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Those Who Disappear and Those Who Say Goodbye: Patterns of Attrition in Long-Term Home Visiting

Colleen E. Janczewski[1] · Joshua P. Mersky[1] · Michael J. Brondino[1]

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Abstract

Most evidence-based home visiting models are designed to support families from pregnancy through a child's second birthday, though programs often struggle to retain families for this long. Previous research on client and program factors that predict attrition has produced mixed results, which may be partly because attrition is typically conceptualized as a homogeneous phenomenon. The current study sampled 991 women who received home visiting services from one of 26 agencies in a statewide network of evidence-based programs. Participants who remained in services were compared to three types of early leavers: those who communicated their intent to leave (active attrition), those whose cases closed due to non-participation (passive attrition), and those who moved from the service area. Within a year of enrollment, 42% of women exited services. Cox regression results suggested no differences in the timing of service exit among the three attrition types. Multinomial analyses revealed that, when compared to participants who remained in services, active leavers were more likely to be married or cohabitating, while passive leavers were more likely to be younger, African American, unemployed, and to have a home visitor with low job satisfaction. Participants who moved were less likely to be Latina and employed. An early pattern of inconsistent attendance was the strongest predictor of active and passive withdrawal. Rates of attrition varied by home visiting model, though inconsistent attendance was a robust predictor of passive attrition across models. This study underscores the need to scrutinize service duration as a metric of success in home visiting.

Keywords Home visiting · Attrition · Retention · Engagement

Since 2010, the Maternal, Infant, and Early Childhood Home Visiting (MIECHV) program has received over $2.65 billion in federal funding to support evidence-based home visiting programs in the United States (U.S. Department of Health and Human Services, DHHS 2016). These investments were made because home visiting holds the promise of promoting maternal and child health, positive parenting practices, and child development. Yet, the success of these programs hinges, in part, on model fidelity. Among the most important metrics of home visiting fidelity is dosage, which commonly refers to two related factors: frequency of visits and duration of service. Research has shown that home visiting programs, many of which are designed to serve families on a voluntary basis for multiple years, typically struggle to meet model standards for dosage because of missed visits and—the focus of the present study—client attrition (Paulsell et al. 2014).

Client attrition can undermine program effectiveness in multiple ways. First, it may attenuate desired program effects if clients do not receive the intended length of service. Second, if attrition is associated with family characteristics such as demographic or risk factors, then the benefit of home visiting may be distributed unequally among the intended target population (Brand and Jungmann 2014). Differential, non-random attrition also may compromise assumptions related to dosage that are considered essential to the model and foundational to its evidence base. Accordingly, researchers have raised the concern that selection bias among participants who remain in services can lead to results that misrepresent and overestimate the benefits of the program (Duggan et al. 2000; Korfmacher et al. 2008).

Although some brief home visiting models have strong empirical support (e.g., Dodge et al. 2014), most scientific

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✉ Colleen E. Janczewski
janczew2@uwm.edu

[1] Helen Bader School of Social Welfare at the University of Wisconsin-Milwaukee, 2400 E. Hartford Ave, Milwaukee, WI 53201, USA

attention and funding is directed to long-term home visiting programs. In 2016, six out of the 10 evidence-based models funded by MIECHV were designed to serve families for at least 12 months and these long-term models represent the vast majority of funded programs. In fact, out of the 146 model-based programs funded that year, 96% ($N = 140$) were long-term models (Fernandes-Alcantara 2016). Despite their potential benefit, long-term home visiting programs suffer from high attrition rates. Previous studies have reported 12-month attrition rates ranging from 20 to 67% (Damashek et al. 2011) and 24-month attrition rates have been reported as high as 89% (Daro et al. 2003). Attrition challenges have been documented across many evidence-based models, including Nurse-Family Partnership (e.g., Brand and Jungmann 2014; O'Brien et al. 2012;), Healthy Families America (e.g., Daro et al. 2003; Folger et al. 2016; McGuigan et al. 2003), and Early Head Start (e.g., Roggman et al. 2008).

Correlates of Client Attrition

A significant amount of scientific activity has been directed toward understanding predictors of attrition from home visiting programs. Many of these studies have examined client demographic characteristics. Studies have shown that parents who are older and married or cohabitating are less likely to drop out of services (Daro et al. 2003; McGuigan et al. 2003; O'Brien et al. 2012). The relationships between attrition and other demographic characteristics, however, have not been consistently demonstrated across studies. For instance, although it appears that Hispanics are less likely than other racial or ethnic groups to leave early (McGuigan et al. 2003; O'Brien et al. 2012), comparisons of African American and white families have produced inconsistent results (Daro et al. 2003; O'Brien et al. 2012). Studies that have explored the link between attrition and employment status have also reported conflicting findings (Daro et al. 2003; O'Brien et al. 2012).

Similarly, studies have reported mixed conclusions regarding associations between attrition and psychosocial risk factors such as mental health and substance misuse. For instance, although one study reported that maternal depression and anxiety increased the risk of attrition (Folger et al. 2016), other studies have found no such relationship (O'Brien et al. 2012; Roggman et al. 2008), and one study even uncovered a positive relationship between maternal substance abuse and service duration (Duggan et al. 2000). Finally, two studies that used cumulative risk indices found no association between risk scores and early attrition (Brand and Jungmann 2014; Duggan et al. 2000).

In addition to client characteristics, researchers have investigated the extent to which staff and program characteristics influence client attrition. For instance, many studies have considered the possibility that client attrition may be associated with home visitor factors. In the main, research has shown that client attrition is not reliably linked to characteristics such as home visitor age or years of experience (Daro et al. 2003; McGuigan et al. 2003). The available evidence also suggests that client retention rates are unrelated to home visitor caseload (Daro et al. 2003), yet positively related to hours of home visitor supervision (McGuigan et al. 2003). In addition, research has shown that home visitor turnover predicts client attrition (O'Brien et al. 2012), though findings have not been entirely uniform (Brand and Jungmann 2014).

It is also plausible that client engagement in and satisfaction with home visiting services influences retention. Inconsistent engagement, as measured by the ratio of successfully completed home visits to planned visits, is known to correlate with client retention (Brand and Jungmann 2014; O'Brien et al. 2012). Evidence also suggests that clients who initially perceive the program as helpful or needed may be more likely to remain in services (Daro et al. 2003; Holland et al. 2014a; Korfmacher et al. 2008), although one study reported that attrition was unrelated to either client-reported satisfaction in services or perception of helping relationships (Brand and Jungmann 2014).

Types of Attrition

Considering the field's inability to develop robust and generalizable prediction models, it is possible that attrition from home visiting is dependent on various local contingencies or that it is entirely stochastic. It is also possible, however, that attrition is not a homogeneous phenomenon. Most studies have defined service withdrawal as either a binary outcome (e.g., exited within 12 months) or as a continuous outcome reflecting the duration of service. Defining attrition as a homogenous event assumes all early exits are unwanted outcomes, yet some clients may withdraw from services once their needs are met or their goals are achieved. In other words, some instances of attrition may reflect client or program achievement rather than failure.

One potentially important distinction among types of addressable attrition is whether clients communicate their intent to leave. For instance, compared to clients who actively express their intent to withdraw, clients who drop out without communicating their intent (i.e., passive leavers) may be less engaged in services. Passive withdrawal may also be associated with family instability. For instance, a qualitative study found that unstable living situations caused mothers to miss appointments and ultimately drop out of services (Holland et al. 2014a). It is also possible that sociocultural norms shape how an individual disengages from services, though we are unaware of studies that have directly tested this hypothesis. Whatever the reasons, differentiating among attrition types may help to predict and prevent early exits among clients who might benefit from ongoing services.

Recognizing that attrition may be a heterogenous phenomenon, two recent studies defined attrition as "nonaddressable" when a family experienced a miscarriage or infant death, or when they moved from the service area (Brand and Jungmann 2014; O'Brien et al. 2012). "Addressable" attrition included active leavers who declined further services and passive leavers who had excessive missed visits or were unable to be located. However, neither study tested whether the relationship between attrition and potential predictors varied by attrition type.

Distinguishing among attrition types may clarify some of the inconsistent findings reported in previous studies. For example, findings from Korfmacher et al. (1999) showed that overall, the rates of dropouts are higher among paraprofessional home visitors than nurse home visitors, but that the differences among the programs were much larger among passive leavers than active leavers. These findings raise the possibility that the association between attrition and program and family characteristics may depend on how and why a client drops out.

Current Study

The present study examines patterns and predictors among different types of attrition from long-term home visiting programs. The data are from a statewide network of programs that implement evidence-based models and are supported by MIECHV funding. We employ the terms addressable and nonaddressable attrition used by O'Brien et al. (2012) but focus on distinguishing between two types of addressable attrition: active and passive withdrawal. Our primary aim is to understand whether the timing of service exit or factors associated with early attrition vary among clients who actively and passively withdraw. We also distinguish these two groups from a third group of early service leavers—families that move out of the service area. Residential mobility is a common source of nonaddressable attrition and will serve as a point of comparison to active and passive withdrawal. In sum, we aim to answer two questions: (1) Does the timing of service exit differ among clients who actively withdraw, passively withdraw, and move out of the service area? (2) Do demographic, risk, and service factors associated with early exit differ among the three attrition types?

Methods

Description of Evidence-Based Models

This study analyzes data collected from a sample of low-income women who enrolled in one of 26 local implementing agencies in Family Foundations Home Visiting (FFHV) program. Agencies in this statewide network receive support from the federal MIECHV program to implement one of four evidence-based models: Nurse-Family Partnership (NFP), Healthy Families America (HFA), Early Head Start (EHS), and Parents as Teachers (PAT). While there are many similarities among the four models, there are also important distinctions. For example, NFP programs are staffed by nurses, only enroll mothers pregnant with their first child, and discharge families when a child has reached 2 years of age. Programs using the other models have more flexible credentialing requirements for staff, allow for post-partum enrollment (although FFHV encourages prenatal enrollment in all models), and encourage families to stay beyond the child's second year. In addition, HFA programs conduct extended outreach to disengaged clients before officially discharging them.

FFHV has developed guidelines and infrastructure to promote fidelity to core elements of practice across models and enhance cross-model collaboration. For instance, in addition to supporting model-specific training, FFHV uses a university-based professional development team to deliver foundational and advanced training to home visitors, supervisors, and administrators. Local agencies also participate in quarterly grantee meetings and continuous quality improvement initiatives coordinated by the FFHV program. Moreover, local agencies are required to enter client data into a central database. Data elements are designed to be standard across models and include elements related to family retention and attrition.

Sample and Data

The study sample is drawn from a cohort of mothers who enrolled in home visiting services in a Midwest state from October 2014 to June 2016 ($N = 1229$). Participants were followed from enrollment until discharge or for a minimum of 12 months. When a client had multiple enrollment records, we selected the earliest enrollment. We excluded 115 participants whose administrative data could not be matched to a home visit log, described below. Four programs closed during the study period. Participants enrolled within 1 year of a program's closure were excluded from the sample ($n = 79$). Finally, we excluded participants who experienced miscarriages ($n = 6$), child deaths ($n = 7$), or exited for other reasons ($n = 31$). The final sample consisted of 991 clients served by 156 home visitors from 26 local agencies.

Data were drawn from three sources. First, home visitors collected demographic and risk characteristics during home visits and entered the records into a central database. All client-level measures are from assessments scheduled within 90 days of enrollment. Second, a home visit log supplied the number of expected and completed home visits per month for

each client. Third, staff data were drawn from responses to an online staff survey conducted annually from 2014 to 2016. We selected data from the earliest response for each staff member.

Measures

Attrition Outcomes Participant outcomes were categorized as (1) remained in service, (2) actively withdrew, (3) passively withdrew, or (4) moved. The duration of time for *remained in service* was 12-month post-enrollment for the multinomial analyses and 24-month post-enrollment for the Cox regression where right-censored data were not an issue. Clients who stayed beyond either 12 or 24 months were defined as remaining in service, regardless of the reason they ultimately left. Clients who *actively withdrew* left service because they felt it was no longer needed, transferred to a different program, refused service after a change in home visitor, or refused for other reasons such as being dissatisfied or too busy. Clients who *passively withdrew* had cases closed because they participated inconsistently or were unable to be located. The fourth outcome category comprised clients who *moved* out of the local agency's service area.

Client Demographic Characteristics Six client demographic characteristics were included in the multivariate models. Client *age* was measured at the time of enrollment. *Race and ethnicity* used five mutually exclusive categories: non-Hispanic Caucasian, non-Hispanic African American, Hispanic, non-Hispanic American Indian, and another race/ethnicity. We also included four dichotomous measures: *married/cohabitating*, *completed high school*, *employed* (including part-time), and *primiparous*.

Client Risk Characteristics Assessments from home visits were used to measure client psychosocial risk. Retrospective accounts of *adverse childhood experiences* were collected using the Childhood Experiences Survey (CES). The CES includes five measures of household dysfunction and five measures of child maltreatment and results in a cumulative childhood adversity score (range 0–10). The CES has sound internal consistency, test-retest reliability, and predictive validity among home visiting clients (Mersky et al. 2017). A *perceived stress* score was derived from the 10-item Perceived Stress Scale, (PSS), a well-validated measure that produces a total score ranging from 0 to 40, where a score greater than 20 indicates above average stress (Cohen et al. 1983). *Prenatal smoking* distinguishes participants who reported smoking from those who did not smoke during the prenatal period. *Recent drug* use differentiates clients who reported using street drugs in the last year from those who did not. *Transportation problems* denote if home visitors identified a client as having difficulty accessing transportation.

Service Characteristics The multivariate analyses also include service characteristics that may influence attrition risk. *Prenatal enrollment* is a dichotomous measure that indicates whether a client enrolled prior to giving birth. *Early completed visit rate* is the number of completed visits divided by the total number of expected visits, averaged over the first 3 months of service. *Caseload during service episode* is the average number of cases a client's home visitor carried each month during the time the home visitor was assigned to the client. Thus, average caseload can vary across clients for a single home visitor. If a client changed home visitors, we selected the average caseload for the last home visitor assigned to the client. *Job satisfaction* is a dichotomous measure that distinguishes home visitors who report being satisfied or very satisfied with their job from those who are neither satisfied or dissatisfied, dissatisfied, or very dissatisfied. *Home visitor college graduate* is a dichotomous measure that indicates whether the home visitor has a college degree. *Evidence-based model* identifies the home visiting model used in the client's program: EHS, HFA, NFP, or PAT.

Missing Data

The analysis required matching a client with a home visitor and to the visit log. We excluded 115 eligible mothers because we were unable to match their record in the central database to a record in the visit log. Compared to clients with home visit logs, the 115 clients were significantly less likely to be employed or enrolled prenatally, and more likely to have multiple children and to leave before 24 months of service.

The sample had complete information for 12- and 24-month exit outcomes as well as measures for age, race/ethnicity, early completed visit rate, caseload, and home visiting model. The client-level variables missing at least 10% of data included transportation problems (28.7%), adverse childhood experiences (21.0%), prenatal smoking (14.7%), perceived stress (14.5%), and recent drug use (12.9%). Moreover, 26.3% of the job satisfaction and 28.2% of the staff education items were missing from staff survey data.

We conducted multiple imputation to address item-level missing data obtained from the central database and staff survey. We used the Blimp application (2017, Beta 6.81 version) to perform multiple imputation. Blimp can accommodate mixtures of categorical and continuous data and can be applied to multilevel data models (Keller and Enders 2017). All client and service characteristics were used as auxiliary correlates in the imputation models to improve fit. We used a point scale reduction (PSR) factor set at < 1.05 for all parameters to assess convergence and to guide the selection of the imputation model. The final model included 50 imputations, and PSR values did not exceed 1.03 for any parameters.

Analytic Procedure

To describe the sample, we calculated the prevalence or means of attrition outcomes and client and service variables. Multicollinearity was assessed among all covariates prior to conducting multivariate analyses. Variance inflation factors were low (VIF $\leq$ 3.0 for all variables), indicating that multicollinearity was not an issue. The continuous variables—age, adverse childhood experiences, perceived stress, early completed visit rate, and caseload—were grand mean centered in the multivariate analyses.

We used Cox regression models to examine the extent to which attrition type may influence the timing of service exit (research question 1). To compare the three attrition groups, pairwise contrasts were conducted by constructing two regression models that used different attrition types as reference groups. The models also adjusted for demographic, risk, and service measures (results for covariates available upon request). Data were right censored at 24-month post-enrollment. We ran a third model to plot survival curves stratified by attrition type and used quantile regression models to conduct pairwise tests for differences in median weeks enrolled for each attrition type. Confidence intervals and standard errors for the estimates were calculated through a resampling bootstrap approach.

The second research question examines whether predictors of early exit vary by attrition type. Before testing multivariate models, we tested whether the models needed to account for higher-order random effects. We hypothesized that clients were nested within home visitors, who were nested within home visiting models. We constructed a three-level random intercept model without predictors to estimate the intraclass correlation coefficients (ICC), which represent the proportions of variance in attrition risk that was explained by higher-order random effects. To determine if either home visitor or home visiting model should be included as random effects, we tested the probability that the chi-square statistics for the two random intercepts were significantly different from zero.

Next, we entered client and service measures as fixed effects into a binary model that compared clients who stayed to those left for any reasons in the first 12 months (i.e., *any attrition*) and a multinomial model that compared clients who stayed to clients who experienced one of three attrition outcomes—active withdrawal, passive withdrawal, and moved. The results for the multinomial models are reported as relative risk ratios. These ratios represent the change in attrition risk, compared to remaining in services, attributed to a one-unit change in a predictor while holding other variables constant. We used SPSS 23 to calculate pooled Cox proportional hazard models and used SAS 9.4 for the pooled quantile and multilevel regression analyses.

Results

Across attrition types, the 12-month dropout rate for the study sample was 42.3% (Table 1). Passive leavers were the largest portion of early leavers (21.8%), while 13.5% of clients actively withdrew, and a smaller proportion moved out of the service area (7.0%). The average age at enrollment was 24.3. The sample was 36.0% Caucasian, 26.5% African American, 7.3% American Indian, and 20.9% Hispanic, while 9.3% of

Table 1 Description of study measures

Measures	*N*	% or mean (SD)
12-month exit outcome		
Remained in services	991	57.7
Actively withdrew	991	13.5
Passively withdrew	991	21.8
Moved out of service area	991	7.0
Client demographic characteristics		
Age at enrollment (range 12.9–46.9)	991	24.3 (6.2)
Race and ethnicity		
Caucasian	991	36.0
African American	991	26.5
American Indian	991	7.3
Other race	991	9.3
Latina	991	20.9
Married or cohabitating	974	49.7
Completed high school	980	66.2
Employed	970	40.1
Primiparous	989	44.7
Client risk characteristics		
Adverse childhood experiences (range 0–10)	783	3.2 (2.5)
Perceived stress (range 0–40)	847	16.5 (7.7)
Prenatal smoking	845	25.3
Recent drug use	863	18.4
Transportation problems	707	20.5
Service characteristics		
Prenatal enrollment	986	71.9
Early completed visit rate (range 0–258%)	991	84.1 (33.77)
Caseload during service episode (range 1–24)	991	10.7 (4.71)
Home visitor satisfied/very satisfied with job	115	75.7
Home visitor education level		
No college degree	112	18.8
Undergraduate degree	112	53.6
At least some post-undergraduate coursework	112	27.7
Home visiting model		
Early Head Start	991	9.4
Healthy Families America	991	45.0
Nurse-Family Partnership	991	21.4
Parents as Teachers	991	24.2

Clients = 991; staff = 156; local home visiting programs = 26

clients reported other racial/ethnic identities. Nearly half of the sample (49.7%) reported being married or cohabitating, over two-thirds (66.2%) completed high school, 40.1% were employed, and 44.7% were expecting or recently had their first child. Women reported an average of 3.2 adverse childhood experiences, and 41.0% reported four or more childhood adversities (not shown). Participants' average score on the PSS was 16.5, with 30.4% of women reporting above average stress (not shown). Over one-quarter (25.3%) of clients reported smoking during pregnancy, while 18.4% used street drugs within the last year and 20.5% were identified as having transportation problems.

Nearly three-quarters (71.9%) of the sample enrolled in home visiting during pregnancy. The mean rate of expected visits that were successfully completed in the first 3 months post-enrollment was 84.1%, and over one-third (34.1%) of clients completed less than 75% of expected visits (not shown). The mean caseload was 10.7 clients. Approximately three-quarters (75.7%) of home visitors reported being satisfied or very satisfied with their job. Most staff held an undergraduate degree (53.6%) and over one-quarter (27.7%) reported some post-undergraduate education. HFA programs served the largest proportion of clients (45.0%), followed by PAT programs (24.2%), NFP programs (21.4%), and EHS programs (9.4%).

Results from the Cox regression models (Table 2) indicated no significant difference in the hazard ratio for dropout based on attrition type (active vs. passive $p = 0.12$; active vs. moved $p = 0.64$; and passive vs. moved $p = 0.10$). The adjusted survival curves shown in Fig. 1 support these results in that only small differences among exit patterns are visible. Clients who moved had fewer median weeks in service than clients who actively or passively left (results not shown, median = 23.1, 28.9, and 29.8, respectively), but pairwise contrasts in quantile regression models indicated the median length of service did not differ significantly among the three attrition types (results not shown, active vs. passive CI = − 10.75, 1.55; active vs. moved CI = − 3.20, 13.08; passive vs. moved CI = − 2.31, 12.77).

Using a three-level nested model, we tested a binary, unadjusted random intercept model to assess whether high-order cluster effects from home visitors (level 2) and home visiting models (level 3) influenced client attrition. Significant random effects were present at the home visitor level (ICC = 10.8%, $p < 0.01$), but not at the level of the home visiting model (ICC = 2.6%, $p = 0.11$). Thus, the final multilevel models included home visitor as a higher-order random effect, whereas home visiting model was included as a fixed effect in the model. ICC statistics from the final unadjusted random intercept model (Table 3) suggested that home visitor effects accounted for an estimated 12.6% of the total variance between remaining in services at 12 months and leaving early. Results from the multinomial null random intercept model suggested that the amount of variation attributed to home visitors varied by attrition type. Home visitors accounted for approximately 20.7% of the variance in passively leaving, 8.4% in active leaving, and almost no measurable variance in attrition due to moving.

Findings from the dichotomous model, *any attrition*, showed that compared to Caucasian participants, African American participants were almost twice as likely to leave within 12 months of enrollment (OR = 1.91). Clients who were married or cohabitating (OR = 0.72), employed (OR = 0.56), or had high completed visit rates (OR = 0.21) were less likely to leave services within 12 months.

Results from the multinomial model revealed that predictors of attrition varied by attrition type. Specifically, compared to women who were retained in services, those who actively withdrew were less likely to be married or cohabitating (RR = 0.58) and to have high rates of visit completion (RR = 0.31). Mothers who were African American (RR = 2.62) and enrolled in a PAT program (RR = 2.66) were significantly more at risk to passively withdraw. Moreover, age (RR = 0.94), employment (RR = 0.58), higher early visit completion rates (RR = 0.07), home visitor job satisfaction (RR = 0.41), and enrollment in a NFP program (RR = 0.36) were associated with lower risk of passive service exit. Finally, the relative risk of moving out of the service area within 12 months of enrollment was significantly lower for Latinas (RR = 0.23) and clients who were employed (RR = 0.22).

Because there were significant differences in the relative risk of passive attrition by home visiting model, we conducted post hoc descriptive analyses to explore model differences. Using a false-discovery rate approach to adjust alphas, we tested for significant differences in attrition between HFA and other models. Supplemental Table 1 (Online Resource 1) presents the attrition rate by model (NFP = 34.0%; HFA = 41.3%; PAT = 44.7%; EHS = 61.3%). Compared to HFA, EHS had a significantly higher overall attrition rate ($p < 0.001$) and a higher rate of passive attrition ($p < 0.001$). Supplemental Tables 2–5 (Online Resource 2) present multinomial models for each evidence-based model. The significant predictors identified in the primary multinomial model (Table 3) had similar relationships in the model-specific results (Supplemental Tables 2–5), although some results were no longer significant. For example, home visit attendance rate was the strongest predictor of passive leaving in home visiting model-specific analysis.

Discussion

This study analyzed patterns and predictors of three types of attrition from long-term home visiting services: clients who (1) expressed their intent to leave (i.e., active leavers), (2) dropped out due to inconsistent attendance (i.e., passive

Table 2 Difference in timing of service exit by attrition type

Contrasts from Cox regression	Exp(B)	95% CI	*p*
Actively withdrew[a] vs passively withdrew	0.84	[0.68, 1.04]	0.12
Actively withdrew[a] vs moved	1.07	[0.81, 1.42]	0.64
Passively withdrew[a] vs moved	1.27	[0.96, 1.46]	0.10

Exp(B) = predicted change in the hazard rate; 95% CI = confidence intervals; regression models adjust for client-level covariates: age at enrollment, race, married or cohabitating, completed high school, employed, primiparous, adverse childhood experiences, perceived stress, prenatal smoking, recent drug use, transportation problems, prenatal enrollment, visit completion rate, and caseload

[a] Reference category

leavers), or (3) moved out of the service area. Within a year of enrollment, 42% of sample participants had dropped out for one of these three reasons. The 12-month attrition rate, which is comparable to rates reported in other studies (e.g., Duggan et al. 2000), is concerning given that the four home visiting models in this study encourage family participation until the child turned 2 years of age or longer.

As shown in Table 2 and Fig. 1, multivariate Cox regression models revealed no significant differences in when service exit occurs among the three attrition types. There also were no significant differences in median service duration using quantile regression contrasts. These results suggest that the type of attrition was unrelated to the timing of attrition.

We also examined the extent to which client and service characteristics predicted the three attrition types. Home visitors contributed significant variance to the risk of addressable attrition—and contributed the most variance to the specific risk of passive withdrawal. Conversely, there was no evidence that variation at the home visitor level predicted withdrawal due to moving, implying that this form of attrition is likely driven by factors outside of the client's service experience. These findings highlight the importance of distinguishing between addressable and nonaddressable attrition (O'Brien et al. 2012).

Reinforcing this point, multivariate multilevel models (Table 3) showed that the estimated effects of client and service characteristics on attrition varied by attrition type. Specifically, clients who were married or cohabitating were less likely to actively withdraw from services. To the extent that marriage and cohabitation denote greater family stability than does single parenthood, active leavers may be a more advantaged client group than passive leavers. Passive withdrawal was more likely among clients who were younger, African American, and unemployed. Previous studies have linked these demographic characteristics to attrition (Brand and Jungmann 2014; McGuigan et al. 2003; O'Brien et al. 2012), although Daro et al. (2003) reported lower rates of attrition among African American and unemployed clients.

We found no associations between any type of attrition and psychosocial risk factors such as stress, smoking, drug use, transportation problems, and childhood adversities. Other studies have reported inconsistent associations between indicators of client risk and attrition (Damashek et al. 2011). Clients with higher risk profiles may not be at an increased risk of attrition if programs allocate more resources to engaging and retaining these clients. Programs also may be better equipped to meet the needs of lower-risk clients in a shorter time frame. These clients may fulfill their goals prior to the prescribed program length and withdraw from services early.

We found only one common predictor of passive and active leaving—the rate of completed home visits within the first 3 months of services. Other studies have also found strong correlations between lower rates of participation in home visits and the risk of attrition (Brand and Jungmann 2014; O'Brien et al. 2012). Thus, early adherence to model standards for completed visits appears to be a robust predictor of client retention. These findings suggest that, to the extent attrition is addressable, programs can use information about early visit rates to target their engagement strategies.

Two higher-order fixed effects were associated with passive attrition: home visitor job satisfaction and home visiting model. Job satisfaction was associated with passive attrition, suggesting that home visitors who are less satisfied with their jobs may be less effective at engaging their clients (Wasik 1993). In turn, clients who are more engaged or who have a stronger relationship with their home visitors may be more likely to communicate with their home visitors about withdrawing from services. A broader inference of this finding is that job satisfaction is an alterable predictor of attrition. Therefore, home visiting programs may indirectly reduce addressable and undesirable attrition through various means of increasing staff satisfaction such as facilitating professional advancement and enhancing the agency's work environment (Gill et al. 2007; Wasik 1993). Home visiting model was also associated with passive attrition. Compared to similar clients in HFA programs, NFP clients were at a lower risk of passive withdrawal and PAT clients were at a higher risk—a finding that was replicated in the supplemental post hoc descriptive analysis of attrition outcomes by model. We also conducted supplemental multivariate analyses by home visiting model. The results generally aligned across models and supported the findings of the primary analysis. Thus, although the evidence-based models varied in retention rates, lower rates of visitation in the first 3 months of service was the most robust predictor of passive attrition across models.

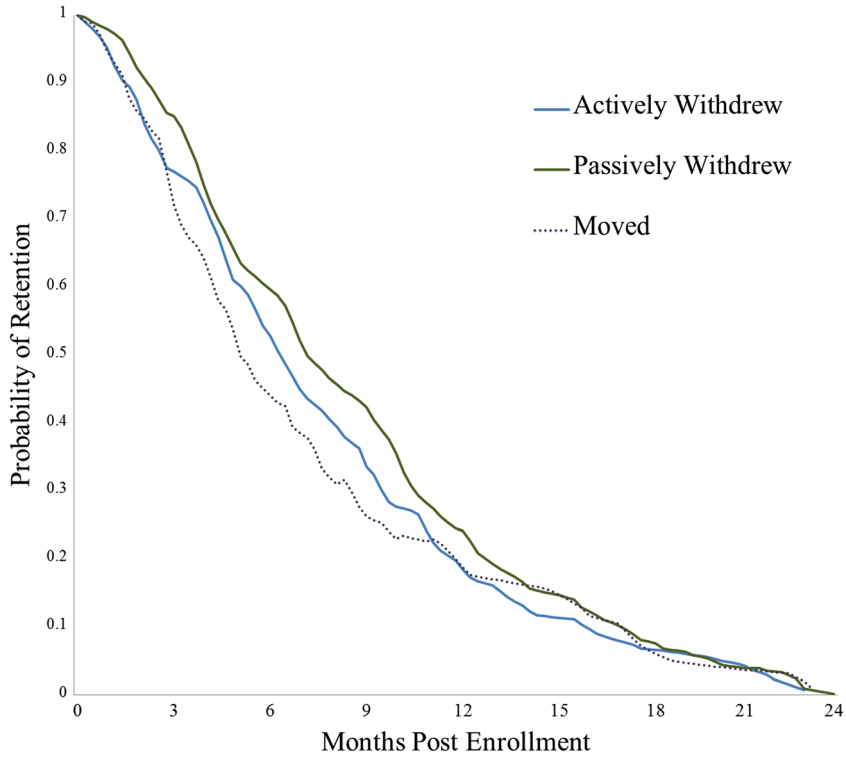

Fig. 1 Survival plots showing the probability of home visiting retention for three types of early attrition

Client mobility out of the service area was also included as an attrition type because it is a common and largely nonaddressable source of attrition. As hypothesized, clients who moved were distinct from clients who passively or actively withdrew from services. Compared to Caucasian participants, Latinas were at lower risk of moving. Clients who were employed also were less likely to move. Again, to the extent that these factors correlate with family socioeconomic stability, clients who move out of the area may be a less advantaged group relative to other clients. Perhaps more meaningful is the fact that we found few significant associations between moving and factors that are commonly associated with attrition. These results lend further support to the assertion that some forms of attrition are not easily predicted or altered.

Limitations

Although the generalizability of results is strengthened by using data sourced from a state-administered network of agencies that implement evidence-based home visiting services, model-specific practices may account for some unexplained variance in our results. For example, we were restricted to using program enrollment and discharge dates to calculate service duration, whereas first and last visit dates may more accurately reflect the true time clients participated in service. As a result, we may have overestimated the duration of services for passive leavers from HFA programs, which encourage home visitors to engage in a lengthy creative outreach process before discharging clients who participate inconsistently.

Another limitation is potential bias due to non-random missing data. This is a common challenge in attrition studies because programs typically do not gather data on clients after they exit services. Of particular concern were the 115 clients for whom we could not match to home visit logs and who, when compared to the effective sample, were more likely to enroll postpartum, be unemployed, have multiple children, and withdraw from services early. We were unable to address this source of missing data, though we did address other missing data by applying multiple imputation methods.

In addition, we used a two-level model, with staff as the higher-order random effect, which may not precisely represent the complex structure of the variation that occurs when implementing programs in multiple agencies and communities (Daro et al. 2003). Similarly, we were unable to model interaction effects due to the complexity of the modeling approach. The post hoc subgroup analyses should be interpreted with caution, given the methodological issues associated with this approach (see Supplee et al. 2013) and the likely loss of power that occurred when employing smaller subgroup samples. Future studies using large samples with normally distributed outcomes may produce more stable estimations of complex cluster and moderation effects.

A final limitation is that, although we analyzed 24 months of service data in the Cox regression models, the multinomial regression analyses were limited to 12 months. This decision

Table 3 Dichotomous and multinomial regression results at 12 months

	Dichotomous[a]		Multinomial[a]					
	Any attrition		Actively withdrew		Passively withdrew		Moved	
	OR	95% CI	RR	95% CI	RR	95% CI	RR	95% CI
Age at enrollment	0.97	[0.94, 1.00]	1.00	[0.96, 1.04]	0.94**	[0.90, 0.98]	0.99	[0.94, 1.04]
Race and ethnicity								
Caucasian	1.00		1.00		1.00		1.00	
African American	1.91*	[1.21, 3.01]	1.59	[0.83, 3.05]	2.62**	[1.47, 4.65]	0.98	[0.44, 2.18]
American Indian	0.64	[0.29, 1.39]	0.59	[0.19, 1.78]	0.75	[0.27, 2.05]	0.45	[0.11, 1.87]
Other race	1.17	[0.66, 2.07]	1.02	[0.44, 2.36]	1.28	[0.61, 2.07]	0.92	[0.37, 2.25]
Latina	0.82	[0.51, 1.31]	1.04	[0.52, 2.06]	1.12	[0.59, 2.00]	0.23**	[0.09, 0.62]
Married or cohabitating	0.72*	[0.52, 0.99]	0.58*	[0.36, 0.94]	0.82	[0.54, 1.24]	0.86	[0.48, 1.54]
Completed high school	0.89	[0.63, 1.26]	0.92	[0.56, 1.51]	0.85	[0.55, 1.31]	0.86	[0.47, 1.58]
Employed	0.56**	[0.41, 0.77]	0.95	[0.60, 1.49]	0.58**	[0.38, 0.88]	0.22**	[0.11, 0.44]
Primiparous	1.05	[0.69, 1.60]	0.99	[0.54, 1.80]	1.16	[0.68, 2.00]	0.95	[0.45, 2.01]
Adverse child experiences	1.02	[0.95, 1.09]	1.00	[0.90, 1.12]	0.99	[0.90, 1.09]	1.10	[0.96, 1.25]
Perceived stress	0.99	[0.97, 1.02]	0.99	[0.96, 1.02]	1.00	[0.97, 1.03]	0.99	[0.95, 1.03]
Prenatal smoking	1.29	[0.84, 1.98]	1.32	[0.72, 2.44]	1.58	[0.91, 2.73]	0.81	[0.37, 1.76]
Recent drug use	1.33	[0.86, 2.05]	1.52	[0.84, 2.76]	1.44	[0.83, 2.49]	0.83	[0.33, 1.98]
Transportation problems	1.10	[0.69, 1.76]	0.94	[0.50, 1.78]	1.24	[0.70, 2.22]	1.05	[0.43, 2.54]
Prenatal enrollment	1.01	[0.67, 1.52]	1.30	[0.70, 2.40]	0.96	[0.57, 1.63]	0.67	[0.34, 1.34]
Early completed visit rate	0.21**	[0.13, 0.35]	0.31**	[0.16, 0.62]	0.07**	[0.04, 0.14]	1.46	[0.67, 3.21]
Caseload	0.99	[0.94, 1.04]	0.99	[0.92, 1.07]	1.02	[0.96, 1.08]	0.98	[0.91, 1.06]
Home visitor job satisfaction	0.58	[0.36, 0.96]	0.93	[0.45, 1.93]	0.41**	[0.23, 0.74]	0.73	[0.32, 1.67]
Home visitor college graduate	1.19	[0.57, 2.49]	0.95	[0.37, 2.45]	1.98	[0.23, 0.74]	1.13	[0.35, 3.67]
Evidence-based model								
Healthy Families America	1.00		1.00		1.00		1.00	
Nurse-Family Partnership	0.54	[0.26, 1.10]	0.44	[0.16, 1.24]	0.36*	[0.14, 0.87]	1.18	[0.43, 3.25]
Parents As Teachers	1.57	[0.93, 2.63]	0.80	[0.37, 1.73]	2.66**	[1.42, 5.00]	1.30	[0.59, 2.85]
Early Head Start	1.30	[0.69, 2.48]	0.91	[0.36, 2.28]	1.57	[0.74, 3.33]	1.44	[0.54, 3.84]
ICC from unadjusted model	12.6%		8.4%		20.7%		< 1%	

[a] Served at least 12 months is reference outcome. OR = odds ratio; CI = confidence intervals; RR = relative risk ratio; ICC = estimated intraclass correlation, reported as percent of variance explained **$p < 0.01$; *$p < 0.05$

was driven by the need to avoid bias introduced from right-censored data. Service exits beyond the first year may be associated with different client and service characteristics.

Conclusion

Despite these limitations, the present study may help to inform how the field of home visiting defines attrition. Whereas most studies measure attrition as a homogenous outcome, we distinguished between active and passive leavers, thereby extending research that suggests clients who communicate their desire to end services may differ from those who do not (Korfmacher et al. 1999). We distinguished these two types of addressable attrition from a third type, moving out of the service area, which is largely nonaddressable.

Results showed that the rate of completed visits in the first 3 months of service was the only significant correlate of both forms of addressable attrition. Otherwise, prediction models varied across attrition types. Married or cohabitating clients were less likely to actively disengage from services. Clients who were African American, younger, and unemployed were more likely to passively drop out. Unemployed clients were also more likely leave service because they moved out of the service area, while Latinas were less likely than non-Hispanic Caucasians to move out of the service area. Taken together, these findings indicate that client demographics are an important consideration when predicting different forms of addressable and nonaddressable attrition. Looked through another lens, the findings suggest that the status quo for client engagement in these programs may be insufficient to retain clients with certain socioeconomic profiles.

Conversely, attrition rates did not vary according to indicators of psychosocial risk. Countervailing forces may help to explain these null findings. Although clients who present with significant challenges such as high stress levels, substance use, and transportation problems may be at an elevated risk of attrition, they also may be more likely to perceive home visiting as necessary or helpful. In addition, programs may offset these risks by allocating greater resources toward retaining clients with complex needs. In other words, our data may reveal the effects of what programs do routinely to engage and retain clients that they perceive to be in the greatest need of services and social support.

Ultimately, large-scale studies of administrative databases like this one are useful to the extent that they yield knowledge that can be translated into program improvements. To this end, this study offers two cross-model applications: First, differentiating attrition types may improve the precision of prediction models and thereby generate insights as to when and how programs should attempt to prevent attrition. Toward that end, we encourage implementation scientists and program innovators to distinguish among multiple forms of attrition. Second, we urge researchers to test the prevailing perspective that all attrition is undesirable and that, by extension, the prescribed program duration is optimal. Evidence-based, long-term home visiting models are generally guided by a "more is better approach" (e.g., Durlak and DuPre 2008; Paulsell et al. 2014), and thus, they typically define successful program completion by length of service. However, the expected dose-response relationship may be complicated by the differential capacity of families before they enter services: Holland et al. (2014b) found mothers with the lowest attendance in an NFP program were also the most educated and experienced the best outcomes. In fact, the evidence that longer service duration is always associated with improved program outcomes is remarkably thin (Sweet and Appelbaum 2004). Reifying model standards for service duration ignores the possibility that some clients may accrue significant benefits in a shorter period, even if they leave services prematurely.

There is a growing recognition that home visiting programs may be made more consequential and efficient by aligning model dosage and duration with family need (Holland et al. 2014a, b). There is also evidence to suggest that attrition rates are lower in long-term programs when service providers are less directive and more flexible in adapting the program to the needs of families (O'Brien et al. 2012). In addition, some clients may perceive longer programs to be unnecessarily burdensome, which could hinder enrollment and engagement efforts. Brief home visiting models are increasingly being looked to as a strategy to bring home visiting to a universal scale and increase population health impact (Dodge et al. 2014). These models may complement more intensive home visiting, as the former can prompt referrals to the latter for families with more significant needs. Ultimately, an integrated and flexible system of brief and long-term services may help to advance the Health Resources and Service Administration's new *precision home visiting* agenda, which aims to identify "what works, for whom, and in what contexts to achieve specific outcomes" (Home Visiting Applied Research Collaborative n.d.).

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflicts of interest.

Research Involving Human Participants and/or Animals This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent This study was a secondary data analyses where formal consent was not required.

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