Application-Level and State-Level Predictors of SSI/SSDI Outcomes in a National Sample of Adults Experiencing Homelessness or at Risk of Homelessness

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The research reported herein was performed pursuant to a grant from Policy Research, Inc. as part of the U.S. Social Security Administration's (SSA's) Improving Disability Determination Process Small Grant Program. The opinions and conclusions expressed are solely those of the author(s) and do not represent the opinions or policy of Policy Research, Inc., SSA or any other agency of the Federal Government

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Acknowledgments

This study would not have been possible without the assistance of several colleagues. First, I would like to thank both Margaret Lassiter and Kristin Lupfer of the SOAR Technical Assistance Center for providing access to SOAR data, consultation during the data cleaning process, and feedback on interpreting study findings. You are both always so supportive, knowledgeable, and eager to provide assistance – thank you! Second, I would like to thank my mentors, Drs. Sarah Desmarais and Shevaun Neupert, for their patience, expert (especially, statistical!) guidance, and enthusiasm throughout this project. A project of this magnitude and significance would not have been possible without your support! Finally, I would like to thank my research assistant, Melissa Truelove, for her data gathering and coding expertise. Your timely and detail-oriented work was exceptional!

Abstract

Homelessness affects nearly one-sixth of the U.S. population over the course of a lifetime. Even greater numbers of U.S. adults are at risk for homelessness, including Veterans, justice-involved adults, and adults with mental illnesses. This broader at-risk population represents a heterogeneous pool of adults who comprise several subgroups, are vulnerable for similar reasons, and could benefit from financial and health care resources. A growing body of research suggests disability income, including Supplemental Security Income and Social Security Disability Insurance, may promote community integration in this broader population. However, adults at risk of homelessness experience difficulty accessing disability benefits. The SSI/SSDI Outreach, Access, and Recovery (SOAR) program was developed to improve disability application outcomes in this population. To date, however, few studies have investigated factors associated with successful disability application outcomes for SOAR-assisted applications or among homeless populations. To that end, this study investigated factors associated with the receipt of disability benefits and the efficient processing of disability applications in a national sample of 6,361 adult applicants applying for benefits through the SOAR model from 2006 to 2015. Multilevel modeling was used to explore application- and state-level predictors of application outcome (approved, not approved) and application processing time (days). Results identified several applicant characteristics associated with more successful applications, including male gender, older age, and living in an institutional setting. SOAR critical components, including collection and submission of medical records, preparation of a medical summary report, and a co-signed application, additionally predicted application success. In contrast, consultative exams predicted longer processing times and lower likelihood of application approval. Although state-level characteristics were not associated with application outcome or processing time, states with high SSI/SSDI award rates had more pronounced effects of application characteristics on application outcome and processing time. Findings suggest the need for research into why certain groups may be disadvantaged in the disability determination process and whether broader implementation of SOAR critical components could improve the efficiency of the disability determination process across all SSI/SSDI applications.

Introduction

Background and Study Context

In the United States, 14.0% of the population will experience homelessness over the course of a lifetime. Over 7% of the population will experience literal homelessness (e.g., sleeping outside, in a shelter, or at the home of a friend or family; Link et al., 1994). According to 2010 estimates, 1.6 million adults experience homeless in a given year (Paquette, 2010). Homeless status is associated with a variety of negative health outcomes, including higher rates of illnesses (Schanzer, Dominguez, Shrout, & Caton, 2007) such as vision impairments, skin problems, and tuberculosis (Gelberg, Andersen, & Leake, 2000). Homeless adults also experience higher rates of hospitalization (Martell et al., 1992). Most significantly, homeless adults have higher rates of mortality, with estimates ranging from 3.5 to four times those of the general population (Barrow, Herman, Córdova, & Struening, 1999; Hibbs et al., 1994).

Numerous factors have been shown to increase risk of homelessness in the adult population. These include low socioeconomic status, presence of mental health issues, substance use, low family functioning, and childhood and intimate partner abuse (Bassuk, Rubin, & Lauriat, 1986; Breakey et al., 1989; Browne & Bassuk, 1997; Shelton, Taylor, Bonner, & van den Bree, 2009). The prevalence of risk factors among homeless adults suggests even greater numbers of adults in the United States are at risk for homelessness. This broader at-risk population represents a heterogeneous pool of adults who are vulnerable for similar reasons.

Adults who are at increased risk of homelessness include Veterans, adults with mental illnesses, and justice-involved adults. For example, one national study of Veterans receiving VA benefits (N = 1,120,424) found that presence of severe mental illness was associated with an increased risk of homelessness among Veterans (Ellen L. Edens, Kasprow, Tsai, & Rosenheck, 2011). Additionally, mental illness alone is a significant risk factor for homelessness. A recent meta-analysis of 29 studies published between 1979 and 2005 with samples from Western countries found high prevalence rates of depression (11.4%), psychosis (12.7%), and substance use (37.9%) among homeless adults (Fazel, Khosla, Doll, & Geddes, 2008). Finally, in a sample of 6,462 adults incarcerated in United States jails, rates of homelessness were roughly 7.5 to 11.3 times greater than in the general U.S. population; furthermore, these rates were higher among adults with mental illness and substance use (Greenberg & Rosenheck, 2008).

Together, these subgroups compose a particularly high-risk and vulnerable population of adults who are at risk for homelessness, have overlapping needs, and could benefit from similar financial and health-related resources. Specifically, prior research has established needs for medical, mental health, dental, and eye care as well as access to prescription medication among homeless adults (Baggett, O'Connell, Singer, & Rigotti, 2010). Veterans, similarly, are in need of medical and mental health treatment services (Schell et al., 2011) as well as substance use counseling and support (Tessler, Rosenheck, & Gamache, 2005). Justice-involved adults with mental illnesses are in need of specialized and coordinated behavioral health services at the junction of criminal justice, health, and community systems (Lurigio & Swartz, 2000; Weisman, Lamberti, & Price, 2004).

Disability benefits, including Supplemental Security Income (SSI) and Social Security Disability Insurance (SSDI), provide one avenue of access to financial and health care resources among adults at risk for homelessness. Briefly, SSI and SSDI are two national income support programs administered by the Social Security Administration (SSA) that provide stipends to low-income, disabled adults. Disability benefits not only provide adults with income (e.g., Rosenheck, Dausey, Frisman, & Kasprow, 2000), but also facilitate access to health insurance. In 32 states and the District of Columbia, adults who receive SSI are also eligible for Medicaid, and in all states, adults who qualify for SSDI are Medicare-eligible 24 months after first receipt of benefits. A growing body of research suggests receipt of disability benefits may produce positive community integration outcomes. Specifically, receipt of disability income has been shown empirically to be associated with increased access to mental health treatment among adults with mental illnesses (Elinson, Houck, & Pincus, 2007), higher income and increased quality of life among veterans (Rosenheck et al., 2000) and lower rates of recidivism among justice-involved adults (Lowder, 2015).

SSI/SSDI Outreach, Access, and Recovery (SOAR)

The SSI/SSDI Outreach, Access, and Recovery Program (SOAR) is a national initiative funded by the Substance Abuse and Mental Health Services Administration (SAMHSA) and designed to increase disability application rates among adults experiencing homelessness by training case managers on the disability determination process. Since 2006, SOAR has been implemented in every U.S. state, over 50,000 applications for SSI and SSDI have been processed using the SOAR model, and an average of 65% of SOAR-assisted applications have been approved at initial application (SOAR Technical Assistance Center, 2016). Although originally designed for homeless populations, this program has expanded its scope in recent years to serve other populations at risk of homelessness, including justice-involved adult and Veterans (e.g., SAMHSA SOAR TA Center, 2014; Telford, 2013). In fact, as of 2015, over 20 states reported collaborations between SOAR providers and criminal justice agencies (SOAR Technical Assistance Center, 2016).

Part of the uniqueness of the SOAR model is the completion of several "critical components" as part of the application process. Specifically, SOAR case managers formally serve as the client's representative during the application process by completing a SSA-1696 Appointment of Representative form. Moreover, whereas medical records are traditionally collected by the SSA for SSI/SSDI applications, the SOAR case manager collects and submits medical records in addition to completing a medical summary report to synthesize a client's relevant medical and personal history. Case managers are also encouraged to acquire a signature from a psychiatrist or medical doctor on the medical summary report, thereby making it medical evidence in the disability determination process. Finally, applications may be pulled by a supervisor to conduct a quality review of the application before the application is submitted to SSA (Lassiter, 2015). Consequently, the national SOAR implementation provides a unique opportunity to explore factors influencing application outcomes among homeless adults and adults at-risk of homelessness, with particular attention to applicant characteristics, application components, and state-level factors that may predict better outcomes.

Statement of Problem

Prior research has established that homeless adults and adults at risk of homelessness face difficulty accessing disability benefits (Burt et al., 1999; Dennis, Lassiter, Connelly, & Lupfer, 2011). Yet, homeless adults identify receipt of income and employment assistance as critical needs to successful rehabilitation (Rowe, Styron, & David, 2015). However, research on disability outcomes is scarce, particularly within the past decade and particularly among adults who are homeless or at-risk of homelessness. Specifically, there has been no systematic

investigation of differences in application outcomes across subgroups, including, for example, adults experiencing literal homelessness versus those at risk of homelessness, adults in institutional (e.g., hospital, jail, etc.) settings, and adults with Veteran status. Additionally, no study has explored systematically how SOAR critical components impact the success of disability applications in this population. Furthermore, to my knowledge, prior research has not addressed how state-level factors (e.g., sociodemographic characteristics or structure of Disability Determination Services) impact application outcomes. Finally, we know little regarding how applicant- and application-related factors interact with state-level factors to attenuate or strengthen disability application outcomes.

The Proposed Study

To that end, the present study investigated the impact of applicant-level, application-level, and state-level factors on disability application outcomes in a national sample of adults experiencing homelessness or at-risk of homelessness who applied for disability benefits through the SOAR model. My specific research aims were to examine: **Aim 1**) The extent to which *characteristics of applicants* (e.g., currently homeless, Veteran status, etc.), characteristics of applications (e.g., submission of medical records, completion of quality review of application, etc.), and *state-level factors* (e.g., SSI/SSDI award rate, median household income, etc.) were associated with application outcomes; **Aim 2**) The extent to which *applicant*, *application*, and *state-level factors* interacted to influence application outcomes; and **Aim 3**) Which factors emerged as the most robust predictors of application outcomes after controlling for other significant variables.

Method

I conducted a secondary analysis of data collected by the SOAR Technical Assistance (TA) Center Online Application Tracking (OAT) system from 2006 to present (approximate N = 9,719) using Multi-Level Modeling, a state of the art statistical methodology for examining predictive relationships in nested data.

Sample

The original sample included 9,717 SSI or SSDI applications processed through SOAR in 39 states. However, application outcome data were available only for N = 6,361 applications, representing the final study sample. Applicants were an average age of 43.02 (SD = 12.39, Range: 18-96) and were predominantly male (64.0%, n = 4,059). The majority of applicants were literally homeless (58.1%, n = 3,698) versus at-risk of homelessness (41.9%, n = 2,663).

Procedure

Data sources. Data were requested from and provided by SOAR TA Center staff for all SSI/SSDI applications processed through SOAR and recorded on the SOAR OAT system. Application data included applicant characteristics (e.g., demographic information, housing status, etc.), application components (e.g., whether SOAR critical components were completed for the application), and application outcomes (e.g., whether an application was approved by SSA). State-level variables were collected from publicly available records on <u>www.disability-benefits-help.org</u>, <u>www.ssa.gov/policy/docs/statcomps/index.html</u>, and <u>www.census.gov</u>.

Data cleaning. The original dataset included 12,144 SOAR applications. Because SOAR OAT data were self-reported by case managers, I took additional steps to improve the accuracy of records in consultation with SOAR TA Center staff. First, applications submitted prior to 2006 were removed due to data discrepancies and incomplete records for early SOAR OAT data (n =

42). Second, data on SSI or SSDI reconsiderations after an initial application decision were removed from the dataset to simplify analyses and include only decisions resulting from an initial application. Third, cases where the applicant was under 18 (n = 134) were removed from the dataset to focus on only adult applicants. Fourth, two variables were computed measuring 1) time between protecting filing date and application date, and 2) time between application date and disposition date. Cases that had negative values on either variable, reflecting possible errors in data entry, were subsequently removed from analysis (n = 34 cases). Finally, consistent with study aims, applicants who were not listed as literally homeless or at-risk of homeless were excluded from analysis (n = 2,217). The data cleaning process resulted in a sample of 9,717 SOAR applicants, of which application outcome data were available for 6,361 applicants.

Variables

Level 1 (L1) predictors. Level 1 (i.e., L1) predictors included both applicant characteristics as well as application components. Applicant characteristics consisted of whether an applicant was living in a jail, hospital, or residential treatment setting (*Institutional*; 0 = No, 1 = Yes), Veteran status (*Veteran*; 0 = No, 1 = Yes), whether an applicant was receiving public assistance at the time of application (*Assistance*; 0 = No, 1 = Yes), homeless status (*Homeless*; 0 = At Risk, 1 = Literally Homeless), gender (*Gender*; 0 = Male, 1 = Female), and age (*Age*; continuous). *Age* was grand-mean centered to examine age-related effects relative to an "average" age of SOAR applicant.

Application components included whether medical records were collected and submitted with the application (*Medical Records*; 0 = No, 1 = Yes), whether a medical summary report was completed and submitted with the application (*Medical Summary Report*; 0 = No, 1 = Yes), whether the medical summary report was co-signed by a physician or psychiatrist (*Co-Signed*; 0 = No, 1 = Yes), whether a quality review of the application was conducted by a SOAR trainer or supervisor (*Quality Review*; 0 = No, 1 = Yes), and whether a consultative exam was ordered by Disability Determination Services (DDS) (*Consultative Exam*; 0 = No, 1 = Yes).

Level 2 (L2) predictors. Predictors explaining level 2 (i.e., L2) variance included state-level sociodemographic characteristics and disability factors. Sociodemographic characteristics of states included percentage of population identifying as Hispanic Latino (*Hispanic Latino*; continuous), percentage of population identifying as non-White (*non-White*; continuous), and median household income (*Median Income*; continuous). State-level disability factors included the average SSI/SSDI award rate (*Award Rate*; continuous), the number of SSI/SSDI applications processed in a state (*Applications Per Capita*; continuous), and whether a state had centralized or decentralized DDS (*Centralized/Decentralized*; continuous). All continuous L2 predictors were grand-mean centered to create meaningful intercepts and reduce the possibility of multicollinearity in interaction terms. Thus, effects generated by grand-mean centered predictors examined effects relative to an average level of that variable across states. Additionally, a linear transformation (i.e., each value was multiplied by 1,000) was conducted on *Applications Per Capita* to scale the variable consistent with other variables under analysis.

Dependent variables. Two dependent variables were used. *Processing time* (continuous) measured the time (in days) from the date of application to the date of decision. *Application outcome* measured whether or not the application was approved (0 = Denied, 1 = Approved).

Analyses

Prior to the main study analyses, multicollinearity between predictors was tested via bivariate Pearson correlations using a cutoff of .90 (Tabachnick & Fidell, 2013). The strongest correlation emerged between applications per capita and median household income (r [9,715] = .68, p < .001); however, because this value was below the threshold for possible multicollinearity, both variables were retained in subsequent analyses.

To address the central study aims, all subsequent analyses employed Multi-Level Modeling (MLM), a statistical technique for nested data (i.e., observations are nested within a larger grouping; Raudenbush & Bryk, 2002). In contrast to other statistical methods, MLM does not require equal sample sizes in each group and can be used even when there is missing data. These considerations make MLM an especially robust technique for analyzing large datasets with incomplete, nested data. In the present study, SOAR applications (Level 1; L1) were nested within states (Level 2; L2). Comparable to regression analyses, various Greek symbols are associated with coefficient values related to variables (e.g., the slope or intercept). The intercept, β_0 is defined as the expected score on the dependent variable for an applicant. The L1 slope, β_1 , is the expected association between a L1 predictor and the dependent variable for an applicant. The average score on the dependent variable for the sample when all other variables are at their mean levels is represented by γ_{00} . The average effect of a L1 predictor on the dependent variable is represented by γ_{10} (subsequent L1 variables are labeled γ_{20} , γ_{30} , etc.). The average effect of a L2 predictor on the dependent variable is represented by Y01 (subsequent L2 variables are labeled Y02, Y03, etc.) Cross-level interactions are noted by a gamma term and numbers corresponding to the L1 and L2 predictors (e.g., γ_{11} denotes an interaction term between the L1 predictor γ_{10} and the L2 predictor γ_{01}). In the present study, cross-level interactions tested whether between-applicant associations with dependent variables depended on state-level characteristics. Random effects, or the extent to which there is between-state variability in the slope of a L1 effect, are represented by τ_{11} . Residual L2 variability in the dependent variable is represented by τ_{00} and the residual L1 variability is represented by σ^2 .

In MLM, preliminary analyses are conducted to determine that sufficient variability in a dependent variable exists at both levels of analysis in order to justify further analyses (e.g., Nezlek, 2001; Raudenbush & Bryk, 2002). After sufficient variability is established at each level, bivariate and multivariate analyses may be conducted with predictors at each level of analysis. First, preliminary analyses were conducted using an unconditional null model to establish significant variability at L1 (between applications) and L2 (between states) for each dependent variable to justify further analyses (Nezlek, 2001; Raudenbush & Bryk, 2002).

Second, in the absence of relevant theory on relationships between study variables, a modelbuilding strategy was employed. To address Aim 1, bivariate MLM models were conducted between each individual predictor and dependent variable. In models testing L1 predictors with application processing time, the slope between the predictor and dependent variable was allowed to vary to test for random effects. To address Aim 2, cross-level interactions with individual L1 and L2 predictors were estimated based on variables showing significant associations with dependent variables (and for L1 variables, significant variability in the slope). To decompose interactions for interpretation, effects were probed four times: at each level of a dichotomous variable (i.e., 0 or 1) and at +/- 1SD above and below the mean of a continuous variable. If the latter specification did not yield significant slopes or contrasts, effects were probed at +/- ½ SD and then at +/- mean levels. For interactions on the continuous outcome, effects were estimated using the QuantPsy calculator (Preacher, Curran, & Bauer, 2006). Finally, to address Aim 3, six multivariate models were estimated with significant predictors from the bivariate and cross-level interaction analyses. These models included: Model 1) L1 predictors on application processing time; Model 2) L1 predictors on application outcome; Model 3) Cross-level interactions of applicant-related (L1) predictors with disability (L2) factors on application outcome; Model 4) Cross-level interactions of application-related (L1) predictors of application sof applicant-related (L1) predictors with disability (L2) factors on application sof application outcome; Model 5) Cross-level interactions of applicant-related (L1) predictors with disability (L2) factors on application sof application processing time; and Model 6) Cross-level interactions of application-related (L1) predictors with disability (L2) predictors on application sof application processing time; and Model 6) Cross-level interactions of application processing time; and Model 6) Cross-level interactions of application processing time; and Model 6) Cross-level interactions of application processing time; and Model 6) Cross-level interactions of application processing time; and Model 6) Cross-level interactions of application processing time.

Results

Descriptives

The average time to decision (i.e., processing time) for SOAR applications was 93.96 days (*SD* = 96.52, Range = 0 to 1,504). The approval rate for all initial applications was 70.4% (n = 4,464). Of participants who had valid data, 28.3% (n = 1,675) were receiving some type of public assistance at the time of application. Less than a quarter, 11.7%, of participants were living in an institutional setting (e.g., jail, hospital) at the time of application (n = 716). Similarly low numbers of participants (8.3%, n = 500) identified as Veteran status. With respect to application components, medical records were collected for 94.1% of applicants (n = 4733). Medical summary reports, however, were submitted for only 74.9% of applicants (n = 4733). Around half of applications had medical summary reports that were co-signed by a psychiatrist or physician (52.6%, n = 3323). Quality review was conducted for 70.3% of applications (n = 4440). Consultative exams were ordered for 29.3% of applications (n = 1685).

Unconditional Null Models

First, preliminary analyses were conducted to determine whether significant variability existed at L1 and L2 for both dependent variables to justify the MLM procedure. Results showed that 15.8% of the variability in processing time existed between states (at L2) and 84.2% of variability in processing time existed between applicants (at L1). Similarly, although percent variability explained at each level is not computed for dichotomous outcomes (Guo & Zhao, 2000; Raudenbush & Bryk, 2002), there was significant L1 ($\sigma^2 = 0.98$, SE = 0.02, p < .001) and L2 ($\tau_{00} = 0.87$, SE = 0.27, p < .001) variability in odds of application approval. Results for both outcomes provided sufficient justification to proceed with the subsequent MLM analyses.

Aim 1: Bivariate Analyses

Processing time. Bivariate analyses for L1 variables showed significant effects of gender on application processing time ($\gamma_{10} = 11.24$, SE = 4.56, p = .014). Specifically, female applicants had a generally longer processing time relative to male applicants, though there was significant variability around this slope ($\tau_{11} = 346.98$, SE = 158.88, p = .014), suggesting this trend was not consistent across states. Institutional status was also associated with processing time, with applicants living in institutional settings experiencing a shorter application processing time relative to applicants in non-institutional settings ($\gamma_{10} = -22.19$, SE = 7.03, p = .014). Applicants who were already receiving public assistance at the time of SOAR application experienced a longer application processing time relative to applicants not receiving public assistance ($\gamma_{10} = -22.19$, SE = 7.03, p = .014).

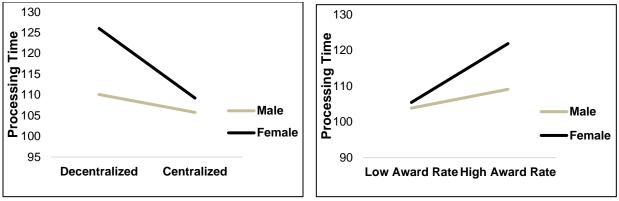
16.26, SE = 5.17, p = .002). Finally, applicants for whom a consultative exam was ordered experienced a significantly longer application processing time relative to applicants for whom a consultative exam was not ordered ($\gamma_{10} = 28.64$, SE = 10.41, p = .006); however, there was significantly between-state variability in this slope ($\tau_{11} = 2,905.74$, SE = 10.41, p = .006), suggesting this trend was not consistent across states. All other predictors showed no significant associations with processing time (ps > .05). For L2 analyses, no state-level variables were significantly associated with application processing time (all ps > .05).

Application outcome. Bivariate analyses for L1 variables showed a significant effect of age on odds of application approval, such that higher age was associated with greater odds of application approval (OR γ_{10} = 1.01, 95% CI [1.01, 1.01], p < .001). Gender additionally was associated with odds of application approval, with female participants having a lower odds of application approval relative to males (OR $\gamma_{10} = 0.73, 95\%$ CI [0.65, 0.82], p < .001). Institutional status positively predicted odds of application approval, with applicants living in institutional settings showing a greater odds of application approval relative to applicants living in non-institutional settings (OR γ_{10} = 1.98, 95% CI [1.59, 2.47], p < .001). Public assistance was negatively related to application approval. Applicants who were receiving public assistance at the time of application had a lower odds of application approval relative to applicants not receiving public assistance at the time of application (OR $\gamma_{10} = 0.75, 95\%$ CI [0.65, 0.86], $p < 10^{-10}$.001). Various application-related variables also demonstrated significant bivariate associations with application outcome. Specifically, receipt of medical records ($OR\gamma_{10} = 1.85, 95\%$ CI [1.44, 2.40], p < .001), completion of a medical summary report (OR $\gamma_{10} = 1.21, 95\%$ CI [1.05, 1.39], p= .009), and a co-signed application (OR γ_{10} = 1.37, 95% CI [1.20, 1.56], p < .001) were all significantly associated with greater odds of application approval. In contrast, applicants for whom a consultative exam was ordered had a lower odds of application approval relative to applicants for whom a consultative exam was not ordered, $OR\gamma_{10} = 0.43$, 95% CI [0.38, 0.49], p < .001. All other predictors showed no significant associations with application outcome (ps >.05). Additionally, at L2, no state-level predictors showed significant associations with application outcome (all ps > .05).

Aim 2: Cross-Level Interactions

Cross-level interactions were estimated using variables showing significant variability in the application processing time slope (i.e., *Gender* and *Consultative Exam*) and all significant predictors of application outcome. Because no L2 variables emerged as significant predictors of application processing time or application outcome in bivariate models, L2 variables relevant to the disability determination process were selected to estimate cross-level interactions. These variables included *Award Rate, Applications Per Capita*, and *Centralized/Decentralized*.

Processing time. With respect to application processing time, four significant interactions emerged. First, a significant gender by centralized/decentralized DDS emerged ($\gamma_{11} = -12.47$, *SE* = 4.99, *p* = .012). Post-hoc analysis of slopes and contrasts suggested that among states with a decentralized DDS, female applicants had a significantly longer processing time relative to males, *p* = .002 (see Figure 1). Second, a significant gender by award rate interaction emerged ($\gamma_{11} = 2.90$, *SE* = 1.33, *p* = .029), such that among states with high award rates, female applicants had a longer processing time relative to males (*p* < .001), see Figure 2.



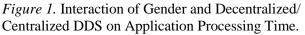
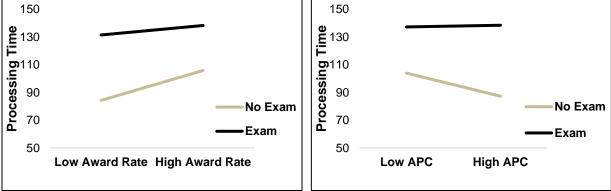
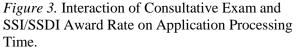
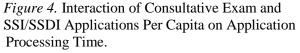


Figure 2. Interaction of Gender and SSI/SSDI Award Rate on Application Processing Time.

Third, a consultative exam by award rate interaction emerged ($\gamma_{11} = -3.81$, SE = 1.40, p = .006). Mainly, in states with low and high award rates, applicants for whom a consultative exam was ordered had significantly longer application processing times (ps < .001); however, this effect was more pronounced in states with low award rates (see Figure 3). Finally, results showed a significant consultative exam by applications per capita interaction ($\gamma_{11} = 2.47$, SE = 0.75, p < .001), such that in states with both high and low applications per capita, applicants for whom a consultative exam was ordered had significantly longer application processing times (ps < .001), but this effect was more pronounced in states with a high volume of applications (see Figure 4).







Application outcome. A total of seven significant cross-level interactions were observed between L1 predictors of age, institutional status, and consultative exam with L2 state-level disability factors. First, three age-related interaction effects were observed. Results showed a significant age by award rate interaction ($OR\gamma_{11} = 1.01, 95\%$ CI [1.00, 1.01], p < .001), such that in states with high award rates, applicant age was positively associated with higher odds of application approval, OR = 1.04, p < .001. Additionally, a significant age by centralized/decentralized DDS interaction emerged ($OR\gamma_{11} = 1.01, 95\%$ CI [1.00, 1.02], p =.045). Specifically, in states with centralized DDS, applicant age was positively associated with higher odds of application approval, OR = 1.01, p < .001. Finally, a significant age by applications per capita interaction was observed ($OR\gamma_{11} = 1.00, 95\%$ CI [1.00, 1.00], p < .001); however, due to the small effect, this interaction was not probed further. Second, two interactions were observed involving institutional status. Results showed a significant institutional by award rate interaction (OR $\gamma_{11} = 0.72, 95\%$ CI [0.64, 0.82], p < .001), such that in states with award rates both lower and higher than average, applicants living in institutional settings were more likely to have an application approved relative to applicants living in non-institutional settings, ORs = 1.35-1.39, $ps \le .048$. Furthermore, an interaction between institutional status and applications per capita was observed (OR $\gamma_{11} = 1.07, 95\%$ CI [1.00, 1.15], p = .042), such that in states with a high volume of applications per capita, applications living in non-institutional settings had significantly greater odds of application approval relative to applicants living in institutional settings, OR = 43.29, p = .034.

Third, two interactions involving consultative exam emerged. Results showed a significant consultative exam by award rate interaction ($OR\gamma_{11} = 1.13$, 95% CI [1.06, 1.21], p < .001), such that in states with both low and high award rate, applicants for whom a consultative exam was requested had a significantly lower odds of application approval, ORs = 0.24-0.37, ps < .001. Additionally, results showed a consultative exam by applications per capita interaction ($OR\gamma_{11} = 0.90$, 95% CI [0.87, 0.94], p < .001). Similar to the previous interaction, regardless of whether the state had low or high volume of applications per capita, applicants for whom a consultative exam was requested had significantly lower odds of application approval relative to applicants for whom a consultative exam was not ordered, but this effect was stronger in states with a low volume of applications (OR = 123.46) than a high volume (OR = 6.95), all $ps \le .010$.

Aim 3: Multivariate Models

Model 1. Full results for Model 1 are presented in Table 1. In this model, all L1 predictors showing significant bivariate associations with application processing time were included in the model. Results showed significant effects of receipt of public assistance (p < .001) and consultative exam (p < .001) on application processing time in addition to a trending effect of institutional status (p = .058), controlling for the L1 effect of gender. This model explained 31.7% of between-applicant variability in application processing time.

Model 2. Full results for Model 2 are presented in Table 2. In this model, all L1 predictors showing significant bivariate associations with application outcome were included. Results showed significant effects of gender (p < .001), age (p < .001), institutional status (p < .001), receipt of public assistance (p < .001), submission of medical records (p < .001), and consultative exam (p = .014) on application outcome, controlling for the effects of completion of a medical summary report and a co-signed application.

Model 3. Full results for Model 3 are presented in Table 3. This model tested all significant cross-level interactions involving applicant-related L1 predictors on application outcome. Multivariate results revealed three significant interactions. First, there was a significant institutional by award rate interaction such that in states with high application award rates, adults living in institutional settings were more likely to be approved for benefits relative to adults in non-institutional settings (OR = 1.40, p = .033). Second, there was a significant age by award rate interaction. In states with high award rates, each additional year of age was associated with 1.05 times greater odds of application approval (p = .042). Third, there was a significant centralized/decentralized DDS by age interaction. In states with centralized DDS, each additional year of age was associated with 1.01 times greater odds of application approval (p < .001).

Model 4. Results for Model 4 are presented in Table 4. This model included all significant cross-

level interactions involving application-related predictors on application outcome. Multivariate results showed two significant interactions: consultative exam by SSI/SSDI award rate and consultative exam by SSI/SSDI applications per capita. Specifically, in states with low award rates, applicants for whom a consultative exam was ordered had significantly lower odds of application approval (OR = 0.22, p < .001). Additionally, in states with both high and low applications per capita, applicants for whom a consultative exam was ordered had lowered odds of application approval, but this effect was more pronounced in states with a low volume of applications (OR range: 0.10-0.01, $ps \le .013$).

Model 5. Results for Model 5 are outlined in Table 5. This model included cross-level interactions involving applicant-related predictors on application processing time. However, no significant interaction effects were observed, controlling for L1 variables of institutional status, gender, public assistance and L2 variables of centralized/decentralized and award rate. L1 effects in this model accounted for 18.8% of between-applicant variability in application processing time. L2 effects accounted for 50.3% of between-state variability in application processing time.

Model 6. Results for the final multivariate model, Model 6, are presented in Table 6. This model involved all cross-level interactions including application-related predictors on application processing time. One significant interaction between consultative exam and applications per capita was observed, controlling for the other effects. Specifically, those who had a consultative exam ordered had significantly longer processing times across all states relative to those for whom a consultative exam was not ordered, but this effect was greater in states with a high volume of applications per capita (ps < .001). The traditional methods of accounting for variance explained by predictors resulted in negative variance explained at L2. As a result, I employed the Snjiders and Bosker (2011) method of calculating variance to generate plausible values. Results showed that L1 effects accounted for 3.9% of between-applicant variability in application processing time.

Discussion

Adults who are at risk of homelessness or experiencing literal homelessness are not only in need of enhanced services, but may face barriers to accessing needed services and benefits, including benefits administered through the SSI and SSDI programs. Although programs have been developed to increase application approval rates within this population (e.g., the SOAR model), few studies have examined factors predicting successful applications. To that end, this study examined application- and state-level factors associated with successful disability application outcomes (i.e., application approval and processing time) in a national sample of adults experiencing homelessness or at risk of homelessness who were applying for benefits via the SOAR model. Below, I summarize and discuss the study findings.

Summary of Findings

Aim 1. In Aim 1, I investigated the extent to which applicant characteristics, application components, and state-level factors were associated with or predicted application outcomes. First, several applicant characteristics emerged as predictors of application approval and processing time. Particularly, higher age was associated with higher odds of approval, a finding possibly reflecting that older adults are generally at greater need for income support and more likely to have a chronic medical condition that may qualify them for a disability. Indeed, this finding is consistent with research on differences between younger and older homeless adults,

where older homeless adults report greater access to income and also are more likely to selfidentify as having a disabling or chronic condition (i.e., illness or injury; Garibaldi, Conde-Martel, & O'Toole, 2005; Hecht & Coyle, 2001). This finding is also consistent with broader increases in social security disability income payrolls as a function of changes to the retirement age for social security beneficiaries, whereby older adults are increasingly more likely to receive disability income in lieu of social security (Duggan, Singleton, & Song, 2007).

Additional applicant characteristics found to be associated with application outcomes included gender, receipt of public assistance, and institutional status. Specifically, women had longer processing times and lower odds of application approval relative to men. These findings are perplexing since homeless women report similar levels of behavioral health conditions relative to men (Edens, Mares, & Rosenheck, 2011) and additionally have distinct needs. Older homeless women, in particular, are in need of income support and face unique barriers to rehabilitation, including family problems and abuse (Kisor & Kendal-Wilson, 2002). Although these findings do not speak to causes for poorer application outcomes among women, they suggest that homeless women may be especially disadvantaged by the disability determination process.

Adults receiving public assistance at the time of application were also found to have a much longer processing time and lower odds of application approval. Though these findings did not distinguish between type of public assistance, they are consistent with some existing literature on public benefits. For example, some recipients of state-funded Temporary Assistance for Needy Families (TANF) who cannot meet the work requirements of TANF due to a disability may not meet the high threshold for a persistent disability for social security disability programs. As a result, these individuals may be underserved by both public assistance programs (Nadal, Wamhoff, & Wiseman, 2003). Despite this, TANF recipients are increasingly incentivized to apply for SSI benefits (which constitute the majority of SOAR applications) because SSI benefits are not time-limited, do not carry a work requirement, and are typically larger in sum than those provided by TANF (Nadal et al., 2003). Currently, the SOAR model encourages prospective applicants to apply for benefits regardless of whether or not they currently receive public assistance (K. Lupfer, personal communication, April 29th, 2016). However, these findings suggest that public assistance recipients may be underserved by SSI and SSDI disability programs and in need of additional resources.

In contrast to female applicants and those receiving public assistance, applicants living in institutional settings had shorter processing times and higher odds of application approval. These findings add to growing evidence that justice-involved adults and other institutionalized populations may benefit from the SOAR model and may represent a particularly high-need population (Dennis, Ware, & Steadman, 2014; Lowder, 2015). Justice-involved adults, specifically, may face termination or suspension of existing benefits while incarcerated (Social Security Administration, 2015) and need support in re-establishing benefits upon exit. Indeed, the SOAR model has been increasingly implemented in collaboration with justice settings. For example, upwards of 20 states now report collaborations between SOAR providers and criminal justice agencies (SOAR Technical Assistance Center, 2016). However, these findings support the expansion of the SOAR model to assist institutionalized populations in applying for benefits.

Findings showed no effects of Veteran status or homeless status (i.e., literally homeless vs. atrisk) on application outcomes. However, these findings may be consistent with research showing similar level of needs among homeless adults and veterans (Baggett et al., 2010; Schell et al., 2011; Tessler et al., 2005). Additionally, these findings support the conceptualization of SOAR applicants as a heterogeneous group of individuals with similar levels of risks and needs. Although SOAR was originally designed to assist homeless adults in applying for disability benefits, findings support the expansion of this model into other populations that may be at-risk of homelessness, but not literally homeless.

Second, two main findings emerged from the investigation of application components on application outcomes. Mainly, results showed strong and consistent effects of select SOAR critical components on application approval. Specifically, collection and submission of medical records, preparation of a medical summary report, and a co-signed medical summary report were all associated with higher odds of application approval. These results are consistent with other findings demonstrating the importance of SOAR critical components on application outcomes (Lassiter, 2015). However, they call into question the importance of the quality review, which was the only critical component that did not yield significant effects on either outcome. Although SOAR is a program that has shown successful application outcomes relative to all SSI/SSDI applications (SOAR Technical Assistance Center, 2016), the fidelity of the SOAR model remains understudied. Whether all five critical components contribute to a greater likelihood of application approval is an important direction for future research. According to the present results, the gathering and submission of medical records, the submission of a medical summary report, and obtaining a physician signature on the application all play a key role in application success. Yet, in 30% of cases, the medical summary report is not completed and in almost 50% of cases the application is not co-signed. Importantly, practitioners play a key role in the fidelity of implementation of any new program or intervention (Fixsen, Blase, Naoom, & Wallace, 2009). However, no research to date has examined the role of SOAR case managers in the application process or investigated factors impacting the completion of SOAR critical components. These are critical avenues for future investigation.

Whether or not a consultative exam was ordered emerged as the most consistent predictor of poorer application outcomes, including longer processing time and lower odds of application approval. With respect to processing time, consultative exams are expected to require a longer processing time because the applicant must meet with a physician who collects additional medical evidence to evaluate the disability claim (Social Security Administration, 2016). With respect to application approval, consultative exams may reflect an overall lower quality application. Typically, request for a consultative exam indicates that the medical evidence provided in the initial application is insufficient for DDS to make a decision on the disability claim (Social Security Administration, 2016). In SOAR's context, this request may reflect a lack of adherence to SOAR critical components, unavailable medical records, or limited community resources for updated medical assessments (K. Lupfer, personal communication, April 29th, 2016). A post-hoc analysis suggested that although applicants for whom a consultative exam was ordered were actually more likely to have medical records submitted with the application (X^{2} [1] = 6.49, p = .011), they were less likely to have a medical summary report submitted with the application (X^2 [1] = 26.65, p < .001). This could reflect several scenarios. Medical records, although available, could have been inadequate to complete a medical summary report to establish comprehensive evidence of the disability. Alternatively, this could reflect failure of the case manager to complete the medical summary report even though records were available. Indeed, although records were collected for the vast majority (upwards of 95%) of applicants, the medical summary report was only completed in around 70% of applications. Lower application approval rates could also reflect underreporting of behavioral health conditions, specifically, by physicians seeing an applicant for a consultative exam. Although homeless adults have high

prevalence rates of behavioral health conditions (Fazel et al., 2008), providers supplying medical evidence may underreport behavioral health functioning relative to disability claimants (Marfeo et al., 2015). These effects may be more pronounced if the claimant is seeing a new provider who is unfamiliar with the claimant's medical history.

Third, no significant findings emerged supporting associations between state-level factors and application outcomes. Although preliminary analyses showed significant state-level variability in both application processing time and application outcome that could be explained by state-level predictors, no significant effects emerged. These findings suggest that other state-level factors, unmeasured in the present study, may be affecting application outcomes. Additionally, these results suggest that application-level variables, which explained more variability in application outcomes, may be more relevant to the disability determination process for SOAR applicants.

Aim 2. In Aim 2, I explored the extent to which applicant, application, and state-level factors interacted to influence application outcomes. Findings of these cross-level interactions showed three strong trends. First, in states with high SSI/SSDI award rates, female applicants had longer processing times, applicants of higher age had greater odds of approval, applicants in institutional settings had greater odds of approval, and applicants for whom a consultative exam was ordered had lower odds of approval. Although applicants living in institutional settings had higher odds of approval in states with generally high award rates, they had lower approval rates in states with a high volume of applications per capita. This trend likely reflects that application award rates were generally lower in states with a higher volume of applications, but also suggests that applicants living in institutional settings may fare better in the disability determination process in states with a lower volume of applications and higher award rates.

With respect to the structure of disability determination services, in states with centralized disability determination services, older adults had significantly better application outcomes. In states with decentralized disability determination services, female applicants had significantly longer processing times relative to males, suggesting that female applicants are most disadvantaged in these states. Adults for whom consultative exams were ordered had generally low approval rates and higher application processing times across all states; however, these effects were most pronounced in states with a higher volume of applications and lower award rates. No other state-level trends were observed from cross-level interactions, suggesting that application-level factors were more relevant for application outcomes.

Aim 3. Finally, in Aim 3, I explored which factors emerged as the most robust predictors of application outcomes after controlling for other significant predictors in multivariate models. Receipt of public assistance and consultative exam showed the strongest independent effects on application processing time, accounting for other significant predictors from bivariate models. Age, gender, institutional status, and receipt of public assistance all showed independent associations with likelihood of application approval after controlling for other application-level variables, suggesting these factors are both robust and unique contributors to likelihood of approval. After controlling for these application, submission of medical records and consultative exams emerged as the most robust application predictors of application outcome.

In multivariate models testing cross-level interactions, states with high award rates continued to show positive effects of higher age and institutional status on odds of application approval. Additionally, effects of consultative exams on odds of approval were strongest in low award

states and states with a low volume of applications per capita. Effects of consultative exams on processing times were strongest in states with a high volume of applications per capita. However, the effect of consultative exams on application outcomes was relatively consistent across all states and across all multivariate models, suggesting consultative exams have a particularly negative and strong effect on the disability determination process for SOAR applicants.

Implications

Disability determination process. These findings have three specific implications for the disability determination process. First, among adults who are homeless or at-risk of homelessness, there are specific groups who appear to be disadvantaged in the disability determination process. These groups include female applicants, applicants living in non-institutional settings, applicants receiving public assistance, and applicants for whom a consultative exam is ordered. Not only are these groups disadvantaged due to lower rates of application approval, they may also decrease the overall efficiency of the disability determination process as a result of longer application processing times. Whether or not these differences are systematic across a broader sample of SSI/SSDI applicants remains to be seen. However, these findings warrant additional inquiry given that these groups represent particularly vulnerable populations who are generally in need of enhanced services and face barriers to employment.

Second, specific aspects of the SOAR model appear to contribute to better application outcomes and may increase the efficiency of the disability determination process. In particular, submission of medical records, preparation of a medical summary report, and a co-signature result in higher odds of application approval and may contribute to the shorter time-to-decision for SOARassisted applications. These findings warrant consideration of whether SSI/SSDI applicants more broadly, or non-SOAR providers assisting with applications, could be incentivized to complete these components as part of the standard application. For example, applications with completed components could be routed for separate, more efficient processing, which would incentivize applicants to submit a more complete application in exchange for a shorter processing time.

Third, and finally, these findings draw attention to systematic differences in application outcomes between applicants of different ages, gender, and institutional status in high-award rates. However, important questions remain. Do these differences exist systematically across all SSI/SSDI applications? What factors may explain these trends? Do these findings suggest that these groups are treated unfairly in the disability determination process, or are there other factors, unmeasured in the present study, that account for these differences? These are important areas for further inquiry with a broader sample of SSI/SSDI applicants.

Advances research. This study advances research on disability outcomes in three critical ways. First, although several studies have examined outcomes following disability receipt (Elinson et al., 2007; Lowder, 2015; Rosenheck et al., 2000), less research has examined predictors of disability receipt among particularly vulnerable populations who have been historically disadvantaged in the disability determination process (Burt et al., 1999; Dennis et al., 2011, 2014). The national SOAR implementation provided an opportunity to address this gap in the literature by examining predictors of disability receipt among homeless adults or adults at risk of homelessness who completed SOAR-assisted applications. Second, this study applied a statistically rigorous analytic strategy to analyze data from a national program, which may serve as a useful model for similar evaluations. Third, and most importantly, this study identified multiple predictors of SSI/SSDI application outcomes, which suggest important directions for future research on whether these relationships are truly causal or whether factors unaccounted for in the present study influence these predictive relationships.

Limitations and Future Directions

Findings from the present study should be considered together with several limitations. Primarily, although this study used a national dataset of SOAR-assisted applications, application outcome data were not available for all applications and not all states reported application data via the SOAR OAT system. Moreover, findings from this study may not generalize to the entire population of SSI/SSDI applicants, given the generally higher approval rate and shorter processing time for all SOAR-assisted applications. Additionally, the sample size for L2 predictors was small (N = 39), which may have affected the ability to detect significant effects of L2 predictors on application outcomes. Finally, although this study identified predictors and correlates of application outcomes, it did not speak causally about why specific groups or specific application components would be associated with better or worse application outcomes.

Together with study limitations, findings suggest several directions for future research. First, a broader investigation of group differences in application outcomes would inform whether differences as a function of gender, age, institutional status, and receipt of public assistance persist among all SSI/SSDI applicants. Second, further investigation into the post-consultative exam disability determination process is needed to explain why these exams result in lower odds of application approval. Third, research into the essential elements of the SOAR model is warranted to establish the fidelity of the model. Findings of this study question the role of the quality review in the SOAR application process and highlight the need for research examining factors associated with the completion of SOAR components. Fourth, there is a need for exploration into whether elements of the SOAR model could be incorporated into the disability application process more generally to increase the efficient processing of applications and decrease the necessity of consultative exams. Fifth and finally, there is a need for exploration into whether state-level differences in application outcomes persist among all SSI/SSDI applicants. Between-group differences were particularly prominent in states with high award rates, which suggests the need for more systematic investigation into whether specific groups benefit more from living in a state with high award rates relative to other groups.

Conclusion

The purpose of this study was to explore predictors of SSI/SSDI application outcomes among adults at-risk of homelessness or experiencing homelessness and applying for benefits through the SOAR model. Findings suggested that specific groups may be disadvantaged in the disability determination process, including female applicants, those receiving public assistance, and younger applicants. Consultative exams emerged as the most robust predictor of poorer application outcomes, including lower likelihood of application approval and longer processing time. In contrast, SOAR critical components were largely associated with higher rates of application approval. Although state-level characteristics alone did not predict application outcomes, there were distinguishing features of states with especially high application award rates. These findings highlight the importance of further research into why certain groups may be disadvantaged in the disability determination process and whether broader implementation of SOAR critical components could improve the efficiency of the disability determination process for all SSI/SSDI applications.

References

- Baggett, T. P., O'Connell, J. J., Singer, D. E., & Rigotti, N. A. (2010). The unmet health care needs of homeless adults: A national study. *American Journal of Public Health*, 100(7), 1326–1333. http://doi.org/10.2105/AJPH.2009.180109
- Barrow, S. M., Herman, D. B., Córdova, P., & Struening, E. L. (1999). Mortality among homeless shelter residents in New York City. *American Journal of Public Health*, 89(4), 529–534.
- Bassuk, E. L., Rubin, L., & Lauriat, A. S. (1986). Characteristics of sheltered homeless families. *American Journal of Public Health*, 76(9), 1097–1101.
- Breakey, W. R., Fischer, P. J., Kramer, M., Nestadt, G., Romanoski, A. J., Ross, A., ... Stine, O. C. (1989). Health and mental health problems of homeless men and women in Baltimore. *JAMA*, 262(10), 1352–1357.
- Browne, A., & Bassuk, S. S. (1997). Intimate violence in the lives of homeless and poor housed women: Prevalence and patterns in an ethnically diverse sample. *American Journal of Orthopsychiatry*, 67(2), 261–278. http://doi.org/10.1037/h0080230
- Burt, M. R., Aron, L. Y., Douglas, T., Valente, J., Lee, E., & Iwen, B. (1999). *Homelessness: Programs and the people they serve*. Washington, DC: Urban Institute.
- Dennis, D., Lassiter, M., Connelly, W. H., & Lupfer, K. S. (2011). Helping adults who are homeless gain disability benefits: The SSI/SSDI Outreach, Access, and Recovery (SOAR) program. *Psychiatric Services*, 62(11), 1373–1376. http://doi.org/10.1176/appi.ps.62.11.1373
- Dennis, D., Ware, D., & Steadman, H. J. (2014). Best practices for increasing access to SSI and SSDI on exit from criminal justice settings. *Psychiatric Services*, 65(9), 1081–1083. http://doi.org/10.1176/appi.ps.201400120

- Duggan, M., Singleton, P., & Song, J. (2007). Aching to retire? The rise in the full retirement age and its impact on the social security disability rolls. *Journal of Public Economics*, 91(7–8), 1327–1350. http://doi.org/10.1016/j.jpubeco.2006.12.007
- Edens, E. L., Kasprow, W., Tsai, J., & Rosenheck, R. A. (2011). Association of substance use and VA service-connected disability benefits with risk of homelessness among veterans. *The American Journal on Addictions*, 20(5), 412–419. http://doi.org/10.1111/j.1521-0391.2011.00166.x
- Edens, E. L., Mares, A. S., & Rosenheck, R. A. (2011). Chronically homeless women report high rates of substance use problems equivalent to chronically homeless men. *Women's Health Issues*, 21(5), 383–389. http://doi.org/10.1016/j.whi.2011.03.004
- Elinson, L., Houck, P., & Pincus, H. A. (2007). Working, receiving disability benefits, and access to mental health care in individuals with bipolar disorder. *Bipolar Disorders*, 9(1–2), 158–165. http://doi.org/10.1111/j.1399-5618.2007.00431.x
- Fazel, S., Khosla, V., Doll, H., & Geddes, J. (2008). The prevalence of mental disorders among the homeless in Western countries: Systematic review and meta-regression analysis. *PLoS Med*, 5(12), e225. http://doi.org/10.1371/journal.pmed.0050225
- Fixsen, D. L., Blase, K. A., Naoom, S. F., & Wallace, F. (2009). Core implementation components. *Research on Social Work Practice*, 19(5), 531–540. http://doi.org/10.1177/1049731509335549
- Garibaldi, B., Conde-Martel, A., & O'Toole, T. P. (2005). Self-reported comorbidities, perceived needs, and sources for usual care for older and younger homeless adults. *Journal of General Internal Medicine*, 20(8), 726–730. http://doi.org/10.1111/j.1525-1497.2005.0142.x

- Gelberg, L., Andersen, R. M., & Leake, B. D. (2000). The Behavioral Model for Vulnerable
 Populations: application to medical care use and outcomes for homeless people. *Health Services Research*, 34(6), 1273–1302.
- Greenberg, G. A., & Rosenheck, R. A. (2008). Jail incarceration, homelessness, and mental health: A national study. *Psychiatric Services*, 59(2), 170–177. http://doi.org/10.1176/appi.ps.59.2.170
- Guo, G., & Zhao, H. (2000). Multilevel modeling for binary data. *Annual Review of Sociology*, 26(1), 441–462. http://doi.org/10.1146/annurev.soc.26.1.441
- Hecht, L., & Coyle, B. (2001). Elderly homeless: A comparison of older and younger adult emergency shelter seekers in Bakersfield, California. *The American Behavioral Scientist*, 45(1), 66–79.
- Hibbs, J. R., Benner, L., Klugman, L., Spencer, R., Macchia, I., Mellinger, A., & Fife, D. K.
 (1994). Mortality in a cohort of homeless adults in Philadelphia. *The New England Journal of Medicine*, *331*(5), 304–309. http://doi.org/10.1056/NEJM199408043310506
- Kisor, A. J., & Kendal-Wilson, L. (2002). Older homeless women: Reframing the stereotype of the bag lady. *Affilia*, 17(3), 354–370. http://doi.org/10.1177/0886109902173006
- Lassiter, M. (2015). SOAR critical components. Delmar, NY: SOAR Technical Assistance Center.
- Link, B. G., Susser, E., Stueve, A., Phelan, J., Moore, R. E., & Struening, E. (1994). Lifetime and five-year prevalence of homelessness in the United States. *American Journal of Public Health*, 84(12), 1907–1912. http://doi.org/10.2105/AJPH.84.12.1907
- Lowder, E. M. (2015). *The role of the SOAR model in successful community reintegration*. Report prepared for Policy Research, Inc.

- Lurigio, A. J., & Swartz, J. A. (2000). *Changing the contours of the criminal justice system to meet the needs of persons with serious mental illness*. Rockville, MD: National Institute of Justice.
- Marfeo, E. E., Eisen, S., Ni, P., Rasch, E. K., Rogers, E. S., & Jette, A. (2015). Do claimants over-report behavioral health dysfunction when filing for work disability benefits? *Work* (*Reading, Mass.*), 51(2), 187–194. http://doi.org/10.3233/WOR-141847
- Martell, J. V., Seitz, R. S., Harada, J. K., Kobayashi, J., Sasaki, V. K., & Wong, C. (1992).
 Hospitalization in an urban homeless population: the Honolulu Urban Homeless Project. *Annals of Internal Medicine*, *116*(4), 299–303.
- Nadal, M., Wamhoff, S., & Wiseman, M. (2003). Disability, welfare reform, and supplemental security income. *Social Security Bulletin*, 65(3).
- Nezlek, J. B. (2001). Multilevel random coefficient analyses of event- and interval-contingent data in social and personality psychology research. *Personality and Social Psychology Bulletin*, 27(7), 771–785. http://doi.org/10.1177/0146167201277001
- Paquette, K. (2010). Current statistics on the prevalence and characteristics of people experiencing homelessness in the United States. Rockville, MD: SAMHSA.
- Preacher, K. J., Curran, P. J., & Bauer, D. J. (2006). Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis. *Journal of Educational and Behavioral Statistics*, 31(4), 437–448. http://doi.org/10.3102/10769986031004437
- Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Newbury Park, CA: SAGE.

- Rosenheck, R. A., Dausey, D. J., Frisman, L., & Kasprow, W. (2000). Outcomes after initial receipt of social security benefits among homeless veterans with mental illness. *Psychiatric Services*, 51(12), 1549–1554. http://doi.org/10.1176/appi.ps.51.12.1549
- Rowe, M., Styron, T., & David, D. H. (2015). Mental health outreach to persons who are homeless: Implications for practice from a statewide study. *Community Mental Health Journal*, 52(1), 56–65. http://doi.org/10.1007/s10597-015-9963-4
- Schanzer, B., Dominguez, B., Shrout, P. E., & Caton, C. L. M. (2007). Homelessness, health status, and health care use. *American Journal of Public Health*, 97(3), 464–469. http://doi.org/10.2105/AJPH.2005.076190
- Schell, T. L., Tanielian, T., Farmer, C. M., Jaycox, L. H., Marshall, G. N., Schell, T. L., ...Wrenn, G. (2011). A needs assessment of New York State veterans. Santa Monica, CA:RAND Corporation.
- Shelton, K. H., Taylor, P. J., Bonner, A., & van den Bree, M. (2009). Risk factors for homelessness: Evidence from a population-based study. *Psychiatric Services*, 60(4), 465– 72.
- Snijders, T. A. B., & Bosker, R. J. (2011). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. SAGE.
- SOAR Technical Assistance Center. (2014). 2014 SOAR outcomes summary. Delmar, NY.
- SOAR Technical Assistance Center. (2016). 2015 national SOAR outcomes. Delmar, NY.
- Social Security Administration. (2015). *What prisoners need to know*. Baltimore, MD. Retrieved from https://www.ssa.gov/pubs/EN-05-10133.pdf

- Social Security Administration. (2016). Consultative examinations: A guide for health professionals. Retrieved May 12, 2016, from https://www.ssa.gov/disability/professionals/greenbook/ce-guidelines.htm
- Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics*. Boston: Pearson Education.
- Telford, R. P. (2013). Justice-involved adults with serious mental illness and the disability determination process. Report prepared for Policy Research, Inc.
- Tessler, R., Rosenheck, R., & Gamache, G. (2005). Declining access to alcohol and drug abuse services among veterans in the general population. *Military Medicine*, *170*(3), 234–238.
- Weisman, R. L., Lamberti, J. S., & Price, N. (2004). Integrating criminal justice, community healthcare, and support services for adults with severe mental disorders. *Psychiatric Quarterly*, 75(1), 71–85. http://doi.org/10.1023/B:PSAQ.0000007562.37428.52

Multivariate Model of Unstandardized Coefficients (and Standard Errors) for Level 1 Predictors on Application Processing Time

11 0		
Fixed Effects	<i>B</i> (SE)	р
Processing time, β_0		
Intercept, γ_{00}	84.63 (6.28)	<.001
Gender slope, β_1		
Intercept, γ_{10}	1.68 (2.17)	.438
Institutional slope, β_2		
Intercept, γ_{20}	-6.32 (3.34)	.058
Assistance slope, β_3		
Intercept, γ_{30}	10.58 (2.59)	<.001
Consultative slope, β_4		
Intercept, γ_{40}	41.18 (4.51)	<.001
Random Effects		
Between-state residual variability (τ_{00})	1,008.72 (349.61)	.002
Consultative exam slope (τ_{11})	295.67 (216.28)	.086
Between-applicant residual variability (σ^2)	5,286.34 (105.18)	<.001

Fixed Effects	<i>B</i> (SE)	OR	95% CI	р
Processing time, β_0				<u>^</u>
Intercept, γ_{00}	0.57 (0.22)	1.78	[1.14, 2.76]	.015
Gender slope, β_1				
Intercept, γ_{10}	-0.27 (0.07)	0.77	[0.67, 0.88]	<.001
Age slope, β_2				
Intercept, γ_{20}	0.01 (0.003)	1.01	[1.00, 1.02]	<.001
Institutional slope, β_3				
Intercept, γ_{30}	0.52 (0.13)	1.69	[1.32, 2.16]	<.001
Assistance slope, β_4				
Intercept, γ_{40}	-0.18 (0.08)	0.83	[0.72, 0.97]	.020
Medical records slope, β_5				
Intercept, γ_{50}	0.67 (0.17)	1.96	[1.41, 2.72]	<.001
Medical summary report slope, β_6				
Intercept, γ_{60}	-0.05 (0.10)	0.95	[0.78, 1.16]	.646
Co-signed slope, β ₇				
Intercept, γ ₇₀	0.15 (0.09)	1.16	[0.96, 1.40]	.112
Consultative exam slope, β_8				
Intercept, γ_{80}	-0.84 (0.07)	0.43	[0.37, 0.50]	<.001
Random Effects				
Between-state residual variability (τ_{00})	0.64 (0.22)			.002
Between-applicant residual variability (σ^2)	0.94 (0.02)			<.001

Multivariate Model of Unstandardized Coefficients (and Standard Errors) for Level 1 Predictors on Application Outcome

			/	
Fixed Effects	<i>B</i> (SE)	OR	95% CI	р
Application outcome, β_0				
Intercept, γ_{00}	0.40 (0.28)	1.50	[0.86, 2.62]	.163
Award rate, γ_{01}	0.04 (0.08)	1.04	[0.90, 1.20]	.613
Centralized/decentralized, γ_{02}	0.40 (0.36)	1.50	[0.74, 3.02]	.259
Applications per capita, γ_{03}	0.07 (0.05)	1.08	[0.98, 1.18]	.115
Age slope, β ₁				
Intercept, γ_{10}	<0.01 (<0.01)	1.00	[0.99, 1.01]	.569
Age by award rate, γ_{11}	0.01 (<0.01)	1.01	[1.00, 1.01]	<.001
Age by centralized/decentralized, γ_{12}	0.01 (<0.01)	1.01	[1.00, 1.02]	.041
Institutional slope, β_1				
Intercept, γ_{20}	0.72 (0.12)	2.05	[1.63, 2.58]	<.001
Institutional by award rate, γ_{21}	-0.30 (0.07)	0.74	[0.65, 0.85]	<.001
Institutional by applications per capita, γ_{23}	< 0.01 (0.04)	1.00	[0.93, 1.08]	.892
Random Effects				
Between-state residual variability (τ_{00})	0.78 (0.26)			.002
Between-applicant residual variability (σ^2)	0.97 (0.02)			<.001

Multivariate Model of Unstandardized Coefficients (and Standard Errors) Exploring Cross-Level Interactions on Application Outcome (Applicant-Level Predictors)

Multivariate Model of Unstandardized Coefficients (and Standard Errors) Exploring Cross-
Level Interactions on Application Outcome (Application-Level Predictors)

Fixed Effects	<i>B</i> (SE)	OR	95% CI	р
Application outcome, β_0				
Intercept, γ_{00}	1.18 (0.18)	3.25	[3.25, 2.30]	<.001
Award rate, γ_{01}	-0.0005 (0.08)	1.00	[0.86, 1.16]	.995
Applications per capita, γ_{02}	0.10 (0.05)	1.11	[1.01, 1.22]	.032
Consultative exam slope, β_1				
Intercept, γ_{10}	-0.99 (0.07)	0.37	[0.32, 0.43]	<.001
Consultative exam by award rate, γ_{11}	0.08 (0.04)	1.08	[1.00, 1.16]	.037
Consultative exam by applications per capita, γ_{12}	-0.09 (0.02)	0.91	[0.88, 0.95]	<.001
Random Effects				
Between-state residual variability (τ_{00})	0.83 (0.29)			.002
Between-applicant residual variability (σ^2)	0.96 (0.02)			<.001

Fixed Effects	<i>B</i> (SE)	р
Processing time, β_0		
Intercept, γ_{00}	96.51 (8.99)	<.001
Centralized/decentralized, γ_{01}	6.05 (11.11)	.590
Award rate, γ_{02}	0.25 (2.07)	.904
Gender slope, β_1		
Intercept, γ_{10}	6.60 (4.04)	.102
Gender by centralized/decentralized, γ_{11}	-5.42 (4.83)	.262
Gender by award rate, γ_{12}	0.95 (1.28)	.459
Institutional slope, β_2		
Intercept, γ_{20}	-16.46 (3.39)	<.001
Assistance slope, β_3		
Intercept, γ_{30}	11.84 (2.66)	<.001
Random Effects		
Between-state residual variability (τ_{00})	719.89 (225.79)	<.001
Between-applicant residual variability (σ^2)	6,288.53 (118.21)	<.001

Multivariate Model of Unstandardized Coefficients (and Standard Errors) Exploring Cross-Level Interactions on Application Processing Time (Applicant Predictors)

Fixed Effects	<i>B</i> (SE)	р
Processing time, β_0		
Intercept, γ_{00}	94.38 (8.22)	<.001
Award rate, γ_{01}	4.86 (3.53)	.177
Applications per capita, γ_{02}	-1.00 (2.17)	.648
Consultative exam slope, β_1		
Intercept, γ_{10}	42.01 (2.80)	<.001
Consultative exam by award rate, γ_{11}	-2.51 (1.49)	.091
Consultative exam by applications per capita, γ_{12}	2.02 (0.79)	.010
Random Effects		
Between-state residual variability (τ_{00})	1,975.03 (556.52)	<.001
Between-applicant residual variability (σ^2)	6,864.75 (129.67)	<.001

Multivariate Model of Unstandardized Coefficients (and Standard Errors) Exploring Cross-Level Interactions on Application Processing Time (Application Predictors)