A LONGITUDINAL ANALYSIS OF BLACK WOMEN'S EXPERIENCES WITH A DOMESTIC VIOLENCE HOUSING FIRST (DVHF) INTERVENTION

By

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ABSTRACT

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Black women are at an increased risk for intimate partner violence (IPV). The complex interrelationships among housing instability, risk, and severity of abuse among IPV survivors has been established in the research literature, particularly for Black women who are often standing at the intersection of poverty, race, and gender, which results in having fewer financial resources and options for affordable housing. A promising innovation that is gaining national popularity is the Domestic Violence Housing First (DVHF) model, which involves providing survivor-driven mobile advocacy and flexible funding to meet the immediate housing needs of survivors. While preliminary evidence suggests the beneficial impacts of DVHF on improving survivors' safety, housing stability, and well-being, there is little research that rigorously evaluates the impact of DVHF on the outcomes of Black survivors. To address this gap, the current study examined the long-term impact of the DVHF model on the safety, housing stability, and depressive symptoms of 61 homeless or unstably housed Black survivors who had recently sought DV services from one of five agencies located in the Pacific Northwest region of the United States. Results indicate that those who received the DVHF model experienced less revictimization compared to those who received services as usual. These findings are promising and have useful implications for Black survivors, DV agencies, policy makers instituting relevant laws, and grant-making institutions funding survivor-related programs/services.

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In conclusion, this dissertation is a fulfillment of God’s promise to me, and a reminder that trusting in God is always the best decision.

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INTRODUCTION

Domestic Violence (DV) is a common problem worldwide, that has multiple negative immediate and long-term consequences for survivors and their loved ones. DV can impact a survivor's physical health, mental health, and economic outcomes (Black et al., 2011; Rivara et al., 2019; Smith et al., 2018). DV is also noted as a leading cause of homelessness among women and children, and the association between DV victimization, housing instability, and homelessness has been documented in previous studies (Baker et al., 2010; Clough et al., 2014). DV affects individuals from all racial/ethnic backgrounds; however, Black women are disproportionately affected by multiple and more severe forms of DV when compared to other groups of women (Smith et al., 2017). Black women are also disproportionately impacted by homelessness (Roschelle, 2017). DV survivors often require extensive support to improve their well-being, and community based DV service agencies play a critical role in providing advocacy and social services to increase safety, prevent future abuse, and improve the psychosocial well-being of survivors.

Despite the prevalence and impact of DV victimization among Black women, too little is known about their experiences engaging with services offered by community-based DV agencies. This significant gap in the literature highlights the need for research examining the unique experiences of Black women seeking help from DV agencies. Considering that DV and housing instability are serious problems for Black women, this study examined the impact of a housing intervention for Black DV survivors seeking help from five (5) community based DV agencies located in the Pacific Northwest region of the U.S. Specifically, this study examined the effectiveness of a promising Domestic Violence Housing First (DVHF) intervention model on improving survivors' safety, housing stability, and mental health.

LITERATURE REVIEW

Definition of Domestic Violence

Domestic Violence (DV) is a broad term used to encompass any systematic pattern of abusive behaviors or threats of actions used by one partner to gain or maintain power and control over another partner in an intimate (or formerly intimate) relationship (United Nations [UN], 2021). The use of such behaviors by individuals who cause harm is purposeful and deliberate. Domestic violence is also referred to as intimate partner violence (IPV). Intimate partner relationships include current or former spouses (domestic partners, civil union spouses, common-law spouses, and married spouses), boyfriends/girlfriends, dating partners, on-going sexual partners, and individuals who have a child together (Breiding et al., 2015). DV impacts individuals across various backgrounds regardless of sociodemographic characteristics such as age, gender, sexual orientation, education, marital status, religion, national origin, economic status, or ability.

Forms of Domestic Violence

DV takes on various forms which may include, but are not limited to, physical abuse, sexual abuse, emotional abuse, economic/financial abuse, and stalking. Various forms of DV often co-occur such that an individual may experience one or more forms of abuse simultaneously.

Physical abuse. Physical abuse is the most thought of form of DV and involves the use of physical force. It refers to any behaviors that are physically aggressive and involve bodily harm or threat of harm. This may include, but is not limited to, acts of violence ranging from shoving, kicking, grabbing, and slapping to assault with a weapon, destruction of property, strangulation, and homicide (Catalano, 2012).

Sexual abuse. This refers to the exploitative use of sex by forcing or coercing a partner into sexual contact or activity without the person's consent. Sexual abuse can also occur in instances where a partner is unable to consent such as drug/alcohol facilitated incidents. It includes but is not limited to actions that involve forcing or manipulating a partner into sex or performing sex acts, purposely hurting a partner during sex, forcing a partner to engage in sexual acts with a third party, or holding a person down during sex (Breiding et al., 2015).

Emotional abuse. Emotional abuse and psychological abuse are often used interchangeably in the literature (Henning & Klesges, 2003; Kelly, 2004). As a non-physical form of abuse, emotional abuse is often overlooked because it can be less obvious and is not always illegal. This form of abuse targets the emotional and psychological well-being of the victim and involves any non-physical behaviors/actions that the individual who causes harm uses to cause fear, undermine, or invalidate their partner's sense of self-esteem and self-worth through verbal aggression, intimidation, isolation, or ridicule. Emotional abuse may include actions such as verbal abuse/name-calling, constant criticism, public embarrassment, withholding affection, isolating one's partner from family and friends, emotional blackmail, or threatening to physically hurt either themselves, the victim's children, or pets (Carney & Barner, 2012).

Economic abuse. Economic/financial abuse, which is an often-overlooked form of DV, refers to efforts by an individual who causes harm to control or exploit the victim by disrupting their financial resources (Adams et al., 2008, 2020; Postmus et al., 2020). Economic abuse often falls under three broad categories which include employment-related abuse (such as preventing partner from going to work/school or sabotaging employment; Adams & Beeble, 2019), preventing access to funds (such as deciding when and how a partner can use monetary funds or demanding that assets be in the name of the individual who causes harm; Adams et al., 2020), and coerced debt (such as forcing the partner to obtain loans, credit cards, or forcing the partner to sign financial documents; Adams et al., 2020). Other forms of economic/financial abuse may include intentionally withholding necessities such as food, clothing, shelter, personal hygiene products and/or medication, refusing to pay court-ordered child support, stealing/destroying the victim's belongings, or requiring justification for expenses, and repeatedly filing costly lawsuits against the victim (Gans & Jayasinghe, 2012; Postmus et al., 2012).

Stalking. Stalking can be described as a pattern of unwanted contact (involving two or more acts) directed at the victim that results in feelings of fear and safety concerns (Logan & Walker, 2017a). Stalking varies in its duration, intensity, and frequency, and stalkers utilize different strategies and locations. Common stalking tactics include unwanted contact, unwanted phone calls, and physical surveillance (Logan, 2010). Locations may include stalking the victim at work, school, or home (Logan, 2020a). Some stalking behaviors are criminal (such as property invasion or damage), while others are not crimes on their own (such as sending gifts or text messages) but can become criminal when part of a stalking course of conduct.

Incidence and Prevalence of Domestic Violence

DV is pervasive in the U.S. society and there is compelling evidence of its prevalence, incidence, and far-reaching impacts. In 2019 alone, there were nearly 700,000 intimate partner violence victimizations in the U.S. (Morgan & Kena, 2019). While DV is still thought to be underreported, its increasing prevalence continues to be documented in the available literature. The Centers for Disease Control and Prevention (CDC) National Intimate Partner and Sexual Violence Survey (NISVS) found that about one in three women and one in ten men report experiencing contact sexual violence, physical violence, and/or stalking by an intimate partner during their lifetime (Smith et al., 2018). In addition, approximately 48.4% of women and 48.8%

of men report experiencing at least one psychologically aggressive behavior by an intimate partner during their lifetime (Breiding et al., 2014). Research has also documented a range of economic abusive behaviors with one study reporting a 94% prevalence of economic abuse victimization among participants (Postmus et al., 2012).

Although DV affects both men and women such that both can be victims or offenders, more women experience DV, and more men cause harm (Modi et al., 2014). For example, data from the National Crime Victimization Survey (NCVS) indicated that 76% of DV victimization between 2003 and 2012 was committed against females compared to 24% committed against males (Truman & Morgan, 2014). In addition to experiencing greater rates of victimization, women are also more likely to experience severe victimization. The most extreme form of DV is intimate partner homicide and in a study of intimate partner murder-suicides, 89% of the offenders were males who acted alone while 96% of the victims were female (Violence Policy Center, 2018). The frequency and severity of DV vary but research indicates that a greater percentage of intimate partner violence victims experience repeat violence when compared to non-intimate partner violence victims (Oudekerk & Truman, 2017).

Impact of Domestic Violence

DV is a serious public health problem that impacts individuals, families, and broader society in several ways. These include physical, mental health, and economic impacts.

Physical health outcomes. Physical health consequences of DV may include but are not limited to acute bodily injury ranging from relatively minor injuries (such as cuts and bruises) to chronic conditions (such as gastrointestinal disorders, frequent headaches, and chronic pain), gynecological and reproductive health problems (such as adverse pregnancy outcomes, pelvic inflammatory disease, and sexually transmitted infections including HIV/AIDS), permanent disability and even death (Barrick et al., 2013; Black, 2011; Smith et al., 2018; Stubbs & Szoeke, 2021). These outcomes have been extensively documented in literature as one study that retrospectively reviewed the medical charts of patients with a history of DV victimization found that 88% of patients reported multiple brain injuries (CárdenasJavier, 2017), while a review of homicide victimization from 1980 to 2008 revealed that one in five homicide victims were murdered by an intimate partner (Cooper & Smith, 2011).

Mental health outcomes. The mental health consequences of DV have also been well documented in the literature. Negative mental health outcomes associated with DV victimization may include but are not limited to emotional distress, psychological symptoms (such as generalized anxiety disorder, post-traumatic stress [PTSD], and depression), suicide ideation, self-harm, sleep, and eating disorders, and substance misuse (Mechanic et al., 2008; Black, 2011; Bosch et al., 2017; Smith et al., 2018). In a study of women in DV shelters, 77% of participants reported experiencing anxiety while 51% reported depressive symptoms in the 12 months before the study (Helfrich et al., 2008). Similarly, another study found diminished life satisfaction, increased levels of depression, and high suicide risks among individuals who reported experiencing DV (Liu et al., 2021).

Economic outcomes. DV can also lead to negative economic impacts which may affect not only victims and their family members, but businesses, governments, and the broader society. On an individual level, one study reported that the lifetime cost of intimate partner violence for survivors was $103,767 per female victim and $23,414 per male victim in 2014 (Peterson et al., 2018). The economic burden of DV on survivors includes direct tangible costs such as out-of-pocket health service utilization costs (e.g., medical, and mental health care), property damage and loss, and indirect tangible costs such as lost productivity, lower earnings from employment, and barriers on educational achievement (Adams et al., 2013). On a societal level, the economic impact of DV includes the provision of government-funded social services, criminal justice response, and medical care (Peterson et al., 2018; Rivara et al., 2019). Employers and organizations may also incur economic costs due to the lost productivity of employees in the workplace (Chan & Cho, 2010). Even after DV ends, the financial impact of the victimization remains for survivors.

Domestic Violence Against Black Women

There are existing racial/ethnic differences in the prevalence rates of DV. Compared to other racial/ethnic groups, Black women are disproportionately vulnerable to and impacted by DV. Nationally representative studies have consistently reported that Black women experience intimate partner violence at rates higher than white females. According to the 2010 – 2012 CDC NISVS survey, 45% of non-Hispanic Black women experience contact sexual violence, physical violence, and/or stalking by an intimate partner in their lifetime compared to 37% of White women (Smith et al., 2017). Furthermore, estimates from the 2011 NISVS survey indicate about 54% of Black women reported experiencing psychological aggression by an intimate partner in their lifetime (Breiding et al., 2014). Studies have also reported that the risk for serious violent victimization is highest among Black women compared to women of other racial/ethnic groups (Warnken & Lauritsen, 2019). Black women are also more likely to die by intimate partner homicide with one study reporting that 51% of black adult female homicides were related to intimate partner victimizations (Petrosky et al., 2017).

Risk factors for intimate partner violence among Black women include but are not limited to age, parenting status, geographical location, education, employment, and income. Specifically, young women between the ages of 18 and 24 experience the highest rates of DV across racial groups (Lacey et al., 2016). Additionally, having dependent children under the age of 18 is associated with experiencing higher rates of DV among Black women (Stockman et al., 2016). Geographical location is also considered a risk factor, as residing in impoverished neighborhoods has been associated with higher rates of DV among Black women (Bent-Goodley, 2011; Lacey et al., 2016). Additionally, Black women are disproportionately impacted by poor social and environmental disparities such as low education, low income, high rates of poverty and welfare dependence, chronic unemployment, and underemployment rates, which results in Black women having fewer economic resources and increases their risk for abuse (Sabri et al., 2014).

In addition to disproportionately experiencing DV victimization, Black women are more likely to experience negative outcomes. These may include negative mental health outcomes such as suicide ideation, PTSD, anxiety, drug and/or alcohol misuse, and anxiety disorder (Lacey & Mouzon, 2016; Lacey et al., 2021). Depression is also a negative mental health outcome associated with the experience of abuse among Black women. Studies have shown that Black women who experience intimate partner violence have higher rates of depression compared to women who have not experienced abuse (Houry et al., 2006). In one study, Black women who experienced severe physical and psychological violence were significantly likely to have co-occurring PTSD and depression problems (Sabri et al., 2013). Similarly, another study of women seeking treatment in an emergency department found that depressive symptoms were a direct effect of experiencing intimate partner violence among Black women (Leiner et al., 2008). Another study found that lifetime abuse among Black women was associated with elevated levels of depression (Ramos et al., 2004). Black women who experience abuse also report having limited physical, emotional, and financial support which may further exacerbate the negative mental health impacts of abuse (Graf et al., 2021). Additionally, lethal violence victimization is highest against Black women compared to other racial/ethnic groups (Warnken & Lauritsen, 2019). These findings underscore DV as a prominent health issue impacting Black women.

Housing Instability and Homelessness among Black Women

While there is limited research on Black women's experiences with homelessness, nationally representative studies have documented the issue of homelessness and housing instability among Black people. Black people represent only 13% of the U.S. population, yet account for 21% of people living in poverty and 39% of people experiencing homelessness (Roschelle, 2017). According to HUD's 2020 Annual Homelessness Assessment Report to Congress (AHAR), 53% of the people in families experiencing homelessness were Black. Furthermore, Black people made up the largest percentage of individuals accessing shelters annually, a disparity that has persisted over time (HUD, 2021). Experiences of structural racial discrimination and socioeconomic burden places Black women in the U.S. at an increased risk for experiencing housing instability, which is a precursor for homelessness. Black women experience higher rates of economic inequality and are more likely to have greater rates of poverty, lower earnings, and work in less-desirable jobs (Michener & Brower, 2021). As a result of these poor social and environmental conditions, Black women may experience difficulties paying for basic amenities such as food, clothing, and housing. Black women also suffer from severe and persistent forms of mental disorders and addiction (Jones et al., 2020; Lacey et al., 2021), which contribute to homelessness.

Domestic Violence as a Common Pathway to Homelessness

Researchers have started examining the complex relationship between DV, housing instability, and homelessness. Specifically, DV is noted as one of the leading causes of homelessness and housing instability for women and children with data from the National Center for Children in Poverty (NCCP) indicating that more than 80% of women with children who are experiencing homelessness have experienced violence (Aratani, 2009). In one study, over half of the adult women (71%) experiencing homelessness had at least one experience with violence or abuse (Pittman et al., 2018). Economic abuse victimization can lead survivors into a cycle of poverty, which increases the risk of falling into homelessness (Postmus et al., 2012). A person causing harm can intentionally destroy a victim's financial stability through economic abuse tactics. Experiencing DV can also lead to negative health outcomes (such as depression and physical injuries) which may impact a victim's job and housing stability. Because of the tools that individuals who cause harm may have at their disposal, many survivors of DV are faced with the impossible choice of remaining in abusive relationships where they continue to experience victimization or leaving the relationship and risking homelessness. As a result, issues of securing safe and affordable housing and having the economic resources to maintain housing continue to be major sources of concern among survivors who are still with, intend to leave or have recently left their abusers (Clough et al., 2014).

In instances where survivors decide to leave, there might be an urgent need for emergency shelter for survivors who do not have alternative housing options. Such survivors may be able to access temporary housing from DV shelters. However, there is an overwhelming demand for shelter services, and seeking housing from DV shelters may not be a sustainable option for all survivors (NNEDV, 2020). Survivors who may not need emergency shelter often experience several housing barriers when attempting to secure housing which impacts their ability to maintain stable housing (Gezinski & Gonzalez-Pons, 2019). These barriers may include eviction records and denial of housing benefits due to violence and criminal action of others, economic barriers such as lack of affordable housing options, unemployment, and living-wage jobs, discrimination due to the violent and criminal acts of perpetrators, and impact of economic abuse such as having a destroyed credit score or no access to the family's finances (Baker et al., 2010; Clough et al., 2014; Kofman et al., 2018).

For Black women, the experience of DV is not only gendered, but influenced by racism, economic inequalities, and other forms of discrimination, thus increasing their risk for homelessness and further victimization. Black women are often standing at the intersection of poverty, race, and gender, which results in having fewer financial resources and options for affordable housing, facing greater housing discrimination, and higher eviction rates (Phillips, 2014). Considering that Black women have higher rates of poverty, are more likely to become homeless, and are more likely to experience DV (Roschelle, 2017), there is an urgent need to provide resources and services that can turn the tide and improve the outcomes of Black women.

Domestic Violence Community Services

The negative impact of DV on the physical, mental health, and economic outcomes of survivors necessitate a robust response to support their recovery and well-being (Kulkarni et al., 2012). DV agencies are community-based public or private organizations that provide a range of prevention and response services to survivors. Since the 1970s, DV intervention organizations and shelter services have played an integral role in responding to the needs of survivors and preventing future abuse through the provision of advocacy and support services (Grossman & Lundy, 2011). As part of their response services, DV agencies often provide a combination of residential and non-residential services (Wood et al., 2021). Residential services include emergency shelters for immediate, short-term safety, and transitional housing, a temporary accommodation designed as a steppingstone between emergency shelter and permanent housing

(Bennett et al., 2004; Baker et al., 2009; Davies & Lyon, 2014). Non-residential services for survivors who do not need, or are not interested in residential placement, may include a 24-hour crisis hotline where survivors and their loved ones can speak to advocates about abusive experiences or inquire about available resources/services to address their needs, information, and referral, counseling and support groups, transportation, translation services, programs for children and teenagers, community education/outreach programs, and advocacy (Lyon et al., 2012; Goodman et al., 2016). Advocacy involves the provision of broad-based services tailored to meet the needs of survivors and their families and may include safety planning, legal assistance, financial help, employment, education, obtaining medical care, safety planning, and housing assistance (Macy et al., 2009; Lyon et al., 2012; Sullivan & Goodman, 2019). DV agencies are staffed by victim advocates who provide advocacy services by working closely with survivors to empower them and connect them with community resources. Advocates also provide liaison services and intervene with community programs on behalf of DV survivors (Rivas et al., 2016).

The wide reach and impact of community based DV services are extensively documented in the literature. The National Network to End Domestic Violence identified 1,887 DV agencies across the United States; in one 24-hour period in 2019, 88% (1,669) of these agencies provided shelter, advocacy, or counseling services to 77,226 survivors. Specifically, 42,964 received emergency shelters, transitional housing, or other housing services while 34,262 received non-residential services (NNEDV, 2020). Studies examining the effectiveness of DV services on improving survivor-related outcomes have reported positive outcomes such as a decrease in abuse (Wood et al., 2021), increase in self-efficacy and safety-related empowerment (Lyon et al., 2012; Sullivan et al., 2018), increase in emotional and social support (Constantino et al., 2005;

Sullivan & Virden, 2017), and improved mental health outcomes, including reduced depression and PTSD (Perez et al., 2012; Gray et al., 2015). Taken together, these findings demonstrate the practical impacts of community-based services provided by DV agencies.

As housing has become more limited nationally, DV advocates have increased their efforts to assist DV survivors with obtaining safe and stable housing. A promising model that is gaining popularity is the Domestic Violence Housing First (DVHF) model. DVHF is an adaptation of the Housing First (HF) model for DV survivors. The Housing First (HF) model is an approach to addressing the multidimensional problem of homelessness that prioritizes the immediate provision of permanent housing to individuals experiencing homelessness. The HF model deviates from traditional treatment models which require individuals experiencing homelessness to first address their behavioral health problems (e.g., mental health and substance use issues) and participate in service programs to make them housing-ready and/or housing deserving or coupling housing assistance with treatment. Instead, the HF model prioritizes housing without any preconditions, barriers, or expectations of participation in treatment. In this model, homeless families and individuals have access to supportive services but it is not a requirement for attending to their housing needs (Padgett et al., 2016; Pearson et al., 2009). The HF approach is based on the values that housing is a right and individuals deserve access to basic amenities/necessities in life such as food, clothing, and housing, before addressing other behavioral health issues or service needs (Tsemberis et al., 2004).

DVHF maintains the tenets of the HF approach by centering the timely provision of intensive, mobile advocacy and flexible funding to ensure survivors who are homeless or unstably housed can obtain safe and stable housing. This approach is implemented in community-based settings by DV agencies. The core elements of the DVHF approach are survivor-driven mobile advocacy, flexible financial assistance, and community engagement (Sullivan & Olsen, 2016). Survivor-driven mobile advocacy refers to an advocacy model that centers the needs of survivors, respects their agency in defining what safety looks like for them, ensures that advocates utilize trauma-informed practices, are mobile, and can safely meet with survivors in the community. Another core element of the DVHF model is the flexible financial assistance which involves the provision of temporary financial assistance to survivors to support their immediate needs which may be directly or indirectly related to safe and stable housing such as rent, utilities, childcare, and transportation for work. The DVHF model promotes tailoring financial and support assistance to the individual needs of survivors (Sullivan et al., 2019). The third element of DVHF is community engagement, which refers to the process whereby DV advocates proactively work collaboratively with service providers and key community members (e.g., healthcare professionals, legal systems, and school administrators) to respond to the needs of survivors.

Preliminary evidence of the DVHF model suggests that the intervention improves outcomes of survivors by increasing well-being, safety, access to and retention of safe and stable housing (Mbilinyi, 2015; Sullivan et al., in press). There is also evidence that suggests flexible funding yields positive benefits for the children of survivors. In one qualitative study with mothers who received flexible funding, participants reported that access to safe and stable housing reduced environmental stressors and improved their children’s safety, mood, and behaviors (Bomsta & Sullivan, 2018). Taken together, these findings underscore the importance of examining the long-term effects of the DVHF model on survivors’ outcomes, particularly Black women who are greatly impacted by DV.

Current Study

Despite the disproportionate prevalence of DV against Black women, and the increasing awareness of DV as a problem impacting Black women's well-being, there is sparse research on the experiences of Black women with community based DV services. In addition, the association among DV, homelessness, and housing instability for Black women warrants the development and evaluation of community based DV interventions that prioritize the housing needs of survivors while also attending to other advocacy needs identified.

Research evidence from the larger longitudinal DVHF Demonstration Evaluation study which examined the impact of the DVHF model (i.e., mobile advocacy and flexible funding assistance) on the outcomes of 406 homeless and unstably housed survivors from diverse racial/ethnic backgrounds over a two-year period found that survivors who received DVHF reported greater housing stability, increased safety, and lower levels of depression over time compared to those who received services as usual (SAU; Sullivan et al., 2022). While these results are promising, the extent to which these findings hold true for Black survivors is currently unknown. The parent study also examined race/ethnicity differences and found no evidence that minority status impacts survivors' outcomes over time (Sullivan et al., 2022). However, it is still important to specifically examine the outcomes of Black survivors. As such, the purpose of the current study was to evaluate the effectiveness of the DVHF approach on the safety, housing stability, and depression of Black survivors. Specifically, this study tested the following hypothesis:

Hypothesis: Compared to survivors who received SAU, survivors who received DVHF would experience less revictimization, greater housing stability, and reduced depression across two years.

MATERIALS AND METHOD

Participants

Participants in this investigation were drawn from a larger, quasi-experimental, longitudinal study examining the impact of the DVHF intervention on the safety, housing instability, and well-being of DV survivors and their children. Participants in the larger study were recruited from five DV agencies located in the Pacific Northwest region of the United States. Two of the DV agencies are in rural areas while three are in urban areas. The current investigation analyzed the outcomes of study participants self-identifying as Black across five time points (baseline, 6 months, 12 months, 18 months, and 24 months). While there are 76 Black participants in the larger study, only data from participants who completed all interviews across the five time points (n = 66) were included in this analysis.

Procedures

Eligible clients seeking help from the five participating DV agencies were invited by agency staff to hear more about the research study. Only clients who had recently experienced DV, were homeless or at risk of becoming homeless, had entered services within the prior three weeks, and could speak in English or Spanish, or agreed to participate with the assistance of an interpreter, were eligible to participate in the study. Recruitment efforts were structured such that agency staff approached the client about the study within 10 days of receiving services. Survivors were interviewed five times over 24 months, with interviews occurring every six months (baseline, 6 months, 12 months, 18 months, and 24 months after seeking services). The baseline interviews were conducted in person by trained interviewers, and the privacy and safety of participants were prioritized in the interview process. All subsequent interviews were conducted either in person, by telephone, or video conference depending on each participant's availability and preference. Study participants received $50 for each interview completed. The study was approved by Michigan State University's Institutional Review Board (IRB).

Measures

Safety. For the current analysis, measures of physical abuse, emotional abuse, sexual abuse, stalking/harassment, and economic abuse from the larger study were used to assess safety. A modified version of the 28-item Composite Abuse Scale (CAS) was used to assess physical abuse, emotional abuse, sexual abuse, and stalking/harassment (Hegarty et al., 1999; Loxton et al., 2013). To capture multiple indicators of stalking behaviors in different contexts, two items in the CAS ("harass you at work" and "hang around outside your house") were replaced with a new item ("repeatedly follow you, phone you, and/or show up at your house/work/another place"). To also address abusive behaviors that were not adequately captured in the original scale, four new items were added: 1) stalk you, 2) strangle you, 3) demand sex, whether you wanted to, or not, and 4) force sexual activity. The original response options were modified, and participants responded to items referring to events over the prior six months using a 6-point scale ranging from 0 = "never" to 5 = "daily." At baseline, an additional response option "not in the last 6-months, but it has happened in the past" was included and was not calculated in the scale scores.

The final measure included 33 items across four subscales: emotional abuse, physical abuse, stalking/harassment, and sexual abuse. 13 items measured emotional abuse ($\alpha = 0.89$), 11 items measured physical abuse ($\alpha = 0.91$), 4 items measured stalking ($\alpha = 0.86$), and 3 items measured sexual abuse ($\alpha = 0.94$).

Economic abuse was measured using the 14-item Revised Scale of Economic Abuse (SEA-2; Adams et al., 2019). Participants responded to items referring to events over the prior six months using a 5-point scale ranging from 0 = "not at all" to 4 = "quite often." At baseline, an additional response option “not in the last 6-months, but it has happened in the past” was included and was not calculated in the scale scores. Cronbach’s alpha for the measure was 0.93.

Housing instability. Housing instability was assessed using a 7-item Housing Instability Scale which was created for the larger study. The Housing Instability Scale is a modified version of the 10-item Housing Instability Index (Rollins et al., 2012). To ensure items were relevant to participants, four of the 10 Housing Instability Index items related to issues with landlords were removed as many of the study’s participants did not have landlords. To address homelessness, which was not captured in the original scale, one item was added “Have you been homeless or had to live with family or friends to avoid being homeless?” Five of the seven scale items included dichotomous yes/no responses. The remaining two items “In the past 6-months, how many times have you moved?” and “How likely is it that you will be able to pay for your housing this month?” were re-coded in a dichotomous yes/no format. One item, “Do you expect that you will be able to stay in your current housing for the next 6-months?” was reverse-coded so that a response of “no” was counted as a risk factor. Each item in the scale was then scored as 0 = not a risk factor and 1 = a risk factor. Scores ranged between 0 and 7, with higher scores indicating greater instability. The 7-item housing instability scale was validated for the larger study and showed concurrent and predictive validity. Cronbach’s alpha for the scale was 0.79.

Depression. Depression was assessed using the 9-item Patient Health Questionnaire (PHQ-9; Kroenke, Spitzer, & Williams, 2001) from the larger study. Participants responded to items referring to feelings over the prior two weeks using a 4-point scale ranging from 0 = “not at all” to 3 = “nearly every day.” Scores ranged between 0 and 27 with specific cut-off scores indicating the presence and degree of depression in the participants. A score of 0 indicates no symptoms; 1 to 4 indicates minimal depression; 5 to 9 indicates mild depression, 10 to 14 indicates moderate depression, while 15 to 27 indicates severe depression. Cronbach's alpha for the 9-item measure was 0.86.

Services received from the agency. Survivor interviews and agency records were examined to determine the type of services participants received. At each time point after baseline, participants responded to the question "What type of services have you received from [agency name] over the last six months?" in a yes/no format, from the following service options: counseling, support group, shelter, transitional housing, financial help, advocacy, referrals, and other (participants who selected this option were asked to specify the additional services received). Participants also responded to the question "Has there been a staff member from [agency name] who has been helping you work on housing and getting other things you might need from the community?" and responses were dichotomized in a yes/no format. In addition to data collected from the survivor interviews, all participating agencies systematically documented the services provided to participants throughout the project. Specifically, agencies recorded the service start and end dates, types of services received, and the amount of time agency staff spent working with survivors.

Flexible funding. Agency records from participating agencies were examined to determine who received flexible financial assistance. Throughout the project, all participating agencies systematically documented how flexible funding was utilized. Specifically, each agency recorded whether a participant received funding, how much the participant received, when they received it, what it was intended for, and the funding sources.

Determining who received DVHF. To determine who received the DVHF model, the categorization process utilized in the larger study was maintained in this analysis. Specifically, the DVHF category includes participants who received any combination of flexible funding and housing-focused advocacy between intake and the 6-month interview. In contrast, the services as usual (SAU) category includes participants who did not receive housing-focused advocacy and flexible financial assistance that aligns with the DVHF model but received any other services from the agency. These typically included counseling, support groups, non-housing-related advocacy, shelter, and referrals between intake and the 6-month interview. Within the subsample of 66 Black participants, five were removed from analyses because they reported receiving no services from the agency and had no agency service record of receiving any services and flexible funding. Of the 61 participants included in the longitudinal analyses, 10 received SAU and 51 received DVHF.

Data Analysis

Data preparation. Missing data analysis was conducted to test for missingness in relevant variables and ensure that missing data did not bias the sample and attenuate effect sizes (Li, 2013). Missing data ranged from 0.3% (n = 1) to 3.6% (n = 12) with depression missing one response and sexual abuse missing 12 responses. Little's MCAR test in SPSS revealed that the data were missing completely at random, χ^2=33.680, DF = 32, p = .39. As such, pairwise deletion was used in the statistical analyses and no imputation was conducted given the reduced sample size (n=61). Psychometric analysis (internal consistency using Cronbach's alpha) was also conducted to verify the psychometric properties of outcome measures. Calculations revealed that all measures had high internal consistency reliability. Finally, data across all time points were inspected for univariate normality. Significant Shapiro-Wilk tests (W<.94 p<.001), discarded absolute univariate normality, yet skewness and kurtosis values were below the cut points of |2| and |6| indicating an approximately normal and univariate distribution except for data on sexual abuse (*Skewness*≤|6.47|, *Kurtosis*≤|44.44|), and physical abuse (*Skewness*≤|5.07|, *Kurtosis*≤|28.17|). See Table 1 for details on the skewness and kurtosis values for sexual and physical abuse across all time points. To counteract the non-normality of the data on sexual and physical abuse, data transformation methods (square, square root, log, and inverse) were computed. The transformed and non-transformed data were tested when computing outcome models for sexual and physical abuse.

Table 1. *Skewness and Kurtosis Values for Sexual Abuse and Physical Abuse Subscales*

	N	Mean	SD	Skewness	Kurtosis
Sexual Abuse					
Baseline	60	1.03	1.39	1.48	1.47
6-months	60	.10	.49	5.65	34.45
12-months	55	.02	.11	4.88	25.11
18-months	60	.06	.26	4.96	26.10
24-months	58	.05	.28	6.47	44.44
Physical Abuse					
Baseline	60	1.13	.96	.66	-.53
6-months	60	.18	.64	4.98	26.56
12-months	55	.07	.26	5.07	28.17
18-months	61	.13	.28	2.85	9.04
24-months	58	.04	.01	2.59	6.38

Descriptive and bivariate analyses. Descriptive analyses were conducted using IBM SPSS 28. Raw scores were converted into mean scores for all scales of interest across the five time points. The means and standard deviations (SD) of outcome variables included in the analyses were computed for the intervention groups and total sample (see Table 2). To identify and control for any existing group differences between the intervention groups at baseline which can otherwise impact outcome trajectories, inverse-probability-weighting (IPW) was completed. IPW estimators are used to model the outcome and the treatment variables to account for the non-random treatment assignment by using IPW weights to estimate corrected regression coefficients that are subsequently used to perform regression adjustments (Morgan & Winship, 2015). The first step involved conducting logistic regression analysis to examine if there were any meaningful differences at baseline between those who received DVHF and those who received SAU. Sixty-two variables and scales were examined and only two factors (Seeking help with finances and Geographical location i.e., rural versus urban) were found to be significantly different with small differences (see Table 3). The significant predictors were then included in the treatment model portion of the IPW estimator to generate weights that were included in all outcome models. As most participants (84%) were recruited from two of the five agencies (both in an urban setting), an independent t-test was conducted on outcome variables to determine if there were any meaningful differences at the agency level. The difference in housing instability scores between agency 1 (Mean = 2.15; SD = 1.88) and agency 2 (Mean = 2.99; SD = 2.10) was significant (t (249) = -3.36; $p < .001$). Additionally, the difference in sexual abuse scores between agency 1 (Mean = 0.15; SD = 0.50) and agency 2 (Mean = 0.35; SD = 0.96) was significant (t (243) = -2.01; $p < 0.05$). Based on these findings, agency was included as a fixed effect in outcome models for housing instability and sexual abuse.

Table 2. *Group and Total Means and (SD) on Outcomes across all timepoints*

	Baseline			6-month			12-month		
	DVHF	SAU	Total	DVHF	SAU	Total	DVHF	SAU	Total
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Housing stability	4.39 (1.68)	5.40 (1.35)	4.55 (1.66)	2.78 (2.20)	4.20 (2.10)	3.01 (2.23)	2.09 (1.76)	3.00 (1.83)	2.24 (1.79)
Total abuse	1.48 (1.07)	1.05 (1.05)	1.41 (1.07)	0.34 (0.66)	0.38 (0.65)	0.35 (0.65)	0.23 (0.42)	0.29 (0.35)	0.24 (0.41)
Physical abuse	1.18 (0.96)	0.88 (0.96)	1.13 (0.96)	0.19 (0.69)	0.11 (0.35)	0.18 (0.64)	0.07 (0.28)	0.06 (0.10)	0.07 (0.26)
Sexual abuse	1.15 (1.44)	0.43 (0.94)	1.03 (1.39)	0.12 (0.53)	0.00 (0.00)	0.10 (0.49)	0.02 (0.11)	0.04 (0.11)	0.02 (0.11)
Emotional abuse	1.67 (1.27)	1.52 (1.47)	1.64 (1.29)	0.29 (0.67)	0.25 (0.78)	0.29 (0.69)	0.29 (0.58)	0.39 (0.72)	0.31 (0.60)
Stalking	2.02 (1.61)	1.38 (1.57)	1.91 (1.61)	0.77 (1.07)	1.17 (1.59)	0.83 (1.17)	0.54 (0.86)	1.09 (1.50)	0.64 (1.01)
Economic abuse	1.33 (1.15)	1.17 (0.92)	1.30 (1.11)	0.25 (0.62)	0.27 (0.79)	0.26 (0.64)	0.21 (0.50)	0.20 (0.44)	0.21 (0.49)
Depression	12.63 (6.80)	9.90 (6.05)	12.18 (6.71)	7.98 (7.01)	9.70 (4.72)	8.26 (6.69)	8.49 (5.62)	6.90 (4.41)	8.23 (5.44)

	18-month			24-month		
	DVHF	SAU	Total	DVHF	SAU	Total
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Housing stability	1.94 (1.78)	2.90 (2.42)	2.10 (1.91)	1.38 (1.48)	1.60 (1.58)	1.42 (1.48)
Total abuse	0.27 (0.40)	0.56 (0.93)	0.32 (0.53)	0.15 (0.30)	0.27 (0.41)	0.17 (0.32)
Physical abuse	0.10 (0.22)	0.28 (0.47)	0.13 (0.28)	0.04 (0.10)	0.03 (0.09)	0.04 (0.10)
Sexual abuse	0.04 (0.17)	0.17 (0.53)	0.06 (0.26)	0.05 (0.29)	0.07 (0.21)	0.05 (0.28)
Emotional abuse	0.29 (0.47)	0.78 (1.25)	0.37 (0.67)	0.18 (0.42)	0.29 (0.53)	0.20 (0.44)
Stalking	0.62 (0.98)	1.01 (1.57)	0.69 (1.09)	0.34 (0.73)	0.68 (0.96)	0.40 (0.77)
Economic abuse	0.19 (0.54)	0.44 (0.81)	0.23 (0.59)	0.14 (0.47)	0.11 (0.28)	0.14 (0.44)
Depression	6.24 (5.07)	9.70 (7.09)	6.80 (5.53)	7.00 (5.90)	7.70 (6.18)	7.12 (5.90)

Table 3. *Baseline Differences Between Recipients of DVHF and Services as Usual*

Variable	beta	Odds Ratio	SE	p	95% CI Lower	95% CI Upper
1. Age	0.067	1.069	0.045	0.136	0.985	1.179
2. Children (y/n)	0.835	2.304	0.790	0.291	0.428	10.432
3. Foster care (y/n)	-1.291	0.275	0.718	0.072	0.065	1.147
4. Trouble getting housing	-0.865	0.421	0.842	0.304	0.059	1.899
5. Inability to make ends meet	-0.749	0.473	0.429	0.081	0.149	9.053
6. Overall abuse (CAS)	0.435	1.545	0.378	0.251	0.781	3.578
7. Drug misuse	-0.339	0.712	0.252	0.179	0.435	1.204
8. English as the primary language	-0.267	0.766	1.1757	0.821	0.098	15.906
9. Homeless as a child (y/n)	-1.338	0.263	0.798	0.094	0.048	1.216
10. Length of relationship with abuser (in months)	0.003	1.003	0.005	0.575	0.995	1.015
11. Length of abuse (in days)	1.345	1.000	1.421	0.924	0.999	1.000
12. Overall physical health	-0.286	0.752	0.287	0.319	0.419	1.318
13. Number of children	0.294	1.343	0.312	0.344	0.759	2.632
14. Use of child	0.212	1.236	0.350	0.545	0.634	2.606
15. Employed in last 6 months (y/n)	0.033	1.033	0.706	0.963	0.239	4.081
16. Feelings about employment	0.099	1.104	0.183	0.587	0.779	1.621
17. Enrolled in school (y/n)	-0.444	0.642	0.769	0.564	0.149	3.348
18. Access to car (y/n)	-0.571	0.564	0.746	0.444	0.112	2.288
19. Driver’s license (y/n)	0.521	1.684	0.696	0.454	0.419	6.805
20. Education level	0.011	1.011	0.171	0.951	0.723	1.431
21. Depression	0.065	1.067	0.056	0.243	0.961	1.199
22. Anxiety	0.061	1.063	0.056	0.271	0.955	1.193
23. PTSD	0.069	1.072	0.133	0.598	0.815	1.387
24. Difficulty paying bills	-0.467	0.627	0.580	0.421	0.170	1.783

Table 3. (cont'd)

Variable	beta	Odds Ratio	SE	P	95% CI Lower	95% CI Upper
25. Borrowed money for rent or mortgage	0.125	1.133	0.758	0.869	0.221	4.729
26. Lifetime homelessness (y/n)	-0.000	0.999	0.000	0.283	0.999	1.000
27. Financial strain	0.108	1.114	0.260	0.677	0.904	2.098
28. Physical disability (y/n)	0.409	1.505	0.747	0.584	0.370	7.615
29.Mental health issues (y/n)	0.783	2.188	0.701	0.264	0.539	8.938
30. Economic abuse - restriction of finances	0.006	1.006	0.261	0.981	0.604	1.717
31. Economic abuse - financial exploitation	0.272	1.313	0.351	0.438	0.695	2.873
32. Alcohol misuse	-0.195	0.823	0.317	0.538	0.456	1.698
33. Internal tools related to safety	0.337	1.401	0.579	0.561	0.429	4.387
34. Tradeoffs related to safety	0.323	1.381	0.395	0.414	0.635	3.089
35. Expectations of support related to safety	-0.370	0.691	0.518	0.475	0.222	1.766
36. Hope	-0.571	0.565	0.755	0.449	0.113	2.267
37. Positive emotions	-0.243	0.784	0.387	0.531	0.351	1.651
38. Negative emotions	-0.129	0.879	0.331	0.695	0.455	1.706
39. Social support	-0.118	0.887	0.299	0.691	0.483	1.592
39. Social support	-0.118	0.887	0.299	0.691	0.483	1.592
40. Quality of life	0.167	1.182	0.280	0.550	0.679	2.082
41. Seeking help with employment (y/n)	0.438	1.55	0.694	0.527	0.385	6.247
42. Seeking help with education (y/n)	-0.241	0.785	0.749	0.747	0.154	3.214
43. Seeking help with finances (y/n)*	1.925	6.857	9.112	0.034	1.089	44.262
45. Seeking help with childcare (y/n)	-0.602	0.547	0.704	0.392	0.126	2.147
46. Seeking help with counseling (y/n)	-0.906	0.404	1.107	0.413	0.020	2.514
47. Seeking help w transportation(y/n)	0.443	1.558	0.769	0.564	0.298	6.693
48. Seeking help with healthcare (y/n)	-0.124	0.882	0.758	0.869	0.211	4.533
49. Seeking help children's needs (y/n)	0.276	1.318	0.692	0.690	0.328	5.293

Table 3. (cont'd)

Variable	beta	Odds Ratio	SE	P	95% CI	
					Lower	Upper
50. Seeking help with food (y/n)	0.032	1.033	0.706	0.963	0.238	4.080
51. Seeking help with clothing (y/n)	0.875	2.4	0.703	0.213	0.589	9.856
52. Seeking help for material goods (y/n)	0.443	1.558	0.769	0.564	0.298	6.693
53. Seeking help with social support (y/n)	0.452	1.571	0.889	0.611	0.209	8.064
54. Physical abuse	0.359	1.432	0.404	0.375	0.683	3.474
55. Emotional abuse	0.090	1.095	0.276	0.743	0.648	1.971
56. Economic abuse	-0.786	0.455	1.111	0.479	0.023	2.869
57. Sexual abuse	0.591	1.806	0.421	0.160	0.931	5.226
58. Stalking	0.285	1.330	0.249	0.252	0.847	2.315
59. Rural/Urban*	-2.219	0.108	0.788	0.004	0.021	0.504
60. Housing instability	-0.412	0.662	0.240	0.087	0.391	1.029
61. Household income	-0.008	0.991	0.143	0.953	0.756	1.343
62. Organization	-0.584	0.557	0.323	0.071	0.273	1.012

*significant $p < .05$.

Longitudinal analyses. All longitudinal analyses were conducted using the MVN, brms, performance, and sjPlot packages in R 4.1. (R Core Team, 2021). Bayesian estimation was used to address the limitations of the relatively small sample size and the unequal group sizes between those who received DVHF and SAU to prevent issues of power and biased parameter estimates (Van De Shoot et al., 2015). Bayesian statistics have increasingly become a popular means of handling small datasets and offer a different approach to hypothesis testing. This is because Bayesian data analysis allows smaller datasets to be analyzed without losing power or precision by using Markov Chain Monte Carlo (MCMC) simulations, thereby making this approach potentially the most information-efficient method to fit a statistical model with small sample sizes (Van De Shoot et al., 2014).

To test the hypotheses, Bayesian-estimated personal growth models using Hierarchical Linear Modeling (HLM) (i.e., time nested in participants, nested in treatment agencies) were used to model outcome trajectories and compare changes across all five time points (baseline, 6-months, 12-months, 18-months, and 24-months) on all dependent variables. HLM is especially useful for evaluating changes in outcome variables through growth models applied to longitudinal data. Growth models allow for the evaluation of how individuals are changing over time, and how specific variables at any level predict where the individuals began and/or the rate at which they change (Anderson, 2012). These analyses provide rich information by allowing the use of multi-wave data and taking systematic individual differences in change into account.

In testing the long-term effects of the intervention on safety, housing stability, and depression, model building applied a step-up strategy which involved a five-step process to determine the best fit model. The first step began with an empty model (i.e., a model without predictors) testing random slopes for time (i.e., linear, quadratic, or cubic terms). The next step involved individually testing fixed person-level covariates (e.g., age, employment, citizenship status, etc.) to identify the most plausible combination of covariates to reduce bias and account for the effect of relevant covariates that may impact final analytic results. The selection of covariates was informed by evidence of the impact of predictors on the outcomes to be observed from the larger longitudinal analyses. Specifically, predictors that were found to be statistically significant as covariates when analyzing outcome variables in the larger longitudinal study were selected for inclusion in this analysis. The third step involved testing for the random effects of the covariates with meaningful effects that were identified in the previous step. The fourth step involved testing for any meaningful differences in outcomes between participants who received DVHF compared to those who received SAU at baseline by including the fixed intercept term for the intervention group to the model. The final step involved testing for the cross-level interactions between time and the intervention group.

All models were computed using four chains starting with 2,000 each and going up to 5,000 iterations as needed to better estimate the posterior distribution, where half of the iterations were discarded as burn-in samples. Model convergence was reached when the trace plots exhibited overlap, the Rhat statistic for each parameter estimate was below 1.01, the Effective Sample Size (ESS) was above 400, late chain-lag autocorrelations were below 0.02 and no divergent transitions were reported.

Predictive capabilities and model comparisons were assessed using leave-one-out cross-validation (LOO) information criterion scores and Bayesian R^2. Computing LOO is an approach to measuring how well the predictions made by the model match the observed data, where smaller LOOIC values are indicative of a better fit (Vehtari et al., 2017). The best-fitting model selected for all outcomes were the models with minimal LOOIC. The hypotheses were tested through regression coefficients and their effects were deemed meaningful if zero was not contained in the corresponding lower and upper bounds of the Bayesian Credible Intervals (CrI; Hespanhol et al., 2019). Credible Intervals were set at 95% to compute the range containing the 95% most probable effect values.

All models were built with increasing complexities. First, models were built using non-informative priors and LOOIC values between non-informative prior models were compared to identify the best-fitting model before incorporating prior distributions. Models were then re-estimated using different sets of beta weight prior distributions of the Time variable assuming medium and big effects on the outcome variable, as well as empty-model-informed intercept priors considering the scale of the dependent variable for computational efficiency purposes and to counteract any absences from univariate normality.

RESULTS

Demographic information collected at baseline revealed that study participants were predominantly female (98%) and heterosexual (90%). Ages ranged from 19 to 56, with an average of 35 years old. Most participants (82%) had children they were responsible for raising at the time of the study. Additionally, most participants had at least a high school diploma (85%) and reported a household income under $35,000 (84%). See Table 4 for more details about participant sociodemographic information.

Table 4. *Sociodemographic Characteristics of Participants at Baseline*

		DVHF (n = 51)		SAU (n = 10)		Total (N = 61)	
Age	(Mean) SD (Range)	36.09 (8.82) (19 – 56)		31.40 (9.15) (20 – 48)		35.32 (8.97) (19 – 56)	
		n	**%**	**N**	**%**	**n**	**%**
Female		50	98.0	10	100	60	98.4
Sexual Orientation							
Heterosexual		43	84.3	10	100	53	86.9
LGBQA		8	15.7	-	-	8	13.1
U.S. Citizen		46	90.2	10	100	56	91.8
Primary Language English		47	92.2	9	90.0	56	91.8
Parenting Minor Children		43	84.3	7	70.0	50	82.0
Has a disability		20	39.2	3	30.0	23	37.7
Employed in the last 6 months		31	60.8	6	60.0	37	60.7
Education							
Less than high school		7	13.7	2	20.0	9	14.8
High school graduate/GED		16	31.4	4	40.0	20	32.8
Vocational/training certificate		4	7.8	-	-	4	6.6
Some college		15	29.4	1	10.0	16	26.2
Associate degree		5	7.8	2	20.0	6	9.8
Bachelor’s degree		3	5.9	-	-	3	4.9

Table 4. (cont'd)

Advanced degree	2	3.9	1	10.0	3	4.9
Household Income						
$0	2	4.2	2	20.0	4	6.9
Under $5,000	14	29.2	-	-	14	24.1
$5,000 to $9,999	6	12.5	2	20.0	8	13.8
$10,000 to $14,999	5	10.4	3	30.0	8	13.8
$15,000 to $24,999	8	16.7	-	-	8	13.8
$25,000 to $34,999	6	12.5	1	10.0	7	12.1
$35,000 to $49,999	3	6.3	1	10.0	4	6.9
$75,000 to $99,999	2	4.2	-	-	2	3.4
$100,000 to $149,999	1	2.1	1	10.0	2	3.4
$150,000 or more	1	2.1	-	-	1	1.7
Relationship						
In a relationship with harm-doer	3	5.9	-	-	3	4.9
Living with harm-doer	1	2.0	-	-	1	1.6
Prior history of homelessness	46	90.2	8	80.8	54	88.5
Homeless as a child/adolescent	14	30.4	5	62.5	19	35.2

DVHF Impact on Safety

Composite abuse. To assess the impact of DVHF on participants' safety (i.e., accounting for combined experiences of physical abuse, emotional abuse, sexual abuse, and stalking) using Bayesian estimation, mildly informative priors were generated considering the measurement scale of the composite abuse scale, descriptive statistics, and approximate univariate normality. The intercept prior was specified as a Student's t distribution with six degrees of freedom centered at mean 3.5 and with a standard deviation of one as a dispersion parameter (i.e. t(6, 3.5, 1)). A Student's t distribution was selected to counteract any skewness, outliers, and non-normality in the data. Beta weight prior distribution for medium effects was specified as normal(-0.5, 1) whereas the big effect prior distributions were specified as normal(-1, 1.5). Out of the three random-slope time models that were tested, a linear time function (LOOIC=998.7) demonstrated the best model fit compared to the quadratic function (LOOIC=1003.4) and the cubic function (LOOIC=1005.2). The linear time model was then re-estimated using medium and big effect prior distributions. Model comparison favored the medium effect size prior distribution model (LOOIC =992.7) over the big effect size priors (LOOIC=999.6).

The next step involved estimating a covariate model. Predictors were individually included in the model as fixed effects. These covariates included 1) age, 2) financial difficulty, 3) parenting status and 4) citizenship status. Age and financial difficulty were grand mean-centered. Parenting and citizenship status were dummy-coded such that “no child” = 0, “has a child” = 1 for parenting status, and “non-U.S. citizen” = 0, “U.S. citizen” = 1 for citizenship status. Age and financial difficulty indicated a meaningful effect and were combined into the same model to test the simultaneous effect of fixed covariates. The fixed covariate model with non-informative priors was then compared to the time model with non-informative priors. The fixed covariate model (LOOIC=989.0) resulted in a better fit compared to the linear time model (LOOIC=998.7). The fixed covariate model was then re-estimated using the two sets of prior distributions, where model fit supported the big effect (LOOIC=994.3) over the medium effect prior distributions (LOOIC=995.4). Results show participants who were older than the average age had lower composite abuse scores at baseline.

As a third step, the covariate model was modified to include random effects of age and financial difficulty. Model comparison indicates the fixed covariate model with non-informative priors (LOOIC=989.0) is preferred over the random model with non-informative priors

(LOOIC=1005.4). In step four, the fixed covariate model was re-estimated to include the intervention group fixed intercept term. The intervention model with non-informative priors (LOOIC= 983.9) resulted in a better fit when compared to the fixed covariate model with non-informative priors (LOOIC=989.0). The intervention model was then re-estimated using the two sets of prior distributions, where results supported the medium effect (LOOIC=983.1) over the big effect prior distributions (LOOIC=983.7). The intervention model displayed meaningful differences in the composite abuse scores for both intervention groups at baseline, as the fixed intercept term did not contain 0 in its credible interval. The fifth step allowed to test for cross-level interactions and determine whether the effect of time differed between intervention groups. The interaction model (LOOIC=980.9) resulted in a better fit when compared to the intervention model (LOOIC= 983.9). The interaction model was then re-estimated using the two sets of prior distributions, where the results supported the big effect (LOOIC=977.9) over the medium effect (LOOIC=984.6). Based on the LOOic values, the final model with the best fit for assessing total abuse was the interaction model. See Table 5 for more details on the final interaction model and coefficient with big effect priors.

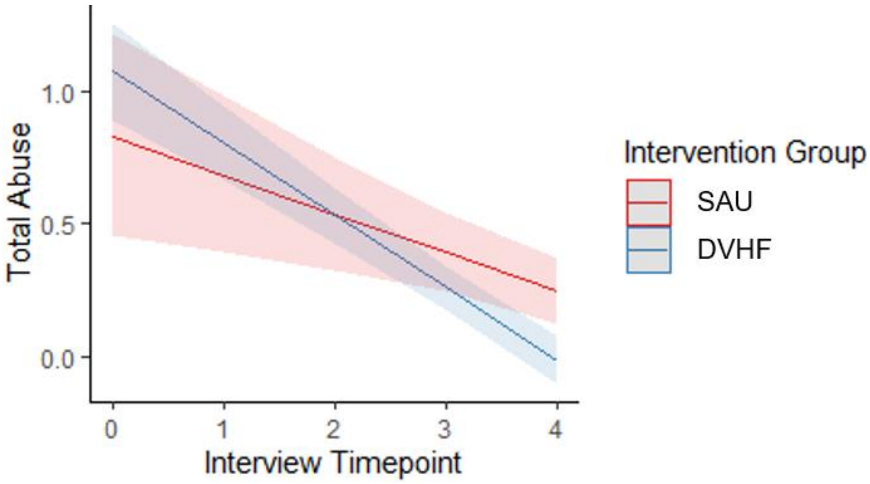
The variance ratio for the final model, which is comparable to the Intraclass Correlation Coefficient (ICC), demonstrated moderate levels of nestedness, where 35% of composite abuse scores could be explained by the participants. For the intervention variables, there were no meaningful differences between participants who received DVHF and those who received SAU for composite abuse scores at baseline and the interaction term suggests a differential effect of time by intervention group (see Table 5) such that there was a steeper time slope for participants who received DVHF compared to those who received SAU (see Figure 1). Finally, the interaction model presents a R^2=0.52 [0.48 – 0.57] over composite abuse scores for participants.

Table 5. *Total Abuse*

	1. Time model				2. Covariate model				3. Random model				4. Intervention model				5. Interaction model			
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
Intercept	1.00	0.10	[0.80 - 1.21]	429	1.00	0.11	[0.80 - 1.22]	671	0.98	0.10	[0.79 -1.18]	1311	1.20	0.14	[0.94 -1.46]	1001	0.80	0.24	[0.34 - 1.28]	621
											Fixed effects									
Time (Linear)	-0.24	0.03	[-0.3 - -0.18]	521	-0.24	0.03	[-0.3 - -0.18]	853	-0.24	0.03	[-0.29 - -0.19]	1560	-0.25	0.03	[-0.30 - -0.19]	1043	-0.14	0.06	[-0.26 - -0.03]	636
Person level																				
Age			-		-0.01	0.00	[-0.02 - 0.00]	2090	-0.01	0.01	[-0.02 - 0.00]	2740	-0.01	0.01	[-0.02 - 0.00]		-0.01	0.01	[-0.02 - 0.00]	2138
Financial Difficulties			-		-0.06	0.06	[-0.19 - 0.07]	1883	-0.05	0.07	[-0.19 - 0.10]	2894	-0.07	0.06	[-0.19 - 0.05]		-0.07	0.06	[-0.19 - 0.06]	2161
Intervention level																				
SAU v DVHF			-				-				-		-0.23	0.10	[-0.44 - -0.04]	1817	0.25	0.27	[-0.29 - 0.77]	661
SAU v DVHF*Time			-				-				-				-		-0.13	0.07	[-0.26 - 0.00]	675
											Random									
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
e0j	0.45	0.01	[0.42 - 0.48]	2531	0.45	0.01	[0.43 - 0.48]	2916	0.45	0.01	[0.42 - 0.48]	3117	0.45	0.01	[0.42 - 0.48]	2884	0.45	0.01	[0.42 - 0.48]	3072
R0j	0.73	0.08	[0.58 - 0.90]	1722	0.73	0.08	[0.59 - 0.90]	1179	0.70	0.08	[0.56 - 0.87]	2051	0.74	0.08	[0.60 - 0.91]	1912	0.72	0.08	[0.58 - 0.89]	1891
											Random effects									
Time (Linear)	0.18	0.02	[0.14 - 0.24]	1936	0.18	0.02	[0.14 - 0.23]	1718	0.18	0.02	[0.14 - 0.23]	2498	0.17	0.02	[0.13 - 0.22]	1250	0.16	0.02	[0.12 - 0.21]	1776
Age			-				-		0.01	0.01	[0.00 - 0.03]	1386			-				-	
Financial Difficulties			-				-		0.12	0.09	[0.00 - 0.33]	1517			-				-	
	Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI	
Variance Ratio (comparable to ICC)	0.40		[0.21 - 0.54]		0.37		[0.19 - 0.52]		0.39		[0.20 - 0.53]		0.35		[0.17 - 0.50]		0.35		[0.17 - 0.49]	
Fit statistics																				
WAIC			972.8				971.8				978.1				960				957	
LOOic			992.7				994.3				1005.4				983.1				977.9	
Bayes R2			0.52				0.52				0.52				0.52				0.52	

Note: M = Mean of posterior distribution, S.D = Standard deviation, 95%CI = 95% Credible Intervals, ESS= Effective Sample Size

Figure 1. *Time*Intervention Interaction Effects for Composite Abuse Scale*



After examining total abuse, each subscale was separately analyzed.

Physical abuse. To assess the impact of DVHF on participants' experience of physical abuse using Bayesian estimation, mildly informative priors were generated considering the measurement scale of the physical abuse subscale, descriptive statistics, and non-normality. The intercept prior was specified as a Student's t distribution with six degrees of freedom centered at mean 3.5 and with a standard deviation of five as a dispersion parameter (i.e. t(6, 3.5, 5)). A Student's t distribution was selected to counteract any skewness, outliers, and non-normality in the data. Beta weight prior distribution for medium effects was specified as cauchy(5, 0.2) whereas the big effect prior distributions were specified as cauchy(5, 0.4). The cauchy distribution was selected to account for the skewness and non-normal distribution of the data. Random-slope models for time were tested using the transformed data (i.e., square, square root, log, and inverse transformations) and non-transformed data. The model with transformed data resulted in divergent transitions signifying a lack of model convergence. As such, model fitting and selection for physical abuse was completed using the non-transformed data. Out of the three random-slope time models that were tested, a cubic time function (LOOIC=785.9) demonstrated the best model fit compared to the linear function (LOOIC=786.6) and the quadratic function

(LOOIC=789.0). The cubic time model was then re-estimated using medium and big effect prior distributions. Model comparison favored the big effect size prior distribution model (LOOIC=777.4) over the medium effect size priors (LOOIC=782.1).

The next step involved estimating a covariate model. Predictors were individually included in the model as fixed effects. These predictors included 1) age, 2) financial difficulty, 3) parenting status, 4) citizenship status, and 5) education level. Age and financial difficulty were grand mean-centered. Parenting status, citizenship status, and education level were dummy-coded such that "no child" = 0, "has a child" = 1 for parenting status; "non-U.S. citizen" = 0, "U.S. citizen" = 1 for citizenship status; and "no high school diploma" = 0, "has high school diploma" = 1 for education level. Financial difficulty and educational level indicated a meaningful effect and were combined into the same model to test the simultaneous effect of fixed covariates. The fixed covariate model with non-informative priors was then compared to the time model with non-informative priors and the fixed covariate model (LOOIC=783.1) resulted in a slightly better fit compared to the cubic time model (LOOIC=783.5). The fixed covariate model was then re-estimated using the two sets of prior distributions, where results supported the big effect (LOOIC=774.9) over the medium effect prior distributions (LOOIC=789.1). Financial difficulty and education level did not have any meaningful effect on participants' physical abuse scores at baseline.

As a third step, the covariate model was modified to include random effects of financial difficulty and educational level. The model comparison indicated the fixed covariate model with non-informative priors (LOOIC=783.1) was preferred over the random model with non-informative priors (LOOIC=787.3). In step four, the fixed covariate model was re-estimated to include the intervention group as a fixed effect. The fixed covariate model with non-informative priors (LOOIC= 783.1) resulted in a better fit when compared to the intervention model with non-informative priors (LOOIC= 785.4). The intervention model displayed equivalent physical abuse scores for both intervention groups at baseline, as the fixed intercept term contains 0 in its credible interval. In the final step, the intervention model was re-estimated to include the interaction term to test for cross-level interactions and determine whether the effect of time differed between intervention groups. The fixed covariate model with non-informative priors (LOOIC=783.1) resulted in a better fit when compared to the intervention model with non-informative priors (LOOIC= 790.1). Based on the LOOic values, the final model with the best fit for assessing physical abuse was the fixed covariate model. See Table 6 for more details on the final covariate model and coefficient with big effect priors.

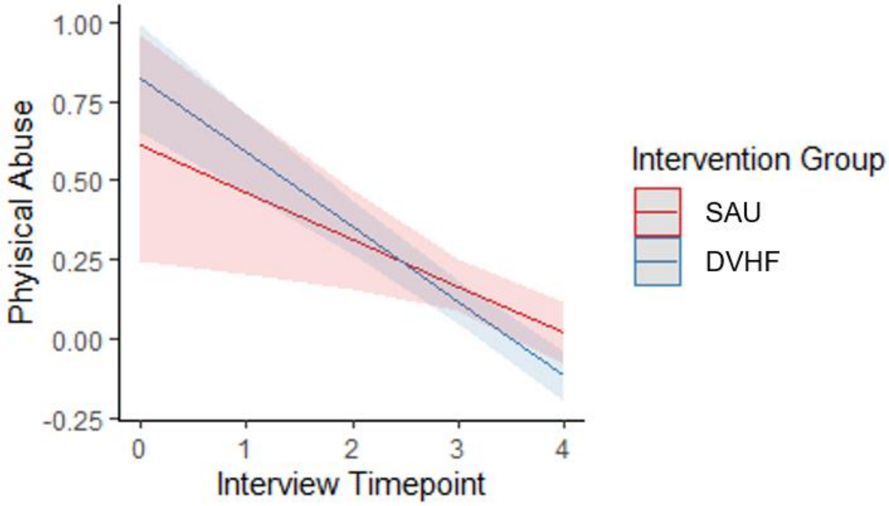
The variance ratio for the final model, which is comparable to the Intraclass Correlation Coefficient (ICC), demonstrated moderate levels of nestedness, where 38% of physical abuse scores was explained by the participants. For the intervention variables, there were no meaningful differences between participants who received DVHF and those who received SAU for physical abuse scores at baseline. The interaction term demonstrated no differential effect of time by intervention group (see Table 6). However, there was a marginally steeper time slope for participants who received DVHF (see Figure 2). Finally, the covariate model presents a R^2=0.53 [0.48 – 0.57] over physical abuse scores for participants.

Table 6. *Physical Abuse*

	1. Time model				2. Covariate model				3. Random model				4. Intervention model				5. Interaction model			
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
Intercept	0.75	0.10	[0.56 - 0.93]	999	0.79	0.10	[0.60 - 0.98]	850	0.78	0.09	[0.59 - 0.96]	903	0.85	0.1	[0.66 -1.05]	964	0.63	0.22	[0.19 - 1.05]	817
											Fixed effects									
Time (Cubic)	-0.07	0.01	[-0.09 - -0.05]	1100	-0.07	0.01	[-0.09 - -0.05]	921	-0.07	0.03	[-0.09 - -0.05]	894	-0.07	0.01	[-0.09 - -0.06]	904	-0.05	0.02	[-0.09 - -0.01]	659
Person level																				
Financial Difficulties			-		-0.03	0.04	[-0.10 - 0.04]	4193	-0.02	0.01	[-0.10 - 0.07]	3877	-0.03	0.04	[-0.11 - 0.04]	3575	-0.04	0.04	[-0.11 - 0.04]	2363
Education Level			-		-0.07	0.05	[-0.16 - 0.02]	4350	-0.06	0.07	[-0.17 - 0.05]	3375	-0.06	0.05	[-0.15 - 0.03]	3949	-0.06	0.05	[-0.15 - 0.03]	3183
Intervention level																				
SAU v DVHF			-				-				-		-0.08	0.05	[-0.15 - 0.03]	3949	0.18	0.24	[-0.28 - 0.66]	3183
SAU v DVHF*TimeCB			-				-				-				-		-0.03	0.02	[-0.07 - 0.02]	729
											Random									
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
e0j	0.37	0.01	[0.35 - 0.40]	3475	0.37	0.01	[0.35 - 0.40]	2647	0.37	0.01	[0.35 - 0.40]	3335	0.37	0.01	[0.35 - 0.40]	3227	0.37	0.01	[0.35 - 0.40]	3133
R0j	0.67	0.07	[0.54 - 0.83]	1787	0.67	0.07	[0.55 - 0.82]	2342	0.66	0.07	[0.53 - 0.82]	1689	0.67	0.07	[0.54 - 0.83]	1644	0.67	0.07	[0.54 - 0.82]	1704
											Random effects									
Time (Cubic)	0.07	0.01	[0.05 - -0.08]	2050	0.07	0.01	[0.05 - -0.08]	2301	0.06	0.01	[0.05 - 0.08]	1672	0.06	0.01	[0.05 - 0.08]	2062	0.06	0.01	[0.05 - 0.08]	1777
Financial Difficulties			-				-		0.06	0.05	[0.00 - 0.17]	2415			-				-	
Education Level			-				-		0.07	0.05	[0.00 - 0.18]	2263			-				-	
	Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI	
Variance Ratio (comparable to ICC)	0.40		[0.21 - 0.55]		0.39		[0.19 - 0.54]		0.40		[0.20 - 0.55]		0.38		[0.19 - 0.53]		0.38		[0.18 - 0.53]	
Fit statistics																				
WAIC			750.8				748.8				756				753.4				755.6	
LOOic			779				774.9				787.3				785.4				790.1	
Bayes R2			0.52				0.53				0.53				0.53				0.53	

Note: M = Mean of posterior distribution, S.D = Standard deviation, 95%CI = 95% Credible Intervals, ESS= Effective Sample Size

Figure 2.*Time*Intervention Interaction Effects for Physical Abuse Scale*



Emotional abuse. To assess the impact of DVHF on participants' experience of emotional abuse using Bayesian estimation, mildly informative priors were generated considering the measurement scale of the emotional abuse subscale, descriptive statistics, and approximate univariate normality. The intercept prior was specified as a Student's t distribution with six degrees of freedom centered at mean 3.5 and with a standard deviation of five as a dispersion parameter (i.e. t(6, 3.5, 5)). A Student's t distribution was selected to counteract any skewness, outliers, and non-normality in the data. Beta weight prior distribution for medium effects was specified as normal(-0.5, 1) whereas the big effect prior distributions were specified as normal(-0.75, 1.5). Out of the three random-slope time models that were tested, a linear time function (LOOIC=1307.7) demonstrated the best model fit compared to the quadratic function (LOOIC= 1313.6) and the cubic function (LOOIC=1318.9). The linear time model was then re-estimated using medium and big effect prior distributions. Model comparison favored the big effect size prior distribution model (LOOIC = 1310.8) over the medium effect size priors (LOOIC= 1310.9).

The next step involved estimating a covariate model. Predictors were individually included in the model as fixed effects. These covariates included 1) age, 2) financial difficulty, and 3) parenting status. Age and financial difficulty were grand mean-centered. Parenting status was dummy-coded where “no child” = 0 and “has a child” = 1. Age was the only predictor that indicated a meaningful effect. The fixed covariate model with non-informative priors was then compared to the time model with non-informative priors. The linear time model with non-informative priors (LOOIC=1307.7) resulted in a better fit when compared to the fixed covariate model with non-informative priors (LOOIC=1316.7). Results show that participants who were older than the average age had lower emotional abuse scores at baseline.

As a third step, the linear time model with non-informative priors was modified to include random effects of age. The model comparison indicated the linear time model with non-informative priors (LOOIC=1307.7) was preferred over the random model with non-informative priors (LOOIC= 1315.8). In step four, the linear time model with non-informative priors was re-estimated to include the intervention group as a fixed effect. The intervention model with non-informative priors (LOOIC= 1307.3) resulted in a better fit when compared to the linear time model with non-informative priors (LOOIC=1307.7). The intervention model was then re-estimated using the two sets of prior distributions, where results supported the big effect (LOOIC= 1305.2) over the medium effect prior distributions (LOOIC=1309.5). The intervention model displayed meaningful differences in emotional abuse for both intervention groups at baseline, as the fixed intercept term did not contain 0 in its credible interval. The fifth step allowed to test for cross-level interactions and determine whether the effect of time differed between intervention groups. The intervention model without priors (LOOIC=1307.3) resulted in a better fit when compared to the interaction model without priors (LOOIC=1311.4). Based on the LOOic values, the final model with the best fit for assessing emotional abuse was the intervention model. See Table 7 for more details on the final intervention model and coefficient with big effect priors.

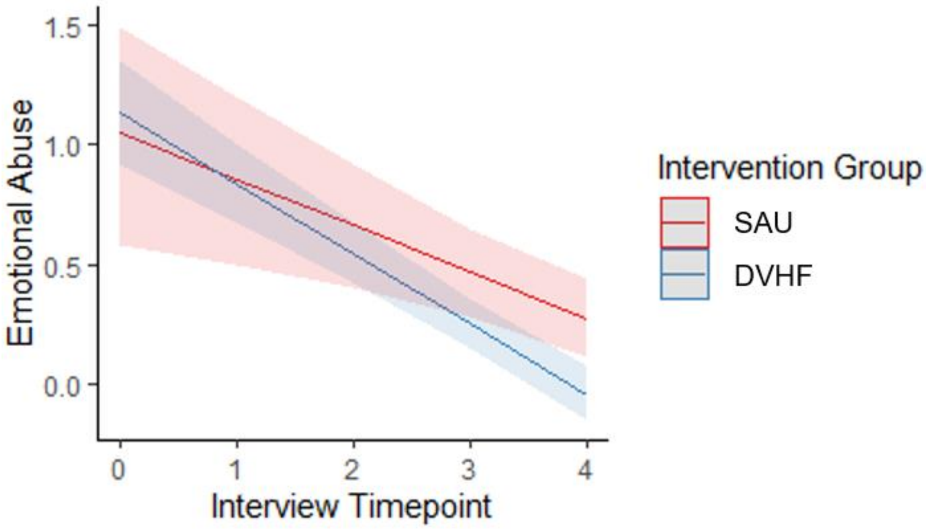
The variance ratio for the final model, which is comparable to the Intraclass Correlation Coefficient (ICC) demonstrated moderate levels of nestedness, where 36% of emotional abuse was explained by the participants. For the intervention variables, there were meaningful differences in the emotional abuse scores between participants who received DVHF and participants who received SAU at baseline. The interaction term demonstrated no differential effect of time by intervention group (see Table 7). However, there was a marginally steeper time slope for participants who received DVHF (see Figure 3). Finally, the intervention model presents an R^2=0.49 [0.43 – 0.54] over emotional abuse scores for participants.

Table 7. *Emotional Abuse*

	1. Time model				2. Covariate model				3. Random model				4. Intervention model				5. Interaction model			
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
Intercept	1.11	0.12	[0.88 - 1.35]	502	1.12	0.12	[0.88 - 1.37]	884	1.11	0.12	[0.89 - 1.35]	928	1.35	0.16	[1.04 -1.67]	819	1.05	0.29	[0.48 - 1.63]	554
Fixed effects																				
Time (Linear)	-0.27	0.03	[-0.34 - -0.20]	667	-0.27	0.03	[-0.34 - -0.20]	1082	-0.27	0.03	[-0.34 - -0.20]	1180	-0.28	0.03	[-0.34 - -0.21]	890	-0.19	0.07	[-0.34 - -0.05]	625
Person level																				
Age			-		-0.01	0.01	[-0.02 - 0.00]	1764	-0.01	0.01	[-0.02 - 0.00]	2221	-0.01	0.01	[-0.02 - 0.00]	1718	-0.01	0.01	[-0.02 - 0.00]	1081
Intervention level																				
SAU v DVHF			-				-				-		-0.27	0.12	[-0.52 - -0.03]	1552	0.09	0.31	[-0.52 - 0.71]	536
SAU v DVHF*Time			-				-				-				-		-0.10	0.08	[-0.26 - 0.06]	616
Random																				
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
e0j	0.59	0.02	[0.55 - 0.63]	2787	0.59	0.02	[0.56 - 0.63]	2821	0.59	0.02	[0.55 - 0.63]	3084	0.59	0.02	[0.56 - 0.63]	2935	0.59	0.02	[0.56 - 0.63]	3032
R0j	0.86	0.10	[0.69 - 1.07]	1739	0.84	0.09	[0.68 - 1.05]	1473	0.83	0.10	[0.65 - 1.04]	1771	0.87	0.09	[0.70 - 1.07]	1676	0.86	0.09	[0.68 - 1.06]	1905
Random effects																				
Time (Linear)	0.21	0.03	[0.16 - 0.28]	1874	0.21	0.03	[0.16 - 0.28]	1940	0.22	0.03	[0.16 - 0.28]	1984	0.21	0.03	[0.16 - 0.27]	2080	0.20	0.03	[0.15 - 0.26]	2226
Age			-		-0.01	0.01	[-0.02 - 0.00]	2440	0.01	0.01	[0.00 - 0.03]	1507			-				-	
	Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI	
Variance Ratio (comparable to ICC)	0.38		[0.20 - 0.52]		0.36		[0.19 - 0.51]		0.37		[0.18 - 0.52]		0.36		[0.18 - 0.50]		0.36		[0.18 - 0.50]	
Fit statistics																				
WAIC			1291.6				1292				1296.6				1286.1				1286.9	
LOOic			1310.8				1316.7				1315.8				1305.2				1311.4	
Bayes R2			0.48				0.48				0.49				0.48				0.49	

Note: M = Mean of posterior distribution, S.D = Standard deviation, 95%CI = 95% Credible Intervals, ESS= Effective Sample Size

Figure 3. *Time*Intervention Interaction Effects for Emotional Abuse Scale*



Sexual abuse. To assess the impact of DVHF on participants' experience of sexual abuse using Bayesian estimation, mildly informative priors were generated considering the measurement scale of the sexual abuse subscale, descriptive statistics, and non-normality. The intercept prior was specified as a Student's t distribution with six degrees of freedom centered at mean 3.5 and with a standard deviation of one as a dispersion parameter (i.e. t(6, 3.5, 1)). A Student's t distribution was selected to counteract any skewness, outliers, and non-normality in the data. Beta weight prior distribution for medium effects was specified as cauchy(5, 0.2) whereas the big effect prior distributions were specified as cauchy(5, 0.4). The cauchy distribution was selected to account for the skewness and non-normal distribution of the data. Random-slope models for time were tested using the transformed data (i.e., square, square root, log, and inverse transformations) and non-transformed data to determine best fit. Divergent transitions were found for all models despite adaptations made to the adapt_delta, stepsize and max_treedepth. Divergent transitions are a technical problem that suggests possible issues with the data or model. This indicates that the findings of the divergent iteration and parameter estimates are unreliable. Models were re-run without the IPW weights to reduce model complexity, thereby increasing the probability of model convergence. Despite this attempt, divergent transitions remained. As such, all results for the sexual abuse model are presented with divergent transitions ranging from 1 to 30, which suggests that the models did not converge.

Out of the three random-slope time models that were tested, a quadratic time function (LOOIC= 956.7) demonstrated the best model fit compared to the linear function (LOOIC=965.0) and the cubic function (LOOIC=974.2). The quadratic time model was then re-estimated using medium and big effect prior distributions. Model comparison favored the medium effect size prior distribution model (LOOIC =974.6) over the big effect size priors (LOOIC= 975.5).

The next step involved estimating a covariate model. Predictors were individually included in the model as fixed effects. These covariates included 1) prior history of homelessness and 2) parenting status. Predictors were dummy-coded such that “has not experienced homelessness” = 0, “has experienced homelessness” = 1 for prior history of homelessness and “no child” = 0, “has a child” = 1 for parenting status. Prior history of homelessness and parenting status indicated a meaningful effect and were combined into the same model to test the simultaneous effect of fixed covariates. The fixed covariate model with non-informative priors was then compared to the time model with non-informative priors. The quadratic time model (LOOIC=956.7) resulted in a better fit compared to the fixed covariate model (LOOIC=969.1). Prior history of homelessness and parenting status did not have any meaningful effect on participants’ sexual abuse scores at baseline.

As a third step, the covariate model was modified to include random effects of prior history of homelessness and parenting status. Model comparison indicated the fixed covariate model with non-informative priors (LOOIC=969.1) was preferred over the random model with non-informative priors (LOOIC=978.2). In step four, the fixed covariate model was re-estimated to include the intervention group fixed intercept term. The time model with non-informative priors (LOOIC= 956.7) resulted in a better fit when compared to the intervention model with non-informative priors (LOOIC=969.4). The intervention model displayed equivalent sexual abuse scores for both intervention groups at baseline, as the fixed intercept term contained 0 in its credible interval. In the final step, the intervention model was re-estimated to include the interaction term to test for cross-level interactions and determine whether the effect of time differed between intervention groups. The time model (LOOIC=956.7) resulted in a better fit when compared to the intervention model (LOOIC= 973.7). Based on the LOOic values, the final model with the best fit for assessing sexual abuse was the time model. See Table 8 for more details on the final time model and coefficient with medium effect priors.

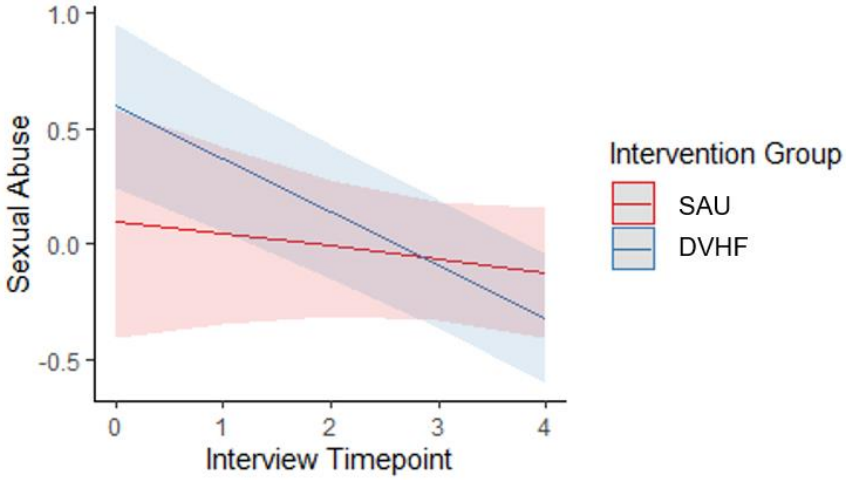
The variance ratio for the final model, which is comparable to the Intraclass Correlation Coefficient (ICC), demonstrated moderate levels of nestedness, where 44% of sexual abuse scores was explained by the participants and organizational-level factors. For the intervention variables, there were no meaningful differences between participants who received DVHF and those who received SAU for sexual abuse scores at baseline and the interaction term suggests no differential effect of time by intervention group (see Table 8). However, there was a marginally steeper time slope for participants who received DVHF (see Figure 4). Finally, the interaction model presents a R^2=0.52 [0.48 – 0.57] over sexual abuse scores for participants.

Table 8. *Sexual Abuse*

	1. Time model				2. Covariate model				3. Random model				4. Intervention model				5. Interaction model			
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
Intercept	0.78	0.45	[0.38 - 2.28]	1507	0.53	0.23	[0.06 - 0.96]	821	0.43	0.28	[-0.14 - 0.92]	304	0.55	0.24	[0.10 -1.00]	905	0.11	0.34	[-0.55 - 0.78]	716
											Fixed effects									
Time (SQ)	-0.10	0.02	[-0.14 - -0.06]	1621	-0.10	0.02	[-0.13 - -0.06]	434	-0.10	0.02	[-0.14 - -0.06]	1079	-0.10	0.02	[-0.14 - -0.06]	637	-0.03	0.04	[-0.12 - 0.05]	594
Person level																				
History of homelessness			-		0.07	0.08	[-0.07 - 0.23]	2300	0.17	0.16	[-0.09 - 0.56]	159	0.08	0.08	[-0.08 - 0.25]	3034	0.08	0.09	[-0.08 - 0.26]	2761
Parenting status			-		0.08	0.07	[-0.04 - 0.21]	2296	0.09	0.08	[-0.06 - 0.24]	3194	0.09	0.07	[-0.05 - 0.23]	2797	0.09	0.07	[-0.04 - 0.23]	3056
Intervention level																				
SAU v DVHF			-				-				-		-0.03	0.07	[-0.16 - 0.10]	2515	0.48	0.31	[-0.12 - 1.07]	1293
SAU v DVHF*TimeSQ			-				-				-				-		-0.08	0.05	[-0.18 - 0.01]	1180
											Random									
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
e0j	0.43	0.01	[0.41 - 0.46]	6686	0.43	0.01	[0.41 - 0.46]	3077	0.43	0.01	[0.41 - 0.46]	3118	0.43	0.01	[0.41 - 0.46]	2938	0.43	0.01	[0.41 - 0.46]	3189
R0j	0.85	0.09	[0.70 - 1.05]	3325	0.85	0.09	[0.69 - 1.04]	1068	0.66	0.24	[0.09 - 1.00]	115	0.86	0.09	[0.70 - 1.05]	969	0.84	0.09	[0.68 - 1.02]	1254
U0j	0.29	0.56	[0.01 - 2.03]	981	0.20	0.34	[0.01 - 1.09]	1049	0.23	0.36	[0.01 - 1.23]	1305	0.19	0.32	[0.00 - 1.16]	769	0.19	0.32	[0.00 - 1.02]	964
											Random effects									
Time (SQ)	0.13	0.02	[0.11 - 0.17]	3386	0.13	0.01	[0.11 - 0.17]	1288	0.13	0.01	[0.11 - 0.16]	2545	0.13	0.02	[0.11 - 0.17]	897	0.13	0.01	[0.11 - 0.16]	1304
History of homelessness			-				-		0.24	0.23	[0.01 - 0.82]	100			-				-	
Parenting status			-				-		0.09	0.06	[0.00 - 0.24]	1892			-				-	
	Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI	
Variance Ratio (comparable to ICC)	0.47		[0.28 - 0.61]		0.48		[0.29- 0.61]		0.47		[0.28 - 0.60]		0.47		[0.29 - 0.61]		0.44		[0.24 - 0.59]	
Fit statistics																				
WAIC			958.1				967				975.6				968.3				967.3	
LOOic			974.6				969.1				978.2				969.4				973.7	
Bayes R2			0.52				0.52				0.52				0.52				0.52	

Note: M = Mean of posterior distribution, S.D = Standard deviation, 95%CI = 95% Credible Intervals, ESS= Effective Sample Size

Figure 4. *Time*Intervention Interaction Effects for Sexual Abuse Scale*



Stalking. To assess the impact of DVHF on participants' experience of stalking using Bayesian estimation, mildly informative priors were generated considering the measurement scale of the stalking subscale, descriptive statistics, and approximate univariate normality. The intercept prior was specified as a Student's t distribution with six degrees of freedom centered at mean 3.5 and with a standard deviation of one as a dispersion parameter (i.e. t(6, 3.5, 1)). A Student's t distribution was selected to counteract any skewness, outliers, and non-normality in the data. Beta weight prior distribution for medium effects was specified as normal(-1, 0.5) whereas the big effect prior distributions were specified as normal(-1, 1.5). Out of the three random-slope time models that were tested, a linear time function (LOOIC=1615.9) demonstrated the best model fit compared to the cubic function (LOOIC= 1619.5) and the quadratic function (LOOIC= 1621.6). The linear time model was then re-estimated using medium and big effect prior distributions. Model comparison favored the medium effect size prior distribution model (LOOIC =1616.6) over the big effect size priors (LOOIC=1621.3).

The next step involved estimating a covariate model. Predictors were individually included in the model as fixed effects. These covariates included 1) parenting status and 2) relationship status. Predictors were dummy-coded such that “no child” = 0, “has a child” = 1 for parenting status and “not in an intimate relationship with harm-doer” = 0, “in a relationship with harm-doer” = 1 for relationship status. Parenting and relationship status indicated a meaningful effect and were combined into the same model to test the simultaneous effect of fixed covariates. The fixed covariate model with non-informative priors was then compared to the time model with non-informative priors. The linear time model (LOOIC=1615.9) resulted in a better fit compared to the fixed covariate model (LOOIC=1620.2). Parenting and relationship status did not have any meaningful effect on participants’ stalking scores at baseline.

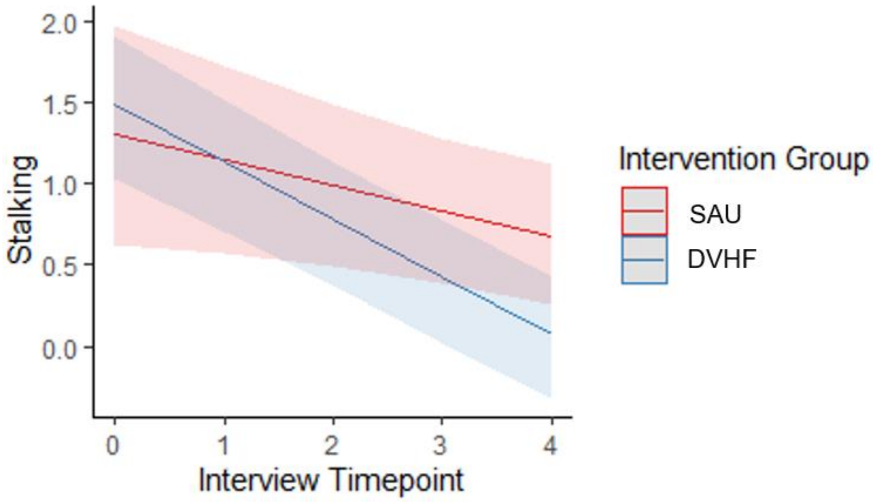
As a third step, the covariate model was modified to include random effects of parenting and relationship status. Model comparison indicated the fixed covariate model with non-informative priors (LOOIC=1620.2) was preferred over the random model with non-informative priors (LOOIC=1628.2). In step four, the fixed covariate model was re-estimated to include the intervention group fixed intercept term. The intervention model with non-informative priors (LOOIC=1608.5) resulted in a better fit when compared to the fixed covariate model with non-informative priors (LOOIC=1620.2). The intervention model was then re-estimated using the two sets of prior distributions, where results supported the big effect (LOOIC=1612.2) over the medium effect prior distributions (LOOIC=1623.6). The intervention model displayed equivalent stalking scores for both intervention groups at baseline, as the fixed intercept term contained 0 in its credible interval. The fifth step allowed to test for cross-level interactions and determine whether the effect of time differed between intervention groups. The intervention model with non-informative priors (LOOIC=1608.5) resulted in a better fit when compared to the interaction model with non-informative priors (LOOIC=1619.9). Based on the LOOic values, the final model with the best fit for assessing stalking was the intervention model. See Table 9 for more details on the final intervention model and coefficient with big effect priors.

The variance ratio for the final model, which is comparable to the Intraclass Correlation Coefficient (ICC), demonstrated moderate levels of nestedness, where 43% of stalking scores could be explained by the participants. For the intervention variables, there were no meaningful differences between participants who received DVHF and those who received SAU for stalking scores at baseline. The interaction term demonstrated a differential effect of time by intervention group (see Table 9) such that there was a steeper time slope for participants who received DVHF compared to those who received SAU (see Figure 5). Finally, the intervention model presents an R^2=0.55 [0.50 – 0.60] over stalking scores for participants.

Table 9. *Stalking*

	1. Time model				2. Covariate model				3. Random model				4. Intervention model				5. Interaction model			
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
Intercept	1.55	0.17	[1.22 - 1.88]	601	1.50	0.26	[0.99 - 2.02]	886	1.48	0.32	[0.87 - 2.09]	2386	1.92	0.31	[1.32 -2.53]	1678	1.31	0.42	[0.48 - 2.13]	855
											Fixed effects									
Time (Linear)	-0.31	0.04	[-0.40 - -0.23]	952	-0.31	0.04	[-0.39 - -0.22]	1002	-0.31	0.04	[-0.40 - -0.22]	3782	-0.32	0.04	[-0.40 - -0.23]	2109	-0.15	0.09	[-0.33 - 0.02]	882
Person level																				
Relationship status			-		0.31	0.47	[-0.62 - 1.22]	1640	0.25	1.08	[-1.94 - 2.41]	4610	0.47	0.46	[-0.42 - 1.39]	2504	0.48	0.47	[-0.42 - 1.37]	1299
Parenting status			-		0.01	0.25	[-0.49 - 0.49]	1129	0.02	0.30	[-0.57 - 0.60]	2855	0.08	0.25	[-0.39 - 0.59]	1622	0.10	0.25	[-0.39 - 0.61]	1353
Intervention level																				
SAU v DVHF			-				-				-		-0.54	0.26	[-1.05 - -0.03]	920	0.16	0.43	[-0.69 - 0.99]	780
SAU v DVHF*Time			-				-				-				-		-0.20	0.10	[-0.39 - 0.00]	902
											Random									
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
e0j	0.75	0.02	[0.70 - 0.80]	3079	0.75	0.02	[0.70 - 0.79]	2894	0.75	0.02	[0.70- 0.80]	7592	0.75	0.02	[0.70 - 0.80]	2566	0.75	0.02	[0.70 - 0.80]	2630
R0j	1.16	0.13	[0.93 - 1.44]	1740	1.17	0.13	[0.94 - 1.46]	1849	1.32	0.22	[0.97 - 1.82]	4509	1.21	0.13	[0.97 - 1.49]	1916	1.18	0.13	[0.94 - 1.46]	1534
											Random effects									
Time (Linear)	0.27	0.04	[0.19 - 0.36]	1946	0.27	0.04	[0.19 - 0.35]	2245	0.27	0.04	[0.19 - 0.35]	5922	0.26	0.04	[0.18 - 0.35]	1863	0.24	0.04	[0.16 - 0.33]	1818
Relationship status			-				-		1.31	1.18	[0.05 - 4.37]	4569			-				-	
Parenting status			-				-		0.56	0.37	[0.03 - 1.40]	729			-				-	
	Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI	
Variance Ratio (comparable to ICC)	0.49		[0.34 - 0.60]		0.47		[0.32- 0.59]		0.46		[-0.18 - 0.59]		0.43		[0.25 - 0.56]		0.44		[0.27 - 0.57]	
Fit statistics																				
WAIC			1591.3				1594.2				1596.4				1593.8				1589.3	
LOOic			1616.6				1624.8				1628.2				1612.2				1619.9	
Bayes R2			0.55				0.55				0.55				0.55				0.55	

Figure 5. *Time*Intervention Interaction Effects for Stalking Scale*



Economic Abuse. To assess the impact of DVHF on participants' experience of economic abuse using Bayesian estimation, mildly informative priors were generated considering the measurement scale of the economic abuse scale, descriptive statistics, and approximate univariate normality. The intercept prior was specified as a Student's t distribution with six degrees of freedom centered at mean 1.5 and with a standard deviation of one as a dispersion parameter (i.e. t(6, 1.5, 1)). A Student's t distribution was selected to counteract any skewness, outliers, and non-normality in the data. Beta weight prior distribution for medium effects was specified as normal(-0.5, 1) whereas the big effect prior distributions were specified as normal(-1, 1.5). Out of the three random-slope time models that were tested, a linear time function (LOOIC=1023.7) demonstrated the best model fit compared to the cubic function (LOOIC= 1029.0) and the quadratic function (LOOIC=1029.4). The linear time model was then re-estimated using medium and big effect prior distributions. Model comparison favored the medium effect size prior distribution model (LOOIC=1028.9) over the big effect size priors (LOOIC=1029.2).

The next step involved estimating a covariate model. Predictors were individually included in the model as fixed effects. These covariates included 1) prior history of homelessness, 2) financial difficulty, 3) ability to read English, and 4) employment status. Financial difficulty was grand mean-centered. History of homelessness, ability to read English, and employment status were dummy-coded where “no experience of homelessness” = 0, “has experienced homelessness” = 1 for prior history of homelessness; “does not read English well” = 0, “reads English well” = 1 for the ability to read English; and “not employed in the last six months” = 0, “employed in the last six months” = 1 for employment status. Financial difficulty and employment status indicated a meaningful effect and were combined into the same model to test the simultaneous effect of fixed covariates. The fixed covariate model with non-informative priors was then compared to the time model with non-informative priors. The fixed covariate model with non-informative priors (LOOIC= 1019.6) resulted in a better fit when compared to the linear time model with non-informative priors (LOOIC=1023.7). The fixed covariate model was then re-estimated using the two sets of prior distributions, where results supported the big effect (LOOIC=1022.4) over the medium effect prior distributions (LOOIC=1032.9). Financial difficulty and employment status did not have any meaningful effect on participants’ economic abuse scores at baseline.

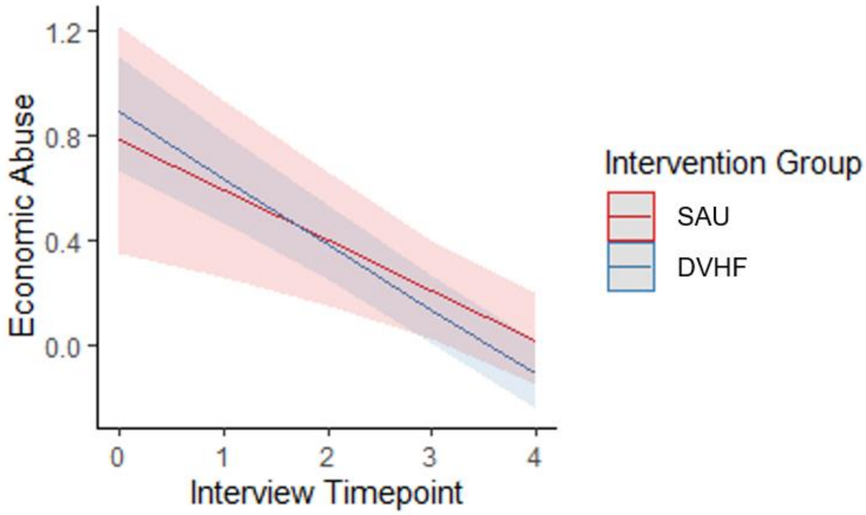
As a third step, the covariate model was modified to include random effects of financial difficulty and employment status. The model comparison indicated the fixed covariate model with non-informative priors (LOOIC=1023.7) was preferred over the random model with non-informative priors (LOOIC= 1026.8). In step four, the fixed covariate model was re-estimated to include the intervention group as a fixed effect. The intervention model (LOOIC=1015.9) with non-informative priors resulted in a better fit when compared to the fixed covariate model with non-informative priors (LOOIC=1023.7). The intervention model was then re-estimated using the two sets of prior distributions, where results supported the big effect (LOOIC= 1017.5) over the medium effect prior distributions (LOOIC= 1021.4). The intervention model displayed equivalent economic abuse scores for both intervention groups at baseline, as the fixed intercept term contained 0 in its credible interval. The fifth step allowed to test for cross-level interactions and determine whether the effect of time differed between intervention groups. The intervention model with non-informative priors (LOOIC=1015.9) resulted in a better fit when compared to the interaction model with non-informative priors (LOOIC=1031.6). Based on the LOOic values, the final model with the best fit for assessing economic abuse was the intervention model. See Table 10 for more details on the final intervention model and coefficient with big effect priors.

The variance ratio for the final model, which is comparable to the Intraclass Correlation Coefficient (ICC), demonstrated moderate levels of nestedness, where 40% of economic abuse scores could be explained by the participants. For the intervention variables, there were no meaningful differences in the economic abuse scores between participants who received DVHF and participants who received SAU. The interaction term demonstrated no differential effect of time by intervention group (see Table 10). However, there was a marginally steeper time slope for participants who received DVHF (see Figure 6). Finally, the interaction model presents a R^2=0.52 [0.47 – 0.56] over economic abuse scores for participants.

Table 10. *Economic Abuse*

	1. Time model				2. Covariate model				3. Random model				4. Intervention model				5. Interaction model			
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
Intercept	0.91	0.11	[0.70 - 1.13]	859	0.87	0.12	[0.63 -1.11]	1075	0.85	0.13	[0.61 - 1.10]	2386	0.96	0.15	[0.66 -1.26]	1153	0.79	0.26	[0.27 - 1.31]	879
											Fixed effects									
Time (Linear)	-0.23	0.03	[-0.29 - -0.17]	984	-0.23	0.03	[-0.30 - -0.18]	1116	-0.24	0.03	[-0.29 - -0.18]	1673	-0.28	0.03	[-0.30 - -0.18]	995	-0.19	0.07	[-0.32 - -0.06]	919
Person level																				
Financial Difficulties			-		-0.10	0.07	[-0.23 - 0.04]	2609	-0.06	0.09	[-0.24 - 0.12]	2347	-0.11	0.07	[-0.25 - 0.03]	2206	-0.11	0.07	[-0.24 - 0.04]	2715
Employed in the last six months			-		0.08	0.09	[-0.11 - 0.26]	2482	0.07	0.10	[-0.12- 0.27]	1724	0.08	0.09	[-0.01 - 0.25]	2157	0.08	0.09	[-0.10 - 0.26]	2296
Intervention level																				
SAU v DVHF			-				-				-		-0.11	0.11	[-0.32 - 0.09]	1838	0.09	0.28	[-0.45 - 0.64]	895
SAU v DVHF*Time			-				-				-				-		-0.06	0.07	[-0.20 - 0.09]	1000
											Random									
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI		M	S.D.	95% CI	ESS
e0j	0.46	0.02	[0.44 - 0.50]	3140	0.46	0.02	[0.43 - 0.49]	3222	0.46	0.01	[0.43 - 0.49]	3176	0.46	0.01	[0.44 - 0.49]	3035	0.75	0.04	[0.68 - 0.82]	2874
R0j	0.78	0.08	[0.63 - 0.96]	1576	0.79	0.08	[0.64 - 0.97]	2255	0.76	0.10	[0.58 - 0.97]	2240	0.79	0.09	[0.64 - 0.98]	1760	0.73	0.12	[0.49 - 0.97]	1168
											Random effects									
Time (Linear)	0.20	0.03	[0.15 - 0.25]	1871	0.19	0.02	[0.15 - 0.25]	2251	0.19	0.03	[0.15 - 0.25]	2553	0.19	0.03	[0.15 - 0.25]	2020	-0.19	0.07	[-0.32 - -0.06]	919
Financial Difficulties			-				-		0.24	0.13	[0.02 - 0.52]	940			-				-	
Employed in the last six months			-				-		0.14	0.10	[0.01 - 0.39]	628			-				-	
	Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI	
Variance Ratio (comparable to ICC)	0.42		[0.25 - 0.56]		0.40		[0.23- 0.54]		0.42		[0.25 - 0.56]		0.40		[0.22 - 0.54]		0.39		[0.21 - 0.53]	
Fit statistics																				
WAIC			1002				998				1005.4				995.9				1000.8	
LOOic			1028.9				1022.4				1026.8				1017.5				1031.6	
Bayes R2			0.52				0.52				0.53				0.52				0.52	

Figure 6. *Time*Intervention Interaction Effects for Economic Abuse Scale*



DVHF Impact on Housing Stability

To assess the impact of DVHF on participants' housing stability using Bayesian estimation, mildly informative priors were generated considering the measurement scale of the housing instability scale, descriptive statistics, and non-normality. The intercept prior was specified as a Student's t distribution with six degrees of freedom centered at mean 3.5 and with a standard deviation of five as a dispersion parameter (i.e. t(6, 3.5, 5)). A Student's t distribution was selected to counteract any skewness, outliers, and non-normality in the data. Beta weight prior distribution for medium effects was specified as normal(-1, 1) whereas the big effect prior distributions were specified as normal (-1, 2). Out of the three random-slope time models that were tested, a linear time function (LOOIC= 2125.0) demonstrated the best model fit compared to the quadratic function (LOOIC=2125.8) and the cubic function (LOOIC= 2131.3). The linear time model was then re-estimated using medium and big effect prior distributions. Model comparison favored the big effect size prior distribution model (LOOIC=2129.0) over the medium effect size priors (LOOIC= 2133.4).

The next step involved estimating a covariate model. Predictors were individually included in the model as fixed effects. These covariates included 1) financial difficulty, 2) citizenship status, 3) employment status 4) ability to read English, 5) prior history of homelessness, 6) parenting status, and 7) relationship status. Financial difficulty was grand mean-centered. All other covariates were dummy-coded where “non-U.S. citizen” = 0, “U.S. citizen” = 1 for citizenship status; “not employed in the last six months” = 0, “employed in the last six months” = 1 for employment status; “does not read English well” = 0, “reads English well” =1 for the ability to read English; “has not experienced homelessness” = 0, “has experienced homelessness” = 1 for prior history of homelessness; “no child” = 0, “has a child” = 1 for parenting status; and “not in an intimate relationship with harm-doer” = 0, “in an intimate relationship with harm-doer” = 1 for relationship status. Financial difficulty and parenting status indicated a meaningful effect and were combined into the same model to test the simultaneous effect of fixed covariates. The fixed covariate model with non-informative priors was then compared to the time model with non-informative priors. The fixed covariate model with non-informative priors (LOOIC=2118.2) resulted in a better fit when compared to the linear time model with non-informative priors (LOOIC=2125.0). The fixed covariate model was then re-estimated using the two sets of prior distributions, where results supported the big effect (LOOIC=2120.1) over the medium effect prior distributions (LOOIC=2120.5). Results show that participants who were experiencing higher than average financial difficulties had higher housing instability scores at baseline. Parent also had higher housing instability scores at baseline.

As a third step, the covariate model was modified to include random effects of financial difficulty and parenting status. The model comparison indicated the fixed covariate model with non-informative priors (LOOIC=2118.2) was preferred over the random model with non-informative priors (LOOIC=2124.7). In step four, the fixed covariate model was re-estimated to include the intervention group as a fixed effect. The fixed covariate model with non-informative priors (LOOIC=2118.2) resulted in a better fit when compared to the intervention model with non-informative priors (LOOIC=2127.3). The intervention model displayed equivalent housing instability scores for both intervention groups at baseline, as the fixed intercept term contained 0 in its credible interval. The fifth step allowed to test for cross-level interactions and determine whether the effect of time differed between intervention groups. The fixed covariate model (LOOIC=2118.2) with non-informative priors resulted in a better fit when compared to the interaction model with non-informative priors (LOOIC=2125.2). Based on the LOOic values, the final model with the best fit for assessing housing stability was the fixed covariate model. See Table 11 for more details on the final covariate model and coefficient with big effect priors.

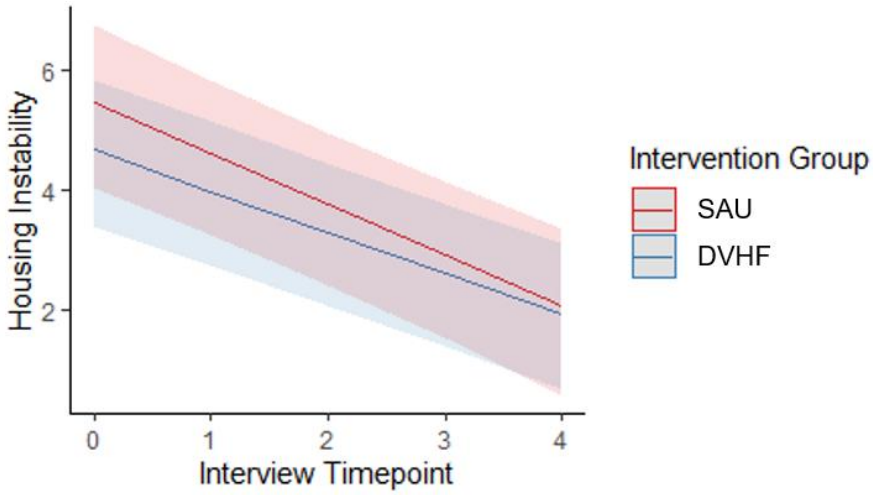
The variance ratio for the final model, which is comparable to the Intraclass Correlation Coefficient (ICC), demonstrated moderate levels of nestedness, where 34% of housing instability scores could be explained by the participants and organizational-level factors. For the intervention variables, there were no meaningful differences in the housing instability scores between participants who received DVHF and participants who received SAU at baseline. The interaction term demonstrates no differential effect of time by intervention group (see Table 11). However, there was a marginally steeper time slope for participants who received DVHF (see Figure 7). Finally, the interaction model presents a R^2=0.62 [0.57 – 0.66] over housing instability scores for participants.

Table 11. *Housing Instability*

	1. Time model				2. Covariate model				3. Random model				4. Intervention model				5. Interaction model			
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
Intercept	4.31	0.96	[2.44 - 6.27]	1310	4.96	0.91	[3.16 - 6.82]	1213	4.84	0.87	[2.93 - 6.56]	3460	5.19	0.83	[3.41 - 6.73]	3252	5.44	0.92	[3.53 - 7.11]	3073
											Fixed effects									
Time (Linear)	-0.72	0.07	[-0.86 - -0.59]	1390	-0.72	0.07	[-0.86 - -0.58]	1016	-0.72	0.07	[-0.86 - -0.58]	3886	-0.72	0.07	[-0.86 - -0.58]	3278	-0.86	0.16	[-1.19 - -0.55]	2140
Person level																				
Financial Difficulties			-		0.69	0.23	[0.25 - 1.15]	952	0.72	0.23	[0.26 - 1.18]	4616	0.68	0.23	[0.24 - 1.13]	2418	0.67	0.22	[0.24 - 1.09]	2892
Parenting status			-		-0.83	0.36	[-1.55 - -0.11]	1115	-0.81	0.41	[-1.63 - -0.02]	3142	-0.77	0.36	[-1.47 - -0.07]	2979	-0.77	0.37	[-1.51 - -0.06]	2905
Intervention level																				
SAU v DVHF			-				-				-		-0.49	0.37	[-1.22 - 0.24]	2376	-0.79	0.49	[-1.77 - 0.14]	2297
SAU v DVHF*Time			-				-				-				-		0.18	0.18	[-0.17 - 0.54]	2234
											Random									
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
e0j	1.14	0.04	[1.07 - 1.21]	2385	1.14	0.04	[1.07 - 1.21]	2930	1.14	0.04	[1.07 - 1.21]	7864	1.13	0.04	[1.07 - 1.21]	7317	1.13	0.04	[1.06 - 1.21]	6787
R0j	1.46	0.18	[1.14 - 1.83]	1838	1.24	0.17	[0.94 - 1.58]	2066	1.28	0.26	[0.82 - 1.86]	5115	1.22	0.17	[0.92 - 1.58]	4346	1.23	0.16	[0.92 - 1.58]	4497
U0j	1.24	1.03	[0.25 - 3.97]	1384	1.25	0.94	[0.28 - 3.77]	2041	1.22	1.02	[0.25 - 3.91]	4466	1.16	0.93	[0.23 - 3.63]	3972	1.17	0.99	[0.23 - 3.81]	4640
											Random effects									
Time (Linear)	0.45	0.07	[0.34 - 0.59]	1510	0.45	0.06	[0.33 - 0.58]	1747	0.45	0.07	[0.33 - 0.59]	5270	0.45	0.07	[0.33 - 0.59]	3824	0.46	0.07	[0.33 - 0.59]	4169
Financial Difficulties			-				-		0.28	0.23	[0.01 - 0.88]	3005			-				-	
Parenting status			-				-		0.61	0.48	[0.02 - 1.80]	675			-				-	
	Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI	
Variance Ratio (comparable to ICC)	0.42		[0.26 - 0.55]		0.34		[0.15 - 0.48]		0.33		[0.14 - 0.49]		0.32		[0.13 - 0.48]		0.32		[0.24 - 0.59]	
Fit statistics																				
WAIC			2095.7				2089.1				2089.8				2088.2				2087.6	
LOOic			2129				2120.1				2124.7				2127.3				2125.2	
Bayes R2			0.61				0.62				0.62				0.62				0.62	

Note: M = Mean of posterior distribution, S.D = Standard deviation, 95%CI = 95% Credible Intervals, ESS= Effective Sample Size

Figure 7. *Time*Intervention Interaction Effects for Housing Instability Scale*



DVHF Impact on Depression

To assess the impact of DVHF on participants' experience of depression using Bayesian estimation, mildly informative priors were generated considering the measurement scale of the depression scale, descriptive statistics, and approximate univariate normality. The intercept prior was specified as a Student's t distribution with six degrees of freedom centered at mean 12 and with a standard deviation of five as a dispersion parameter (i.e. t(6, 12, 5)). A Student's t distribution was selected to counteract any skewness, outliers, and non-normality in the data. Beta weight prior distribution for medium effects was specified as normal(-1, 3) whereas the big effect prior distributions were specified as normal(-2, 5). Out of the three random-slope time models that were tested, a cubic time function (LOOIC=3477.6) demonstrated the best model fit compared to the linear function (LOOIC=3477.8) and the quadratic function (LOOIC=3481.3). The cubic time model was then re-estimated using medium and big effect prior distributions. Model comparison favored the medium effect size prior distribution model (LOOIC=3476.4) over the big effect size priors (LOOIC=3482.9).

The next step involved estimating a covariate model. Predictors were individually included in the model as fixed effects. These covariates included 1) disability, 2) education level, 3) financial difficulty, 4) parenting status, 5) relationship status and 6) citizenship status. Financial difficulty was grand mean-centered. All other covariates were dummy-coded where "no disability" = 0, "has a disability" = 1 for disability; "no high school diploma" = 0, "has high school diploma" = 1 for education level; "no child" = 0, "has a child" = 1 for parenting status; "not in an intimate relationship with harm-doer" = 0, "in an intimate relationship with harm-doer" = 1 for relationship status; and "non-U.S. citizen" = 0, "U.S. citizen" = 1 for citizenship status. Disability and parenting status indicated a meaningful effect and were combined into the same model to test the simultaneous effect of fixed covariates. The non-informative prior model with parenting status as a fixed effect (LOOIC= 3474.6) was a better fit than the non-informative prior combined model (3477.3). The non-informative prior covariate model with parenting status as a fixed effect was then compared to the time model with non-informative priors. The fixed covariate model with non-informative priors (LOOIC=3474.6) resulted in a better fit when compared to the cubic time model with non-informative priors (LOOIC=3477.6). The fixed covariate model was then re-estimated using the two sets of prior distributions, where results supported the medium effect (LOOIC=3476.3) over the big effect prior distributions (LOOIC= 3479.2). Results showed that participants who did not have a child had lower depression scores at baseline.

As a third step, the covariate model was modified to include random effects of parenting status. The model comparison indicated the fixed covariate model with non-informative priors (LOOIC=3474.6) was preferred over the random model with non-informative priors (LOOIC=3481.0). In step four, the fixed covariate model was re-estimated to include the intervention group as a fixed effect. The fixed covariate model with non-informative priors (LOOIC=3474.6) resulted in a better fit when compared to the intervention model with non-informative priors (LOOIC=3484.2). The intervention model displayed equivalent depression scores for both intervention groups at baseline, as the fixed intercept term contained 0 in its credible interval. The fifth step allowed to test for cross-level interactions and determine whether the effect of time differed between intervention groups. The fixed covariate model with non-informative priors (LOOIC=3474.6) resulted in a better fit when compared to the interaction model (LOOIC=3486.0). Based on the LOOic values, the final model with the best fit for assessing depression was the fixed covariate model. See Table 12 for more details on the final covariate model and coefficient with medium effect priors.

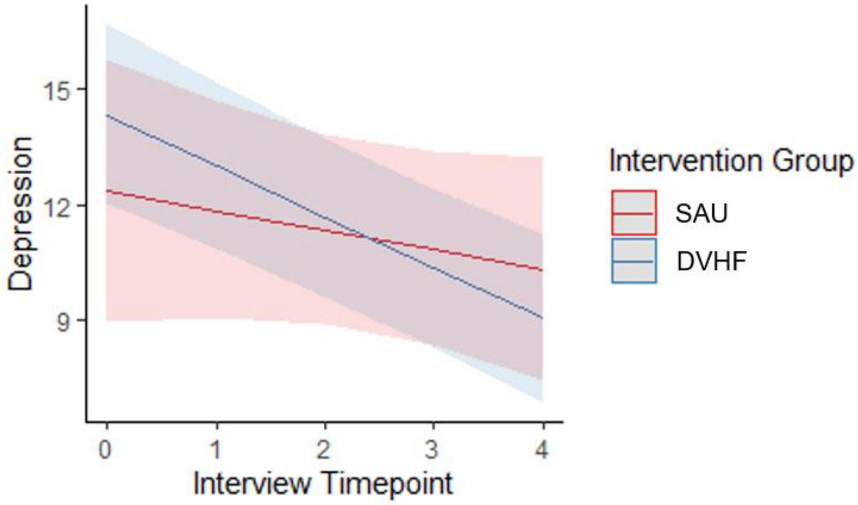
The variance ratio for the final model, which is comparable to the Intraclass Correlation Coefficient (ICC), demonstrated moderate levels of nestedness, where 56% of depression scores was explained by the participants. For the intervention variables, there were no meaningful differences in the depression scores between participants who received DVHF and participants who received SAU. The interaction term demonstrated no differential effect of time by intervention group (see Table 12). However, there was a marginally steeper time slope for participants who received DVHF (see Figure 8). Finally, the interaction model presents an R^2=0.62 [0.58 – 0.69] over depression scores for participants.

Table 12. *Depression*

	1. Time model				2. Covariate model				3. Random model				4. Intervention model				5. Interaction model			
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS
Intercept	10.92	0.85	[9.23 - 12.58]	620	13.98	1.38	[11.26 - 16.76]	694	13.98	1.34	[11.35 - 16.57]	2404	14.03	1.67	[10.72 -17.29]	2592	12.39	0.20	[8.12 - 16.75]	1305
											Fixed effects									
Time (Cubic)	-0.39	0.09	[-0.57 - -0.21]	783	-0.38	0.09	[-0.56 - -0.20]	856	-0.39	0.09	[-0.56 - -0.22]	3656	-0.39	0.09	[-0.56 - -0.21]	2913	-0.17	0.21	[-0.59 - 0.25]	1333
Person level																				
Parenting status			-		-3.81	1.33	[-6.43 - -1.19]	702	-3.83	1.33	[-6.51 - -1.24]	2347	-3.81	1.33	[-6.39 - -1.15]	3362	-3.84	1.34	[-6.48 - -1.22]	1912
Intervention level																				
SAU v DVHF			-				-				-		-0.08	1.39	[-2.78 - 2.71]	2201	1.91	2.20	[-2.49 - 6.17]	1413
SAU v DVHF*Time			-				-				-				-		-0.26	0.24	[-0.74 - 0.21]	1470
											Random									
	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI	ESS	M	S.D.	95% CI		M	S.D.	95% CI	ESS
e0j	3.29	0.11	[3.09 - 3.50]	3388	3.29	0.10	[3.09 - 3.49]	2664	3.28	0.11	[3.09 - 3.50]	7587	3.29	0.11	[3.09 - 3.50]	7731	3.28	0.10	[3.09 - 3.50]	7101
R0j	6.15	0.65	[5.02 - 7.53]	1025	6.03	0.63	[4.92 - 7.36]	1289	5.91	0.83	[4.39- 7.72]	4699	6.01	0.62	[4.91 - 7.37]	4497	6.02	0.63	[4.90 - 7.36]	3750
											Random effects									
Time (Cubic)	0.62	0.07	[0.50 - 0.78]	1133	0.62	0.07	[0.50 - 0.78]	1167	0.62	0.07	[0.49 - 0.77]	5549	0.62	0.07	[0.50 - 0.77]	4332	0.62	0.07	[0.49 - 0.77]	3557
Parenting status			-				-		1.60	1.38	[0.07 - 5.33]	940			-				-	
	Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI		Ratio		95% CI	
Variance Ratio (comparable to ICC)	0.62		[0.49 - 0.71]		0.56		[0.40- 0.68]		0.56		[0.40 - 0.68]		0.55		[0.38 - 0.67]		0.54		[0.38 - 0.66]	
Fit statistics																				
WAIC			3434.3				3432.3				3430.7				3432.3				3432.9	
LOOic			3476.4				3476.3				3481				3484.2				3486	
Bayes R2			0.62				0.62				0.62				0.62				0.62	

Note: M = Mean of posterior distribution, S.D = Standard deviation, 95%CI = 95% Credible Intervals, ESS= Effective Sample Size

Figure 8. *Time*Intervention Interaction Effects for Depression Scale*



DISCUSSION

The purpose of the current study was to examine the impact of the DVHF model on Black survivors' safety, housing stability, and depression over time. As hypothesized, Black survivors who received the DVHF model experienced less combined abuse over two years compared to those receiving SAU. Further analyses of the abuse subscales revealed that survivors who received DVHF experienced less stalking over time compared to those who received SAU. Considering that one of the main goals of the intervention is to improve survivors' safety, this is a promising result. While survivors who received SAU also noted a decline in combined abuse and stalking over time, evidence from the current study indicates that the mobile advocacy and flexible funding provided through DVHF resulted in a differential effect for recipients over time such that the DVHF model was more effective in reducing revictimization. These findings align with previous research that has noted the impact of DVHF for increasing safety among survivors (Sullivan et al., 2022). As abuse against Black women is associated with economic instability, such that Black survivors are more likely to experience socioeconomic hardships such as poverty (Michener & Brower, 2021), it is possible that the mobile advocacy and flexible funding received through DVHF were instrumental in alleviating some economic difficulties experienced by Black survivors, which in turn decreased their experience of abuse. It is also possible that the mobile advocacy received through DVHF was instrumental in helping Black survivors navigate the systemic and community barriers to accessing services and resources created by racist policies and societal structures, which in turn decreased their experience of abuse. Finally, it is possible that the mobile advocacy and flexible funding received through DVHF was helpful in providing resources to address the economic and social difficulties experienced by Black survivors as a result of stalking.

The current study did not find any differential effect of the DVHF model on participants' experience of physical abuse, emotional abuse, sexual abuse, or economic abuse when compared to SAU. While the hypotheses about the impact of DVHF on these forms of abuse were not supported, the outcome models suggest a promising interaction evidenced by the marginally steeper time slope for DVHF recipients, which implies that the DVHF model could better improve survivors' safety related to these forms of abuse. A study with a larger number of participants might show that the DVHF model is more effective. It is also notable that, while DVHF recipients on average reported higher levels of sexual and emotional abuse at baseline when compared to survivors who received SAU, DVHF recipients on average reported lower levels of sexual and emotional abuse at the 24-month interview.

Additionally, the current study did not find any differential effect of the DVHF model on participants' housing stability and depression when compared to SAU. However, similar to the findings on abuse, the outcome models suggest a promising interaction evidenced by the marginally steeper time slope for DVHF recipients, which implies that the DVHF model could better improve survivors' housing stability and depression. Examining the impact of DVHF in a larger study might reveal that the model works better than SAU. It is also notable that, while DVHF recipients on average reported higher levels of depression at baseline when compared to survivors who received SAU, DVHF recipients on average reported lower levels of depression at the 24-month interview. While the hypothesis that DVHF would lead to greater housing stability and reduced depression when compared to SAU was not supported, the evidence suggesting the possible beneficial impact of the DVHF model compared to SAU is promising and additional research is needed to further explore these findings.

It is also important to note that survivors in both intervention groups (DVHF and SAU) experienced less revictimization, housing instability, and depression over time. These findings reflect the importance of DV services for Black survivors and aligns with previous research that suggests improved outcomes for survivors who receive support services from DV agencies (Gray et al., 2015; Wood et al., 2021). Advocates at DV agencies work closely with survivors, often using innovative and creative strategies to provide support and resources for survivors to become safer and heal from the trauma of IPV.

Limitations

The results of this study should be considered in light of the following limitations. First, this study only included data from 61 Black participants who had sought help from DV agencies. This study also did not include a representative sample of immigrants, LGBTQ+ survivors, formerly incarcerated survivors, or male survivors. As such, findings cannot be generalized to all Black IPV survivors. Secondly, data utilized in the current study was collected through self-report measures and several items required participants to recollect experiences within the last six months, which could introduce recollection bias in responses. Additionally, the parent study from which this data was drawn utilized a quasi-experimental approach, which did not include random assignment of participants into intervention groups given the nature of the intervention. While pre-existing group differences were identified and controlled for in this analysis, it is still possible that there are differences unaccounted for. This is because the small sample size and unequal intervention groups used in the current study can reduce statistical power and increase Type 1 error rates. Furthermore, while the gold standard in Bayesian analyses is to use strongly informative priors drawn from prior research, too few studies have been conducted that examine the longitudinal impact of interventions on the safety, housing stability, and depression outcomes of Black survivors. Therefore, mildly informative priors were generated for the analyses considering the measurement scales, descriptive statistics, and distribution parameters of outcome variables. The mildly informative priors utilized in this study displayed strong predictive capability. Lastly, the outcome model for sexual abuse resulted in divergent transitions indicating that model convergence was not achieved. As such, the resulting estimates from this model are not reliable and interpretation of these findings is limited. All these limitations suggest the need for larger studies with more diverse samples to further examine the impact of DVHF on safety, housing stability, and well-being of survivors over time.

Implications

The results of this study have implications for policy development and advocacy efforts. Considering the increased burden placed on Black survivors because of structural racism, funding agencies should prioritize resource allocations to culturally specific organizations providing services to communities of color. In addition to providing funds to support mobile advocacy and flexible funding assistance, DV agencies should receive support to build administrative capacity to implement the DVHF model. This may include supporting the development of a learning community for agencies incorporating DVHF into their work to share information and resources on how to implement and evaluate the intervention. Finally, grant making institutions should seek to fund future research to rigorously examine the effectiveness of the DVHF model in diverse settings and with multiply marginalized populations.

The results from this study have practical implications for DV service providers. This study highlights the benefits of the DVHF model for Black survivors and indicates the need for DV agencies to offer services that attend to the unique needs and preferences of survivors. Based on these findings and the results of the parent study (Sullivan et al., 2022), more DV agencies should incorporate the DVHF model into their services. This can begin as a stand-alone pilot program that can subsequently be incorporated into all agency programs. As the process of implementing the DVHF model can be time-consuming and funding sources may have varying restrictions/requirements on how funds are utilized, DV agencies implementing the DVHF model should create a learning community to collaboratively share information and resources about implementing and evaluating the program.

The results of this study can inform future research. Future research should evaluate the long-term efficacy of the DVHF model on the safety, housing stability, and mental health of Black women using larger and more representative samples. These studies can also examine survivor outcomes on other measures of well-being. Additionally, future studies should examine the long-term impact of the DVHF model on the safety, housing stability and well-being of survivors from multiply marginalized populations in different geographical locations such as survivors from other racial/ethnic minoritized backgrounds, LGBTQ survivors, immigrant survivors, formerly incarcerated survivors, and survivors with disabilities/Deaf survivors. Future studies can also utilize qualitative methods to capture the subjective impact of the DVHF model in-depth from the perspective of program recipients. Finally, future studies should include process evaluation of the DVHF model in community-based settings to examine the extent to which these services are administered in a culturally appropriate manner that attends to the unique needs of Black survivors and other multiply marginalized survivors.

Conclusion

Overall, findings from this study provide promising evidence that the DVHF model leads to increased safety for Black IPV survivors over time compared to those receiving SAU. Considering that Black survivors are disproportionately impacted by IPV, the DVHF model is an innovative approach to reducing IPV against Black survivors. In conclusion, these results further support evidence from the larger longitudinal study which demonstrates the differential long-term impact of the DVHF model above SAU for IPV survivors on several outcomes. The continued exploration of the implementation process and long-term efficacy of the DVHF model for Black survivors in diverse settings is needed to better understand the unique benefits of each component of the model, the circumstances under which the intervention is most effective, and modifications that can further improve its efficacy for communities of color.

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