Public Health Nurse Tailored Home Visiting and Parenting Behavior for Families at Risk for Referral to Child Welfare Services, Colorado: 2018–2019

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Objectives. To examine public health nurse (PHN) intervention tailoring through the Colorado Nurse Support Program (NSP). Our 2 specific aims were to describe the NSP program and its outcomes and to determine the effects of modifying interventions on short- and long-term outcomes among NSP clients.

Methods. In our retrospective causal investigation of 150 families in Colorado in 2018–2019, intervention effects were modeled via longitudinal modified treatment policy analyses.

Results. Families served by PHNs improved in terms of knowledge, behavior, and status outcomes after receiving multidimensional, tailored home visiting interventions. Case management interventions provided in the first month of PHN home visits had lasting effects on behavior outcomes, and 2 additional case management interventions in the first month were estimated to have even more of an impact.

Conclusions. Modern causal inference methods and real-world PHN data revealed a nuanced, fine-grained understanding of the real impact of tailored PHN interventions.

Public Health Implications PHN programs such as the NSP and use of the Omaha System should be supported and extended to advance evaluations of intervention effectiveness and knowledge discovery and improve population health. (*Am J Public Health*. 2022;112(S3):S306–S313. https://doi.org/10.2105/AJPH.2022.306792)

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Public health nurse (PHN) home visiting is known for its tailored interventions and its effectiveness for high-risk populations such as families that have multiple complex social and health needs and whose children have the potential for long-term sequelae of early childhood adverse events.[1–5] Intervention tailoring, defined as personalizing care to meet specific client needs, is key to PHN intervention effectiveness.[2–6]

For decades, policymakers have mandated outcome evaluation to ensure PHN home visiting program effectiveness and justify continued funding. Administrators have responded to these mandates by adopting formal protocols (e.g., evidence-based guidelines[7]) and programs (e.g., the Nurse Family Partnership)[6] that, in turn, generate data through routine PHN documentation for program evaluation and research.[8–12] Use of PHN-generated data sets for causal modeling is in its infancy; however, interventions tailored to meet diverse client needs create problematic data confounding with respect to the numbers and types of interventions a client receives and their outcomes.[13] Adjustment for this confounding is critical to understanding the impact of PHN interventions.[13]

In PHN home visiting, clients receive a series of PHN visits, and in each visit interventions are applied. Over time, client characteristics, outcomes, and interventions vary, creating a rich source of information but also complex, time-varying confounding.[13] The numbers and types of interventions delivered at a visit depend on the client's baseline health information, the numbers and types of interventions delivered in the past, and how the client responded to those interventions. These dynamics need to be taken into account in assessing the effects of interventions and their timing. As confounding is especially strong given the nature of PHN intervention tailoring, traditional methods of estimating time-varying intervention effects such as marginal structural models may result in biased or highly variable estimates of effects.[14,15]

Recent work in causal inference has focused on estimating causal effects that depend on the observed number of interventions.[16–18] These methods aim to answer questions such as "What would outcomes look like if, counter to fact, the numbers of interventions everyone received were slightly different than in reality?" The control group accounts for the observed data, and a comparison is made with the hypothetical population that received slightly more (or fewer) interventions. These approaches are referred to as modified treatment policies (MTPs), as they examine what occurs when the application of a treatment or intervention is slightly modified from actuality.[16]

The confounding present in this hypothetical comparison tends to be less difficult to adjust for than that associated with marginal structural models provided that the hypothetical increase or decrease in interventions is not too large,[16,17] as MTPs require weaker assumptions. This stems from the fact that the counterfactual questions they pose are not drastically different from how interventions were applied in reality. MTPs have been extended to address time-varying interventions (longitudinal MTPs [LMTPs]) and are capable of answering counterfactual questions that depend on both individual characteristics and intervention timing, as in PHN intervention tailoring.[16]

Given the complexity and longitudinal nature of the PHN intervention tailoring problem, correspondingly complex and rich longitudinal data sets are needed to examine such intervention modifications. The data must incorporate information on the factors that affect PHN intervention tailoring to control for potentially time-varying confounding.

Although PHN home visiting programs have often employed electronic health records as documentation,[9–12] 1 PHN support program generated data that were suitable for the study of both interventions and outcomes over time. The Nurse Support Program (NSP) was designed as a collaborative partnership between a local public health district and a number of county human service departments in Colorado to support families in need. PHNs visit families biweekly to provide evidence-based, tailored interventions known to maintain family integrity, improve family dynamics, and facilitate positive behavior change.[6,7] Case management (CM) referrals to community resources for emergency funding, health care services, substance use cessation, or grief services are made only when appropriate and when needed by families. To be eligible for the program, families must be referred by child protective services and qualify for assistance from Colorado Works–Temporary Assistance to Needy Families. Established in the early 2000s for a single county, the NSP has grown to include agreements with 3 counties served by the public health district.

In response to the need to evaluate the effects of the interventions on client outcomes, the NSP implemented a comprehensive measurement, decision support, and documentation process in 2013 using the Omaha System,[8] a research-based nursing classification intervention and outcome system. This system has been employed to guide, document, and evaluate diverse PHN services including PHN home visiting programs across populations and settings in the United States and globally.[7,8]

Using NSP data generated through routine PHN documentation, we examined intervention tailoring using LMTPs to deepen understanding about the impact of PHNs in terms of improving and optimizing intervention tailoring and outcomes. Our 2 study aims were (1) to describe the NSP and outcomes using PHN-generated Omaha System data and (2) to determine the effects of modifying interventions on short- and long-term outcomes among NSP clients.

METHODS

This retrospective, collaborative study involved practicing PHNs and academic researchers.

Instrument

The Omaha System consists of 3 relational instruments with documented psychometric properties: the Problem Classification Scheme (client assessment and problem list), the Problem Rating Scale for Outcomes (problem evaluation), and the Intervention Scheme (used for care planning and services; Table B, available as a supplement to the online version of this article at http://www.ajph.org).[19,20] The Omaha System exists in the public domain, and evidence-based encoded interventions for PHN home visiting practice are available online at the system's Web site.[7] The NSP provides extensive Omaha System training and mentoring, including specific guidelines for practice and documentation (e.g., identifying which system problems should be assessed in common scenarios, how often a system problem should be rated, and how to document tailored NSP interventions).[8] Monthly practice sessions support uniformity in system use. Quality of documentation is measured quarterly through peer and supervisor reviews with reflective feedback.

Analysis

We used R version 4.1.1 in conducting all of our analyses.[21] For our first aim (providing a description of the NSP), standard descriptive and inferential statistics were used to analyze program data. We used LMTPs, which allow for interventions to be longitudinally measured and for a counterfactual increase or decrease in interventions to occur at any specified time point of interest, for our second aim (assessing the effects of intervention modifications). Here the causal effect is the expected change in outcomes given the intervention modification: $E[Y(A_k+\delta)]-E[Y]$, where $E[Y(A_k+\delta)]$ is the expected potential outcome if the intervention at month k is modified by shifting the number of interventions by δ (for this study, $\delta=+2$ and –2) and $E[Y]$ is the expected outcome in the observed data.[22] Those who receive more interventions often have more problems and worse outcomes and are otherwise different from those who receive fewer interventions; therefore, there is confounding.

The confounding in this study had a complex structure given consideration of time-varying interventions that may depend on what happened in the past. The assumptions required for our aim 2 analysis were as follows: (1) the intervention modifications were plausible in that they were in the range of the observed number of interventions for all individuals, and (2) there was sequential ignorability in that all of the factors affecting the number of interventions received in a given month and the observed data in future months were measured.

Figure 1 shows the directed acyclic graph created on the basis of our study assumptions; arrows depict the causal structures and confounding relationships among the baseline and time-varying covariates, interventions, and outcomes.[23] Our first assumption holds because the intervention modifications explored were small (±2) and there were no modifications that made an individual's number of interventions negative. Because the Omaha System captures information about why PHNs make care decisions, large degrees of the factors needed for our second assumption were measurable, yet some still may remain unmeasured. Given the emphasis on caretaking and parenting in the NSP, outcome variables were classified as caretaking and parenting Knowledge, Behavior, and Status (KBS) scale scores measured on a 5-point Likert scale longitudinally.

Targeted maximum-likelihood estimation,[24,25] an alternative to g-computation and inverse probability weighting, was used to control for the time-varying confounding implied in Figure 1.[26,27] Targeted maximum-likelihood estimation requires estimation of inverse weights and regression functions; for these we used a combination of logistic regression, Bayesian additive regression trees, and others.[28–31]

Modifications to the number of CM interventions were considered because

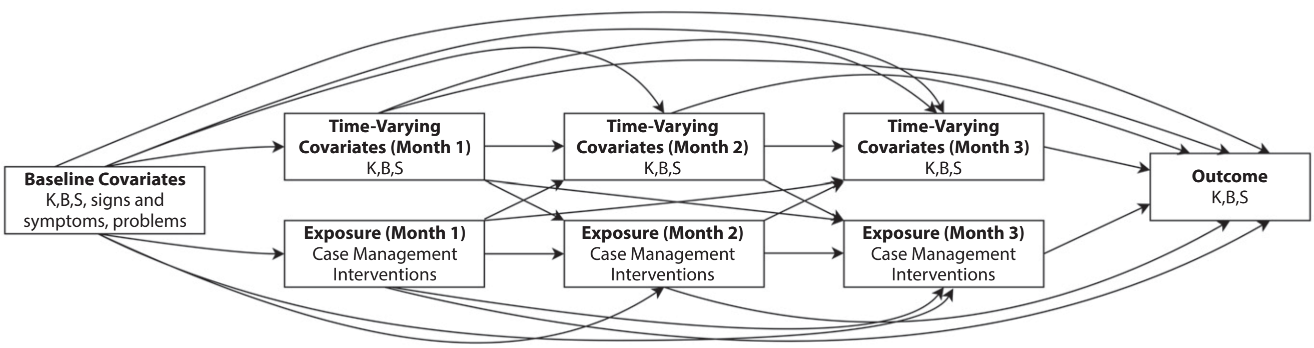

FIGURE 1— Time-Dependent Confounding, Interventions, Baseline Information, and Knowledge, Behavior, and Status Outcomes for Clients: Colorado, 2018–2019

Note. B = behavior; K = knowledge; S = status. The diagram illustrates how previous outcomes and interventions can affect future interventions and shows the causal ordering of data required for a longitudinal modified treatment policy analysis. Each arrow represents a relationship among variables and the direction of the relationship.

variations in these interventions had been associated with differential outcomes in previous research.[7] Hypothetical increases of 2 CM interventions were modeled at month 1, month 2, and month 3 separately. Similarly, we modeled hypothetical decreases of 2 CM interventions separately at months 1, 2, and 3. Modifications of 2 interventions were selected because a modification of 1 intervention may not be clinically relevant and larger modifications may deviate too substantially from the observed number of interventions, which would induce stronger confounding and more difficult adjustments. For each analysis, the change in month 4 KBS scores and the change in scores at the final measurement were estimated. Positive changes indicated that KBS outcomes were improved by the hypothetical change in the number of CM interventions, whereas negative changes indicated that outcomes were worsened.

Study Cohort

The data used in this study were generated through routine documentation of NSP PHN home visits in multiple counties with the Omaha System from May 2017 to December 2019. For the LMPT analysis, only data for primary caregivers were used. The variables used are summarized in the following sections; a full list of the variables is provided in Table A (available as a supplement to the online version of this article at http://www.ajph.org). The unit of analysis was the primary caregiver for each family.

Covariates, Exposures, and Outcomes

Baseline covariates. We controlled for total numbers of problems, signs or symptoms, and overall baseline KBS scores for each case to adjust for baseline information. Both total numbers of signs or symptoms for all problems and the total number for each problem were included. In addition, the presence of each sign or symptom for the caretaking and parenting problem was considered. The first KBS scores for each problem and each case were extracted to calculate mean baseline KBS scores across all problems as a baseline control variable. The overall mean KBS scores and first KBS scores for income and caretaking and parenting were included as baseline covariates. The baseline KBS data for other problems were excluded because of the amount of missing data (50% or more).

Exposures. Exposures were operationalized as the numbers of CM interventions in each of months 1, 2, and 3.

Time-varying covariates. In practice, health care providers adjust their care based on prior assessments and interventions, and thus KBS scores (monthly mean KBS scores overall and for each problem) and interventions were considered as time-varying confounders. In each case, the numbers of interventions were calculated for all problems and caretaking and parenting interventions provided in each month by all categories (teaching, guidance, and counseling; treatments and procedures; CM; and surveillance) to adjust the estimate of relationships between CM interventions and client outcomes. Each time-varying covariate was used to adjust the effect of subsequent exposure on the outcome (Figure 1). For instance, we controlled for the total numbers of teaching, guidance, and counseling; CM; and surveillance interventions during month 1 in studying the effects on outcomes of CM interventions delivered during months 2 and 3. There were limited amounts of missing data for caretaking and parenting and overall KBS variables in month 3 (25%–35% of the sample). We addressed this issue via multiple imputation with the R package and random forest imputation; indicators of missing data were included as additional time-varying covariates.[32]

Outcomes. Outcomes were operationalized as knowledge, behavior, and status with respect to the caretaking and parenting problem: (1) the first measured of each of the knowledge, behavior, and status outcomes monthly from month 4 to the final month and (2) the knowledge, behavior, and status outcomes measured in the last month of visits (which occurred in month 4 or later). Thus, there were 6 outcome variables (3 outcome measures × 2 time points) analyzed in 6 independent models. There were no missing outcomes.

RESULTS

A total of 339 individuals in 150 families were served by PHNs in the NSP in 2018–2019. Their services and outcomes and the findings of the causal intervention effectiveness analysis are described in the sections to follow.

Nurse Support Program Characteristics

As noted, 150 families (consisting of 339 individuals) were served and discharged from the program during the study period. On average, family primary caregivers had 3.2 signs or symptoms and received 164 interventions for 4.5 problems over 9 months of visits (range = 4–19 months). In addition to caretaking and parenting (100%) and income (93%), the most frequent problems addressed were mental health (37%), the postpartum period (31%), substance use (25%), family planning (23%), and pregnancy (22%). The most common signs or symptoms were difficulty providing physical care or safety (26%), use of recreational drugs (14%), inaccurate or inconsistent use of family planning (14%), and sadness, hopelessness, or decreased self-esteem (10%). The vast majority of interventions involved surveillance (50%), followed by teaching, guidance, and counseling (30%) and CM (20%). By problem, interventions overwhelmingly focused on caretaking and parenting (47%) and income (24%); the remaining problems were addressed in 2% to 6% of interventions.

The mean and median numbers of CM interventions were 4.1 and 3 (range = 0–28), respectively, in month 1; 2.67 and 2 (range = 0–28) in month 2; and 2.09 and 1 (range = 0–16) in month 3. Outcomes improved significantly overall for knowledge (from 2.88 [less than basic knowledge on admission] to 3.56 [basic to adequate knowledge on discharge]), behavior (from 3.45 [inconsistently appropriate behavior] to 4.05 [appropriate behavior]), and status (from 3.66 [moderate to minimal signs or symptoms] to 4.11 [less than minimal signs or symptoms]; all $Ps < .01$). Trends were similar across problems with some variability.

Case Management Intervention Effects

The LMTP intervention tailoring analysis focused on primary caregivers, whose demographics were provided in aggregate by the NSP. Clients were on average 29.9 (SD = 8.6) years of age and were primarily female (94%) and unmarried (68%). Omaha System data for LMTP analyses were available for 146 primary caregivers who received PHN visits for at least 4 months.

A hypothetical increase of 2 CM interventions in month 1 was estimated for caretaking and parenting behavior outcomes at both month 4 (change = 0.07; $P = .02$) and the final month (change = 0.11; $P < .01$; Figure 2). Conversely, a hypothetical decrease of 2 CM interventions during month 1 was estimated to result in a decrease in caretaking and parenting final behavior outcomes (change = −0.07; $P = .01$; Figure 2). Although not significant, a hypothetical increase of 2 CM interventions in month 1 was positively related to status outcomes for month 4 (change = 0.06; $P = .16$) and the final month (change = 0.04; $P = .27$). Finally, a hypothetical increase of 2 CM interventions in any month did not result in a significant change at month 4 or the final month in knowledge outcomes (changes from −0.01 to −0.05; $P = .89$ to .07).

DISCUSSION

This retrospective study of existing PHN data justifies LMTPs as appropriate methods for analyzing public health nursing practice, demonstrates the value and effectiveness of the NSP, and provides additional evidence of the importance of intervention tailoring. The NSP descriptive analysis showed that outcomes among families served by PHNs improved after the families received multidimensional, tailored home visiting interventions, in line with findings from numerous previous studies such as those examining PHN home visiting data sets[9–12] and the Nurse Family Partnership.[6]

Our retrospective longitudinal analysis involving advanced statistical techniques indicated that CM interventions provided early on during PHN home visits had a lasting impact on behavior outcomes. The finding that a reduction in the number of CM interventions in the first month of PHN visits resulted in worse behavior outcomes indicated that the number of CM interventions applied in the first month had a positive impact on behavior outcomes and that 2 more CM interventions in the first month may have even more of an effect. Further research with additional and larger data sets is needed to confirm and extend these findings.

Our findings regarding NSP program characteristics and outcomes demonstrate the importance and value of attention to program and documentation fidelity support for NSP PHNs. This aligns with Omaha System guidance to ensure the validity of findings when standardized documentation data are repurposed for evaluation and research.[8] NSP program leaders affirmed that the findings observed reflected fidelity with program goals, expected assessments, and evidence-based interventions. This lends important process and content validity to our intervention tailoring findings and results. The rigor of the program and the findings related to the data lends confidence that PHNs both intervened appropriately and documented correctly. Generating such valuable data may be time consuming; therefore, administrators and PHNs must ensure that workflows are optimized to reduce documentation burden.[8,33]

The small but significant improvement in short- and long-term caretaking and parenting behavior is meaningful given the granularity of our analysis. Such fine-grained guidance derived

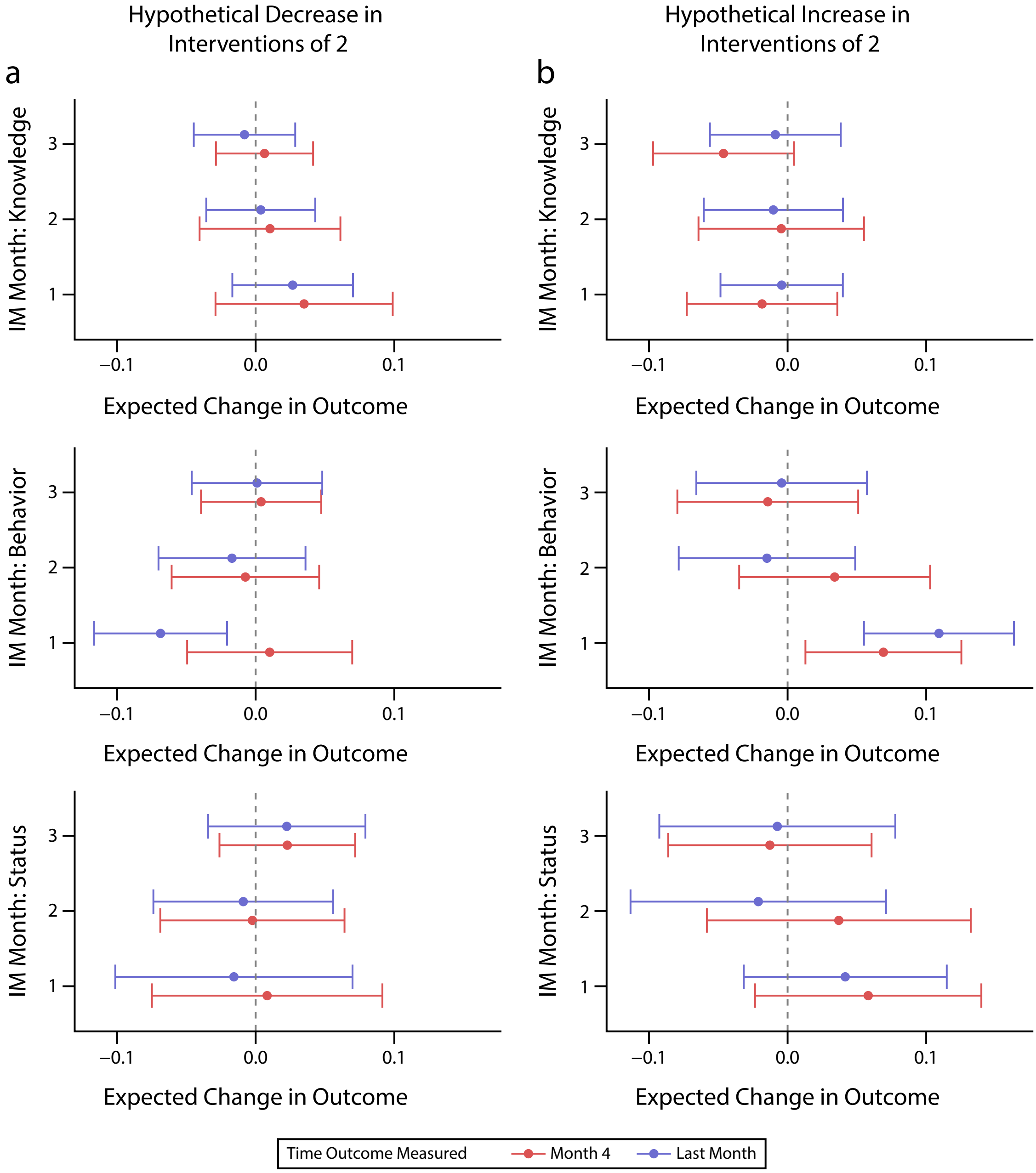

FIGURE 2— Expected Changes in Knowledge, Behavior, and Status Outcomes Under Hypothetical (a) Decreases by 2 and (b) Increases by 2 in the Number of Case Management Interventions: Colorado, 2018–2019

Note. IM = intervention modification. When interventions are modified in a given month, they are held fixed in all other months. A positive change means that outcomes improve with a given hypothetical modification in interventions. Error bars represent 95% confidence intervals.

from PHNs' own data aids in optimizing intervention tailoring and acknowledges that interventions are already well tailored. The broad practice recommendation that 2 additional CM interventions be considered in the first month of services acknowledges that problem, target, and care description intervention components are absent. Such broad advice is useful in that it allows for intervention tailoring on the part of PHNs, who can direct CM interventions to areas that may be of the most benefit for a specific client.[9–12] In future LMTP research, various intervention components should be examined with respect to their impact on PHN outcomes.

There are unique data considerations in using LMTPs. The longitudinal intervention and KBS outcome data generated through routine documentation during PHN NSP home visiting were extracted manually to achieve our goal of understanding how PHNs may improve intervention strategies and optimize outcomes. This study demonstrates that adherence to documentation protocols and data extraction processes is fruitful. Therefore, improving documentation and data extraction procedures is warranted and critical for future research.

This study has introduced LMTPs as a way of assessing the impact of PHN interventions and their tailoring when granular, longitudinal PHN data are available. LMTPs are useful for informing incremental, as opposed to revolutionary, changes in practice because they focus on questions concerning what would occur in the event of such changes. We examined the timing of application of interventions; with a larger data set, further examination of interesting modifications would be possible, such as timing and adaptivity to client characteristics (e.g., what outcomes would result if interventions were shifted up or down for those who had low KBS scores at any visit?). However, for the valid use of LMTPs, sufficiently rich data on the many factors affecting PHN intervention tailoring are necessary.

The analytical aim of this study was causal in nature: to understand what changes in outcomes would occur if interventions were modified in certain ways. When aims are explicit, the assumptions required for a valid analysis are transparent. In particular, a valid LMTP analysis requires that all confounders that could affect the number of interventions at any given time point be measured.[34] It is not possible to guarantee that all confounders have been measured, and as such our results are subject to potentially not having a causal interpretation. This can be remedied in future analyses by considering sensitivity analyses assessing the robustness of findings to unmeasured confounders. However, the specificity of the Omaha System data enabled us to capture a substantial number of critical confounders, making our results plausible. Note that although intervention effects may have varied among individual PHNs, our estimated effects can be interpreted as an average over the distribution of such effects.[35]

Limitations

This study had several important limitations. First, the sample size was small, and thus we had limited ability to detect nuanced intervention effects. Second, because it was generated in a single region of the United States, the sample may be limited in terms of its representativeness of PHN clients more broadly. Third, our study was observational, and thus it is possible that the presence of unmeasured confounders biased our results. Future work should be conducted to assess the sensitivity of study results to unmeasured confounders.

Public Health Implications

Decision-makers and administrators should continue to support and extend PHN home visiting programs such as the NSP and use of the Omaha System for the purposes of improving constituent outcomes and population health. Also, they should make data available for advancing evaluations of PHN intervention effectiveness and knowledge discovery. Our study contributes to the body of knowledge supporting investment in members of the PHN workforce as key contributors to improving the health of vulnerable populations. Our findings should be used as evidence to advocate for changes at the policy and system levels to advance and support PHN intervention and outcome work.

Conclusions

This study demonstrates the potential of modern causal inference methods paired with real-world PHN data to deepen understanding of the effects of PHN interventions on outcomes among this group. LMTPs in conjunction with highly detailed Omaha System data showed the feasibility of achieving a more nuanced, fine-grained understanding of the real impact of such interventions. PHNs should consider offering 2 additional CM interventions in the first month to improve behavior outcomes among primary caregivers of families at risk for child welfare service involvement to optimize outcomes through intervention tailoring. Consistent with the results of previous PHN home visiting effectiveness studies, our findings demonstrate the known effectiveness of PHN interventions and outcome measures, reinforcing the importance of maintaining and supporting a qualified PHN workforce and thereby advancing PHN contributions to improve population health. AJPH

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CONTRIBUTORS

J. D. Huling, R. R. Austin, M. M. Doran, V. J. Swarr, and K. A. Monsen conceptualized the study design and analytical strategy. J. D. Huling and S.-C. Lu developed and implemented the statistical analyses. J. D. Huling developed and implemented the causal analyses. All of the authors drafted, wrote, and edited the article.

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

HUMAN PARTICIPANT PROTECTION

The University of Minnesota institutional review board deemed this study not to be human participant research. Full protocol approval was not needed because deidentified data were used.

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