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Unmet basic needs and health intervention effectiveness in low-income populations

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ABSTRACT

In the face of unmet basic needs, low SES adults are less likely to obtain needed preventive health services. The study objective was to understand how these hardships may cluster and how the effectiveness of different health-focused interventions might vary across vulnerable population sub-groups with different basic needs profiles. From June 2010–2012, a random sample of low-income adult callers to Missouri 2-1-1 completed a cancer risk assessment and received up to 3 health referrals for needed services (mammography, pap testing, colonoscopy, HPV vaccination, smoking cessation and smoke-free home policies). Participants received either a verbal referral only (N = 365), verbal referral + tailored print reminder (N = 372), or verbal referral + navigator (N = 353). Participants reported their unmet basic needs at baseline and contacts with health referrals at 1-month post-intervention. We examined latent classes of unmet basic needs using SAS. Logistic regression examined the association between latent classes and contacting a health referral, by intervention condition. A 3 class solution best fit the data. For participants with relatively more unmet needs (C2) and those with money needs (C3), the navigator intervention was more effective than the tailored or verbal referral only conditions in leading to health referrals contacts. For participants with fewer unmet basic needs (C1), the tailored intervention was as effective as the navigator intervention. The distribution and nature of unmet basic needs in this sample of low-income adults was heterogeneous, and those with the greatest needs benefitted most from a more intensive navigator intervention in helping them seek needed preventive health services.

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1. Introduction

Poverty has a negative effect on health outcomes (Fiscella and Williams, 2004; DeFur et al., 2007; Harper and Lynch, 2007; Goldman and Smith, 2002), even after accounting for health risk behaviors that are more prevalent in low SES populations (Lantz et al., 2001). Although poverty is most often measured with monetary indicators like income and income-to-needs ratios (McDonough et al., 2005), multidimensional measurement approaches that consider deprivation across multiple life domains and cumulative hardship provide a richer, more accurate representation of poverty (DeWilde, 2004).

Among these alternative indicators are so-called "basic needs" like adequate housing, food security, personal and neighborhood safety, ability to pay bills and possession of essential material goods. Controlling for income, education, and other demographic characteristics, having greater unmet basic needs is associated with declining physical functioning, increased depression and mortality, and being "high cost users" of health care services (Blazer et al., 2005; Sachs-Ericsson et al., 2006; Blazer et al., 2007; Fitzpatrick et al., 2015).

There are 46.7 million people in poverty in the U.S. (U.S. Census Bureau, 2015), and although there is currently no national surveillance system for basic needs, a similar number (49 million) are classified as food insecure (Feeding America, n.d.) and over half of those in poverty (52%) are classified as having "severe housing cost burden", defined as spending >50% of their income on housing (Desmond, 2015).

There is variability in how unmet basic needs are experienced by vulnerable populations and the degree to which specific basic needs are associated with income-based indicators of poverty as well as health outcomes. For example, even among those within the same income-to-needs ratio category, the types and patterns of unmet basic needs reported differ by family structure and other characteristics (Mayer and Jencks, 1989). And while some basic needs like food security and paying bills are strongly associated with monetary definitions of poverty, other needs like quality housing and neighborhood safety are less strongly associated (Iceland and Bauman, 2007). Food insecurity is also strongly associated with high cost health care utilization (Fitzpatrick et al., 2015).

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Given the impact of unmet basic needs on health outcomes and the heterogeneity of unmet basic needs experienced by low-income populations, the objective of this study was to understand how these hardships may cluster and how the effectiveness of different health-focused interventions might vary across vulnerable population subgroups with different basic needs profiles. This secondary analysis of a unique prospective intervention study addresses both questions.

2. Methods

The Institutional Review Board at Washington University in St. Louis approved this study. The parent study that provided the data for this secondary analysis is registered in ClinicalTrials.gov (#NCT01027741).

2.1. Study setting

The study took place at United Way 2-1-1 Missouri, a telephone information and referral helpline that serves 99 of 114 counties in the state and received 160,000 calls in 2013. 2-1-1 is a federally designated dialing code (like 9-1-1 for emergency services) that links callers to health and social services in their community (Daily, 2012). Callers are predominantly poor and seeking help with basic needs like paying utility bills and getting food (Kreuter, 2012; Thompson et al., 2016). Although relatively few callers contact 2-1-1 about health services, studies have shown that the health needs of 2-1-1 callers greatly exceed those of the general population (Purnell et al., 2012; Kreuter et al., 2012; Eddens et al., 2011).

2.2. Study sample and recruitment

From June 2010 to June 2012, after receiving standard service, a random sample of callers to 2-1-1 Missouri was selected to participate in a surveillance phase of the project by completing a brief health risk assessment. Of these, 10,472 callers (58%) were eligible for the risk assessment (age ≥ 18, living in Missouri, English-speaking, calling with a service request for themselves, willing to provide date of birth and gender, not currently in extreme crisis). Nearly all of these (95%; n = 9947) were invited to take the risk assessment and 4761 (48%) completed it. Completers with at least one prevention need (n = 3816) were invited to participate in the trial phase of the project, a longitudinal intervention study. Those who agreed, consented and completed a baseline assessment (n = 1521; 40%) were then randomized to one of three study groups. Participants who also completed the 1-month follow up (n = 1090; 72%) comprise the analysis sample.

Drop-out rates did not differ by study group, nor were drop-outs different from completers in experiencing any of the seven unmet basic needs. They were younger (39.7 vs. 43.9 years) and more likely to be poor (62% vs. 55% income <$10K/year), employed (29% vs. 19%) and have a child at home (63% vs. 51%). Additional details of the study design and methods are available in a previous report (Kreuter et al., 2012).

2.3. Risk assessment to identify prevention needs

Items from the 2008 Behavioral Risk Factor Surveillance System were used to assess needs for mammography, Pap testing, colonoscopy, HPV vaccination for self and daughter, smoking cessation and smoke free home policies, recommended prevention behaviors that are available for free or low cost to low-income populations in most states. Referrals were offered to women ages 40 and older who had no mammogram in the last year; women ages 18 and older who had no Pap test with the last two years[1]; men and women ages 50 and older who had no colonoscopy in the last 10 years; women ages 18–26 and those with a female child ages 9–17 years old living in their home who had not received the HPV vaccination; current smokers; and those without a total ban on smoking in their household. Prevention referrals were limited to three per caller consistent with standard 2-1-1 procedure.

If a caller had more than three needs, a prioritization algorithm determined which health referrals he or she received. In descending order, the priorities were: colonoscopy, mammography, HPV vaccine for self or girl in home, Pap test, smoking cessation, and smoke free home policy. This order was set to maximize statistical power for each health outcome based on the expected proportion of the sample (from lowest to highest) that would need the referral, not on the public health importance or the strength of evidence for the recommended cancer control measure.

2.4. Interventions

Participants were randomized to one of three intervention groups. Of those who completed the baseline and 1 month follow up, 365 (34%) received verbal referral only, 372 (34%) received verbal referral + tailored print reminder, and 353 (32%) received verbal referral + navigation.

2.4.1. Verbal referral

Based on each caller's responses to the risk assessment questions, a computer algorithm identified and prioritized their prevention needs, which were addressed moments later by a 2-1-1 information specialist who delivered a scripted referral (Kreuter et al., 2012). Referrals consisted of three parts: (Fiscella and Williams, 2004) *risk assessment feedback* (e.g., "You said you've never had a mammogram"); (DeFur et al., 2007) *recommended action and importance* (e.g., "Once you turn 40, getting a mammogram every 1 to 2 years is the best way to fight breast cancer. Mammograms can find breast cancer when it's easier to treat and cure"); and, (Harper and Lynch, 2007) *offer of referral* to a free or low-cost service (e.g., "There's a good chance you can get a free mammogram through a program called Show Me Healthy Women. Would you like the phone number for that program?"). For each accepted referral, the information specialist identified the closest service provider to the caller's residence and verbally shared the referral phone number and/or address, information about its hours of operation, and documentation that may be required to obtain services.

2.4.2. Tailored print reminder

Within one working day of receiving the verbal referral, participants in this group were mailed a printed tailored reminder (4-page full color booklet) of the health referral they received. The reminder consisted of: (Fiscella and Williams, 2004) a short *personal story* tailored to the problem that led the participant to call 2-1-1 and the prevention referral to which the participant has been referred (i.e., modeling (Lemelin et al., 2009)); (DeFur et al., 2007) an accompanying *matched photo* personalized to the participant's age, race, and gender; (Harper and Lynch, 2007) *action details* providing a clear and simple summary of information the caller would need to access the prevention referral(s); and (Goldman and Smith, 2002) *motivation and preparation* information describing why the preventive health service was important and suggesting questions to ask when contacting the referral. All content adhered to health literacy and health communication best practices, and was written at a Flesch-Kincaid 4th Grade Level. The tailored personal story addressed up to three cancer-control needs.

2.4.3. Navigator/health coach

Navigators (called "coaches" to participants) explained each needed preventive health service and its importance, answered callers' questions, elicited and addressed barriers to action with a

[1] Recommendations for Pap testing changed during the study period. In the first four months of recruitment, women ages 18–26 were offered referrals if they had not Pap test in the last year.

variety of strategies including arranging transportation, making appointments, and providing verbal reminders to the participant. Two women similar in age to the average 2-1-1 caller were given extensive training by a counseling psychologist and a social worker who had previously worked as a navigator. Training consisted of mastering health content for the six focus areas, problem-solving techniques, counseling concepts and approaches, and research protocol and documentation. Many cycles of rehearsal and feedback preceded the launch of the intervention, after which navigator calls were recorded, monitored and discussed.

Participants received their first navigator call within one working day of completing the baseline assessment and receiving the verbal referral. The initial call introduced the navigator, explained the navigation relationship and sought to establish rapport. Then a flyer was mailed to the participant containing the name, picture and contact information for their navigator. The navigator re-contacted the participant soon after to ensure receipt of the flyer and follow up on any issues since their initial conversation. Telephone interactions continued for up to four months with the number, length and frequency of calls determined by participants' needs, interest and willingness. Either navigator or participant could initiate a call. On average, participants engaged in three calls with a navigator (M = 3.1, SD = 1.8), which lasted slightly longer than five minutes each (M = 16.2 min total, SD = 31.5).

3. Measures

3.1. Unmet basic needs

The baseline survey assessed participants' perceived likelihood that their safety, housing, food, and financial needs would be met in the next month. These items were adapted from Segal's (Segal et al., 1993) Personal Empowerment scale and another scale developed by Blazer (Blazer et al., 2005). Five questions beginning with: "How likely is it that…" included "…someone will threaten to hurt you physically in the next month?", "…you will have a place to stay all of next month?", "…you and others in your home will get enough to eat in the next month?", "…you will have enough money in the next month for necessities like food, shelter and clothing?", and "…you will have enough money in the next month to deal with unexpected expenses?" (1 = very unlikely to 4 = very likely). Participants were also asked to rate the safety of their neighborhood (1 = very unsafe to 4 = very safe) and the amount of space in their home given the number of people living there (1 = not enough living space, 2 = about the right amount, 3 = more than enough). From these items, we created seven dichotomous variables. If a need was very unlikely or unlikely to be met in the next month, it was considered unmet (0), otherwise it was considered met (Fiscella and Williams, 2004); living in an "unsafe" or "very unsafe" neighborhood and reporting "not enough living space" were also considered unmet (0) basic needs.

3.2. Contacting referrals

At 1 month follow-up, participants were asked if they remembered receiving a health referral (yes/no/don't remember). Those who remembered were asked if they had contacted any of the specific health referral(s) they received (yes/no/don't remember). Those who did not remember receiving a health referral were considered to have not contacted any referrals.

3.3. Covariates

Participants' gender, race/ethnicity, education, marital status, income, employment status and general health status were obtained at baseline (Table 1). For ease of LCA interpretation, many variables were dichotomized (e.g., self-rated health: very good/excellent vs good/fair/poor).

3.4. Reasons for calling 2-1-1

For each participant, up to 3 reasons for calling 2-1-1 were recorded. Reasons were collapsed into eight categories: utilities, rent/mortgage, housing, food assistance, employment, home and family, health, and other.

3.5. Data analyses

Analyses were conducted March–July 2015. Latent class analysis (LCA) is used to find groups of cases in multivariate categorical data (Lanza and Rhoades, 2013). We used a two-step approach for the analysis. First, we examined whether the sample was heterogeneous with regard to participant's basic needs using a LCA. The LCA was based on the seven dichotomous measures of unmet basic needs. PROC LCA in SAS v9.2 was used to estimate a series of latent class models from 2 to 4 classes to identify distinct subgroups of participants with different basic needs. Akaike Information Criterion (AIC) and the sample-size

Table 1
Participant characteristics; 2010–2012 Missouri 2-1-1.

Mean age (years; SD)	43.9 (13)
Gender (n = 1090)	%
Female	85.6
Race/ethnicity (n = 1085)	
African-American	59.2
White	30.1
Other	10.5
Income (n = 1054)	
< $10,000	47.1
Education (n = 1089)	
Less than high school	28.7
Employment (n = 1090)	
Employed	18.9
Marital status (n = 1089)	
Never married	38.8
Children in home (n = 1090)	
Child aged <18 years living in home	50.7
Health insurance (n = 1089)	
None	38.8
Public (Medicare or Medicaid)	36.6
Private	7.7
More than one type	13.4
Self-rated general health (n = 1088)	
Poor	18.2
Fair	31.8
Good	30.3
Very good	14.3
Excellent	5.4
Service request from 2-1-1 (n)[a]	
Bills (794)	72.8
Home and family (457)	42.1
Employment (95)	8.7
Health (97)	8.9
Housing (59)	5.4
Other (134)	12.3
Needed preventive health service (n)[b]	
Colonoscopy (406)	53.5
Mammogram (570)	65.8
HPV for self (119)	76.5
HPV for girl aged <18 years (232)	66.4
Pap test (932)	26.8
Smoking cessation (1090)	62.5
Smokefree home policy (1090)	54.4

Note: Values may not equal 100% due to missing data; "Don't know" and "Refused" responses were excluded from analysis. GED = General Educational Development test; HPV = human papilloma virus.

[a] Percent of total (N = 1090). Total percent is >100 because participants could have more than one service request.

[b] Percent is calculated as percent of eligible. Number eligible is in parentheses.

Table 2
Percent unmet basic needs in full study sample and by latent class; 2010–2012 Missouri 2-1-1.

Basic needs items	Full sample (n = 1081)	C1: Fewer needs (n = 292)	C2: Many needs (n = 228)	C3: Money needs (n = 561)
Unlikely to have enough money for unexpected expenses in the next month[a]	89.2	65.4	100.0	97.2
Unlikely to have enough money for necessities in the next month[a]	70.4	2.4	98.3	94.5
Not enough living space in my home	27.0	24.0	97.4	0
Neighborhood is unsafe from crime[b]	21.6	23.6	27.9	48.5
Unlikely to get enough to eat in the next month[a]	15.8	1.7	28.1	18.2
Unlikely to have a place to stay all of next month[a]	16.0	5.5	26.8	17.1
Likely to be threatened physically in the next month[c]	4.8	3.1	10.1	3.6

[a] Percent "unlikely" + "very unlikely".
[b] Percent "unsafe" + "very unsafe".
[c] Percent "very likely" + "somewhat likely".

adjusted Bayesian Information Criterion (BIC) were calculated. A lower AIC or BIC value suggests a better fitting and more parsimonious model. After determining the optimal number of latent classes based on both fit indices and the conceptual interpretability of each class solution, the following covariates were added to the LCA model: gender, income, race, age, education, employment status, having a child in the home, marital status (never married vs. ever married), and self-rated health. Non-significant covariates were removed from the final model. Similar to a multinomial regression model, the LCA regresses the probability of class membership on each covariate. Beta coefficient tests for predicting latent class membership by covariates and odds ratios and 95% confidence intervals were calculated.

Second, participants were classified into one of the subgroups resulting from the LCA and we examined descriptive statistics by class. For each latent class separately, chi-square analyses were used to examine the association between calling a referral and study group. Then we estimated a binary logistic regression model predicting the probability of calling any health referral by latent class assignment, intervention group (verbal referral only, verbal referral + tailored reminder, verbal referral + navigation), and the interaction between the two variables. Odds ratios (OR) and 95% confidence intervals (CI) of the interaction are reported.

4. Results

4.1. Participant characteristics

Participant characteristics did not significantly differ across the three intervention groups. Participant characteristics are shown in Table 1; most participants were women, African American or White, and reported very low income. Participants' mean age was 43.9 years. Most participants had called 2-1-1 seeking help with bills (73%) and/or home and family needs like food, clothing, and household goods (42%). Rates of unmet cancer prevention needs varied by the percent eligible for each service. Ten percent of the analysis sample had 4 or more needs, but only received three referrals, consistent with 211 procedures.

4.2. Identifying latent classes of unmet basic needs

Fit statistics for the 2 to 4 class models are shown in Supplement Table 1, which support a three class solution. The frequency of the seven binary basic needs is shown in Table 2 for each class. Compared to the other latent classes, Class 1 (C1) had relatively few unmet basic needs and comparatively greater financial security. Class 2 (C2) had relatively greater unmet needs. Class 3 (C3) had specific unmet needs for money.

4.3. Relationships between covariates and latent classes

The final LCA model included race, marital status, income, employment status, having a child in the home, and self-rated health. Odds ratios and 95% confidence intervals for covariates of latent class membership are shown in Table 3. Participants in latent class C1 were less likely to be white and earn less than $10,000/year, and were more likely to be employed, have a child in the home, and report better health compared with those in C3 (Table 3). Participants in latent class C2 were significantly more likely to have a child in the home compared with those in C3. Participants in latent class C2 were more likely to have never been married and earn less than $10,000/year, and less likely to be employed or in good health compared with C1 (Table 3).

4.4. Predicting health referral contacts by latent class and intervention group

Table 4 shows the results of the logistic regression analysis. Of the participants in C1, those who were assigned to receive the tailored or navigator intervention were more likely to contact a health referral than those who received a verbal referral only. The difference between the tailored and navigation interventions was not statistically significant (Table 4). Of the participants in C2 and C3, those assigned to receive the navigator intervention were more likely to contact a health referral than those who received a tailored reminder or verbal referral only (Table 4).

Table 3
Odds ratios for covariates for latent class membership and p-values of beta parameter tests; 2010–2012 Missouri 2-1-1.

	Latent class			
	(C1 vs C3)	(C2 vs C3)	(C2 vs C1)	p-Value[a]
White vs. African American/other	**0.45 (0.27–0.75)**	0.69 (0.39–1.25)	1.55 (0.83–2.90)	**0.0041**
Never married vs. ever married	0.74 (0.47–1.15)	1.42 (0.75–2.69)	**1.94 (1.11–3.38)**	**0.0261**
<$10,000 vs. ≥$10,000	**0.64 (0.42–0.98)**	1.06 (0.66–1.69)	**1.66 (1.04–2.64)**	**0.0480**
Employed vs. other	**1.77 (1.09–2.86)**	0.69 (0.35–1.34)	**0.39 (0.21–0.72)**	**0.0028**
Child in home vs. none	**2.29 (1.36–3.85)**	**4.16 (1.91–9.03)**	1.82 (0.77–4.27)	<**0.0001**
Self-rated health (Very good/excellent vs. good/fair/poor)	**1.90 (1.17–3.08)**	0.58 (0.29–1.17)	**0.31 (0.16–0.58)**	<**0.0001**

C1 = Fewer needs; C2 = Many needs; C3 = Money needs.
[a] p-Value from the significance test for the multinomial logistic regression coefficient predicting latent class membership.

Table 4
Contacted any cancer control referral at 1-month follow-up by latent classes of unmet basic needs assessed at baseline; 2010–2012 Missouri 2-1-1.

Latent classes of unmet basic needs	% contacted a referral					OR (95% CI)		
	All	Verbal referral	Tailored reminder	Navigator	χ^2 p-value	Tailored reminder vs. verbal referral	Navigator vs. verbal referral	Navigator vs. tailored reminder
C1 (n = 292; 26.8%)	22.3%	12.1%	25.2%	30.2%	0.0083	**2.45 (1.16–5.15)**	**3.14 (1.47–6.71)**	1.28 (0.68–2.42)
C2 (n = 228; 20.9%)	26.3%	18.8%	21.2%	39.2%	0.0088	1.16 (0.52–2.57)	**2.78 (1.30–5.95)**	**2.40 (1.19–5.95)**
C3 (n = 561; 51.5%)	23.7%	19.3%	20.7%	31.1%	0.0131	1.09 (0.66–1.82)	**1.89 (1.18–3.03)**	**1.73 (1.08–2.78)**

Note. The number of participants assigned to latent classes does not equal 100% due to missing data.
C1 = Fewer needs; C2 = Many needs; C3 = Money needs.

5. Discussion

We observed three distinct patterns of unmet basic needs within this low-income population. Common intervention approaches promoting preventive health services were differentially effective among participants with different patterns of unmet basic needs.

Our findings reinforce those of previous studies that have shown that unmet basic needs are heterogeneous in economically vulnerable populations (DeWilde, 2004; Mayer and Jencks, 1989; Roy and Raver, 2014). In our sample of nearly universally low-income adults, there was wide variability in the experience of unmet basic needs, especially in the areas of financial, housing, and food security. The use of latent class analysis is a strength of the study. In much of the research examining multiple indicators of poverty, investigators have created indices of disadvantage by summing the number of needs or harmful exposures a person experiences. While there is clear evidence that such cumulative disadvantage has harmful and dose-response effects on human health (Bauman et al., 2006; Lemelin et al., 2009; Johnson-Lawrence et al., 2015), a simple additive approach treats different types of needs as interchangeable. Latent class analysis provides additional information by identifying underlying subgroups that are mutually exclusive and differ qualitatively on the types and patterns of needs experienced (DeWilde, 2004; Moisio, 2004; Rose et al., 2009).

Our study extends previous work by demonstrating for the first time that the effectiveness of different interventions targeted to low SES populations can vary by basic-needs profiles. The relatively greater effectiveness of the navigator intervention among participants with the most unmet basic needs reinforces a foundational aim of navigation: To improve health outcomes by reducing barriers experienced by low-SES and minority individuals (Paskett et al., 2011). Although the navigation intervention tested in this study was not designed to address basic needs (Kreuter et al., 2012), the flexibility and client-centric orientation of this approach likely presents many opportunities for navigators to help in addressing basic needs (Jean-Pierre et al., 2011; Ferrante et al., 2011).

The relative ineffectiveness of the tailored intervention among those with multiple unmet basic needs may be due to the fact that these individuals are less likely to pay attention to the materials or even remember receiving them (Capelletti et al., 2015), perhaps because they are focused on more pressing problems, fear that the mailed reminder is a bill, or are living in temporary housing and do not receive mail regularly. For participants with fewer basic needs (C1), mailed tailored reminders were just as effective as a navigator in getting participants to contact a health referral. Given that navigator interventions are generally more intensive, time consuming, and costly (Jandorf et al., 2013), this finding has considerable practical implications.

Because intervention outcomes differ by participants' basic needs, finding new ways to quickly and accurately identify subgroups of economically vulnerable individuals could help in targeting health disparity-reducing strategies in the same way that personalized medicine is revolutionizing treatment protocols for many diseases (Chadwell, 2013). More research is needed to identify a minimal set of basic needs or other indicators of deprivation that can be efficiently and reliably measured and that predict a better (or lesser) response to different evidence-based, health promoting interventions. It may also be useful to determine whether the types of health needs vary by basic need profile, since some interventions may be more effective than others in stimulating responses to referrals for certain health behaviors and services (Kreuter et al., 2012).

A possible limitation of the study is the relatively small number of basic needs we measured. Our brief assessment included only 1 or 2 items each for housing, food, safety and financial needs. It's possible that additional indicators within these categories (e.g., housing quality) and/or additional categories (e.g., sleep) could alter or enrich the latent classes that emerged from our analyses. Recent studies have tested navigation-type interventions that address a similar set of basic needs as in our study, as well as other social needs like child care, education and job opportunities (Haas et al., 2004; Garg et al., 2015). Like our findings, they demonstrate success in improving health or other outcomes in part by linking individuals with existing community resources. It is not clear how such interventions would work in developing countries or low-resource contexts where such help may be less available. Future research should continue to explore a broader set of basic and social needs variables and the effects of hybrid health interventions that address them.

Because participants who were lost to follow-up between the baseline and 1-month assessment differed on several demographic variables, we repeated the latent class analysis with the baseline only sample. Results showed the same number and interpretation of latent classes as the 1-month sample (data not shown). The equivalence across samples suggest stability of the classes.

6. Conclusion

There is increasing recognition that unmet basic needs are strongly and independently associated with a range of negative health outcomes in vulnerable populations. Newer still are findings suggesting that although unmet basic needs can undermine certain prevention interventions (Capelletti et al., 2015), the likelihood of prevention interventions working increases when basic needs are addressed (Thompson et al., 2016). Findings from the current study advance our understanding by comparing effects of multiple interventions among subgroups of low-income adults with different sets of unmet basic needs. Scientific inquiry has only scratched the surface in this promising area of health disparities research and practice. If further research confirms and extends the findings reported here, the public health implications would be considerable, requiring fundamentally different intervention approaches.

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Conflict of interest

All authors have no conflicts of interest.

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