Optimizing integrated behavioral healthcare implementation in primary care settings using latent class analysis

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Abstract

Access to high-quality behavioral health services is a struggle for millions of Americans and an ongoing frustration for many medical and mental health professionals who refer for or provide this care. Over the past several decades, several models of care have been developed in attempts to improve this access, but with varying degrees of success in implementation and dissemination. Integrated behavioral healthcare, or IBH, is an umbrella term for these models, which aim to bring mental health professionals into primary care medical clinics for more direct mental health access. The current research consists of two studies that examine a community sample of 102 primary care medical clinics that were in varying stages of implementation of the IBH practice approach. In the first study, I used latent class analysis to identify classes of clinics based on their implementation of IBH processes and structures and then examined the influence of context variables on the likelihood that an implementation structure will result. Results were four classes of clinics: Low IBH, Structural IBH, Partial IBH, and Strong IBH; Partial IBH clinics tended to be more rural, in smaller organizations, and to serve lower SES-risk patients. There were noticeable differences in levels of implementation for many of the components of IBH, which has implications for supporting current and future IBH implementation projects toward success. In the second study, I explored the possibility that IBH implementation classes moderate health disparities. Results indicated that IBH may improve healthcare management in some disparate situations, but that IBH alone cannot resolve healthcare disparities and is likely only one of many primary care innovations that practices must adopt to address healthcare disparities.

Keywords: integrated behavioral healthcare, primary care behavioral health, practice transformation, healthcare management outcomes, healthcare disparities, behavioral healthcare access, mental healthcare access, latent class analysis

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Overview

The system of care for mental health in the United States has significant gaps. It is difficult for many people to receive mental health care they need, particularly when it comes to prevention and early intervention. This gap in available resources is due to layers of systemic issues ranging from historical medical philosophy which separated the mind from the body (Cassel, 1982; Compton-Phillips & Mohta, 2018; Runyan, 2018) to structural racism which prevents patients of color from receiving the same quality of services as white patients (Byrd & Clayton, 2001; Churchwell et al., 2020). The result is that the U.S. as a whole has a heavy mental health disease burden (Murray et al., 2013), and this burden is even more concentrated in minority populations and those who have reduced socio-economic resources (Cook et al., 2019). In order for all patients to receive high-quality mental healthcare, a transformation of the healthcare system must occur and is beginning to occur.

Currently, many people who seek treatment for a mental health condition start with their primary care medical provider (PCP; Olfson, 2016). PCPs assess the problem and may refer patients to specialty behavioral health providers (such as licensed psychotherapists, psychiatrists). However, the referral system for behavioral health is difficult to navigate for both patients and providers, and there is a shortage of behavioral health providers (e.g., Hacker et al., 2014). Because of these challenges, primary care medical providers often end up treating patients that need specialized care (Tynan, 2016). In addition to the issues that arise when a patient voices a concern about a behavioral health issue, there is a larger percentage of the population who either are unaware that they have a behavioral health issue or who never seek treatment for it, even from their

PCPs (Mojtabai et al., 2016). For these patients, a more proactive approach is necessary to screen and assess for mental health concerns and provide treatment recommendations. However, the current structure of the medical appointment and primary care medical providers' training are not very compatible with providing behavioral health services, particularly in situations where medication may not be the best option (Acri et al., 2018). Providers also indicate hesitation around increasing screening when there is not a clear workflow to provide the patient with efficacious treatment (Gardner, 2014; Taliaferro et al., 2013).

Theoretical Frameworks

Integrated Behavioral Healthcare

Integrated behavioral healthcare is defined as "The care that results from a practice team of primary care and behavioral health clinicians, working together with patients and families, using a systematic and cost-effective approach to provide patient-centered care for a defined population" (Peek & The National Integration Academy Council, 2013). It typically occurs through a shift in practice at a medical clinic to incorporate personnel and resources who specifically address mental health concerns. There are several practice models of IBH, which will be explained in more detail shortly. The recently developed IBH Cross-Model Framework (Stephens et al., 2020) operationalizes the core principles, processes, and structures necessary for a clinic to provide IBH such as team-based care, population-based care, and presence of a behavioral health clinician; this framework will be used throughout this dissertation. The IBH Cross-Model Framework allows the ability to look at any medical clinic with an IBH lens and defines the characteristics of IBH that should be present.

Implementation of IBH is complex and requires a concerted effort to reorganize the way a clinic functions (e.g., Brown-Johnson et al., 2018). Some healthcare organizations are already undertaking a redesign of their behavioral health service delivery, with variable outcomes (Yonek, Lee, Harrison, Mangurian, & Tolou-Shams, 2020). Others have not yet begun to incorporate behavioral healthcare into primary care settings. Peek (2008) identified three different worlds in healthcare: clinical (those working with patients), operational (those organizing and managing healthcare personnel and systems), and financial (those managing reimbursement for care), which sometimes seem to have disparate goals but which he indicates must work together to maintain a quality healthcare system. Change across all three worlds is fundamental to successful IBH implementation. The Quadruple Aim (Bodenheimer & Sinsky, 2014) provides a framework for harmonizing the sometimes seemingly disparate goals of the three worlds of healthcare. The Quadruple Aim focuses on enhanced patient experience, healthcare provider and staff work life satisfaction, improved population health, and reduced costs. In order for each of these goals to be substantively met, behavioral health needs to be considered an essential component of the healthcare system. While there have been increasing calls by professional organizations to consider behavioral healthcare equivalent to and essentially intertwined with physical healthcare (Ader et al., 2015; Baird et al., 2014; Committee on Psychosocial Aspects of Child and Family Health and Task Force on Mental Health, 2009), the clinical, operational, and financial worlds of healthcare have not yet caught up with this philosophy shift. This is where implementation science is essential.

Implementation Science

Implementation science is an emerging field in social science and can be defined as "the scientific study of methods to promote the systematic uptake of research findings and other evidence-based practices into routine practice, and, hence, to improve the quality and effectiveness of health services" (Eccles & Mittman, 2006, p. 1). There are many frameworks currently utilized in implementation science, but they generally fall into "process" (e.g., EPIS; Aarons, Hurlburt, & Horwitz, 2011) or normalization process theory; May et al., 2009), "determinant" (e.g., Consolidated Framework for Implementation Research; Damschroder et al., 2009), or "evaluating" (e.g., Glasgow et al., 1999; Proctor et al., 2011) categories (Damschroder, 2020). Process frameworks demonstrate *how* implementation occurs (e.g., exploration, adoption decision, active implementation, and sustainment; Aarons et al., 2011), determinant frameworks demonstrate *where* implementation occurs, or *the elements by which* it occurs (e.g., the individual, inner setting, outer setting, the intervention itself; Damschroder et al., 2009), and evaluating frameworks demonstrate *how well* it occurs (e.g., fidelity to the intervention, spread/reach of intervention in the organization/population; Proctor et al., 2011). In this study due to the cross-sectional nature of the data, we will generally focus on "determinants" of implementation.

The Consolidated Framework for Implementation Research (CFIR) is one of the most widely used determinant frameworks in implementation science. Fundamentally, it presents a comprehensive taxonomy of intervention implementation in health services, and provides an understanding for how implementation constructs are categorized and related (Damschroder et al., 2009). Key areas of implementation include (1) characteristics of the intervention itself (e.g., complexity), (2) the process of implementation (e.g., planning), (3) characteristics of the individuals in the setting (e.g., knowledge and beliefs about the intervention), (4) the inner setting (e.g., culture), and (5) the outer setting (e.g., external policies and incentives) (Damschroder et al., 2009). Using these constructs, health services researchers can structure their implementation and assessment of interventions, whether they be individual or system-level interventions. Examining each area of constructs prior to an implementation project, or in evaluation of it, may allow for a greater chance of success and better understanding of the implementation outcomes. In the present study, the most relevant implementation areas are *the intervention itself* (i.e., integrated behavioral healthcare), *the inner setting* (e.g., clinic size), and *the outer setting* (e.g., clinic rurality, clinic area race/ethnicity, policies impacting healthcare services).

Implementation outcomes put forth by Proctor et al. (2011) provide health services researchers an understanding of “how” to assess success of an implementation project, while Damschroder et al. (2009)’s CFIR provides the “where” to assess success. Implementation outcomes may include acceptability, adoption, appropriateness, feasibility, fidelity, implementation cost, penetration, and sustainability (Proctor et al., 2011). In the present study, relevant implementation outcomes include *adoption* (i.e., intention or decision to engage in an innovation or practice) and *fidelity* (i.e., the degree to which an intervention was implemented as intended by the developers; Proctor et al., 2011).

Critical Theory

As identified above, healthcare access and quality are not equitably distributed across the population. There are many people in the United States that do not have access to the care they need, or do not receive quality care when they seek treatment. *Critical theory* (Falk-Rafael, 2005; Morrow & Malcoe, 2017; Swartz, 2014) seeks to examine and challenge power structures through social science knowledge. A foundational tenet of critical theory is that oppressive structures of relationships exist and indeed create the society in which we live; yet precisely because they are so foundational, they are rarely identified and examined (Swartz, 2014). Falk-Rafael (2005) linked critical theory to the practice of nursing and identified that the key role of public health nurses has long been to address adverse *social determinants of health* (SDOH; i.e., inadequate housing, poor working conditions, lack of access to healthy food), yet indicates that a shift toward the hierarchical medical model reduced nurses' capacity to engage in whole-person care. "Whole-person care" has become something of a buzzword in the current healthcare environment and has been a driving force in increasing integration of medical care and mental health care (Gold, Green, & Peek, 2017; Twomey & Steinberg, 2016). Yet it is very difficult for those in the current system to be able to embrace the true meaning of equally valuing patients regardless of socioeconomic status, race/ethnicity, or other social positions of power and inequity, and of co-creating solutions to the challenging contexts in which patients attempt to live healthy lives (Morrow & Malcoe, 2017).

When examining an intentional shift in the healthcare system, it is important to ensure that those with less resources are lifted up. Only in this way can we achieve not only a more integrated system with easier access to behavioral healthcare, but also ensure that access is available for all who need it. Therefore, this dissertation will examine how various results reflect current inequities in the healthcare system and suggest solutions for resolving them. Consistent with critical theory, this study will focus on (1) the inequitable distribution of access to mental health care and whether IBH can increase equity, as well as (2) how to ensure that mental healthcare is not merely a mirage of care, but actually improves the lives of the patients it purports to serve.

The Current Studies

The current studies examine how a sample of primary care clinics have implemented IBH using a person-centered analysis approach, and then examine contexts and outcomes associated with the resultant clinic profiles. Person-centered analysis, specifically either latent class or latent profile analysis, is an analytic approach utilized when it is hypothesized that there are homogenous groups present within a heterogeneous sample (Lanza et al., 2012). The groups are not known ahead of time but rather understood through statistical analysis of the data. Person-centered analysis has been utilized for understanding IBH implementation (specifically, fidelity) at the level of the individual provider (Beehler et al., 2015), and for other aspects of mental health services at the level of the facility (Mauro et al., 2016). Therefore, a promising and innovative strategy that has not yet been pursued is clinic-level IBH implementation through a person-centered approach. It is hypothesized that clinics may also follow patterns in their adherence/fidelity to elements of IBH similar to that found by Beehler and colleagues (2015). In addition to classifying clinics, recent developments in latent class analysis allow us to consider how the resulting classes relate to distal outcomes and/or predictors (Asparouhov & Muthén, 2019; Nylund-Gibson et al., 2014). This ability means that we can examine relationships between homogenous groups of clinics and other variables.

In the first of the present studies, I identified classes of clinics based on their implementation of IBH processes and structures and then examined the influence of context variables on the likelihood that an implementation structure will result. In the second study, I explored the possibility that IBH implementation classes moderate health disparities.

Study 1: Implementing integrated behavioral healthcare in varied clinical settings: Using the Cross-Model Framework to describe a normative sample of clinics

Integrated behavioral health (IBH) is a rapidly growing approach to care in primary care settings that can improve patient outcomes related to mental health and chronic condition care, increase patient and provider satisfaction, improve access to care, and reduce overall health care costs (Archer et al., 2012; Possemato et al., 2018; Robinson & Reiter, 2016). Clinics with IBH utilize behavioral health providers within their clinics to provide integrated medical and behavioral healthcare to target whole-person care, use evidence informed behavioral and mental health interventions, and improve care management across all primary care teams. With both providers in the same space, using the same equipment and seeing patients in concert, providers can have frequent, brief interactions that convey critical, whole-person health information (Hunter et al., 2018; Hunter & Goodie, 2010).

Common Models of IBH

Two prominent models of IBH include the Collaborative Care Model (CoCM; Unützer, Harbin, Schoenbaum, & Druss, 2013) and the Primary Care Behavioral Health model (PCBH; Reiter, Dobmeyer, & Hunter, 2018). Each model has a slightly different operational and clinical structure, but there are many common principles and themes. Briefly, CoCM is a highly structured model that always includes the primary care provider (PCP), a care manager (typically a licensed behavioral health professional or nurse), a psychiatric consultant, and the patient (Unützer et al., 2013). Components of CoCM include a patient registry, regularly-scheduled formal consultation between the psychiatric consultant and the care manager, and “enrolling” patients into the program to target specific diagnoses, such as depression (Unützer et al., 2013). PCBH includes a behavioral health clinician physically integrated into the clinic care structures who typically sees patients with behavioral health or physical health conditions with a behavioral component (i.e., diabetes); clinics with PCBH may or may not also utilize a registry and psychiatric services/consultation (Hunter & Goodie, 2010; Reiter et al., 2018). Generally speaking, CoCM is more diagnosis-specific and structured, whereas PCBH focuses on population health of all patients, regardless of diagnosis and not requiring that patients formally enroll in structured services. CoCM and PCBH are not necessarily mutually exclusive, and in fact many organizations and clinics that implement IBH include components of both models (Hunter & Goodie, 2010).

IBH Cross-Model Framework

As indicated above, CoCM and PCBH are two common models of IBH. Clinics may also choose to implement certain aspects of IBH but not intentionally follow either CoCM or PCBH, such as clinics that co-locate behavioral health clinicians with medical providers but do not fully integrate them into a care team structure. All of these approaches can be considered to be under the "umbrella" of IBH, yet are different enough that until recently it was challenging to compare clinics across models. The IBH Cross-Model Framework is a recently-developed framework (i.e., a step up in abstraction from models) which identifies the key core components of any IBH program (Stephens et al., 2020). The authors first defined 25 processes (exemplifying five principles, e.g., patient-centered care, team-based care) and nine structures (e.g., behavioral health provider, shared EHR) using a consensus-based approach from 31 experts. For example, the principle "population-based care" is defined as "Ensure limited services reach the most patients while targeting the patients most in need" (Stephens et al., 2020). They then validated the framework by surveying 61 experts and stakeholders in the IBH model to assess importance and measurability of each process/structure. CoCM, PCBH, co-located care, and other models of IBH can therefore be seen as under the “umbrella” of the Cross-Model Framework. See Figure 1 for a full articulation of the Cross-Model Framework. The current study examined IBH implementation across a heterogenous sample of clinics that used various models of IBH in their practices and it was therefore essential to utilize a framework that was able to capture this variation successfully.

Variability in Implementation of IBH

Some research on IBH implementation has shown varying adherence to the core components of IBH. Beehler, Funderburk, King, Wade, & Possemato (2015) completed a latent class analysis (LCA) with Veterans’ Health Administration IBH behavioral health providers and found that these providers fell into one of five groups based on their fidelity to a specific IBH model, including the domains of (1) Clinical Scope and Interventions; (2) Practice and Session Management; (3) Referral Management and Care Continuity; and (4) Consultation, Collaboration, and Interprofessional Communication. One group demonstrated high fidelity across all domains, the second group demonstrated high fidelity across domains (1), (2), and close on (3), three groups fell in the moderate fidelity range on all domains, and the last group was moderate on domain (1) but lower on the other domains, including low fidelity on domain (4). In fact, domain (4) Consultation, Collaboration, and Interprofessional Communication was consistently the lowest for all groups except the first group (Beehler et al., 2015). While this study considered how provider-level differences affected membership in the groups, more understanding of how context affects IBH implementation is needed. Context refers to the *outer setting* in CFIR, or the “economic, political, and social” setting (Damschroder et al., 2009). In addition to not examining context, Beehler, Funderburk, King, Wade, & Possemato (2015) only examined the practice patterns of individual behavioral health providers. These differences may also be driven by clinic-level implementation. In particular, different clinical contexts potentially provide different resources to support IBH implementation based on factors such as patient demographics, geographic location, and practice size. A recent study by Unützer and colleagues (2020) examined the relationship between clinic characteristics and depression treatment outcomes in clinics having implemented collaborative care. Their findings further supported the suggestion that context may impact implementation, which subsequently may impact outcomes. What Unützer and colleagues (2020) did not actually assess, however, was the result of implementation of collaborative care, using the level of implementation support the clinic received as a proxy for implementation outcomes (i.e., fidelity to the CoCM model, etc., see Proctor et al., 2011). In other words, they did not assess whether the clinics were successfully following the CoCM model, rather assumed that more intensive implementation support resulted in successful implementation.

Review of the literature leads to the conclusion that there are several gaps in the research on global transformation of practices from traditional primary care models to integrated primary care models (Kwan & Nease, 2013). The first gap is that a community sample of clinics has not been described in terms of their IBH implementation status. The second gap is that clinic context (i.e., outer setting) has not been examined when considering the implementation status of the clinics. However, context is key in understanding which clinics engage in IBH and to what degree. Kwan & Nease (2013) point out that the heterogeneity in effect sizes of the impact of IBH implementation on clinical outcomes likely means that there are additional variables (i.e., contextual variables) that influence the effectiveness.

Contextual factors such as patient populations, practice sites, and community variables have been shown to drive differences in quality and access to care. First, rural clinics are associated with less access to behavioral healthcare due to geography and economic distress, cultural differences and stigma of behavioral health concerns, and less available quality care or specialized care when compared to urban clinics (Jensen & Mendenhall, 2018; Stamm et al., 2007). Second, socioeconomic risk has been found to be a contributing factor to mental illness, likely through a bidirectional and compounding relationship between stress mechanisms and reduced functionality (Santiago, Kaltman, & Miranda, 2013). People with low incomes are also less likely to have access to behavioral health services and struggle to remain engaged when they do, due to logistical barriers, prohibitive cost, lack of high quality health insurance, cultural stigma, childcare issues, and many other difficulties associated with living in poverty (Santiago et al., 2013). Third, racial and ethnic minorities across the United States persistently struggle to obtain equitable access to all healthcare services, but especially behavioral healthcare (Agency for Healthcare Research and Quality, 2019; Cook et al., 2017). This is compounded by racial and ethnic minorities' greater risk of poverty as well as a shortage of bilingual and culturally competent providers (Holden et al., 2014). Fourth, some organizations use practice size, for example, patient population and provider totals, as drivers for determining staffing needs for behavioral health providers (Briggs et al., 2016; Kearney et al., 2015). Smaller practices may therefore be less likely to incorporate integrated behavioral health providers. And lastly, previous research has indicated that organization size can impact innovation implementation success; specifically, larger organizations tend toward more successful implementation due to more resources and more effective implementation policies, practices, and climates (Jacobs et al., 2015; Kaplan et al., 2010). For all the above factors, there has been very little research regarding their relationship to IBH implementation, especially regarding a community sample of clinics implementing IBH in their own ways.

The Current Study

Given the large variability of IBH and complexity of contextual factors effecting IBH implementation, this study examines whether consistent patterns of IBH exist across a diverse set of primary care practices and the role of key contextual factors across a large set of diverse primary care practices. Namely the study aimed to: 1) demonstrate the ability of the IBH Cross-Model Framework to be operationalized through an existing integration measure used to drive improvements of IBH, 2) examine patterns of IBH implementation according to the Cross-Model Framework, and 3) examine the association of various contextual factors (i.e., clinic location, organization size, practice size, racial/ethnic make-up of the area, and clinic-level socioeconomic risk of the patients) with patterns of IBH implementation.

Methods

Participants

The sample included *N* = 102 primary care clinics across 14 healthcare organizations from across the state of Minnesota. Clinics were part of Minnesota health care organizations that were members of the MN Health Collaborative, a collaborative effort activated by the Institute for Clinical Systems Improvement (ICSI) to addresses the major health and social concerns around opioids and mental health in the state of Minnesota. Fourteen organizations were approached, encompassing 331 clinics, with 102 (31%) clinics responding to the survey request, which included Family Medicine, Pediatrics, and Internal Medicine clinics. The response rate was partly due to organizations being the intermediary for providing clinics with the survey information – some organizations chose to only forward the information to a subset of clinics, and there was a range among the organizations included regarding the amount of encouragement to participate. A total of 106 surveys regarding individual clinics were returned. Four surveys were excluded due to the responses representing more than one clinic in a single survey. Clinics were located across the state of Minnesota, including urban, suburban, and rural settings. Of the 102 clinics, 83 reported their estimated patient populations, for a total of 1,336,800 (*M* = 16,106, *median* = 8,746) patients. Using the median to estimate the missing patient population data, the clinics covered approximately 1.5 million patients, or about 27% of the population of Minnesota.

Procedures

Surveys were collected from each clinic by ICSI as part of their work through the MN Health Collaborative, to conduct a baseline assessment of IBH. Clinics were requested to have at least two people, at least one provider and one administrator, collaboratively complete the survey by discussing each item and agreeing on a score with only one final survey submission; submissions ranged from 1-7 participants per clinic (*M* = 2.09, *SD* = 1.08). Participating staff at each clinic indicated their roles which included medical providers, behavioral health providers, nurses, and administrators. Surveys were completed via SurveyMonkey.

Measures

Site Self Assessment (SSA)

The SSA (Scheirer et al., 2010) is an 18-item measure of patient/family-centered integrated care developed for the Maine Health Access Foundation, and is recommended for use by the US Agency for Healthcare Research and Quality (https://integrationacademy.ahrq.gov/products/behavioral-health-measures-atlas/measure/c8-site-self-assessment-evaluation-tool). The developers modeled the SSA after the Assessment of Primary Care Resources and Supports for Chronic Disease Self-Management (PCRS; Brownson et al., 2007), a validated tool developed for primary care teams to self-assess their current delivery and identify areas for improvement (Scheirer et al., 2010). However, the SSA has not itself been validated psychometrically. The ICSI staff involved in selection of a measure of integration, however, found the SSA to have the best face validity of the multiple measures they considered (J. Monkman, personal communication). Participants rated their clinic on a scale 1-10, with grouping descriptions for clusters on the scale of 1, 2-4, 5-7, and 8-10, using scale anchors customized to each question, for example: “Patient care that is based on (or informed by) best practice evidence for BH/MH and primary care” with the grouping descriptions (1) “…does not exist in a systematic way,” (2-4) “…depends on each provider’s own use of the evidence; some shared evidence-based approaches occur in individual cases,” (5-7) “…evidence-based guidelines available, but not systematically integrated into care delivery; use of evidence-based treatment depends on preferences of individual providers," and (8-10) "follow evidence-based guidelines for treatment and practices; is supported through provider education and reminders; is applied appropriately and consistently" (Scheirer et al., 2010).

Clinic Rurality

Rurality was based on the USDA Rural-Urban Commuting Area Codes (RUCA) of the clinic ZIP code (obtained from https://ruralhealth.und.edu/ruca). This scale ranged from 1-10 based on population density and commuting patterns, and research has demonstrated the utility of treating the scale as a continuous variable rather than using categories such as urban, suburban, and rural (Yaghjyan et al., 2019).

Clinic-level Patient SES Risk

Determined by MNCM (MN Community Measurement, 2020a), this variable was a composite, clinic-level score of: patient-level risk factors (i.e., health insurance product type - commercial, Medicare, Medicaid, uninsured, unknown), patient age, and deprivation index. The deprivation index was reflective of analysis of each clinic's patient home address data. It includes patient ZIP code-level averages of poverty, public assistance, unemployment, single female with child(ren), and food stamp usage. Each clinic has a unique risk score for each clinical outcome because the specific patients included for each disease varies. For this study, clinic risk scores were included for depression follow-up, adult and child asthma, vascular disease, and diabetes. Scores for each clinic were averaged among these outcome risk scores to create a total clinic risk score, weighted by the number of patients reported for each outcome.

Clinic Area Race/ethnicity Make-up

Race/ethnicity for each clinic's city location (incorporating the full city population) was obtained from the 2017 American Community Survey (obtained from https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2017/). Estimated counts and percentages of White, Black, American Indian, Asian, Hawaiian/Pacific Islander, other, and two races/ethnicities were included.

Organization Size

Organization size was based on number of primary care clinics for each health service organization. Number of clinics was obtained through Minnesota Community Measurement data and verified by conferring with ICSI personnel.

Practice Size

Practice size was reported by clinic personnel on their SSA responses. It was measured as the estimated active patient population, that is number of patients that had been seen in roughly the last year.

Analytic Plan

To address the three aims, we first created a crosswalk to map the SSA to the IBH Cross-Model Framework to examine how well it covered the various processes and structures in the framework. Upon completion of the SSA-Cross-Model Framework crosswalk, each construct was dichotomized into two options: the clinic had achieved fully integrated IBH on the given component (defined as a score of 8-10) or not fully integrated (defined as a score of 1-7). Each composite score was then dichotomized such that any score 7.5 and above was labeled "2" (integration fully achieved) and below was labeled "1" (integration not fully achieved).The decision to dichotomize was made for several reasons: 1) Although it reduced answer variability, dichotomous variables allowed a clearer interpretation of the results in the context of the IBH Cross-Model Framework; 2) The sample size meant that retaining the full 1-10 spectrum (and running a latent profile analysis instead of a latent class analysis) led to restrictions on the number of classes that could converge from the data, and on balance, a more complete understanding of the classes was important, and 3) the goal of the analysis was to focus on whether clinics had successfully implemented each component, making a dichotomous result a rational approach.

Next, we conducted a latent class analysis to identify various clusters of IBH implementation using the cross-walked IBH Cross-Model Framework categories of processes and structures. The final class count was determined through an examination of the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), adjusted BIC, and bootstrap likelihood ratio test (BLRT; Lanza, Bray, & Collins, 2012; Nylund, Asparouhov, & Muthén, 2007). For the final aim, the five specified context variables (i.e., rurality, area race/ethnicity, patient SES risk, clinic size, and organization size) were examined as predictors of class membership. Mplus 8.4 was used for both the latent class analysis and subsequent examination of class difference (Muthén & Muthén, 2017). The automatic 3-step process available in Mplus was used (R3STEP; Asparouhov & Muthén, 2014). This approach first estimates classes without the influence of covariates and then incorporates classification uncertainty to examine covariates as predictors of class membership. Methodological studies have demonstrated this strategy is generally superior to the previously advised approach, that is, to assign most-likely class membership to each case in the sample and then examining group differences (Asparouhov & Muthén, 2014).

Missing Data Management

We investigated whether the missing data appeared to be missing completely at random (MCAR), missing at random (MAR), or non-ignorable. Complete data were present for all SSA answers and therefore all Cross-Model Framework components. Complete data were also present for all clinics' rurality measurement and organization size. Data missing included clinic SES risk ratio (21.6%), clinic area racial/ethnic make-up (2.9%), and clinic size (18.6%). Upon manual review of missing values, many appeared to be merely due to the nature of the clinic, i.e., clinics that did not serve children (such as internal medicine clinics) or did not provide child/adolescent data, and pediatrics clinics typically did not provide adult data. We used multiple imputation (20 imputations) procedures in the Mplus automatic 3-step process to manage these missing data.

Managing Nested Data

The COMPLEX feature of Mplus which adjusts standard errors and the chi-square test of model fit was used to address nesting of the 102 clinics across the 14 healthcare organizations (range = 1-27 clinics per organization). This approach considered the stratification, non-independence of observations, and unequal probability of selection inherent in nested data, without requiring a multilevel approach.

Results

Clinic Sample Description

There was a total of 102 clinics in the sample. See Table 1 for full clinic descriptives. Clinics tended to be slightly higher SES-risk (M = 1.05, SD = 0.1) and more urban than rural (M = 2.22 on RUCA scale, SD = 2.6). Clinics were largely embedded in larger organizations (M = 23.16 clinics per organization, SD = 11.83), and patient population sizes varied widely, from 196 patients to 120,000 patients (M = 16,106 patients). Clinics were generally located in majority White areas (*M* = 79.7%) which reflects the race/ethnicity make-up of the state of Minnesota (83.7% White; https://www.census.gov/quickfacts/MN), where the clinics were located.

The clinics tended to fall in the mid-range for all 18 SSA components (see Table 2), scoring lowest (*M* = 5.01, *SD* = 2.39) on “Patient/family input to integration management” and highest (*M* = 8.04, *SD* = 1.79) on “Screening and assessment for emotional/behavioral health needs.”

Crosswalk of SSA with IBH Cross-Model Framework

The first author and a staff member from ICSI completed an initial draft of the SSA-Cross-Model Framework crosswalk. This initial version allowed for multiple categories to overlap, such that one SSA question may have matched several processes of the Cross-Model Framework. The first author then determined final categories for the crosswalk and a second ICSI staff member reviewed and confirmed the final draft (see Table 2).

In order to create the Cross-Model Framework components for analysis, composite scores were created from the SSA data based on mappings. A total of nine composite scores were thus identified for each of the five principles and across four of the nine structures: (1) patient-centric care (3 items, α = .67), (2) treatment to target (4 items, α = .83), (3) use evidence-based behavioral treatments 2 items, (α = .62), (4) conduct efficient team care (4 items, α = .72), and (the following are all one-item) (5) population based care, (6) sustainable fiscal strategies, (7) physical integration, (8) organizational leadership support for integrated care, and (9) shared EHR system.

The Cross-Model Framework composite scores showed that clinics generally scored lowest on the physical integration of a behavioral health provider into the clinic (M = 5.17, SD = 2.74, and highest on population-based care (M = 8.04, SD = 1.79). As detailed in the Methods section, the Cross-Model Framework components were dichotomized for the latent class analysis.

Defining Clusters of IBH Implementation

Latent class modeling (Asparouhov & Muthén, 2019; Lanza et al., 2012) was used to empirically derive clusters of clinics using the Cross-Model IBH Framework indicators. Starting at two classes and proceeding to five classes (after which the model no longer converged), we examined appropriate fit criteria. Entropy was above 0.8 for all models, indicating a clear fit between cases and their classes. See Table 4 for class enumeration details. After examining the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), adjusted BIC, and bootstrap likelihood ratio test (BLRT), some decision criteria indicated each of the 2, 3, and 4 classes could be appropriate (see Table 3). Theoretically, the most interpretable and applicable solution was the 4-class solution; upon reviewing the results it appeared that the 4-class solution identified unique classes fundamentally important to the study of IBH implementation. In addition, this solution was the lowest on AIC and Adjusted BIC; therefore, it was selected for the final model (see Figure 2). The four classes were identified as: Strong IBH (23.1% of clinics), Structural IBH (7.9%), Partial IBH (29.4%), and Low IBH (39.6%).

Estimated probabilities (see Table 5) demonstrate the differences in the classes. Strong IBH clinics had overall estimated probabilities of 70% or above for all nine principles and structures except for funding integration, which was at 61.9%. This means that 61.9% of the clinics in this class answered that they are fully integrated on their funding between behavioral and medical funding streams (e.g., funding and financial resources are shared). The Low IBH class had no principle or structure probability above 70%, with the closest being population-based care at 57.9%. Structural IBH was the smallest group and demonstrated a pattern where all clinics in the class indicated full funding integration. They also scored highly on population-based care (87.6%), physical integration (86.3%), and organizational leadership support (75.5%), but differed from the Strong IBH class with low probability of integration in conduct efficient team care (29.5%) and mixed probabilities on the remaining five principles and structures. Finally, the Partial IBH class all reported engaging in population-based care, and mixed probabilities of using evidence-based treatments (57.4%) and shared EHR systems (62.3%). Forty-one percent of the Partial IBH class reported having a behavioral health clinician physically on-site with shared physical resources (shared waiting room, etc.) and only 30% reported conducting efficient team care.

Examining Role of Contextual Factors with IBH Implementation

Contextual factors, including rurality, race/ethnicity, patient risk ratios, organization size, and practice size, were examined as predictors of membership in the four resulting IBH implementation classes from the latent class analysis (see Table 6). Because we made no specific hypotheses of which classes might vary and in what manner, we examined all pairwise class differences. Upon examining these pairs, Partial

IBH was the only class to demonstrate differences with all other classes. Partial IBH clinics were more likely to be urban than clinics in other classes (Low IBH: $p < .001$, *OR* = 1.62 (95% CI: 1.29-2.03); Structural IBH: $p = .04$, *OR* = 1.87 (95% CI: 1.02-3.44); Strong IBH: $p < .001$, *OR* = 1.40 (95% CI: 1.20-1.63)). Partial IBH clinics were less likely to be high risk than Structural IBH clinics ($p = .04$, *OR* = 969498.75 (95% CI: 12.37-*unable to read*)). Partial IBH clinics were less likely to be within larger healthcare organizations than were Strong IBH clinics ($p = .04$, *OR* = 1.05 (95% CI: 1.00-1.10)).

Discussion

We set out to describe a community sample of primary care clinics' implementation of IBH in the context of what is already known about IBH, i.e., utilizing an established framework. This study succeeded in both addressing this gap in the current literature as well as successfully mapping a self-report measure of integration to an accepted IBH framework. Additionally, it is the first study to demonstrate that IBH implementation can be categorized at the clinic level. Because IBH transforms the way a clinic functions with regard to mental health, it is important to examine it at this level (Kwan & Nease, 2013). Categorizing clinics by their IBH implementation will allow us to begin to see which elements of IBH are related within common profiles of implementation and hypothesize for future research where and how to intervene in the implementation process to increase a clinic's success at achieving full integration. Some potential areas of research include considering where incentives may be for each IBH Cross-Model Framework component; examining how buy-in at multiple levels, from clinic staff such as receptionists, to medical providers, to administrators and managers and finally to executive-level management, influences the successful implementation of

IBH; and applying organizational readiness theories and measurements to better assess and manage individual and system-level readiness prior to initiating IBH implementation. Finally, this is also is the first study to consider on a broad scale what relationship various contexts may have to a clinic's IBH implementation. We now have a better understanding of whether clinics in various contexts and serving various populations are likely to have implemented, or not, the various processes and structures of IBH.

This study found that it was reasonable to map a clinic-level self-report measure of integration (Scheirer et al., 2010) to a framework (Stephens et al., 2020). While the self-report did not encompass all aspects of the framework (missed five of the nine structures and did not encompass all of the 25 processes included in the five main principles), what it did capture was consistent with the concepts of the framework. Future research might examine (1) additional measures of integration and their ability to map to the Cross-Model Framework, and (2) whether mapping different measures of integration to the framework varies the patterns of integration developed.

This study has demonstrated that there may be normative patterns for where clinics are at in the spectrum of IBH implementation. While there are clinics that demonstrate almost universal high integration (Strong IBH clinics), these clinics tended to have one vulnerability, and that is funding integration. There are also clinics with predictably low IBH integration, which is likely any clinic that has not begun the IBH implementation process. A number of these clinics had achieved population-based care (58%) and shared their EHR with behavioral health providers (46%). These are likely due to state policies requiring certain screening and reporting for mental health and use of electronic medical records. Then there are two mixed classes. It appears that some clinics are able to implement some principles and structures more than others. Many of the reporting clinics had made progress toward IBH (i.e., 86% of Structural and 41% of Partial IBH clinics had a behavioral health provider onsite who shared clinic space and resources with the medical providers). However, many were seemingly experiencing barriers, particularly around team processes central to the Cross-Model Framework (i.e., only 30% of Structural and 7% of Partial IBH clinics scored high on team-based care). Team-based care in this study encompassed four processes, with two in particular that have been shown to improve rates of integration, namely buy-in of providers and physician, team, and staff training (Eghaneyan et al., 2014). The low level of team-based care occurred in all classes except the Strong IBH class; team-based care was low even in clinics with strong organizational leadership support for IBH and even when actual physical integration and funding integration had already occurred. This finding demonstrates the importance of assessing the specific components of integration within clinics that have IBH, which may explain the variation in clinical outcomes (i.e., depression remission) in studies such as Unützer et al. (2020). It also provides specific targets for implementation intervention and support.

Overall, the results indicated that contextual factors do not play a large role in where IBH has been implemented or how successful it has been. Only one contextual factor, rurality, was consistent across all class comparisons (i.e., Partial clinics were more likely to be urban than all other clinics). It may be that different contextual factors have a greater impact, and this line of inquiry should continue to be examined. In addition, there were some small differences of note. Structural IBH clinics tended toward higher SES risk patients than Partial IBH clinics. This was only a contrast between two classes and not across the board, so conclusions drawn are tentative. It is possible that clinics with higher SES risk patients had moved toward implementing elements of IBH more than clinics with lower SES risk patients, particularly the structures of IBH such as physical integration and funding integration, and had stronger leadership support for IBH. Patients with higher SES risk often have more complex biopsychosocial and care management needs (Cook et al., 2019), and these clinics may find that coordinating care is easier in an IBH model. However, some Structural IBH clinics were either still in the implementation process or had hit barriers in implementing patient-centric care, treatment to target, evidence-based practice use, team-based care, and shared EHR. Increasing implementation support for these clinics in these specific domains may improve provider and patient satisfaction and clinical outcomes.

Strong IBH clinics only differed from Partial IBH clinics by being in larger organizations. Larger organizations likely have more resources for clinics to implement IBH and can supplement insufficient funding streams more easily, which may be particularly important since many of the Strong IBH clinics did not have full funding integration (Jacobs et al., 2015; Kaplan et al., 2010).

The sum of the differences between Partial IBH clinics and the others, namely that Partial IBH clinics were urban, tended to be in smaller organizations and tended to serve higher-SES patients, indicates that these clinics likely referred patients elsewhere for mental health treatment. Research has demonstrated that higher-income and more dense urban areas have more availability of mental health providers (Holzer et al., 2000); in addition, smaller organizations may have fewer resources to initiate practice transformation (Kaplan et al., 2010). It is possible that the more traditional separateness of care works well enough for these clinics; this is a potential question for future research.

Another potential point of interest in the findings of clinic context were the negative findings: there were no differences in race/ethnicity make-up of the area or clinic size. This provides some initial indication that even smaller clinics may be finding ways to implement IBH. A limitation with the race variable was that it was based on the whole city where the clinic was located, rather than the patient population of the clinic itself; however, it does indicate that more or less racially diverse areas do not necessarily differ in their access to IBH services.

More research is needed within this framework to drill down into clinics which exemplify the four classes and assess barriers and facilitators to IBH implementation, to further tailor implementation strategies for success. It is likely that even within the more homogenous classes, there is variation in both barriers and facilitators, but they may be more homogenous than the sample at large.

Limitations and Future Directions

This study has several limitations to note. First, while a sample size of 102 clinics is a large number of clinics, for the sake of a latent class analysis, it is a small number, particularly when extracting four classes. While the four-class solution was the best option for this dataset, the classes should be replicated and validated with new and/or larger samples. Second, the SSA was not developed to operationalize the Cross-Model Framework, but rather the crosswalk of the measure to the framework was an aspect of this study. Therefore, we were unable to test all aspects of the Framework, and it is likely that not all nuances of each principle or structure were represented in the indicators utilized in this study. Other measures of integration should be mapped onto the Cross-Model Framework to validate both the measures, the framework, and to move the field toward a more consistent methodology of measurement. In addition, mapping existing measures may allow for comparison across previous studies that has not yet been possible. A final limitation of the study is that while the SSA was typically completed by more than one employee at each clinic, it was still a self-report measure, and the variable number of reporters could have resulted in varied accuracy in reporting across clinics. It is possible that staff completing the SSA may have not accurately represented their clinics, reporting either greater integration or less integration than another form of assessment would have provided, and this possibility introduces an element of potential error into the IBH class structure. However, while in-depth interviews or observational assessments may be more rigorous and have less potential for bias than self-report fidelity, there is argument for a balance between efficiency and effectiveness (Schoenwald et al., 2011); in the case of the current study, observational or in-depth interviews at 102 clinics would likely be cost-prohibitive. Additionally, two of the composite scales for Cross-Model Framework processes had somewhat low reliability (patient-centric care, α = .62 and use evidence-based behavioral treatments, α =.67), introducing some additional potential for error in the stability of those constructs.

Conclusions

This study contributes to the field in three ways. We provided evidence that mapping self-report measures of integration onto a framework is possible, described the integration profiles of a community sample of clinics, and demonstrated some differences among these clinics in how they have implemented elements of the IBH approach to primary care. Key conclusions are that there is wide variability in the fidelity to key IBH principles and that implementation efforts should pay attention to barriers and facilitators of the more granular principles and structures, rather than an overall yes/no implementation success. There are a number of barriers to overcome when advocating for and initiating practice transformation, both internal and external. Our study highlights areas where IBH implementation may stall or struggle, components that seem easier to implement than others, and begins a discussion around how context matters in considering IBH implementation.

Table 1.

Clinic Sample Descriptives

Variable	N	Min	Max	M	SD
Clinic weighted risk ratio	87	.94	1.42	1.05	0.10
Clinic RUCA	102	1.0	10.3	2.22	2.60
Organization Size (total number of PC clinics)	102	3	54	23.16	11.83
Clinic size (active patient population)	83	196	120,000	16,106.02	20,111.82
% White	99	46.80	99.20	79.72	13.32
%Black	99	0.00	28.00	8.55	7.45
% Native American	99	0.00	3.80	0.68	0.58
% Asian	99	0.00	18.00	5.40	4.64
% Hawaiian/Pacific Islander	99	0.00	0.30	0.02	0.04
% Other	99	0.00	18.30	2.45	2.79
% Multiracial	99	0.10	5.40	3.14	1.39

Note: PC = primary care

Table 2. *Crosswalk of Cross-Model Framework Principles and Structures with Site Self-Assessment Questions*

		Cross-Model Framework Principles					**Structures**			
SSA	*M* (*SD*)	Patient-centric Care	Treatment to Target	Use EBTs	Conduct Efficient Team Care	Population-Based Care	Financial billing sustainability	Admin. support and supervision	EHR	Behavioral health provider
1. Level of integration: primary care and mental/behavioral health care.	6.08 (2.92)									X
2. Screening and assessment for emotional/behavioral health needs.	8.04 (1.79)					X				
3. Treatment plan(s) for primary care and behavioral/mental health care.	6.43 (2.16)			X						
4. Patient care that is based on/informed by best practice evidence for behavioral health and primary care.	7.13 (1.91)			X						
5. Patient/family involvement in care plan.	7.03 (2.10)	X								
6. Communication with patients about integrated care.	6.03 (2.16)	X								
7. Follow-up of assessments, tests, treatment, referrals and other services.	6.62 (2.05)		X							
8. Social support (for patients to implement recommended treatment).	6.36 (2.16)		X							
9. Linking to community resources.	6.44 (1.92)		X							
10. Organizational leadership for integrated care.	6.16 (2.51)							X		
11. Patient care team for implementing integrated care.	5.54 (2.76)				X					
12. Providers' engagement with integrated care ("buy-in").	6.70 (2.43)				X					
13. Continuity of care between primary care and behavioral/mental health.	6.58 (2.29)		X							

14. Coordination of referrals and specialists.	6.25 (2.10)				X					
15. Data systems/patient records.	7.50 (2.19)								X	
16. Patient/family input to integration management.	5.01 (2.39)	X								
17. Physician, team and staff education and training for integrated care.	5.16 (2.62)				X					
18. Funding sources/resources.	5.17 (2.73)						X			
M *(SD)*		6.02 (1.94)	6.50 (1.82)	6.78 (1.82)	5.91 (2.04)	8.04 (1.79)	6.08 (2.92)	6.16 (2.51)	7.50 (2.19)	5.17 (2.74)

Note: There are five core structures that were not represented among the 18 SSA items and therefore are not shown in the crosswalk.

Table 3.

Descriptives of Clinics' Adherence to the Cross-Model Framework

Cross-Model Framework Principles/Structures	Number of health systems with at least 50% of reporting clinics meeting the top criteria	Percent	Number of clinics meeting the top criteria	Percent
Patient-centered care	1	7.14	24	23.53
Treatment to target	3	21.43	35	34.31
Evidence-based practices	7	50.00	45	44.12
Team-based care	0	0.00	28	27.45
Population-based care	13	92.86	83	81.37
Physical integration	5	35.71	41	40.20
Organizational leadership	3	21.43	39	38.24
Shared EMR	8	57.14	63	61.76
Funding integration	1	7.14	24	23.53
Overall SSA	0	0.00	11	10.78
Total	14		102	

Note: "Top criteria" means 8-10 out of 10 on each SSA question that is encompassed by the Cross-Model Framework process

Table 4.

Latent Class Enumeration (N = 102)

Classes	AIC	BIC	Adj BIC	LL	BLRT	Entropy
1	1137.61	1161.23	1132.80	-559.80	-	-
2	877.23	927.11	867.09	-419.62	0.000	0.956
3	873.26	949.38	857.78	-407.63	0.030	0.882
4	873.21	975.58	852.40	-397.60	0.286	0.852
5	879.51	1008.13	853.36	-390.75	0.308	0.871

Table 5.

Posterior Probabilities by Class (N = 102)

Class	Class label	Cross-model framework processes grouped by principles (left) and structures (right)								
		Patient-centric care	Treatment to target	Use evidence-based behavioral treatments	Conduct efficient team care	Population-based care	Physical integration	Organizational leadership support	Shared EHR system	Funding integration
1	Low IBH	*0*	*0.09*	*0*	*0*	0.58	*0.05*	*0.12*	0.46	*0*
2	Structural IBH	0.52	0.51	0.52	*0.3*	**0.88**	**0.86**	**0.76**	0.51	**1.0**
3	Partial IBH	*0*	*0.15*	0.57	*0.07*	**1.0**	0.41	*0.25*	0.62	*0.05*
4	Strong IBH	**0.84**	**0.96**	**1.0**	**1.0**	**0.96**	**0.83**	**0.88**	**0.96**	0.62

Note: bolded numbers indicate posterior probabilities of .7 or above, while italicized numbers indicate posterior probabilities of .3 or below

Table 6.

Regression Results of IBH Class Membership on Context Variables using Class 3 (Partial IBH) as reference class

	B	*SE*	*p*
Partial IBH vs.			
Low IBH			
Rurality	**0.48**	**0.12**	**0.00**
Clinic-level patient SES risk	4.01	5.60	0.47
Area race (%White)	0.01	0.05	0.91
Org size (#clinics)	0.05	0.04	0.19
Practice size (#patients)	0.01	0.04	0.85
Structural IBH			
Rurality	**0.63**	**0.31**	**0.04**
Clinic-level patient SES risk	**13.79**	**6.85**	**0.04**
Area race (% White)	-0.01	0.06	0.84
Org size (#clinics)	0.00	0.04	0.95
Practice size (#patients)	0.04	0.05	0.33
Strong IBH			
Rurality	**0.34**	**0.08**	**0.00**
Clinic-level patient SES risk	4.17	4.76	0.38
Area race (% White)	0.01	0.04	0.77
Org size (#clinics)	**0.05**	**0.02**	**0.04**
Practice size (#patients)	0.03	0.04	0.39
Note: Bolded lines indicate significance at p < .05 or less			

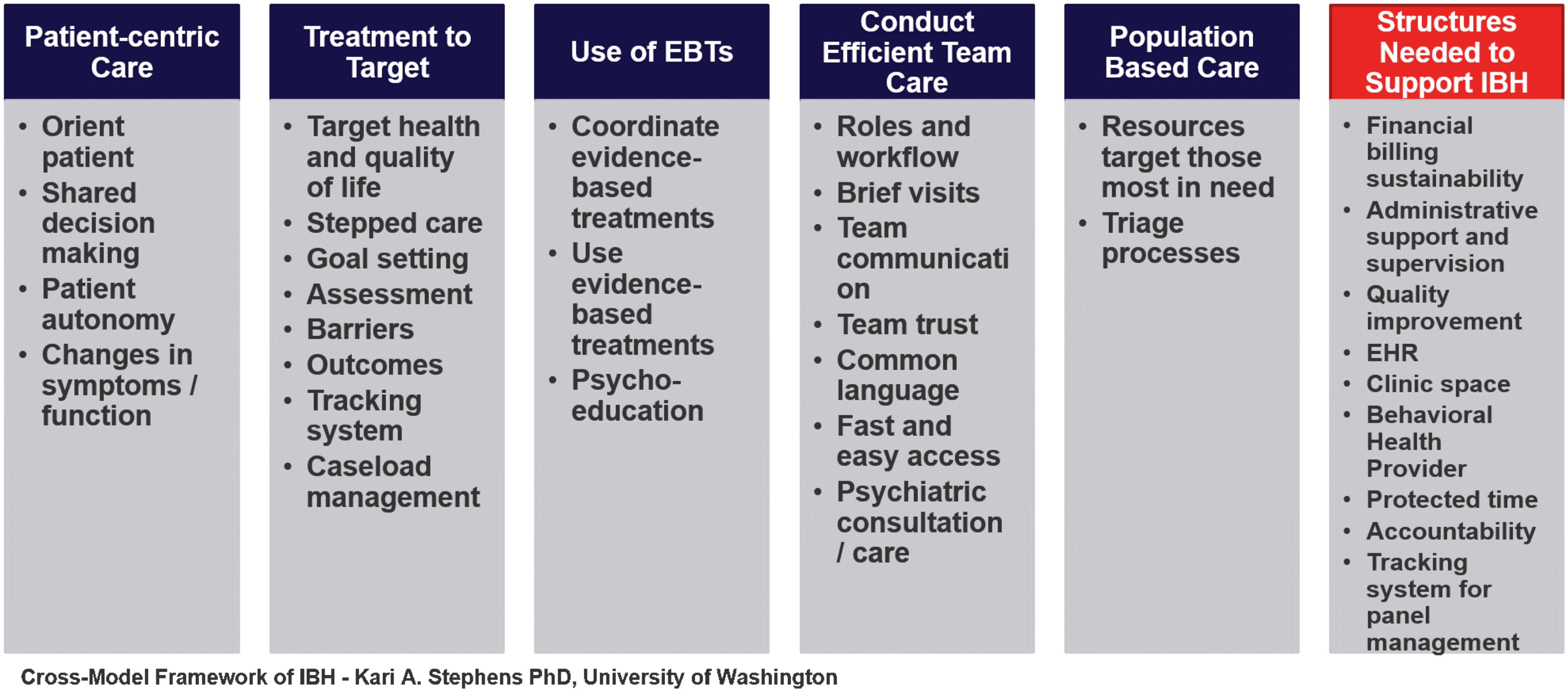

Figure 1. IBH Cross-Model Framework put forth in (Stephens et al., 2020).

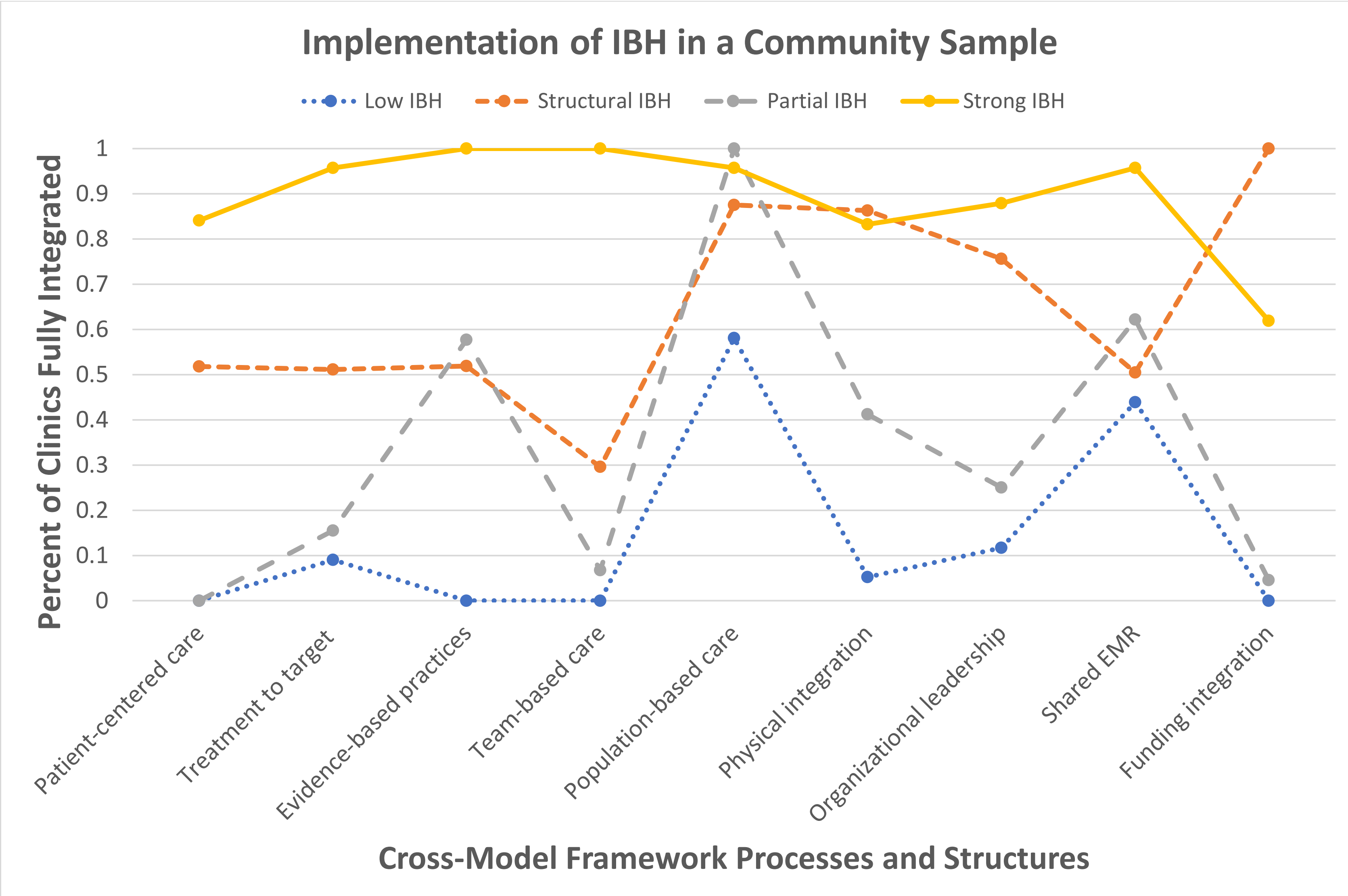

Figure 2. Four-class latent class solution. Low IBH = 39.6%, Structural IBH = 7.9%, Partial IBH = 29.4%, and Strong IBH = 23.1% of sample.

Study 2: The Relationship between IBH Implementation and Clinical Context, Healthcare Management Outcomes, and Health Disparities

There are widespread and significant health and healthcare disparities in the U.S. between distinct groups of people, including racial/ethnic groups, rural and urban residents, and people of lower and higher socioeconomic status. These disparities have wide-ranging and important roots as well as implications for individual patients and their well-being.

Overview of Health and Healthcare Disparities

Generally in the U.S., non-Hispanic White and Asian people experience a superior quality of healthcare than Black, American Indian/Alaska Native, and Latinx people (Agency for Healthcare Research and Quality, 2020). Since 1985, the federal government has been analyzing and reporting on these disparities, and while some have improved, many continue to exist (Agency for Healthcare Research and Quality, 2020). There are two main aspects of these disparities: health disparities and healthcare disparities. The U.S. National Institutes of Health uses the following definitions: "*Healthcare* disparities refer to differences in access to or availability of facilities and services. *Health status* disparities refer to the variation in rates of disease occurrence and disabilities between socioeconomic and/or geographically defined population groups [emphasis added]" (National Information Center on Health Services Research and Health Care Technology, 2021). Health status disparities (hereafter health disparities) and healthcare disparities are linked and both have many contributing factors, including social determinants of health (e.g., safe housing, neighborhood crime rates, living wages) (Alvidrez et al., 2019). Arguably, healthcare disparities are more under the control of healthcare providers and systems to address (and in so doing, may alleviate some health disparities), yet there are still many gaps in research and practice regarding interventions to improve disparities, particularly that place the responsibility for change on organizations and providers rather than patients (Chin et al., 2012).

Ensuring equity to access and availability of high-quality care for all patients can and should be a goal of any healthcare provider or organization. Using an equity-oriented lens in practice is not a new concept; for decades, writers such as Waitzkin (1989) have called for medical encounters to include discussion of the larger social context, and as discussed in the introduction to this manuscript, Falk-Rafael (2005) developed the critical caring mid-range theory which incorporates critical theory into the practice of public health nursing. In the past few years increasingly healthcare systems and providers have begun to take this task upon themselves (e.g., Churchwell et al., 2020), but we are still at the beginning of the road; literally, the first of six steps to reducing health disparities is to recognize that disparities exist and commit to reducing them (Chin et al., 2012).

In the present study, we examined how integrated behavioral health relates to health and healthcare disparities among a community sample of clinics. First, we briefly review what is known about health and healthcare disparities of chronic disease management and depression, and then the current state of the literature on IBH and disparities. We then identify the gaps in research which this study aims to address.

Chronic Disease

There are many diseases that can be labeled chronic; for the purpose of this study, we focus on asthma, diabetes, and vascular disease. All three of these diseases have significant health disparities for non-White populations in the U.S.; for example, in 2018 14.2% of non-Hispanic Black children had an asthma diagnosis, compared to 6.8% of non-Hispanic White children (Agency for Healthcare Research and Quality, 2020). Not only do Black children experience asthma at over twice the rate of White children, they are over four times more likely to experience a hospitalization for asthma than White children, indicating disparities in both contributing factors and possible preventive healthcare quality and/or access discrepancies (Agency for Healthcare Research and Quality, 2020). Cardiovascular disease in adults also is unequally distributed; the American Heart Association indicates that Blacks, Latinos, and Asians (including South Asians) experience both increased risk for cardiovascular disease as well as disparities in healthcare regarding preventive care and adverse cardiovascular events (Carnethon et al., 2017; Palaniappan et al., 2010; Rodriguez et al., 2014; Volgman et al., 2018). The American Heart Association also has indicated in these reports that substantial variation exists within these large, diverse subgroups of race/ethnicity, and that little research has sufficiently disaggregated data on these subgroups; this indicates a structural racism aspect of health research and care that must also be addressed as it both perpetuates generalizations among heterogeneous groups and also prevents better care from occurring due to ignorance (Churchwell et al., 2020).

Overlapping with racial/ethnic health disparities, there are significant disparities in the U.S. regarding access and quality of care along the spectrum of socioeconomic status. People with high income (above 400% of the federal poverty level) typically received higher quality care than those with lesser incomes on over half of the measures tracked by federal government agencies in 2016-2018 (Agency for Healthcare Research and Quality, 2020). Healthcare quality received was even worse for people who struggled with healthcare access due to finances or who had chronic medical conditions such as asthma or diabetes. For example, people with public insurance reported about twice as often that providers didn’t respect what they had to say, compared to people with private insurance (Agency for Healthcare Research and Quality, 2020). People without insurance were significantly less likely to have had their blood pressure checked in the last two years and children without insurance were significantly less likely to have had their height and weight checked in the last two years, compared to those with private insurance (Agency for Healthcare Research and Quality, 2020). Both measures can be considered preventive care for the chronic diseases examined in this paper (e.g., diabetes, vascular disease).

Finally, location can be a contributing factor to worse health status or healthcare quality. Federal government surveys showed that nonmetropolitan (i.e., rural) areas performed worse on about a third of healthcare quality measures compared to suburban areas (which performed the best; Agency for Healthcare Research and Quality, 2020). Particularly salient examples of rural-suburban differences included percent of people who had not received a cholesterol screening in the last 5 years, and percent reporting that providers did not show respect for what patients had to say or did not listen carefully to them. In addition, current disparities do not appear to have improved much since the 2002 measure (Agency for Healthcare Research and Quality, 2020).

Depression

Depression is an increasingly common concern for Americans; from 2011 to 2016 adolescent depression increased from 8.3% to 12.9% (Lu, 2019). Adolescents’ engagement in treatment during that same time period remained stable, however, indicating that untreated depression is a particular growing concern (Lu, 2019). Untreated depression is also a concern for adults; a 2013 survey demonstrated that 58.4% of adults experiencing a major depressive episode received mental health treatment, and that there were significant disparities in access based on race/ethnicity and insurance status (Wang & Xie, 2019). Other studies have consistently demonstrated reduced access to depression care based on race/ethnicity, socioeconomic status (e.g., income, insurance status), and geographic location (Holden et al., 2014; Powers et al., 2020; Saldana et al., 2020; Santiago et al., 2013; Sentell et al., 2007).

Differences in access to depression care are slightly different than chronic disease management. Depression care may be initiated through a person's primary care medical provider, such as through use of anti-depressant medication, in addition to seeking psychotherapeutic treatment in the mental healthcare system that is mostly separate in the U.S. Often it is lack of access to the mental healthcare system that prevents psychotherapy treatment, including barriers such as transportation, fear of stigma from others or internalized stigma about the type of people that go to therapy, cost of care, lack of childcare or time availability (Goodman, 2009; Mohr et al., 2006, 2010; Tuerk et al., 2018). However, a majority of people indicate that they would rather receive psychotherapy than take medication (Dwight-Johnson et al., 2000; Goodman, 2009; Jaycox et al., 2006), and studies have demonstrated improved efficacy of depression treatment when medication and psychotherapy are combined (Cuijpers et al., 2009; Friedman et al., 2004; Karyotaki et al., 2016; Otto et al., 2005). Therefore, the lack of psychotherapy access found among rural, minority, and/or lower SES patients is particularly problematic.

IBH and Health and Healthcare Disparities

Given that there are health and healthcare disparities in both chronic disease management and depression, a question remains about whether integrated behavioral healthcare (IBH) may be one mechanism by which these disparities can be addressed. While IBH cannot address macrosocial determinants of health, IBH providers may be able to help patients individually address and somewhat mitigate the impact of those factors on their health, particularly by providing increased access to high-quality behavioral healthcare to address both depression and behavioral factors involved in chronic disease management. There is quite a bit of research demonstrating that generally, IBH increases access to behavioral healthcare and improves clinical outcomes for both chronic medical conditions and mental illness (Butler et al., 2008; Campo et al., 2018; Dollar et al., 2018; Miller-Matero et al., 2018; Pomerantz et al., 2008, 2014; Sarvet et al., 2010; Vickers et al., 2013). Some research demonstrates that IBH can result in improved access to care for individuals and families with risk factors such as poverty (Cohen et al., 2019; Hodgkinson et al., 2017; Ogbeide et al., 2018), rurality (Burt et al., 2014; Logan et al., 2019; Valleley et al., 2007), and being members of diverse racial/ethnic minorities or limited-English populations (Bridges et al., 2014; Holden et al., 2014; Sanchez & Watt, 2012), when targeted approaches are used for these populations. What has not been examined in previous research is whether IBH can improve access to care on a clinic or population level and if so, at what level IBH needs to be in order to make that impact, or what elements of IBH are most important in making that impact. In other words, given the level of IBH implementation fidelity achieved by a sample of community clinics, examining whether there is a difference in healthcare management outcomes for these groups predisposed to disparities.

Conclusions of Study 1 Implications for the Current Study

Study 1 provided the novel conclusion that there are common patterns of IBH implementation variability in primary care clinics and that these patterns may somewhat vary based on clinic context (i.e., outer setting). These patterns include clinics with Low IBH, Structural IBH, Partial IBH, and Strong IBH. The four newly-discovered patterns provide an opportunity to examine health and healthcare disparities through a more nuanced lens than has been done previously. No research has yet examined IBH and its relationship to health and healthcare disparities within the context of varied implementation of the IBH practice model.

The Current Study

The current study aimed to address the gap in research regarding how variability in IBH implementation relates to improvements in or exacerbations of health disparities. See Figure 3 for the conceptual model. Among a community sample of clinics, the present study specifically aims to: 1) determine the direct relationship between IBH implementation latent classes and healthcare management outcomes (*Figure 3, path a*), 2) determine the direct relationship between clinic context variables including rurality, socioeconomic risk, and race/ethnicity and healthcare management outcomes, otherwise known as healthcare disparities (*Figure 3, path b*), and 3) determine the moderating effects of IBH implementation variation, in the form of latent classes, on the revealed healthcare disparities (*Figure 3, path c*).

Based on the demonstrated gap in research, I made the decision to focus on implementation outcomes (i.e., use of screening tools, follow-up) for depression in order to identify the relationship between IBH implementation and more measurement-based care for behavioral health such as depression. For chronic disease management, the focus was the success of healthcare management in achieving stability within accepted clinical range for patients. There is some indication (Gawande et al., 2019; Miller et al., 2014; Whitlock et al., 2002) that behavioral health services in primary care may assist medical providers in addressing health behavior changes, structural barriers, etc. with their patients in order to achieve better physical health outcomes. The current study aims to contribute to this evidence, particularly regarding the question of how variation in IBH implementation may impact its efficacy in supporting medical providers and patients in addressing these barriers.

Methods

Participants

Participant description is the same as Study 1. Table 1 for clinic descriptives.

Procedures

See Study 1 for a description of IBH data collection. Data for clinic SES risk scores and clinical outcome variables are from Minnesota Community Measurement (MNCM), the contracted data collection organization of the Minnesota Department of Health's statewide healthcare quality reporting system. MNCM data were obtained in consultation with personnel at MNCM, who explained and recommended the use of the MNCM-determined risk scores as one way to examine health disparities (see below for more detail on the risk scores). See the MNCM Methodology report for 2018 for full explanation of data collection procedures (Minnesota Community Measurement, 2018b). Data sources for clinic rurality and clinic area race/ethnicity make-up are detailed below.

The University of Minnesota IRB considered this study not human subjects research and therefore exempt from review.

Measures

Predictors

Clinic Rurality. Rurality is based on the USDA Rural-Urban Commuting Area Codes (RUCA) of the clinic ZIP code (obtained from https://ruralhealth.und.edu/ruca). This scale ranges from 1-10 based on population density and commuting patterns, and research has demonstrated the utility of treating the scale as a continuous variable rather than using categories such as urban, suburban, and rural, when examining health disparities (Yaghjyan et al., 2019).

Clinic-level Patient Risk. Determined by MNCM, this variable is a composite, clinic-level score of patient-level risk factors (i.e., health insurance product type (commercial, Medicare, Medicaid, uninsured, unknown), patient age, and deprivation index). Patient age was included because MNCM has determined that older patients are more compliant with treatment (G. Nelson, personal communication). The deprivation index is reflective of analysis of each clinic's patient home address data. It includes patient ZIP code level averages of poverty, public assistance, unemployment, single female with child(ren), and food stamp usage. Each clinic has a unique risk score for each clinical outcome. For depression remission scores, a clinic's scores may be slightly different because they also include the clinic's patient-level baseline severity band of PHQ-9 scores (moderate (5-9), moderately severe (10, and severe) as a control.

Clinic Area Race/ethnicity Make-up. Race/ethnicity for each clinic's city location (incorporating the full city population) was obtained from the 2017 American

Community Survey (obtained from https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2017/). Estimated counts and percentages of white, black, American Indian, Asian, Hawaiian/Pacific Islander, other, and two races/ethnicities were included.

IBH Latent Classes as Moderators

See Study 1 for a full description of the four latent classes, or Figure 2 for visualization.

Outcomes

All outcomes listed below were obtained from publicly available data from Minnesota Community Measurement. Briefly, Minnesota Community Measurement obtains their data through a state government mandate to all healthcare organizations and clinics in the state (MN Community Measurement, 2020b). In 2008, the Minnesota state legislature passed the Minnesota Health Reform Law which requires the Minnesota Department of Health to establish measures and collect quality data from all healthcare organizations, clinics, and hospitals. Since 2014, MNCM has been the contracted data collection and analysis organization (MN Community Measurement, 2020b). Therefore, all the following measures are required to be reported by all relevant clinics in the state. Selected results are made publicly available.

Adolescent Depression Screening. Depression screening implementation is essential to recognizing and treating adolescent depression systematically (Lewandowski et al., 2016), although of course not sufficient in and of itself to ensure appropriate treatment. Clinics utilized one of several validated screening tools (percentages are for all clinics reporting to MNCM): the Patient Health Questionnaire (2-item (31.4%; Kroenke, Spitzer, & Williams, 2003), 9-item (13.7%; Kroenke et al., 2001), and 9-item modified for adolescents (29.4%; Nandakumar et al., 2019) versions), the Pediatric Symptom Checklist (17-item parent-report (20.5%; Murphy et al., 2016), 35-item youth self-report (4%), and 35-item parent-report (0.9%; Jellinek et al., 1988)), Kutcher Adolescent Depression Scale (0.1%; (LeBlanc et al., 2002), Beck Depression Inventory II (<0.1%; Beck, Steer, & Brown, 1996), Child Depression Inventory II (<0.1%; Kovacs, 2011), and Global Appraisal of Individual Needs screens for mental health and substance abuse (<0.1%; Ives, Funk, Ihnes, Feeney, & Dennis, 2012). Each clinic had a reported score that is a percentage, indicating the number of eligible patients that were successfully screened.

Adult PHQ-9 Utilization. This measure addresses whether a patient with a depression or dysthymia diagnosis was administered the Patient Health Questionnaire 9-item (PHQ-9; Kroenke et al., 2001) during the reporting period (Minnesota Community Measurement, 2018a). Each clinic had a reported score that is a percentage, indicating the number of eligible patients that successfully completed the questionnaire.

Adult Depression Follow-up at 12 Months. This measure addresses whether a patient with a depression or dysthymia diagnosis was administered a follow-up PHQ-9 (Kroenke et al., 2001) within 12 months (+/- 30 days) of an elevated PHQ-9 score (Minnesota Community Measurement, 2018a). Each clinic has a reported score that is a percentage, indicating the number of eligible patients that successfully completed a follow-up PHQ-9 during the timeframe.

Chronic Disease Management. This latent variable was made from four indicator variables: adult optimal asthma control, child optimal asthma control, optimal diabetes control, and optimal vascular disease control. I chose to use a latent variable to represent these four healthcare management outcomes due to idea that theoretically, they should be highly correlated and represent a similar healthcare process. Each clinic had a reported score that is a percentage, indicating the number of eligible patients that were successfully managed during the timeframe.

Adult and Child Optimal Asthma Control. Optimal asthma control is defined as a patient achieving the following: "(1) Asthma well-controlled as defined by the most recent asthma control tool result and (2) Patient not at risk of exacerbation (i.e., fewer than two emergency department visits and/or hospitalizations due to asthma in the last 12 months)" (Minnesota Community Measurement, 2018c, p. 5). Adults included were ages 18-50 and children included were ages 5-17.

Adult Optimal Vascular Care. Optimal vascular care is defined as a patient ages 18-75 with ischemic vascular disease achieving all four of the following: "(1) blood pressure less than 140/90 mmHg, (2) on a statin medication, unless allowed contraindications or exceptions are present, (3) non-tobacco use, and (4) on daily aspirin or anti-platelets, unless allowed contraindications or exceptions are present" (Minnesota Community Measurement, 2018c, p. 4).

Adult Optimal Diabetes Care. Optimal diabetes care is defined as a patient ages 18-75 with Type I or Type II diabetes achieving all five of the following: "(1) HbA1c less than 8.0 mg/dL, (2) blood pressure less than 140/90 mmHg, (3) on a statin medication, unless allowed contraindications or exceptions are present, (4) non-tobacco use, (5) patient with ischemic vascular disease on daily aspirin or anti-platelets, unless allowed contraindications or exceptions are present" (Minnesota Community Measurement, 2018c, p. 3).

Analytic Plan

My initial analytic plan was to model all variable relationships simultaneously through a structural equation model (SEM). However, the sample size and complexity of the model led to non-convergence so the analytic plan had to change. Instead, I planned three separate analytic mixture models. I utilized the BCH manual 3-step approach in Mplus 8.3 to first model the latent classes and then to examine their relationship with distal outcomes (Asparouhov & Muthén, 2019; McLarnon & O'Neill, 2018; Nylund-Gibson et al., 2019). This approach has been recently developed and has been shown to outperform other methodologies in managing bias, particularly stemming from unequal variances across classes; it does this by preventing shifts in class membership when auxiliary variables are introduced later in the analysis, and uses a weighted multiple group analysis (Asparouhov & Muthén, 2019). The first and second steps of the BCH 3-step approach are completed one time, and then the third step is repeated for each auxiliary/distal variable analysis of interest.

First, I examined the direct relationship between IBH latent class assignment and outcome variables, to assess the relationship between IBH latent class membership and clinical outcomes. Second, I examined the relationship between the clinic context variables and the healthcare management outcome variables, to assess the level of health disparity in the data. Third, I examined the moderating effect of IBH latent classes on the relationship between the predictor variables and outcomes to examine whether latent class membership influences health disparities present in the data. I assessed both the within-class relationships between clinic context variables and healthcare management outcomes, as well as between-class differences. Because I made no specific hypotheses of which classes might vary and in what manner, I examined all pairwise class differences to assess the totality of the differences among clinic context, healthcare management, and IBH latent class.

Multilevel Data Management

The dataset utilized for this study is multilevel data. The 102 clinics are nested among 14 organizations. To account for this data non-independence, I utilized the COMPLEX feature in Mplus 8.4 to adjust the standard errors.

Missing Data Management

Missing data were present in 18.6% of values in the variable regarding clinic patient population size, 14.7% of clinic SES risk, and 15.7-33.3% of healthcare management outcome variables. In order to manage missing data and reduce the potential for bias, Mplus 8.4 software implements full information maximum likelihood (FIML) missing data management, which is an often unbiased method for managing missing data even when it is not missing at random (McKnight & McKnight, 2013). Prior to using FIML, I investigated correlates of missingness. Upon manual review of missing values, many appeared to be merely due to the nature of the clinic, i.e., clinics that did not serve children (such as internal medicine clinics) did not provide child/adolescent data, and pediatrics clinics typically did not provide adult data. I also performed pairwise independent-samples *t*-tests to look for patterns of missingness. There was a significant pattern of missingness on healthcare management outcomes from clinics which were part of smaller organizations on adult depression PHQ-9 utilization (t = 2.07, p = .04), diabetes management (t = 2.42, p = .02), and vascular disease management (t = 2.66, p = .009). Clinics with smaller patient populations were less likely to report child asthma management (t = 3.51, p = 001). It is possible that both patterns are due to smaller clinics/organizations being less able to support the necessary staff time to spend reporting quality measures. One additional pattern of missingness was that clinics with higher SES risk patients were significantly less likely to report adult depression PHQ-9 utilization rates (t = 3.56, p = .001), but there was no difference on other outcome measures.

Benjamini-Hochberg False Discovery Rate Procedure

Due to the large number of tests run in the following analyses, I decided to account for this multiple testing due to the potential for Type II errors (i.e., false positives). After completion of the analyses, I undertook the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995) which controls the false positive discovery rate. This procedure can be summarized by the equation $\left(\frac{i}{m}\right) q$ and entails the following steps: I selected a false discovery rate q = 0.1 (10%); for each hypothesis[1], I ranked the resultant p-values of each test from lowest to highest; ranked them (e.g., 1-5; rank is i and total number of tests is m); multiplied each rank by q to obtain a cutoff score which, if a p-value fell above it, was considered a false discovery and excluded from significant results. See Appendix A for a partial example of the results for this procedure. In the results tables, it is indicated where the Benjamini-Hochberg procedure indicates a possible false discovery, and these results were not extensively described or examined further in this paper.

[1] Despite my efforts, I was unable to find an evidence-based recommendation of what number q should be. Some examples I found ranged from .05-.25 (i.e., 5-25%). Because this paper is primarily hypothesis-generating rather than strictly looking for outcomes, I chose .10 to be conservative but not overly strict.

Results

Descriptives and Bivariate Correlations

Descriptions of the clinics themselves and the clinic context variables were detailed in Study 1. Here we examine the healthcare management outcomes and their relationship with clinic context variables, with full results detailed in Table 7. Healthcare management of the four variables that represented the latent construct variable of chronic disease management (optimal control rates for adult asthma, child asthma, diabetes, and vascular disease) averaged from 44.8% for optimal diabetes management to 58.1% for vascular disease. Adult PHQ-9 utilization for depressed patients and adolescent depression screening rates were high at 74.1% and 76.2% respectively, though adult depression twelve-month follow-up was very low at 10.8%.

Of note, the four chronic disease management variables had moderate-to-high correlations (*r*s = .53-.87, *p*s < .001), confirming that the use of a latent variable was appropriate. Other significant correlations between healthcare management outcomes include correlations between adult and child asthma and all three depression measures (*r*s = .34-.54, *p*s ≤ .003); adult depression follow-up with diabetes and vascular disease management (*r*s = .45 and .57 respectively, *p*s < .001), and between adolescent depression screening and adult depression PHQ-9 utilization (r = .29, p = .02) and adult depression twelve-month follow-up (r = .38, p = .002). Interestingly, the correlation between adult depression PHQ-9 utilization and twelve-month follow-up is not significant, though does trend as such (r = .22, p = .06). Generally, it appears that clinics that perform better on one measure are likely to perform better on other measures, though this relationship may be weaker in indexing adult depression compared to following up with those patients.

Correlations between clinic context variables and healthcare management outcome variables were also generally strong. More rural clinics tended to have poorer child asthma control and lower depression screening/utilization/follow-up rates. Clinics serving lower SES patients tended to have poorer management of all four chronic diseases and lower rates of adult depression follow-up, but no trends with either adult depression PHQ-9 utilization or adolescent depression screening. Clinics serving more White racial/ethnic areas had higher rates of adult asthma, diabetes and vascular disease management, and lower rates of adolescent depression screening.

Aim 1: Direct Relationship between IBH Latent Class and Healthcare Management Outcomes

All results for Aim 1 are displayed in Tables 8 (descriptives) and 9 (comparative analysis). There were generally minimal differences between the IBH latent classes' healthcare management outcomes with a few notable exceptions.

I examined differences between IBH classes on chronic disease management. There were two relative differences between classes: Low IBH clinics had significantly better chronic disease management than both Structural IBH clinics ($\Delta M = 12.5$, $p = .03$) and Strong IBH clinics ($\Delta M = 4.81$, $p = .02$).

All IBH classes had adolescent depression screening rate means significantly above zero, meaning clinics in all classes were screening to some extent. Low IBH clinics had significantly lower rates than Partial IBH clinics ($\Delta M = -8.53$, $p = .03$) or Strong IBH clinics (ΔM = -5.74, p = .03). Structural IBH clinics had significantly lower rates than Partial IBH clinics (ΔM = -17.96, p = .005).

All IBH classes had adult depression PHQ-9 utilization and twelve-month follow-up rate means significantly above zero. There were no relative differences between the four classes on either their adult PHQ-9 utilization or twelve-month follow-up rates.

Aim 2: Direct Relationship between Clinic Context Variables and Healthcare Management Outcomes

All results for Aim 2 are displayed in Table 10. Generally, rurality and socioeconomic risk demonstrated the most robust health disparities. For chronic disease management, as both rurality (B = -0.08, p = .01) and socioeconomic risk (B = -9.62, p < .001) increased, adequate management decreased. For adolescent depression screening, as rurality increased, screening rates significantly decreased (B = -0.21, p = .002). Clinic size was also a significant risk factor, with smaller clinics less likely to screen than larger clinics (B = -0.27, p = .01). For adult depression PHQ-9 utilization, there were no disparities. For adult depression follow-up, socioeconomic risk was significant (B = -8.54, p = .02). There was no significant association between race/ethnicity or organization size and any healthcare management outcomes.

Aim 3: Moderating Relationship between IBH Latent Class and the Clinic Context-Outcomes Link

Separate analyses were run for each clinic context variable and healthcare management outcome link, with IBH latent classes as categorical moderating variables. First, for each analysis, I examined within-class relationships of clinic context and healthcare management outcomes, then examined whether there were any significant differences in those relationships across classes. I intended to control for clinic context variables to better examine the unique impact of each clinic context variable separately. However, the moderately-high correlation between socioeconomic risk and race/ethnicity (percent White; r = -.72) in the current sample resulted in problems with multicollinearity and prevented including both variables as covariates simultaneously in some models. Control variables used are identified in each results section below. In addition, at times it was necessary to either manually set starting values or fix parameters in the model in order to obtain model convergence; these are also noted where relevant. Figures 2-13 detail the interactions between class membership and clinic context variables and the healthcare management outcomes; while some differences may appear significant in the figures, due to standard deviation sizes, this was not always the case. Differences that were statistically significant are discussed in the text below.

Socioeconomic Risk

In Study 1, it was demonstrated that Partial IBH clinics had lower SES risk patients than Structural IBH clinics. In this study, Aim 2, it was demonstrated that higher patient socioeconomic risk was related to clinics' lower rates of successful chronic disease management and adult depression follow-up. The following results demonstrate how IBH latent class impacts these relationships. Full results are shown in Tables 11 (regression results) and 12 (comparative analysis). All analyses looking at SES risk as the primary predictor also included clinic rurality as a control variable, with the exception of chronic disease management, where the complexity of the primary analysis (due to the outcome being a latent variable) combined with small sample size prevented use of a control variable due to model non-convergence.

Chronic Disease Management. All classes except Partial IBH (which trended similarly) had significantly negative relationships between socioeconomic risk and chronic disease management, consistent with the Aim 2 results demonstrating disparities by socioeconomic risk. IBH latent class moderated the relationship such that Low IBH clinics had a significantly less negative relationship than Strong IBH clinics (ΔB = 4.97, p = .001). This indicates that, counter to expectations, Low IBH clinics with elevated-risk patient populations manage chronic disease better than clinics with Strong IBH with similar patient populations. See Figure 4 for visualization.

Adolescent Depression Screening. There were no significant relationships within any of the IBH latent classes between socioeconomic risk and adolescent depression screening, consistent with Aim 2 results. Comparative analysis initially indicated that Structural IBH clinics (ΔB = 8.16, p = .03) and Strong IBH clinics (ΔB = -6.39, p = .04; sign reversed due to directionality of test) had a stronger positive relationship between socioeconomic risk and adolescent depression screening than Partial IBH clinics but the Benjamini-Hochberg procedure indicated that these results were possibly false discoveries. See Figure 5 for visualization.

Adult Depression PHQ-9 Utilization. There were no significant relationships within any of the IBH latent classes between socioeconomic risk and adult depression PHQ-9 utilization (i.e., no health disparities), consistent with Aim 2 results. However, comparative analysis revealed that Partial IBH clinics had a stronger positive relationship between socioeconomic risk and PHQ-9 utilization than Structural IBH clinics (ΔB = 10.7, $p < .001$). This indicates that clinics with Partial IBH with elevated-risk patient populations utilized PHQ-9 as an indexing tool more than Structural IBH clinics with similar patient populations. See Figure 6 for visualization.

Adult Depression Follow-up. Low IBH (B = -8.13, p = .004) and Partial IBH (B = -6.86, p = .003) clinics had significantly negative relationships between socioeconomic risk and twelve-month follow-up with adults with depression consistent with the Aim 2 results demonstrating disparities by socioeconomic risk. Comparative analysis did not reveal differences between IBH latent classes' relationship between socioeconomic risk and depression follow-up. This indicates that all classes of clinics followed up with adult depression patients at similar rates. See Figure 7 for visualization.

Summary of Socioeconomic Risk Results. SES risk impacts chronic disease management, but Low IBH clinics seem to have better-managed chronic disease patients than Strong IBH clinics at higher patient SES risk levels. For adult depression PHQ-9 utilization there were no disparities based on SES risk within any of the IBH classes, but there were some differences between classes, namely that Strong IBH clinics performed worse than Partial IBH clinics on adult depression PHQ-9 utilization as patient SES risk increased. SES risk impacts adult depression follow-up, and this was demonstrated in the Low and Partial IBH classes but was mitigated in Structural and Strong IBH clinics.

Rurality

In Study 1, it was demonstrated that Partial IBH clinics were more likely to be urban than clinics in the other three IBH classes. In Aim 2 of this study, it was demonstrated that more rural clinics had lower rates of successful chronic disease management and adolescent depression screening. The following results demonstrate how IBH latent class impacts the relationship between rurality and these healthcare management outcomes. Full results are shown in Tables 13 (regression results) and 14 (comparative analysis). All analyses with rurality as the primary predictor also included clinic area race/ethnicity (percent White) as a control variable, with the exception of adult depression PHQ-9 utilization, where the complexity of the primary analysis combined with small sample size prevented use of a control variable.

Chronic Disease Management[2]. Counter to the overall health disparities result, there were no significant relationships within any of the IBH latent classes between rurality and chronic disease management. There were also no significant class differences in the relationship between rurality and chronic disease management. See Figure 8 for visualization.

Adolescent Depression Screening. Counter to the overall health disparities result, there were no significant relationships within any of the IBH latent classes between rurality and adolescent depression screening. There were also no significant differences class differences in the relationship between rurality and adolescent depression screening. See Figure 9 for visualization.

Adult Depression PHQ-9 Utilization[3]. Strong IBH clinics ($B = -.50$, $p < .001$) had a significantly negative relationship between rurality and adult depression PHQ-9 utilization. This indicates that clinics with Strong IBH that were more rural did not utilize the PHQ-9 for adult patients with depression as much as more urban clinics in this category. In addition, comparative analysis revealed that Structural IBH clinics had a

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[2] In this analysis, residual variance for vascular control (one of the four variables encompassed in chronic disease management) was fixed at .001 for all four classes and for the overall chronic disease management latent variable for the Structural IBH class; in addition, Mplus fixed the variance for chronic disease management for the Strong IBH class.

[3] In this analysis, starting values were manually set at 1 for Low, Structural, and Partial IBH, and residual variance for the outcome was fixed at .01 for the Partial IBH class.

significantly more positive relationship between rurality and PHQ-9 utilization than both Low IBH clinics (*ΔB* = -.26, *p* = .05; sign reversed due to directionality of test) and Strong IBH clinics (*ΔB* = .65, *p* < .001). This indicates that more rural clinics were less likely to be impacted by rurality in their use of PHQ-9 compared to clinics with Low or Strong IBH. Low IBH clinics had a less negative relationship than Strong IBH clinics (*ΔB* = .39, *p* < .001), which means Low IBH clinics were less impacted by rurality in their use of PHQ-9 compared to clinics with Strong IBH, counter to expectation. See Figure 10 for visualization.

Adult Depression Follow-up. Strong IBH clinics (*B* = -.27, *p* = .05) had a significant negative relationship between rurality and adult depression follow-up. Comparative analysis revealed that Low IBH clinics had a significantly less negative relationship between rurality and depression follow-up than Strong IBH clinics (*ΔB* = .08, *p* = .02). However, the Benjamini-Hochberg procedure indicated that both results were possibly false discoveries. There were otherwise no significant differences between or across IBH classes. See Figure 11 for visualization.

Summary of Rurality Results. Rurality is a risk factor for health disparities, but in this sample, IBH class did not have a significant impact on chronic disease management, adolescent depression screening, or twelve-month follow-up. Overall, clinics with Strong IBH that were more rural used the PHQ-9 less for adult depression than urban Strong IBH clinics, and clinics with Structural IBH that were more rural were more likely to utilize the PHQ-9 than other classes of clinics. It is likely that model convergence difficulties and subsequent adjustments, as well as the small sample size, impacted the ability to detect differences within and among classes in some of these analyses.

Race/Ethnicity

In study 1 and in this study so far, race/ethnicity has not been demonstrated to have any significant relationship with either IBH class or with healthcare management outcomes. However, the following results demonstrate there are some significant relationships in the current dataset between race/ethnicity, IBH latent class, and healthcare management. Full results are shown in Tables 15 (regression results) and 16 (comparative analysis). All analyses looking at race/ethnicity as the primary predictor also included clinic rurality and weighted SES risk as control variables, with the exception of chronic disease management, where the complexity of the primary analysis combined with small sample size only allowed for use of clinic rurality as a control variable.

Chronic Disease Management[4]**.** Both Structural IBH clinics (B = .80, p = .01) and Strong IBH clinics (B = .85, p = .01) demonstrated a significantly positive relationship between a clinic's area population being increasingly White and better chronic disease management. This indicates that clinics in these categories that are in Whiter areas do better on this outcome than clinics in these classes that are in more diverse areas. Comparative analysis demonstrated that Partial IBH clinics have a significantly less positive relationship than Strong IBH clinics (ΔB = -.56, p = .04) between area race/ethnicity and chronic disease management, though the Benjamini-

[4] In this analysis, residual variance for the overall chronic disease management latent variable was fixed at .001 for Structural, Partial, and Strong IBH classes.

Hochberg procedure indicated that this result was possibly a false discovery. See Figure 12 for visualization.

Adolescent Depression Screening. Partial IBH clinics demonstrated a significantly positive relationship ($B = .25$, $p = .03$) between a clinic's area population being increasingly White and increased adolescent depression screening rates; however, the Benjamini-Hochberg procedure indicated that this result was possibly a false discovery. Comparative analysis did not reveal differences between IBH latent classes' relationship between area race/ethnicity and adolescent depression screening rates. This indicates that all classes of clinics screened adolescent depression patients at similar rates. See Figure 13 for visualization.

Adult Depression PHQ-9 Utilization. Partial IBH clinics demonstrated a significantly negative relationship ($B = -.78$, $p = .01$) between a clinic's area population being increasingly White and utilization of the PHQ-9 with depressed adult patients. This indicates that Partial IBH clinics are less likely to use the PHQ-9 as a depression indexing tool when located in a less diverse (more White) area than when a clinic in this category was located in a more diverse area. Additionally, comparative analyses demonstrated that all three of the other IBH classes had significantly more equitable results than Partial IBH clinics, where regardless of the clinic's location in more or less diverse areas, their PHQ-9 utilization was similar (Low IBH: $\Delta B = .98$, $p = .02$; Structural IBH: $\Delta B = 1.37$, $p = .01$; Strong IBH: $\Delta B = -1.13$, $p = .01$, sign reversed due to directionality of test). See Figure 14 for visualization.

Adult Depression Follow-up. Structural IBH clinics demonstrated a significantly positive relationship ($B = 47$, $p = .002$) between a clinic's area population being increasingly White and twelve-month follow-up with depressed adult patients. This indicates that Structural IBH clinics located in more White areas are more likely to follow-up with depressed adult patients than clinics in this category located in more diverse areas. Comparative analysis demonstrated that Strong IBH clinics had significantly more equitable results than Structural IBH clinics (ΔB = .59, p = .05). though the Benjamini-Hochberg procedure indicated that this result was possibly a false discovery. See Figure 15 for visualization.

Summary of Race/Ethnicity Results. Race/ethnicity was significantly related to several healthcare management outcomes. Low IBH clinics did not seem to vary in their outcomes based on area racial/ethnic diversity. Disparities in chronic disease management were focused in Structural and Strong IBH clinics and disparities in adult depression twelve-month follow-up were focused in Structural IBH clinics; reverse disparities seemed to exist in adult depression PHQ-9 utilization, where Whiter area clinics were less likely to use the PHQ-9.

Discussion

The current study aimed to answer three questions: 1) what is the direct relationship between IBH and healthcare management outcomes?, 2) what are the disparities present in the current sample?, and 3) how does variation in IBH implementation relate to these healthcare management disparities? IBH can be a powerful tool in managing population mental health and improving access to mental healthcare. Yet this study has demonstrated that there is nuance in the relationship between IBH, as implemented at the time of data collection, and optimal healthcare management outcomes. On both physical and mental health management outcomes, IBH appears to have a mixed effect or, alternatively, is implemented in uneven ways that do not necessarily fulfill the promise of improved access for all patients.

The direct relationship between IBH and healthcare management was notable in that Low IBH clinics had better physical healthcare management while Strong and Partial IBH clinics had better adolescent depression screening. The pattern of Low IBH clinics having better physical healthcare management trended through most of the subsequent analyses as well. There are several possible explanations for this, including: 1) Low IBH clinics focus more on chronic disease management and less on mental health, and therefore have better outcomes; or 2) Although it was not demonstrated in the specific metrics used in this study, the Low IBH clinics may have less complex patients and/or patients that have more resources and are better able to manage their own care, resulting in better outcomes. Regarding adolescent depression screening, it seems unsurprising that clinics with Strong IBH would make this a priority and be successful at it. In addition, Partial IBH clinics tended to be more urban and have high rates of population-based care (see Study 1), which were predictors for better adolescent depression screening. Low IBH clinics had worse adolescent depression screening, which is consistent with previous findings indicating that clinics missing some elements of IBH tend to screen adolescents less consistently (Joseph et al., 2018). As Buchanan, Monkman, Piehler, & August (2020) suggested, the lower rates in clinics without IBH could be related to providers not having a clear clinical pathway for care or not feeling as comfortable with addressing mental health.

The disparities in healthcare management outcomes present in this sample of clinics included rurality and SES risk for chronic disease management, rurality and large clinic size for adolescent depression screening, and SES risk for adult depression follow-up rates. The finding that larger clinics were lower on adolescent depression screening rates relative to smaller clinics was counter to our hypothesis given the little research that has been done around clinic size in IBH implementation (Kearney et al., 2015), but bears further examination in future research. The other disparities were consistent with previous research (Agency for Healthcare Research and Quality, 2020; Holden et al., 2014; Powers et al., 2020; Santiago et al., 2013).

SES risk

The first group of analyses examined whether any IBH classes seemed to have a different pattern than expected for health disparities based on SES risk. Generally, SES risk was a strong predictor of poorer healthcare management in most classes and it appears that overall, IBH implementation class does not have a large impact on healthcare management outcomes when SES risk is high. Yet, Strong and Structural IBH clinics can mitigate some of the loss to follow-up that is often seen in depression management with high SES risk patients. For chronic disease management, Low IBH clinics, which had a smaller difference at higher SES risk relative to other classes, and Partial IBH clinics, which did not have a significant difference across the SES spectrum, seem to be able to mitigate some of the impact of SES. Partial clinics also were shown to have lower rates of SES-risk overall in Study 1, so they were less represented at the higher end of the SES-risk spectrum and that may play a role. Therefore, there is not one pattern of IBH implementation for which there is a clear amelioration of SES risk.

Rurality

The second group of analyses examined whether any IBH classes seemed to have a different pattern than expected for health disparities based on rurality. Rurality was mainly an issue for chronic disease management, and for that outcome there were no differences among classes. This could be due to the small sample size, as only about 25% of the clinic sample was rural and therefore, we did not detect differences between or within classes. Rurality did seem relevant for adult depression PHQ-9 utilization and follow-up; Strong IBH clinics were less likely to use the PHQ-9 when they were more rural, and less likely to follow-up with depressed adult patients. This result seems counter-intuitive and is worth examining further. It may be that rural clinics with IBH available do not find the PHQ-9 beneficial or effective for tracking patients' depression or that they do not have a systematic population-based approach to care. There may also be something unique to rural clinics which have developed a Strong IBH program, such as being a Federally-Qualified Health Center (FQHC; i.e., being in an underserved area and/or serving an underserved population, which provides additional funding to the clinic), serving a transient population, or some other unique feature that makes using the PHQ-9 and follow-up less tenable. There is currently little research regarding this topic, with most research on rural IBH examining the roles and experiences of medical providers and behavioral health clinicians (e.g., Allen, Grier-Reed, & Maples, 2020).

Race/ethnicity

The third group of analyses examined whether any IBH classes seemed to have a different pattern than expected for health disparities based on area race/ethnicity. Structural and Strong IBH clinics had better chronic disease management outcomes as their area's racial/ethnic diversity decreased, meaning that this implementation structure seemed to be particularly effective for patients in Whiter areas (assumed to be more likely to be White themselves). Low and Partial IBH clinics did not change in their chronic disease management across the diversity spectrum. This could be interpreted that clinics with more White patients do better with chronic disease management than clinics that are more racially/ethnically diverse, and that these outcomes are more pronounced in clinics with stronger IBH (Strong and Structural). While the first part of this conclusion is consistent with health and healthcare disparities generally, the improvement in management in Whiter area clinics specifically in Strong and Structural IBH clinics is something to examine with more detail. It is possible – indeed, likely – that social determinants of health (SDOH) and structural racism complicate successful management of chronic disease management beyond what IBH is intended to address. It is also possible that IBH providers may need to either 1) be diversified as a workforce or 2) receive better cultural competency training in order to better engage diverse patients. These conclusions will be addressed in more detail in the comprehensive discussion shortly.

Social Determinants of Health

The results of this study emphasize the significant role that social determinants of health can play in the management of patients' physical and mental health. Healthcare management is not solely the responsibility of the healthcare system, clinic, or provider. A provider can make every attempt to have a patient complete a questionnaire, call them for follow-up, provide prescriptions and instructions on health management, but patients also need to engage with providers and follow medical advice. However, it is critical to not merely place this responsibility with the patients themselves, but to acknowledge that many patients have significant limitations placed on them by their social location. Some populations of patients are impacted more greatly by social determinants of health (SDOH). For example, poverty means that patients have to move more and sometimes suddenly; run out of minutes on their phones; don't have reliable internet access; have more transportation issues with car problems; have less flexible work schedules to allow for appointments; can't afford childcare; can't afford medication (e.g., rationing insulin); are more exposed to environmental hazards; have less access to high-quality foods, less ability to obtain them, and therefore less ability to manage weight, cholesterol and sodium intakes; have less time to spend calling around and attending appointments for specialists to treat mental and physical health conditions; and myriad other logistical and financial issues that can prevent them from being able to engage fully with providers and follow advice. Despite a provider's and patient's best efforts, there are many times that these logistical and financial issues prevent optimal healthcare management from being able to happen. In our study, we demonstrated the likelihood that SDOH continue to have a significant impact on patients' health and healthcare even when IBH has been well-implemented in a clinic. This is not surprising and should be an indication that while IBH can be effective at increasing access to care and even improving the quality of care provided, it is not capable of, and cannot be expected to, overcome fundamental cultural and policy issues that lead to SDOH.

Strengths and Limitations

The present study was the first to examine healthcare disparities in the context of IBH implementation variation and uses a sample of more than 100 clinics that are in various stages of implementing IBH. This study allows a more nuanced understanding of how various patterns of IBH components' existence in clinics may relate to mitigating or exacerbating healthcare disparities. As a primarily hypothesis-generating study, this study met its goal of providing key research questions for future research. Limitations of this study include its cross-sectional nature; there is no ability to state whether a clinic's IBH implementation class causes or is caused by differences in the context of the clinics or in the patients they serve. Also due to the nature of the cross-sectional data and not having information about how long each clinic had IBH or had been attempting IBH implementation, we were not able to examine changes over time in IBH implementation variation and their relationship with context variables or healthcare management outcomes. One further limitation is that due to the sample size and the complex nature of the analyses, many significant and negative results are tentative and need to be confirmed by additional studies. Finally, this study involved data previously collected from a sample of community clinics, with IBH implementation assessed through self-report and with fidelity assessed retrospectively, and therefore it is possible that social desirability bias and/or that error introduced by the manner of fidelity measurement impacted the results.

Conclusion

Focused studies of IBH and its implementation have demonstrated efficacy in improving access to behavioral health services and improvements in outcomes. However, it appears that on a population-based scale, variation in implementation leads to muddling of these patterns. In some instances, Strong IBH seems to have a positive effect, but in many ways, it is insufficient for the task at hand.

Integrated Discussion and Implications

The goal of any innovation in healthcare is to improve life – quality or quantity, for patients, providers, support staff, or others. For integrated behavioral healthcare, this has typically meant improving access to high-quality behavioral healthcare which can lead to improved behavioral healthcare outcomes on both an individual and population level (i.e., greater rates of depression remission). The current studies examined the status of a community-based sample of clinics in various stages of IBH implementation and the relationship between their implementation variation and healthcare management outcomes and disparities. It should be said that a healthcare innovation being disseminated and implemented by individuals, clinics, and healthcare systems will naturally lead to population-wide variation, both planned and unplanned, and a cross-sectional analysis cannot unravel what is cause and what is effect in the variables. Poor healthcare management outcomes may have been a driving force for IBH implementation in some clinics and not in others. Some clinics may have implemented IBH many years prior to this analysis while others were newly in the process. Yet there are many conclusions that can be drawn from the current studies, and more research questions and hypotheses generated for further research. This conclusion provides a critical overview of what was discovered and how that knowledge might move the field forward.

First, it is important to think of IBH implementation in multiple levels. The Consolidated Framework for Implementation Research (CFIR) provides the levels of (1) characteristics of the intervention itself (e.g., complexity), (2) the process of implementation (e.g., planning), (3) characteristics of the individuals in the setting (e.g., knowledge and beliefs about the intervention), (4) the inner setting (e.g., culture), and (5) the outer setting (e.g., external policies and incentives) (Damschroder et al., 2009). The present study examined (1) IBH as the intervention, (4) characteristics like clinic size, and (5) characteristics such as clinic rurality, area race/ethnicity. Not directly examined but essential to the discussion are aspects of the individual level (e.g., implicit bias, provider diversity) and additional elements of the outer setting such as cultural stigma of mental health, social determinants of health, structural racism and other discriminatory practices, and policies (e.g., CMS reimbursement rates and allowances for CPT codes; Duran & Pérez-Stable, 2019; Kilbourne, Switzer, Hyman, Crowley-Matoka, & Fine, 2006; Nelson et al., 2020). In addition to these structures, Proctor et al. (2011) provide a structure of eight implementation outcomes to consider, and we will review the outcomes *adoption* and *fidelity* in the current studies.

Intervention and Implementation Outcomes

There are several aspects of the intervention, in this case IBH, important to note for IBH, including its complexity and the fact that little research has examined the efficacy of implementing some components but not others, or not fully (e.g., adaptation). As presented in Stephens et al. (2020), IBH has five principles implemented as 25 processes, plus nine clinic structures. This is a complex intervention to fully implement, although some of the principles, processes and structures are not necessarily solely the purview of IBH (e.g., team-based care, patient-centric care) and may already be in place in a given setting but just adapted to the IBH model (Stephens et al., 2020). The present study examined how closely community-based clinics have implemented IBH according to the Cross-Model Framework, keeping in mind that this is an after-the-fact evaluation, as the Framework had not yet been published and therefore was not the target for any of the clinics in the present sample. However, the Framework does represent several models of IBH (i.e., Collaborative Care Model) which *were* the targets for these clinics and therefore an approximate evaluation is appropriate. In terms of fidelity to the principles and structures of IBH that were examined in this study, approximately 23% of the clinics (the Strong IBH class) were generally successful. Financial integration was the least successful, with around 60% of these clinics reporting complete financial integration. Structural IBH clinics were all successful at the financial integration structure, but not on several other important principles and the shared EHR structure. Overall, there were only 11 clinics out of the sample of 102 that fully met criteria on all nine measured components. In addition, this study was based on self-report by clinic staff/providers, which may have been impacted by social desirability bias and/or different interpretations of the survey questions by different clinics. It is therefore possible that a different methodology, such as external observation, would result in different achievement rates of these criteria.

Given the limited number of clinics achieving complete fidelity of the model, it is hard to compare this sample to previous research that involved intensive implementation support (e.g., Unützer et al., 2020) particularly in terms of healthcare management outcomes. Yet this study provides an important understanding regarding implementation, namely that full implementation of IBH according to the Cross-Model Framework is difficult to achieve without intentional implementation support. Future research questions may include: What were the implementation process barriers and facilitators? What implementation support has been used in these instances and what implementation strategies may be effective? Might different implementation strategies be effective for given principles or structures? What about for different levels, i.e., for the individual provider, clinic level, and healthcare system level? Retrospectively, evaluating strategies used by implementation managers and prospectively, mapping potential implementation strategies (e.g., Powell et al., 2015) to specific elements of the Cross-Model Framework would be an important next step for developing a potential research-based implementation guide for clinics working to implement IBH. Some retrospective research has been completed on this topic, which indicate similar issues to those found in this study (e.g., difficulty with team-based care), and suggestions for implementation strategies include systems level change management techniques (e.g., "early engagement of administrators, providers, and staff with a focus on buy-in;" Prom et al., 2020). Some other pilot studies have found specific implementation strategies effective, such as using technical assistance (Chaple et al., 2016) practice facilitation (Roderick et al., 2017), or a quality improvement (QI) framework (Herbst et al., 2020). These suggestions and others can be operationalized and tested in future research. Our current study demonstrates that while it is possible for clinics to achieve full IBH implementation without targeted support, a large majority of clinics would likely benefit from guidance on effective implementation strategies. There are several IBH implementation guides already published, but these guides are model-specific (i.e., CoCM (University of Washington AIMS Center, 2020), PCBH (Mountainview Consulting Group, 2013) and/or they primarily focus on the expected outcome (Cohen et al., 2015) rather than highlighting and operationalizing specific implementation strategies. It is also unclear the extent to which many of the implementation strategies have been researched and found to be effective. Finally, it is important to note that implementation is not a one-time process. While initial implementation can be considered “complete,” every organization and individual must continually re-commit to the model in order to maintain fidelity on an ongoing basis, and it needs to be systematically assessed long-term (Breitenstein et al., 2010; Choy-Brown et al., 2021; Mowbray et al., 2003).

To leverage the impact of IBH and to improve equity, it may also be necessary to add other interventions intended to mitigate the effects of SDOH, especially for clinics with large numbers of patients with high SES risk. These interventions could include adding social workers, community health workers, group visits, telehealth, flexible scheduling, transportation support/vouchers, etc.

Individual Level

The current studies did not consider the individual level (i.e., providers, staff members) of implementation, but this is a critical level for future research to consider. As evidenced by the above discussion about implementation fidelity and buy-in, individuals are those that put in place and carry out the work of an intervention. Without buy-in, it is very challenging, if not impossible, to achieve IBH implementation success (A. Beck et al., 2018; Katzelnick & Williams, 2015; C. May, 2013; Robin R. Whitebird, PhD et al., 2014).

There are several other individual factors that this project did not directly assess but which previous research and current frameworks highlight as critical to improving healthcare disparities (Duran & Pérez-Stable, 2019; Kilbourne et al., 2006; Nelson et al., 2020). IBH implementation research would do well to consider assessing for these factors as well, which include implicit bias, cultural competency, and the diversity of providers, for both physical and behavioral health clinicians. The present study found that patients in Whiter areas were more likely to benefit in Structural and Strong IBH clinics than patients in areas with greater diversity, and it is worth tapping the larger literature around contributing factors to healthcare disparities in order to address these in the context of IBH. When minority populations have been the targeted focus of IBH efforts, engagement and improved outcomes have been strong (Bridges et al., 2014; Holden et al., 2014; Sanchez & Watt, 2012). However, in a general context, healthcare disparity factors such as implicit bias and lack of cultural competency may prevent these positive outcomes from occurring. In order to achieve equitable access to high-quality mental healthcare, structural racism and implicit bias need to be addressed by behavioral health providers within themselves and their own practice tendencies as much as the rest of those in healthcare system need to do this. In addition, improving the diversity of the behavioral healthcare workforce and supporting minority behavioral healthcare providers can be an individual as well as organization-level activity (Legha & Miranda, 2020). Each person in a clinic (administrators, primary care providers, behavioral health clinicians, nurses, receptionists, etc.) has the ability to act in anti-racist ways which can change the broader culture over time and contribute to equitable access and care (Legha & Miranda, 2020). These strategies, too, can be subject to testing along with implementation strategies, with the goal not only to achieve high-quality IBH implementation, but an equitable and anti-racist system of care, as suggested by Brownson and colleagues (2021).

Inner Setting

The present study examined aspects of the inner setting including the structural characteristics of clinic size and organization size (Damschroder et al., 2009). Overall, it did not appear that clinic or organization size had a significant impact on healthcare management outcomes, although with the limited research on the topic, the impact cannot be completely discounted. Other critical inner setting characteristics that were not examined in this study but have been in others include (not an exhaustive list) time from initial implementation to effects on clinical outcomes (Carlo et al., 2019) and readiness factors (Blaney et al., 2018; Brown et al., 2018; Chang et al., 2013; Scott et al., 2017). Similar to the individual level, considerations based on equity and addressing structural racism should also be examined at this level.

Outer Setting

The outer setting of IBH implementation includes several of the clinic context variables, such as area race/ethnicity and rurality, as well as social determinants of health, a larger culture of historical and structural racism and cultural stigma against mental illness, and the policy and financing environment in which IBH is being implemented. Numerous papers have been written about the patchwork way in which IBH services are able to be billed and low reimbursement rates, even though this has improved through additional options made available by the Centers for Medicare and Medicaid expanding and adding CPT (current procedural terminology) codes (Kathol et al., 2010; Moise et al., 2018; Society for Adolescent Health and Medicine, 2020; Tynan, 2016). A clear understanding of policy and gaps is particularly difficult in the U.S. due to the piecemeal way that reimbursement occurs, from federal, state, and private payers and guidelines. Without clear, straightforward financial policy and reimbursing and rewarding high-quality behavioral healthcare at similar rates to physical healthcare, dissemination of IBH will continue to be a challenge. These financial policies reflect and reinforce a tendency in U.S. culture to discount, minimize, or dismiss mental health issues as less important or "real" than physical health, and therefore less necessary to be cared for (Compton-Phillips & Mohta, 2018; US Department of Health and Human Services, 2001). Unfortunately this attitude is one of the reasons why specialty care is in short supply, hard to access, and why many people prefer to seek behavioral health services in primary care – it is less stigmatized (Baird et al., 2014; Davis et al., 2018; Miller-Matero et al., 2018). While outer setting variables seem large, diffuse, and out of reach, there have been significant changes in the past decade and policies continue to slowly improve.

Conclusion

The current project examined 1) variation in IBH implementation over a broad sample of clinics, 2) how implementation profiles were impacted by clinic context, 3) how IBH implementation impacts clinical outcomes, and 4) whether IBH implementation variation was related to healthcare disparities in several underserved groups. Findings from this study are that IBH implementation varies considerably with some common patterns, that implementation is selectively impacted by clinic context, and that IBH implementation variation can be related to healthcare disparities. This study demonstrates that IBH implementation has an impact, and that studying implementation processes during and after a clinic's transformation from standard practice to integrated care is critical to the large-scale IBH dissemination effort underway nationally, in order to ensure that the result is high-quality, equitable care.

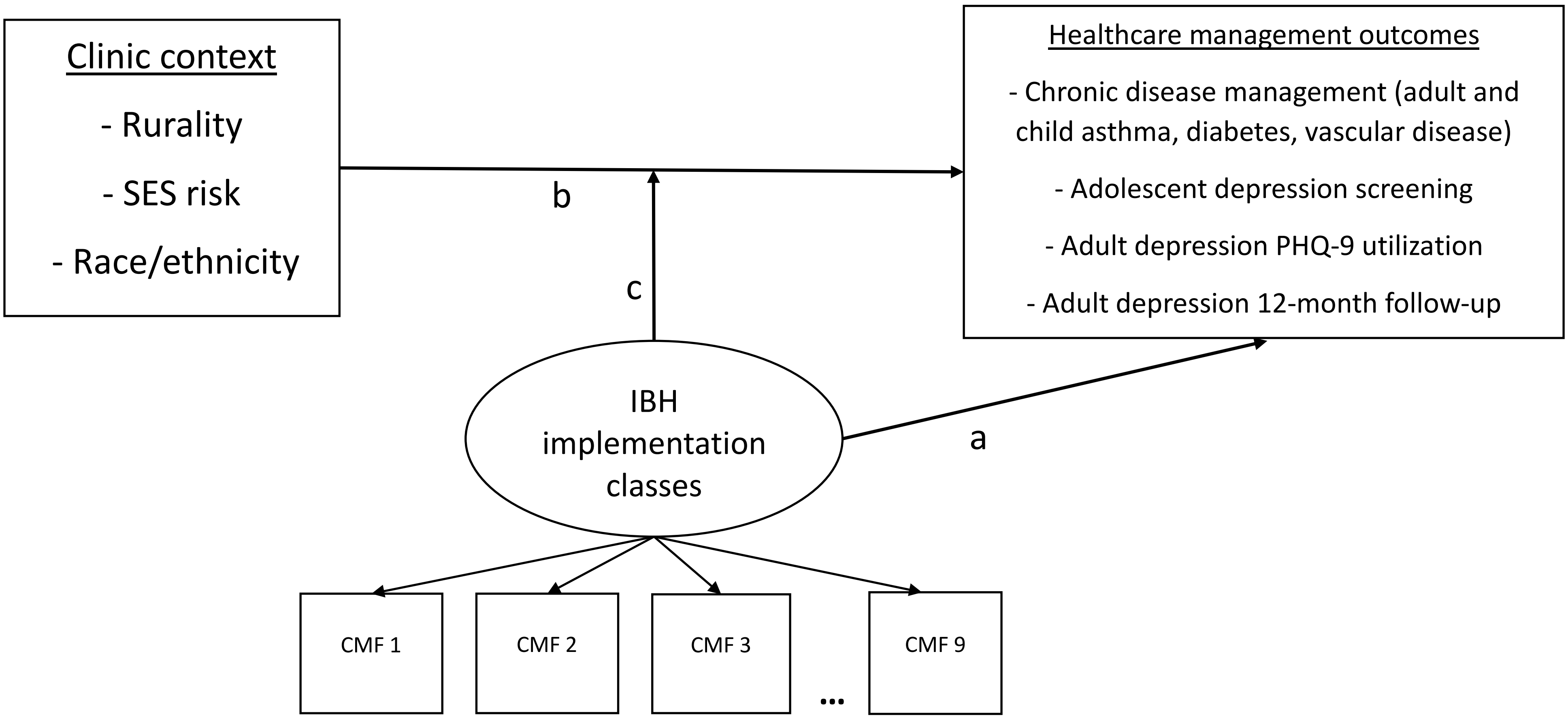

Figure 3.

Conceptual model. CMF # = Cross-Model Framework concept, i.e., team-based care. Pathways examined: a) direct relationship between IBH implementation latent classes and healthcare management outcomes, b) direct relationship between clinic context variables including rurality, socioeconomic risk, and race/ethnicity and healthcare management outcomes, otherwise known as healthcare disparities, and c) moderating effects of IBH implementation variation, in the form of latent classes, on the revealed healthcare disparities.

Table 7.

Descriptives and Correlations in Study Variables

Variable	*M*	*SD*	*N*	Clinic RUCA	Clinic weighted SES risk	Race/ ethnicity (% White)	Adult Asthma	Child Asthma	Diabetes	Vascular	Adult PHQ-9 Utilization	Adult Depression Follow-up
Clinic RUCA	2.2	2.6	102	-								
Clinic weighted SES risk	1.0	0.1	87	-0.15	-							
Race/ ethnicity (% White)	79.7	13.3	99	$.46^{**}$	$-.59^{**}$	-						
Adult Asthma (%)	49.6	17.4	86	-0.11	$-.38^{**}$	$.25^{*}$	-					
Child Asthma (%)	58.0	0.2	68	$-.31^{*}$	$-.35^{**}$	0.04	$.87^{**}$	-				
Diabetes (%)	44.8	10.1	78	0.13	$-.67^{**}$	$.49^{**}$	$.63^{**}$	$.53^{**}$	-			
Vascular (%)	58.1	0.1	77	0.03	$-.68^{**}$	$.35^{**}$	$.66^{**}$	$.55^{**}$	$.83^{**}$	-		
Adult PHQ-9 Utilization (%)	74.1	0.2	79	$-.34^{**}$	0.01	-0.19	$.38^{**}$	$.53^{**}$	-0.05	0.19	-	
Adult Depression Follow-up (%)	10.8	8.6	74	$-.24^{*}$	$-.40^{**}$	0.16	$.51^{**}$	$.54^{**}$	$.45^{**}$	$.57^{**}$	0.22	-
Adolescent Depression Screening (%)	76.2	24.3	81	$-.42^{**}$	-0.05	$-.22^{*}$	$.34^{**}$	$.42^{**}$	0.10	0.15	$.29^{*}$	$.38^{**}$

Table 8.

Healthcare Management Outcomes Descriptives By Class

Healthcare Management Outcomes By Class	*M*	*SD*	*p*
Chronic Disease Management			
Low IBH (Class 1)	2.93	9.18	0.15
Structural IBH (Class 2)	-9.57	3.63	0.11
Partial IBH (Class 3)	2.50	11.38	0.49
Strong IBH (Class 4)	-1.88	12.17	999^
Adolescent Depression Screening			
Low IBH (Class 1)	82.34	13.24	0.00
Structural IBH (Class 2)	72.91	17.08	0.00
Partial IBH (Class 3)	90.87	6.39	0.00
Strong IBH (Class 4)	88.08	7.33	0.00
Adult Depression PHQ-9 Utilization			
Low IBH (Class 1)	70.86	20.00	0.00
Structural IBH (Class 2)	81.10	18.47	0.00
Partial IBH (Class 3)	75.67	15.50	0.00
Strong IBH (Class 4)	71.10	16.87	0.00
Adult Depression Follow-up (12 mo)			
Low IBH (Class 1)	31.18	14.49	0.00
Structural IBH (Class 2)	20.08	11.44	0.00
Partial IBH (Class 3)	29.31	15.20	0.00
Strong IBH (Class 4)	29.66	11.27	0.00

Note: ^ = parameter fixed to avoid singularity

Table 9.

Comparative Analysis of Healthcare Management Outcome Means by IBH Class

Variable and Classes Being Compared	*ΔM*	*SE*	*p*
Chronic Disease Management			
Low IBH – Structural IBH	**12.50**	**5.87**	**0.03**
Low IBH – Partial IBH	0.43	3.49	0.90
Low IBH – Strong IBH	**4.81**	**2.04**	**0.02**
Structural IBH – Partial IBH	-12.07	6.86	0.08
Structural IBH – Strong IBH	-7.69	6.01	0.20
Partial IBH – Strong IBH	4.38	3.64	0.23
Adolescent Depression Screening			
Low IBH – Structural IBH	9.43	8.16	0.25
Low IBH – Partial IBH	**-8.53**	**3.87**	**0.03**
Low IBH – Strong IBH	**-5.74**	**2.69**	**0.03**
Structural IBH – Partial IBH	**-17.96**	**6.38**	**0.005**
Structural IBH – Strong IBH	-15.17	8.01	0.06
Partial IBH – Strong IBH	2.79	3.78	0.46
Adult Depression PHQ-9 Utilization			
Low IBH – Structural IBH	-10.24	7.92	0.20
Low IBH – Partial IBH	-4.80	3.41	0.16
Low IBH – Strong IBH	-0.23	2.56	0.93
Structural IBH – Partial IBH	5.44	9.60	0.57
Structural IBH – Strong IBH	10.01	6.67	0.13
Partial IBH – Strong IBH	4.57	4.85	0.35
Adult Depression Follow-up (12 mo)			
Low IBH – Structural IBH	11.10	8.52	0.19
Low IBH – Partial IBH	1.87	5.96	0.75
Low IBH – Strong IBH	1.52	2.15	0.48
Structural IBH – Partial IBH	-9.23	8.11	0.26
Structural IBH – Strong IBH	-9.57	6.99	0.17
Partial IBH – Strong IBH	-0.34	5.37	0.95

Table 10.

Results of Multiple Regression Models for Clinic Context Variables Regressed onto Healthcare Management Outcomes (Health Disparities)

Outcomes	Clinic Context Variables	*B*	*SE*	*p*
Chronic Disease Management				
	Rurality	-0.08	0.03	**0.01**
	SES risk	-9.62	2.09	**0.000**
	Race/ethnicity	-0.18	0.14	0.18
	Organization size	0.13	0.13	0.31
	Clinic size (Active patient population)	0.08	0.09	0.40
Adolescent Depression Screening				
	Rurality	-0.21	0.07	**0.002**
	SES risk	-4.03	2.72	0.14
	Race/ethnicity	0.06	0.10	0.57
	Organization size	-0.13	0.12	0.29
	Clinic size (Active patient population)	-0.27	0.11	**0.01**
Adult Depression PHQ-9 Utilization				
	Rurality	-0.17	0.09	0.07
	SES risk	-3.49	2.26	0.12
	Race/ethnicity	-0.27	0.30	0.37
	Organization size	-0.37	0.27	0.17
	Clinic size (Active patient population)	0.16	0.10	0.12
Adult Depression Follow-up (12 mo)				
	Rurality	-0.19	0.10	0.07
	SES risk	-8.54	3.68	**0.02**
	Race/ethnicity	-0.22	0.26	0.38
	Organization size	-0.05	0.17	0.79
	Clinic size (Active patient population)	0.00	0.10	0.98

Table 11.

Results of IBH Class Moderating Socioeconomic Risk on Healthcare Management Outcomes

SES Risk → Healthcare Management Outcomes	*B*	*SE*	*p*
By Class			
Chronic Disease Management			
Low IBH (Class 1)	**-5.19**	**1.85**	**0.01**
Structural IBH (Class 2)	**-8.32**	**3.43**	**0.02**
Partial IBH (Class 3)	-20.42	11.35	0.07
Strong IBH (Class 4)	**-10.16**	**2.81**	**0.00**
Adolescent Depression Screening			
Low IBH (Class 1)	-2.59	3.26	0.43
Structural IBH (Class 2)	2.34	3.28	0.48
Partial IBH (Class 3)	-5.82	3.19	0.07
Strong IBH (Class 4)	0.57	0.51	0.26
Adult Depression PHQ-9 Utilization			
Low IBH (Class 1)	-7.24	5.24	0.17
Structural IBH (Class 2)	-11.94	8.84	0.18
Partial IBH (Class 3)	4.29	3.31	0.20
Strong IBH (Class 4)	-6.41	4.65	0.17
Adult Depression Follow-up (12 mo)			
Low IBH (Class 1)	**-8.13**	**2.79**	**0.004**
Structural IBH (Class 2)	-5.81	3.20	0.07
Partial IBH (Class 3)	**-6.86**	**2.32**	**0.003**
Strong IBH (Class 4)	-5.35	3.40	0.12

Table 12.

Comparative Analysis of SES-Risk-Healthcare Management Outcome Slopes by IBH Class

Variable and Classes being Compared	*ΔB*	*SE*	*P*
Chronic Disease Management			
Low IBH – Structural IBH	3.13	3.20	0.33
Low IBH – Partial IBH	15.23	12.01	0.21
Low IBH – Strong IBH	**4.97**	**1.47**	**0.001**
Structural IBH – Partial IBH	12.10	13.32	0.36
Structural IBH – Strong IBH	1.85	3.55	0.60
Partial IBH – Strong IBH	-10.26	11.87	0.39
Adolescent Depression Screening			
Low IBH – Structural IBH	-4.93	4.58	0.28
Low IBH – Partial IBH	3.22	4.43	0.47
Low IBH – Strong IBH	-3.17	3.35	0.35
Structural IBH – Partial IBH	**8.16**	**3.73**	**0.03**$^{+}$
Structural IBH – Strong IBH	1.77	3.12	0.57
Partial IBH – Strong IBH	**-6.39**	**3.05**	**0.04**$^{+}$
Adult Depression PHQ-9 Utilization			
Low IBH – Structural IBH	4.71	9.86	0.63
Low IBH – Partial IBH	-11.52	6.52	0.08
Low IBH – Strong IBH	-0.83	6.02	0.89
Structural IBH – Partial IBH	-16.23	11.56	0.16
Structural IBH – Strong IBH	-5.53	12.85	0.67
Partial IBH – Strong IBH	**10.70**	**3.05**	**0.000**
Adult Depression Follow-up (12 mo)			
Low IBH – Structural IBH	-2.32	3.93	0.56
Low IBH – Partial IBH	-1.27	3.11	0.68
Low IBH – Strong IBH	-2.77	3.70	0.45
Structural IBH – Partial IBH	1.05	3.31	0.75
Structural IBH – Strong IBH	-0.46	2.47	0.85
Partial IBH – Strong IBH	-1.50	2.58	0.56

Note: $^{+}$*Using the Benjamini-Hochberg false discovery rate procedure, this test is no longer significant*

Table 13.

Results of IBH Class Moderating Rurality on Healthcare Management Outcomes

Rurality → Healthcare Management Outcomes	*B*	*SE*	*p*
By Class			
Chronic Disease Management			
Low IBH (Class 1)	-0.06	0.18	0.72
Structural IBH (Class 2)	0.68	0.46	0.14
Partial IBH (Class 3)	-11.31	89.63	0.90
Strong IBH (Class 4)	-0.16	0.40	0.69
Adolescent Depression Screening			
Low IBH (Class 1)	-0.04	0.55	0.94
Structural IBH (Class 2)	0.13	1.45	0.93
Partial IBH (Class 3)	5.89	45.70	0.90
Strong IBH (Class 4)	-0.24	0.37	0.53
Adult Depression PHQ-9 Utilization			
Low IBH (Class 1)	-0.11	0.08	0.18
Structural IBH (Class 2)	0.15	0.15	0.30
Partial IBH (Class 3)	-23.72	184.85	0.90
Strong IBH (Class 4)	**-0.50**	**0.09**	**0.00**
Adult Depression Follow-up (12 mo)			
Low IBH (Class 1)	-0.19	0.14	0.17
Structural IBH (Class 2)	-0.10	0.24	0.69
Partial IBH (Class 3)	-1.11	2.91	0.70
Strong IBH (Class 4)	**-0.27**	**0.14**	**0.05**$^{+}$

Note: $^{+}$*Using the Benjamini-Hochberg false discovery rate procedure, this test is no longer significant*

Table 14.

Comparative Analysis of SES-Risk-Healthcare Management Outcome Slopes by IBH Class

Variable and Classes being Compared	*ΔB*	*SE*	*p*
Chronic Disease Management			
Low IBH – Structural IBH	-0.74	0.61	0.23
Low IBH – Partial IBH	11.25	89.61	0.90
Low IBH – Strong IBH	0.09	0.28	0.74
Structural IBH – Partial IBH	11.99	89.67	0.89
Structural IBH – Strong IBH	0.83	0.79	0.29
Partial IBH – Strong IBH	-11.15	89.48	0.90
Adolescent Depression Screening			
Low IBH – Structural IBH	-0.17	0.92	0.86
Low IBH – Partial IBH	-5.93	45.17	0.90
Low IBH – Strong IBH	0.19	0.19	0.31
Structural IBH – Partial IBH	-5.76	44.26	0.90
Structural IBH – Strong IBH	0.36	1.09	0.74
Partial IBH – Strong IBH	6.12	45.33	0.89
Adult Depression PHQ-9 Utilization			
Low IBH – Structural IBH	**-0.26**	**0.13**	**0.05**
Low IBH – Partial IBH	23.60	184.90	0.90
Low IBH – Strong IBH	**0.39**	**0.11**	**0.000**
Structural IBH – Partial IBH	23.87	184.84	0.90
Structural IBH – Strong IBH	**0.65**	**0.11**	**0.000**
Partial IBH – Strong IBH	-23.21	184.82	0.90
Adult Depression Follow-up (12 mo)			
Low IBH – Structural IBH	-0.10	0.17	0.57
Low IBH – Partial IBH	0.92	2.81	0.74
Low IBH – Strong IBH	**0.08**	**0.03**	**0.02^{+}**
Structural IBH – Partial IBH	1.01	2.70	0.71
Structural IBH – Strong IBH	0.17	0.17	0.30
Partial IBH – Strong IBH	-0.84	2.82	0.77

Note: $^{+}$*Using the Benjamini-Hochberg false discovery rate procedure, this test is no longer significant*

Table 15.

Results of IBH Class Moderating Race/Ethnicity (Percent White) on Healthcare Management Outcomes

Race/Ethnicity →Healthcare Management Outcomes	*B*	*SE*	*p*
By Class			
Chronic Disease Management			
Low IBH (Class 1)	0.34	0.32	0.29
Structural IBH (Class 2)	**0.80**	**0.31**	**0.01**
Partial IBH (Class 3)	0.28	0.34	0.42
Strong IBH (Class 4)	**0.85**	**0.31**	**0.01**
Adolescent Depression Screening			
Low IBH (Class 1)	0.16	0.14	0.26
Structural IBH (Class 2)	-0.19	0.33	0.57
Partial IBH (Class 3)	**0.25**	**0.11**	**0.03**$^{+}$
Strong IBH (Class 4)	0.10	0.37	0.78
Adult Depression PHQ-9 Utilization			
Low IBH (Class 1)	0.20	0.34	0.57
Structural IBH (Class 2)	0.59	0.48	0.22
Partial IBH (Class 3)	**-0.78**	**0.31**	**0.01**
Strong IBH (Class 4)	0.35	0.46	0.45
Adult Depression Follow-up (12 mo)			
Low IBH (Class 1)	0.25	0.21	0.23
Structural IBH (Class 2)	**0.47**	**0.15**	**0.00**
Partial IBH (Class 3)	0.10	0.22	0.65
Strong IBH (Class 4)	-0.13	0.30	0.67

Note: $^{+}$*Using the Benjamini-Hochberg false discovery rate procedure, this test is no longer significant*

Table 16.

Comparative Analysis of Race/Ethnicity-Healthcare Management Outcome Slopes by IBH Class

Variable and Classes being Compared	*ΔB*	*SE*	*p*
Chronic Disease Management			
Low IBH – Structural IBH	-0.46	0.29	0.12
Low IBH – Partial IBH	0.06	0.43	0.88
Low IBH – Strong IBH	-0.51	0.36	0.15
Structural IBH – Partial IBH	0.53	0.55	0.34
Structural IBH – Strong IBH	-0.05	0.53	0.93
Partial IBH – Strong IBH	**-0.58**	**0.28**	**0.04+**
Adolescent Depression Screening			
Low IBH – Structural IBH	0.34	0.26	0.19
Low IBH – Partial IBH	-0.09	0.19	0.63
Low IBH – Strong IBH	0.05	0.45	0.90
Structural IBH – Partial IBH	-0.44	0.34	0.19
Structural IBH – Strong IBH	-0.29	0.52	0.58
Partial IBH – Strong IBH	0.15	0.35	0.67
Adult Depression PHQ-9 Utilization			
Low IBH – Structural IBH	-0.39	0.36	0.28
Low IBH – Partial IBH	**0.98**	**0.41**	**0.02**
Low IBH – Strong IBH	-0.16	0.38	0.68
Structural IBH – Partial IBH	**1.37**	**0.55**	**0.01**
Structural IBH – Strong IBH	0.24	0.59	0.69
Partial IBH – Strong IBH	**-1.13**	**0.45**	**0.01**
Adult Depression Follow-up (12 mo)			
Low IBH – Structural IBH	-0.21	0.28	0.45
Low IBH – Partial IBH	0.15	0.32	0.63
Low IBH – Strong IBH	0.38	0.25	0.13
Structural IBH – Partial IBH	0.37	0.25	0.14
Structural IBH – Strong IBH	**0.59**	**0.31**	**0.05$^+$**
Partial IBH – Strong IBH	0.23	0.39	0.56

Note:$^+$Using the Benjamini-Hochberg false discovery rate procedure, this test is no longer significant

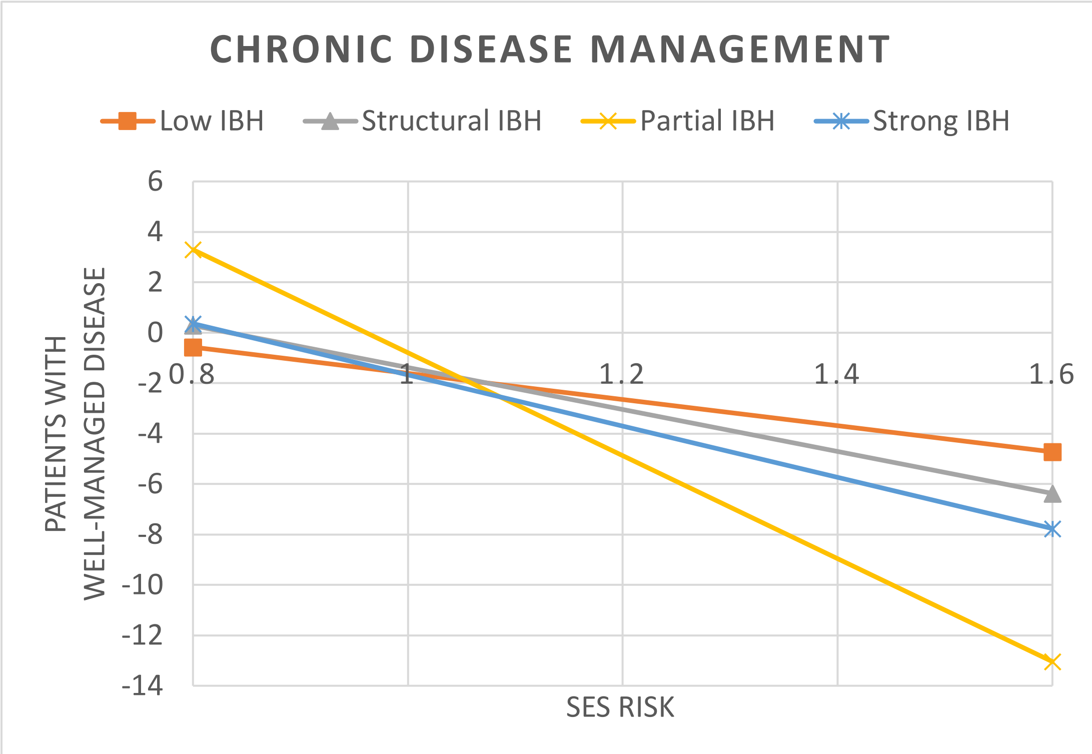

Figure 4. Chronic disease management rates based on SES risk by IBH implementation class.
Note: Due to the nature of the analysis, Y-axis numbers are not a specific percentage.

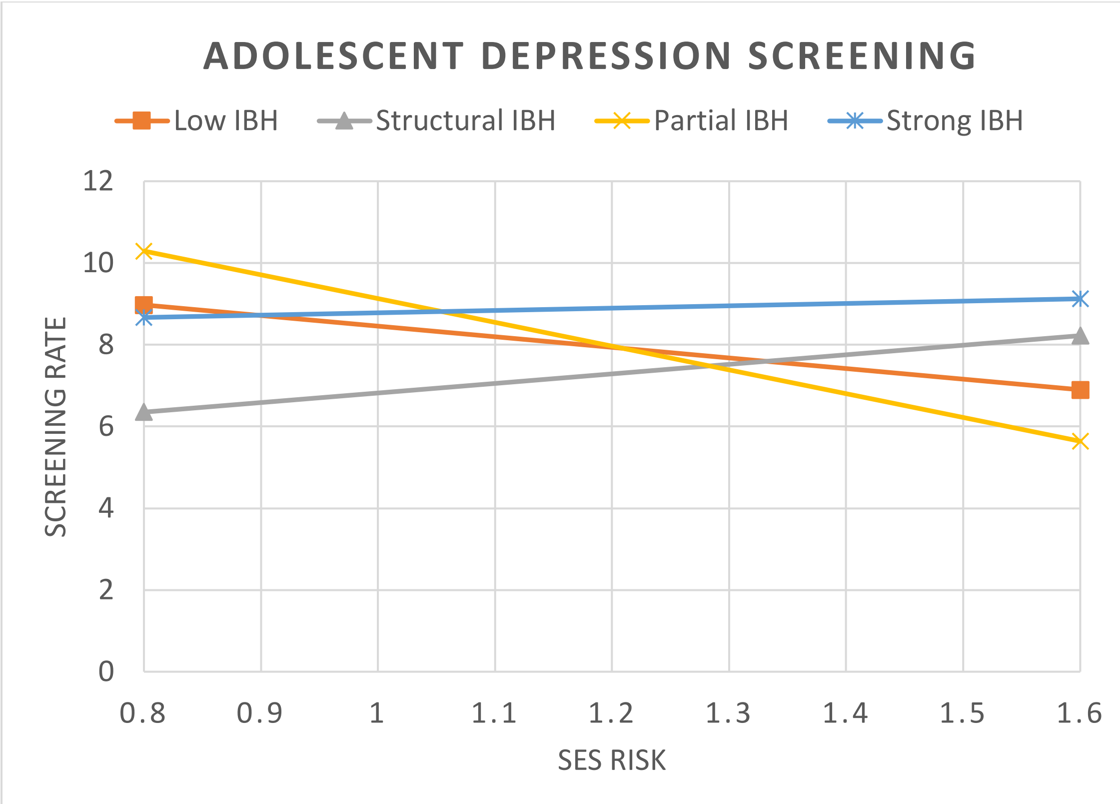

Figure 5. Adolescent depression screening rates based on SES risk by IBH implementation class.
Note: Due to the nature of the analysis, Y-axis numbers are not a specific percentage.

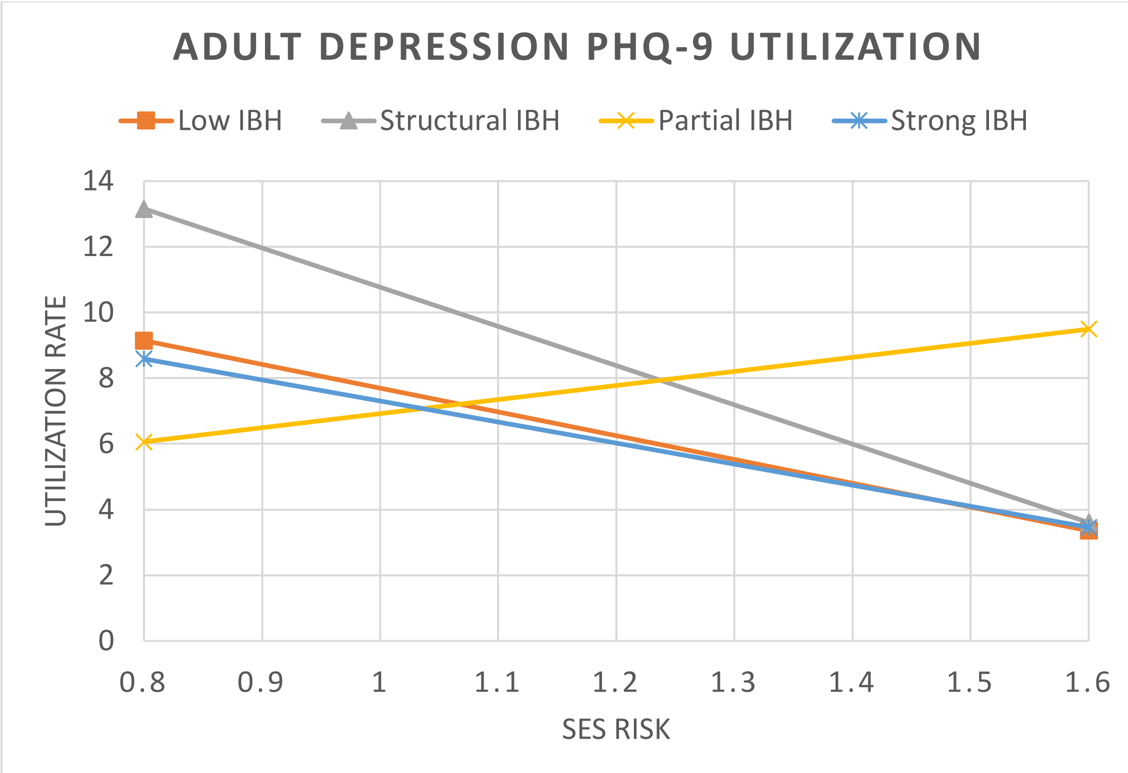

Figure 6. Adult depression PHQ-9 utilization rates based on SES risk by IBH implementation class. *Note: Due to the nature of the analysis, Y-axis numbers are not a specific percentage.*

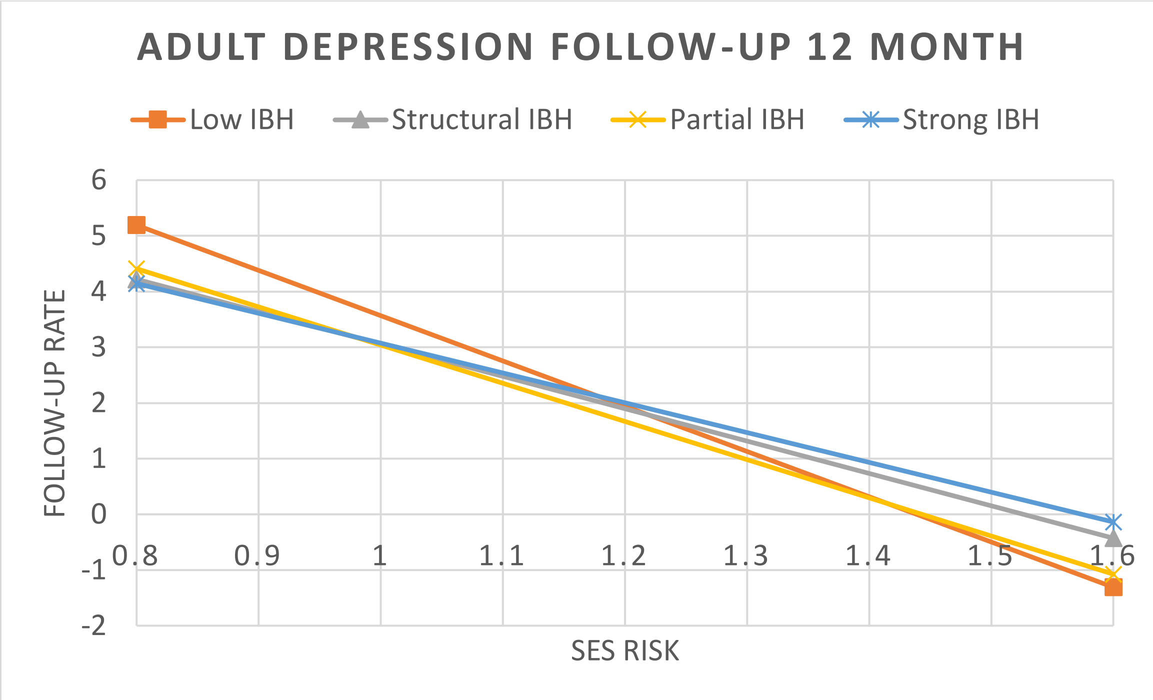

Figure 7. Adult depression 12-month follow-up rates based on SES risk by IBH implementation class. *Note: Due to the nature of the analysis, Y-axis numbers are not a specific percentage.*

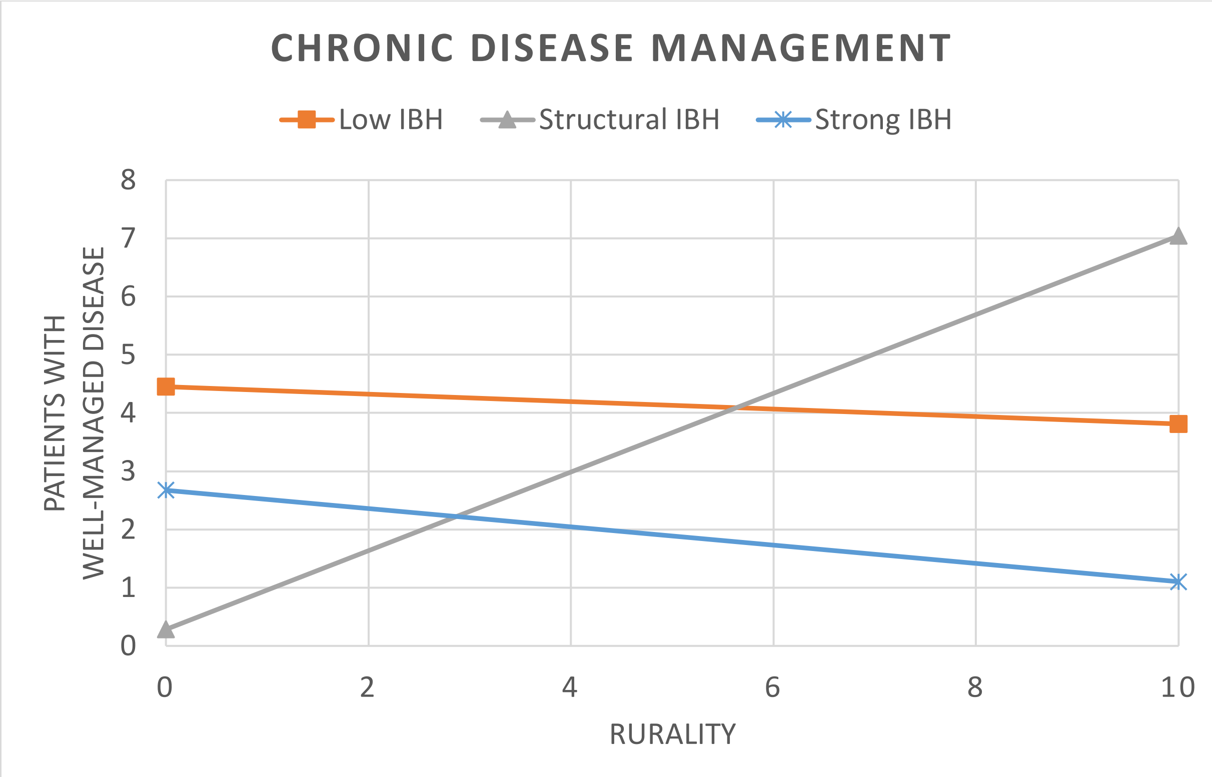

Figure 8. Chronic disease management rates based on rurality by IBH implementation class. *Notes: Due to the nature of the analysis, Y-axis numbers are not a specific percentage. Additionally, there were an inadequate number of Partial clinics that were outside urban areas in order to accurately estimate the relationship between rurality and the healthcare management outcomes in that class, so for clarity, Partial clinic numbers are excluded in the rurality graphs.*

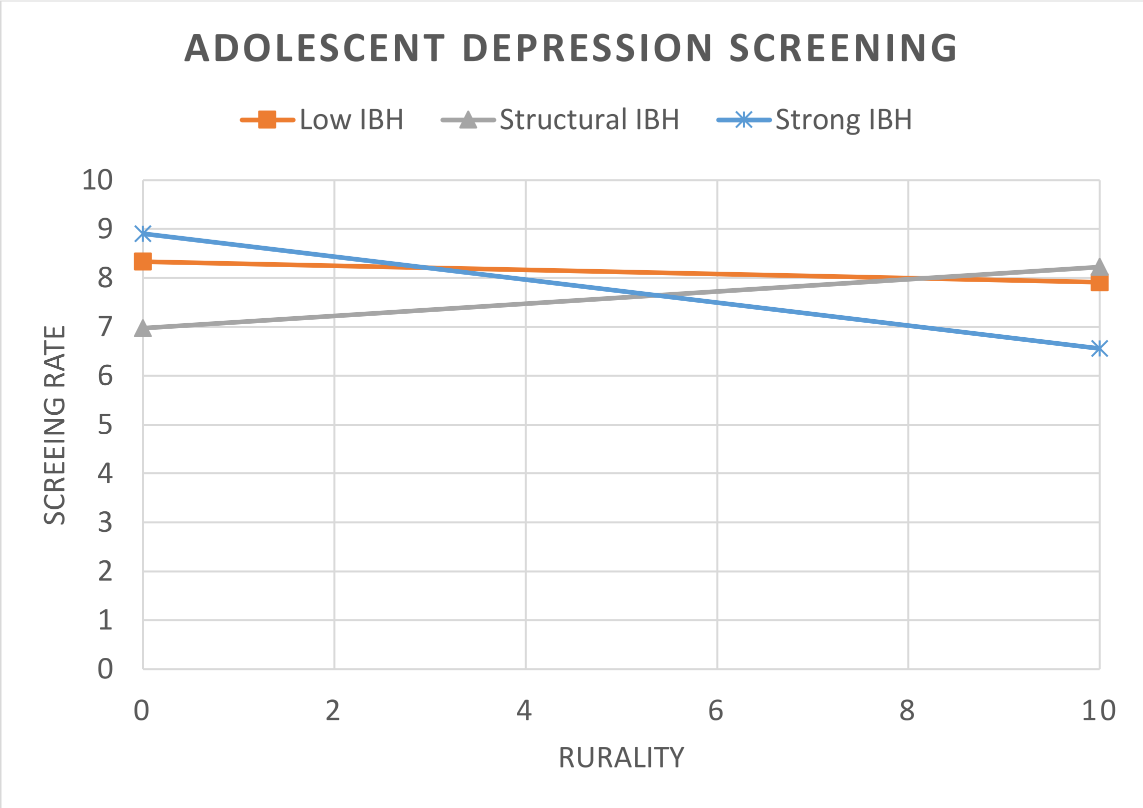

Figure 9. Adolescent depression screening rates based on rurality by IBH implementation class. *Notes: Due to the nature of the analysis, Y-axis numbers are not a specific percentage. Additionally, there were an inadequate number of Partial clinics that were outside urban areas in order to accurately estimate the relationship between rurality and the healthcare management outcomes in that class, so for clarity, Partial clinic numbers are excluded in the rurality graphs.*

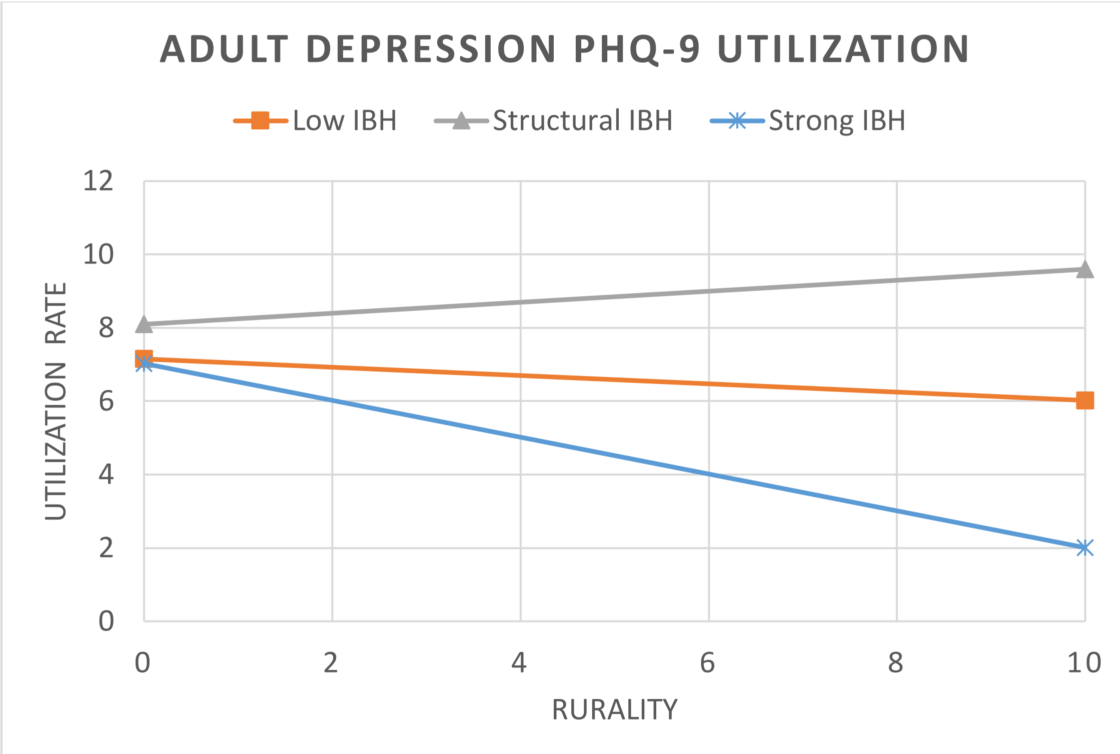

Figure 10. Adult depression PHQ-9 utilization rates based on rurality by IBH implementation class. *Notes: Due to the nature of the analysis, Y-axis numbers are not a specific percentage. Additionally, there were an inadequate number of Partial clinics that were outside urban areas in order to accurately estimate the relationship between rurality and the healthcare management outcomes in that class, so for clarity, Partial clinic numbers are excluded in the rurality graphs.*

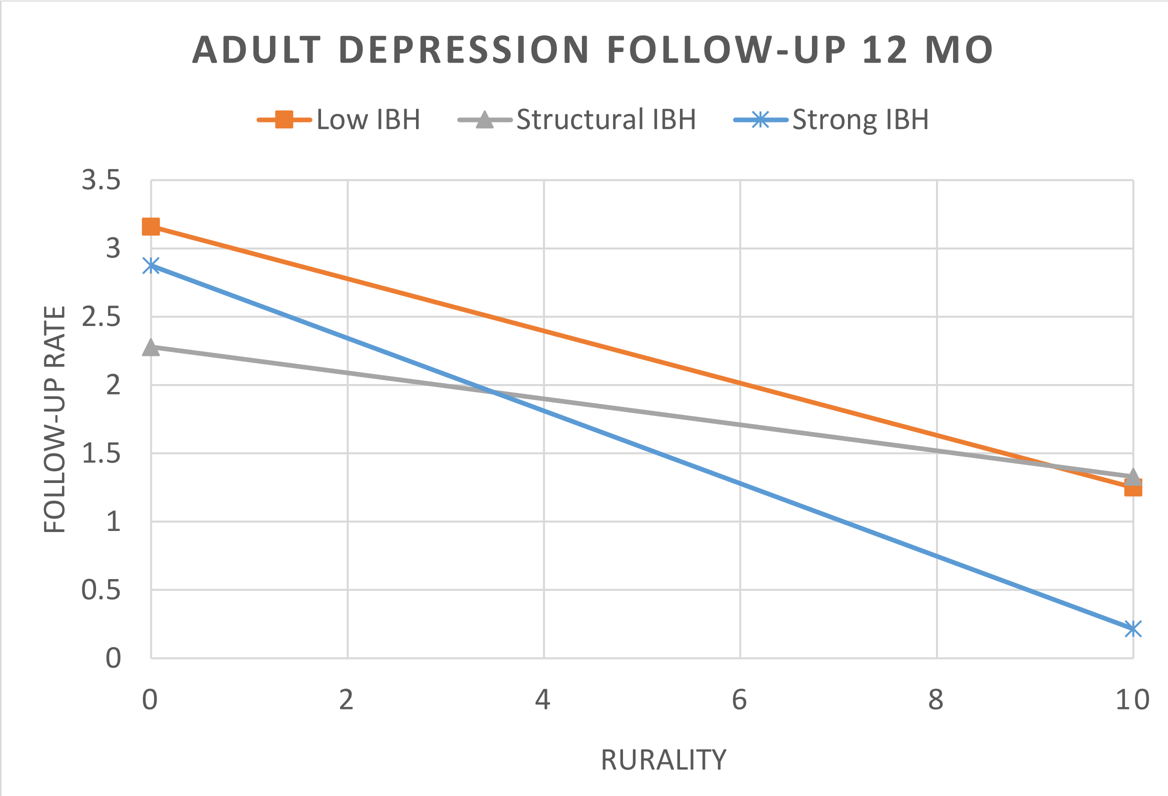

Figure 11. Adult depression 12-month follow-up rates based on rurality by IBH implementation class. *Notes: Due to the nature of the analysis, Y-axis numbers are not a specific percentage. Additionally, there were an inadequate number of Partial clinics that were outside urban areas in order to accurately estimate the relationship between rurality and the healthcare management outcomes in that class, so for clarity, Partial clinic numbers are excluded in the rurality graphs.*

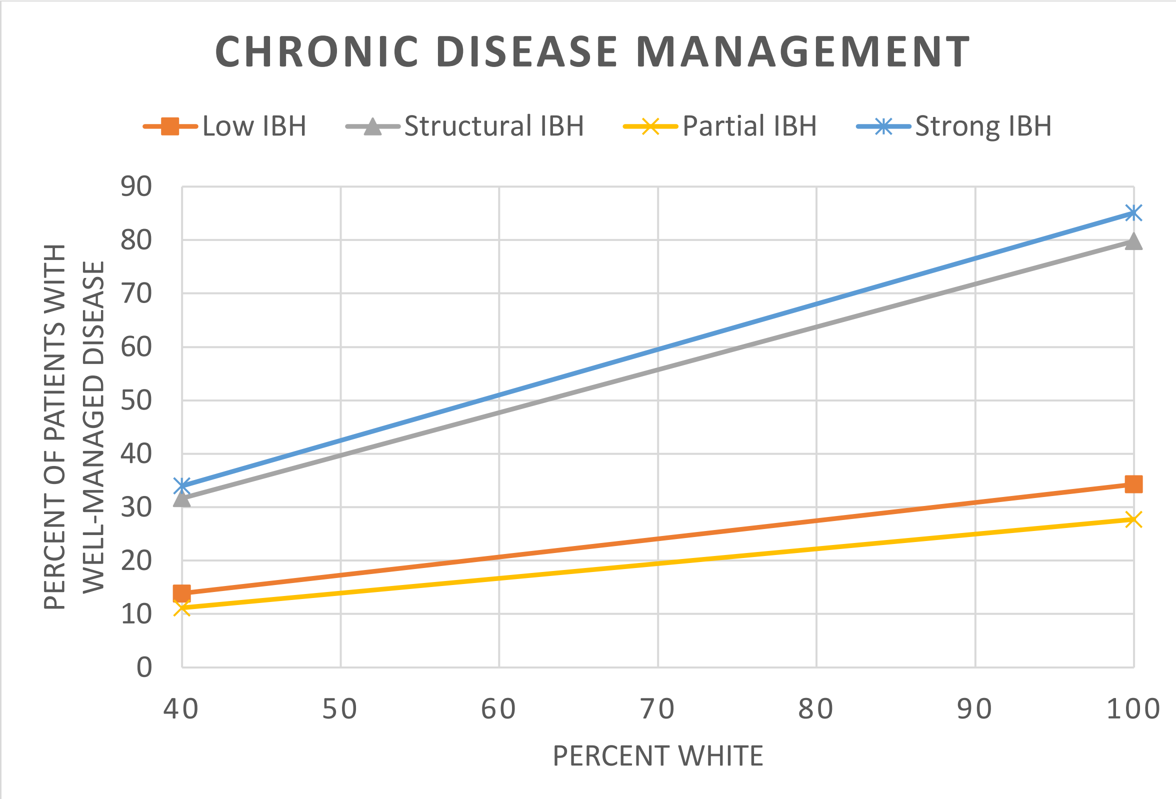

Figure 12. Chronic disease management rates based on area race/ethnicity by IBH implementation class. *Note: Due to the nature of the analysis, Y-axis numbers are not a specific percentage.*

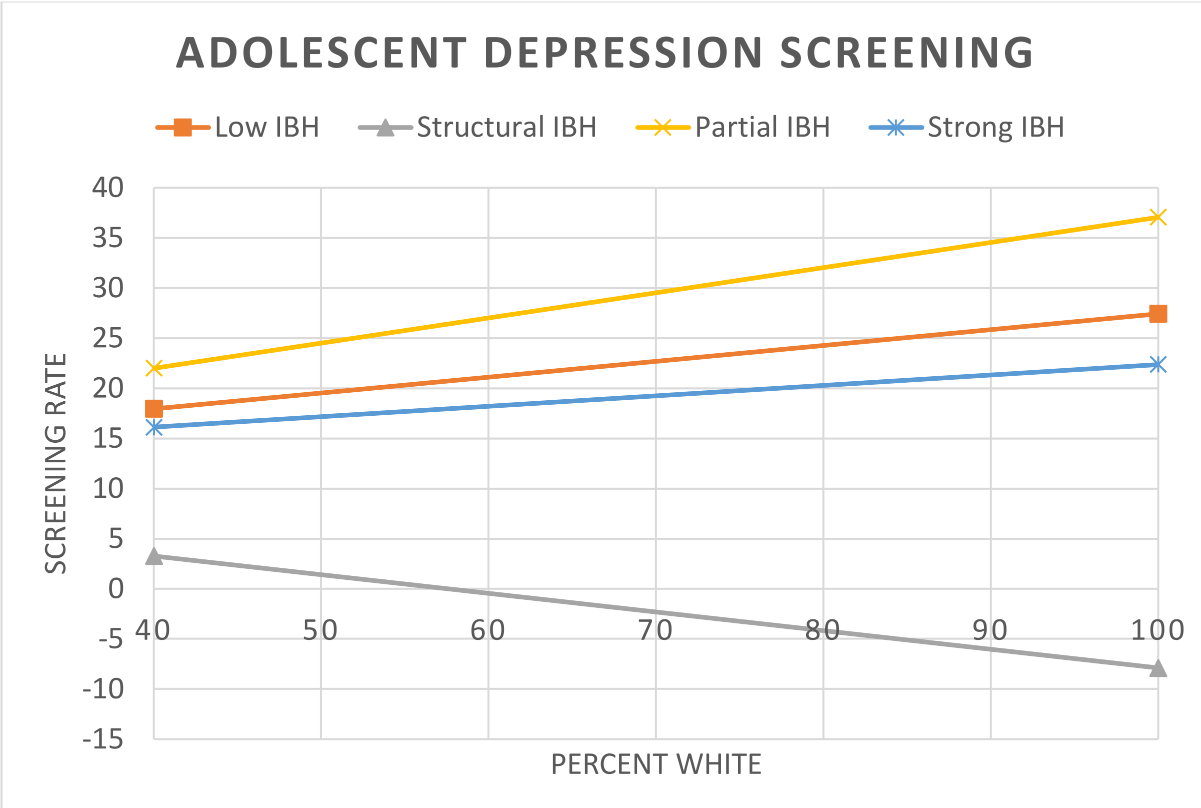

Figure 13. Adolescent depression screening rates based on area race/ethnicity by IBH implementation class. *Note: Due to the nature of the analysis, Y-axis numbers are not a specific percentage.*

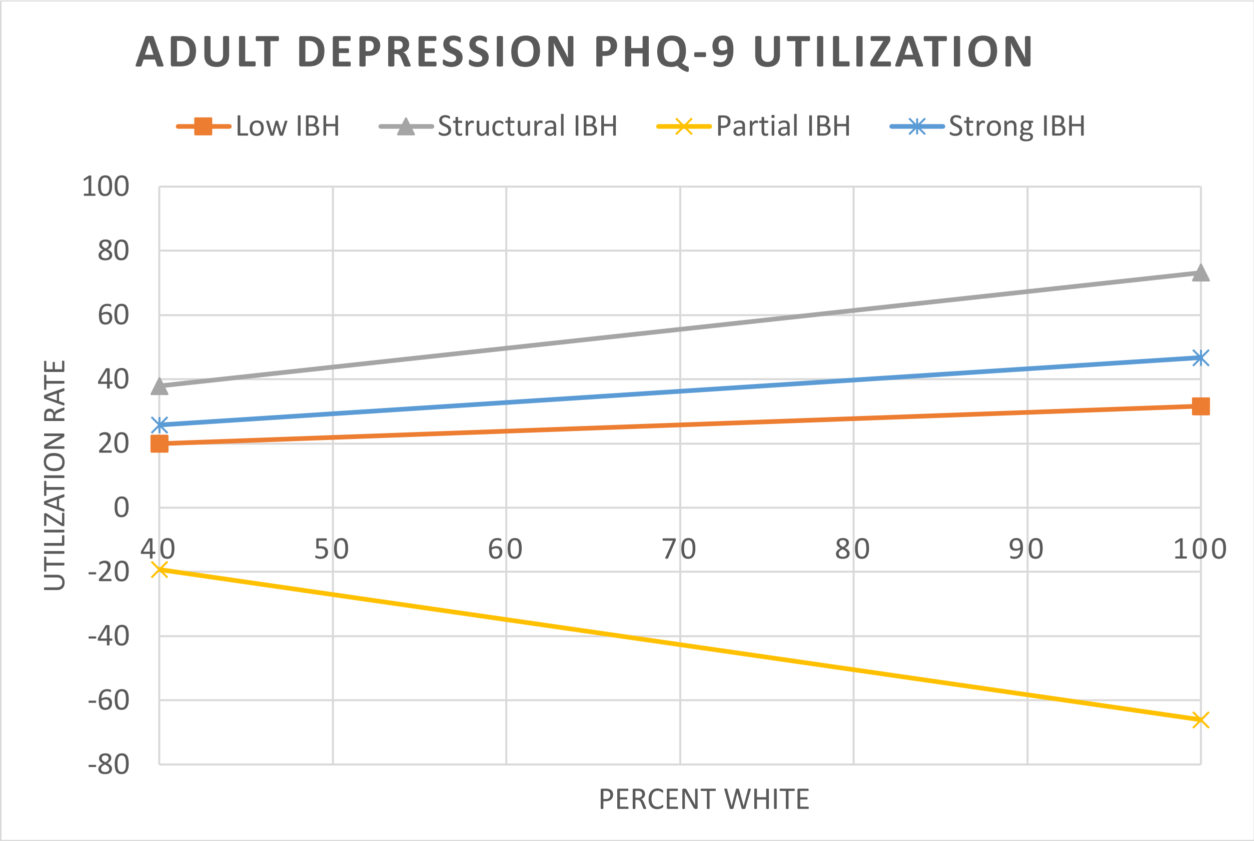

Figure 14. Adult depression PHQ-9 utilization rates based on area race/ethnicity by IBH implementation class. *Note: Due to the nature of the analysis, Y-axis numbers are not a specific percentage.*

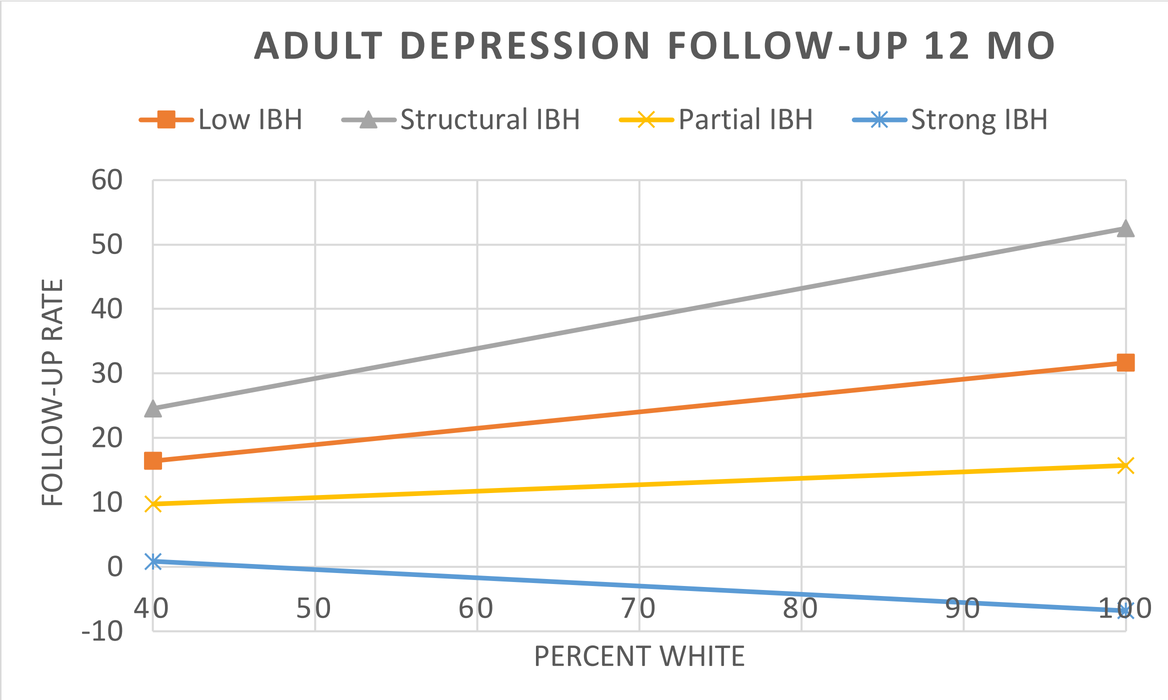

Figure 15. Adult depression 12-month follow-up rates based on area race/ethnicity by IBH implementation class. *Note: Due to the nature of the analysis, Y-axis numbers are not a specific percentage.*

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