factors may be responsible for these differences. For example, variation in recruitment strategies, data collection techniques, rigor of analyses, as well as a targeted health condition(s) complicate the comparison process. These four dimensions are discussed in the following paragraphs.

First, recruitment strategies varied across studies. Some studies recruited participants from the community based on a health condition(s) irrespective of their healthcare use status at baseline, comparable to the recruitment strategy of *m.chat*, and found similar results (Burton et al., 2017; Rettig et al., 1986). Based on the level of healthcare systems engagement of the sample at baseline, the short-term use trajectory after implementing the program may vary, influencing study outcomes. For example, if participants were already complying with the recommended treatment plans and had access to preventive care at baseline, utilization is less likely to increase post-enrollment. On the contrary, if participants were non-users at baseline, there could be an initial spike in their healthcare use. Therefore, it is important to consider the recruitment pool and their expected trajectory of healthcare use when operationalizing the success of an intervention. *m.chat* was comprised of individuals with heightened health needs, living under poverty line, with lack of understanding of quality healthcare and/or lack of access to healthcare services. As a result of these factors, it is not surprising that there was no significant change in short term analysis despite the positive impact of the program on individuals' perceived health.

Second, studies were different concerning the lengths of time for analysis, which could have influenced their respective outcomes. A study explored changes in monthly billing patterns among high utilizers before and after they enrolled in an intensive care management program (Horn, Crandall, Binder, & Sklar, 2017). Researchers reported an increasing trend during the pre-phase leading up to a substantial spike around the time of enrollment followed by a considerable drop during the post-phase (Horn et al., 2017). Furthermore, the control group also followed the same trajectory as the intervention group. This study highlighted an important fact that if the control and intervention groups follow the same trajectory in the short term, it might be necessary to extend the timeframe for analysis to gauge the actual impact (Horn et al., 2017). Other researchers have echoed that the length of follow-up affects healthcare outcomes, particularly when conducting cost-analyses (Ofman et al., 2004).

Third, the data sources used vary from study to study. While some studies utilized comprehensive data from multiple hospitals to explore healthcare use such as our study and found no changes, others included data from only one hospital where participants were recruited (Schmidt et al., 2015; Wheeler, 2003). The latter strategy assumed that participants sought treatment at a single location which may have underestimated the actual extent of use. Furthermore, some studies used self-reported data on healthcare use which is subjected to recall bias (Fleming et al., 2000; Lorig et al., 2001; Smeulders et al., 2009). The operational definition of hospital encounters also varied. Some studies counted the actual number of hospital encounters (including the number of emergency visits and inpatient stays) within the study period in alignment with our method and found no change in healthcare utilization (Schmidt et al., 2015). However, others used estimated use. For example, some researchers used the raw number of hospital encounters for a specific period and calculated annual estimates and reported a significant change in utilization (Fedder et al., 2003; Lorig et al., 2001). Considering the episodic nature of healthcare use, this method of estimation may not be reliable. Others combined healthcare measures such as physician and ED visits, or if an ED visit resulted in hospital admission, it may have been counted as an inpatient visit alone (Burton et al., 2017;

Lorig et al., 2001). These variations could potentially over or underestimate change. Generally, findings from our study aligned with previous studies that followed a similar data collection procedures.

Finally, the majority of studies that showed positive results in one or more healthcare use measures excluded individuals experiencing pressing medical problems (terminal illness such as cancer), or co-morbid conditions (such as alcohol abuse, substance use, and mental health diagnosis) during the recruitment phase (Bourbeau et al., 2003; Cline et al., 1998; Fedder et al., 2003; Lorig et al., 2001; Wheeler, 2003). However, there is evidence in the literature that psychosomatic co-morbidity significantly influences healthcare utilization.(Schneider et al., 2011) For instance, individuals with mental health problems are 2.2 times more costly to the system compared to individuals without these diagnoses (Nikhil, 2013). Excluding people with potentially expensive co-morbidity undermines the complexity of issues faced by high-utilizers. On the contrary, our study included co-morbidities as the program was designed to serve supportive housing residents with high health needs (mental health disorders, substance use problems and chronic health issues). Given the inclusion of complex health conditions in our study, it is not surprising that we found no significant change for the study timeframe compared to positive results from studies with restrictive inclusion criteria. Even with these restrictions, only a few studies reported health condition-specific changes in healthcare use and costs (Bourbeau et al., 2003; Clausen et al., 2016).

In summary, there is mixed evidence in the literature regarding the effectiveness of self-management programs on healthcare utilization. Our findings were supported by studies that followed similar recruitment strategies (recruitment of participants from a community setting) and data collection methods (counting actual hospital encounters from multiple hospitals rather than estimates and/or data from one hospital). Furthermore, one of the significant differences between studies that found different results compared to ours was the exclusion of pressing medical problems (terminal illness such as cancer), or co-morbid conditions (such as alcohol abuse, substance use, and mental health diagnosis) from their analyses, underestimating the complexity of healthcare use among high needs populations.

5.3 Trajectory of healthcare use among high needs populations

Another consideration when interpreting these results is the expected trajectory of healthcare use among high needs population. If there is an expectation that healthcare use would continue to increase without the implementation of *m.chat*, then maintaining use through 24-months post enrollment may be inferred as a positive impact of the program. Studies show an increasing trend in hospitalization among people with mental health conditions. In a systematic review of studies published between 1966 to 1997, authors identified depression or psychological distress among the strongest predictors of high healthcare utilization among chronically ill people (De Boer, Wijker, & De Haes, 1997). Individuals who had depression were hospitalized more often than those without depression (De Boer et al., 1997). Similarly, in a longitudinal cohort study conducted in the United Kingdom to explore the relationship between depression and risk of future emergency hospital admissions among people with chronic physical health conditions, authors found depression to be a strong predictor of future admissions related to their physical health within a year (Guthrie et al., 2016). Additionally, authors identified individuals who lived alone, had heart conditions, experienced life threatening incidences, and had a history of emergency hospitalization within the past year as factors independently associated with increased risk of emergency hospitalization within 12 months (Guthrie et al., 2016).

Another longitudinal study examined housing status and healthcare utilization for individuals with serious mental health problems who were enrolled in supervised residential care between 1973 to 1983. Among those admitted to hospital for psychiatric reasons (41%) during the study period, the mean number of hospital encounters was higher from 1973-1983 compared to 10 years prior to enrollment into the housing program, although the average length of hospital stay was reported to be shorter (Segal & Kotler, 1993). Additionally, in a nationwide study that looked at the trend of hospital utilization and associated costs between 2005 and 2014, authors reported a 12.2% increase in the number of hospital stays for mental and substance use problems.(McDermott, Elixhauser, & Sun, 2017).

In a systematic review looking at changes in healthcare costs associated with disease management programs, authors reported that people with heart conditions were more likely to observe cost-savings and people with depression were the least likely to observe costs-savings over time (De Bruin, Heijink, Lemmens, Struijs, & Baan, 2011). Given that mental health conditions was an inclusion criterion for enrollment into *m.chat*, and evidence in the literature suggesting an increasing trajectory of use over time, it is possible that the program may have played a valuable role in stabilizing use over time. However, a randomized controlled study would be needed to draw these conclusions.

It is also important to consider the average age of our participants. As mentioned in the introduction, the all-cause mortality among 45-64 year old male residents of a PSH program was found to be 4.7 times higher compared to that group in the general population (Henwood et al., 2015). The average life expectancy in the United States is almost 80 years (Xu, Kochanek, Murphy, & Tejada-Vera, 2016). However, the life expectancy of chronically homeless is close to 20 years shorter than the general population (Culhane & Byrne, 2010). In another study that looked at life expectancy of homeless individuals in select cities with high prevalance of homelessness, it ranged from 42 to 52 years (O'Connell, 2005). Given the average age of participants in our study (55 years) and their expected life expectancy, majority of our participants could already be in the last decade of their lives. We know from research that it is the proximity to death that predicts increased healthcare expenditure irrespective of the age (Yang et al., 2003). Hence, we could expect an increasing trajectory of healthcare use and costs among our participants without *m.chat.*

5.4 Costs Analysis

Disease management programs are designed to promote savings through a causal pathway; improvement of quality, leading to prevention of morbidity, then to financial savings resulting from increased treatment compliance and reduced hospitalization (Fireman, Bartlett, & Selby, 2004). However, healthcare utilization studies seldom show substantial overall financial savings (Jack et al., 2017). In a systematic review of 31 papers focused on disease management programs and cost savings published between January 2007 and December 2009, the majority of studies (21) reported an increase in healthcare costs over the course of a year and only 13 studies reported cost savings (De Bruin et al., 2011). The drawback of looking at costs as a proxy to healthcare use improvement is that it provides a narrow viewpoint of a complex issue. Some studies, although not successful at reducing costs, demonstrated improved health outcomes, which are often not reported in cost studies (Jack et al., 2017). Therefore, it is important to look at the improvement in health outcomes and cost effectiveness of the program over the long term to fully understand the impact of a program, rather than cost savings alone.

One study examined healthcare utilization, quality indicators and costs from 1996 to 2002 for adults with four conditions (heart failure, coronary artery disease, and asthma) enrolled in a disease management program. Similar to our findings, authors observed improvements with quality indicators but also found a substantial increase in costs for each of the four conditions during the abovementioned period. The authors argued that without a control group they were unable to assess the cost-effectiveness of their program (Fireman et al., 2004). Some studies that included a control group were able to observe cost effectiveness. For example, in a retrospective matched cohort study of 1114 adults 65 years or older enrolled in an exercise program over a period of 3 years, the authors reported that the total increase in healthcare costs annually was higher among controls compared to participants (Ackermann et al., 2003).

In summary, the evidence for cost savings through the implementation of disease management programs, although promising, is weak. However, a lack of change, as reported by this study should not be dismissed as undesirable without taking into account the expected long-term use trajectory.

5.5 Other factors

During qualitative sessions, participants reported several factors that could have influenced their healthcare utilization, despite their perceptions that *m.chat* improved their self-management, health and awareness through health coaching.

5.5.1 Personal factors

First, participants identified the time it took to get to know the program and their coach and build trust as one of the major reasons that might have prevented them from getting more benefit from *m.chat.* Due to a lack of trust, the majority of participants agreed that they misinformed their coaches about their health and needs during the initial phase. Even after building trust, a small proportion of participants mentioned they continued to lie, as they did not want to disappoint their coach by telling them about their relapses or not accomplishing their goals. When asked what advice they would give to someone thinking about joining *m.chat,* all participants agreed that they would advise people to be open and honest with their coaches from the beginning so they can maximize their benefit from *m.chat.* However, it is hard to assess the actual time it took for each participant to fully engage with the program. Given these delays, it is unclear how long it would take to be able to observe program benefits (Fireman et al., 2004). This is a research question for future analysis of *m.chat* data.

Second, participants reported varying levels of healthcare needs prior to joining *m.chat* which might have influenced the impact of *m.chat* on their healthcare use. For example, individuals with substantive health concerns (e.g., prior stroke) reflected on their healthcare use before and after *m.chat* differently than non-utilizers who started going to their primary care physician as a result of the health coaching. Others also reported that health coaches helped them recognize pressing health needs and seek care which could have resulted in increased hospitalization (for surgeries or other needed care) during the initial phase.

Although health coaches provided support and resources to help improve healthcare utilization outcomes, it can be challenging for people with high healthcare needs to enforce change in the way they access care. In a qualitative study that explored participants' perspectives on reasons for returning to an ED, fear or uncertainty about disease progression was cited as the primary reason for their premature return (Rising et al., 2015). Even participants who had a designated primary care physicians (PCP) indicated they preferred going to the ED without consulting their PCP, given the convenience and expedited process (Rising et al., 2015). Some of our participants echoed this finding regarding their familiarity with existing healthcare options in the community. Another qualitative study found that people from lower socioeconomic backgrounds preferred going to hospitals over ambulatory care because of increased access to hospitals and the belief that hospitals offer a better quality of care at a lower cost (Kangovi et al., 2013). These personal factors may have also influenced healthcare utilization.

5.5.2 Systems level factors

m.chat was designed to work with participants at an individual level to help improve their overall wellbeing. Therefore, it is important to explore systems-level factors that could have influenced healthcare utilization beyond the scope of the program. Participants who reported no change in healthcare use during qualitative sessions pointed out that while *m.chat* improved their awareness of health, healthcare resources in the community did not change. An individual without insurance, for example, continued to view the ED as a primary healthcare choice. Given available community resources, prior experiences, and familiarity with the healthcare systems, some participants also mentioned not wanting to change their approach to accessing care.

There is agreement in the literature that although supportive housing programs have shown tremendous success in addressing homelessness, there are systemic challenges to providing PSH residents with a full spectrum of care intended to improve their overall wellbeing. The availability of services provided through Medicaid-covered benefits is fragmented and can be inflexible for people with trimorbidity (mental health disorders, substance use problems, and chronic health conditions) (Wilkins, 2015). There has been a shift in the role played by supportive housing programs in alignment with Medicaid services to improve healthcare delivery including behavioral health services such as *m.chat* (Wilkins, 2015). However, there are still gaps in the system that needs to be addressed. For example, funded through a Medicaid waiver project, *m.chat* was created to serve as a supplement service to improving overall wellbeing by adding health coaching that was not being offered by existing programs. Additionally, this study was based in Texas, a state without Medicaid expansion (Garfield, Damico, Stephens, &

Rouhani, 2016). This could have influenced participants' access to healthcare. A study that compared healthcare utilization during the second year of Medicaid expansion in Kentucky to the state of Texas and reported improvement in healthcare utilization measures (including an increase in outpatient visits and preventive care, and reduction in ED visits) after expansion (Sommers, Blendon, Orav, & Epstein, 2016). Our findings suggest that there is a need for further collaboration at the systems level to increase access and quality of healthcare available to supportive housing residents.

Some communities have attempted to bridge this gap by integrating healthcare into supportive housing programs and have seen some success. In partnership with a HF agency, the Jefferson Department of Family and Community Medicine developed an integrated on-site person-centered care and monitoring system to address complex health needs among formerly homeless individuals with serious mental illness. Emerging as a community level solution, preliminary research points to the success of this model in meeting the ongoing needs among supportive housing residents. However, the authors discussed challenges related to sustainability, particularly with regards to funding; there is a lack of a reimbursement mechanism for necessary physician care under the existing insurance systems (Weinstein et al., 2013). Nonetheless, this example offers insights for potential partnerships between programs such as *m.chat* and community healthcare resources for increasing collective impact and addressing holistic health needs among supportive housing residents.

In summary, while *m.chat* shows improvement with self-reported health outcomes and perceived health, there are factors that may have also influenced healthcare use; personal level factors (trying to survive under fixed income, lack of money to buy medication, delayed program compliance, and preferrence for hospital system care) and system level factors (limitations of current Medicaid coverage, lack of access to preventive services in the community, and lack of care coordination) are among factors that could have acted as barriers to changing healthcare use patterns.

5.6 Implications of this study

This study was the first to look at changes in healthcare utilization and financial charges among supportive housing residents enrolled in a health coaching program. Through prior evaluation, we know that *m.chat* participants showed improvements in several aspects of self-reported health and well-being (Chhetri et al., 2017). During the qualitative sessions, participants reported high satisfaction with the program and believed that *m.chat* made a positive impact on their overall health by promoting self-management strategies.

Although medical claims data showed no significant changes in healthcare use patterns (including total hospital encounters, inpatient visits, outpatient visits, and emergency visits) and charged amounts, this study highlights the potential success of health coaching programs in stabilizing healthcare utilization among individuals who might otherwise be expected to increase their healthcare utilization over time. However, this conclusion cannot be confirmed without a randomized and controlled research design.

A review of the literature shows the effectiveness of self-management programs on healthcare utilization and cost-savings is inconclusive. This study adds value to this body of research in several ways. The majority of published studies focus on one health condition or disease state versus our study with broader inclusion criteria. Additionally, our study is complex in terms of recruitment, data collection, and analysis compared to most studies that looked at pre-post analysis with less statistical rigor. The inclusion of participants with both mental health conditions and substance use in our study adds value to the literature.

Given the mixed method approach, this study also identified personal level factors (trying to survive under a fixed income, lack of money to buy medication, delayed program compliance, and preferrence for using hospital services) and system level factors (limitations of Medicaid coverage, lack of access to preventive services in the community, and lack of care coordination) that influence healthcare utilizations. This further adds context to our quantitative findings and recognizes opportunities for future collaboration.

There are several other factors that influence healthcare use. For example, in a systematic review of Andersen's Behavior Model of Health Services Use, the authors listed age, gender, race/ethnicity, education, marital status as predisposing factors influencing healthcare utilization (Babitsch, Gohl, & Von Lengerke, 2012). Other studies have reiterated these findings (Green & Pope, 1999; Nelson, 1993; Philbin & DiSalvo, 1998; Getzen, 1992). Income is among enabling factors that influence healthcare utilization (Babitsch et al., 2012). While our study did not report on these covariates, it could be an avenue for future studies to explore.

Moreover, *m.chat* appears to have made a positive impact on participants' perceived health and wellbeing. Given high health needs among participants, delays with program compliance, and other challenges to improving healthcare utilization, future studies should look at long-term influence on healthcare utilization to evaluate the actual impacts of the program.

5.7 Limitations

This study has several limitations. First, we looked at changes in healthcare utilization patterns among supportive housing participants enrolled in a health coaching program. The target population included in this study are hard to reach and have complex multifaceted needs. Therefore, the generalizability of this study results is limited to similar populations. Second, the *m.chat* program used a non-probability purposive sampling method (Hedt & Pagano, 2011). Participants were recruited from RHP 10 Region of North Texas through distribution of flyers, letters, referral from a friend, and self-referral. As the enrollment into *m.chat* was based on purposive sampling, there is a potential for selection bias.

Although the DFWHC data warehouse was identified as the data source for *m.chat* participants, our file did not include complete healthcare use data for all participants. Participants may have visited office-based clinics within DFWHC partner hospitals, other private clinics, urgent care and other healthcare services not listed as members of DFWHC within the study period, which were not included in our data file. This dataset also does not include pharmacy charges (other than hospital ancillary pharmacy charges) which can be a significant driver of costs. This missing information may have underestimated our analysis of healthcare use and costs.

This study included medical claims data. The cost variable included in the dataset is the charged amount (or billed amount) which does not represent the actual cost of care. The charged amount only include the price of a service as valued by the provider (Riley, 2009). While the charged amount may sometimes represent the actual cost expected to be paid by the uninsured, for the insured population, the actual cost is negotiated between insurance providers and healthcare providers which can be considerably different from billed charges (Riley, 2009). Additionally, given the variation in formulas used, the actual payment for the same billed cost varies from one provider to another; Medicaid payments might be different from Medicare payments for identical services (Riley, 2009). Therefore, the charged amounts used in our cost analysis do not represent the true cost of care.

For the focus groups we reached out to *m.chat* participants who had agreed to be contacted for future research activities during their most recent monthly assessment prior to the program end date. Only 181 participants out of the total 653 *m.chat* participants were identified as eligible for focus groups based on their answer to this question. This may represent selection bias in the focus group data.

Finally, due to lack of a control group, it is difficult to assess the true impact of *m.chat* on participants' healthcare use outcomes. However, this study was the first to shed light on healthcare utilization patterns among supportive housing residents enrolled in a unique health coaching program. Our findings can inform future intervention designs dedicated to serving high users of healthcare systems with complex health needs.

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