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The Role of Screening, Brief Intervention, and Referral to Treatment in Reducing Criminal Behavior: A Person-centered and Ecological Approach

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THE ROLE OF SCREENING, BRIEF INTERVENTION, AND REFERRAL TO TREATMENT IN REDUCING CRIMINAL BEHAVIOR: A PERSON-CENTERED AND ECOLOGICAL APPROACH

by

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ABSTRACT

Substance abuse treatment programs are a promising approach to reducing criminal behavior. However, these programs are not equally effective for all participants. Research shows that individuals at high risk for criminal recidivism usually benefit from high-intensity treatment programs, while those at lower risk benefit more from low-intensity, community-based approaches. In addition, there is evidence that individuals at moderate risk for criminal recidivism can actually be harmed by high-intensity treatment programs, leading to higher than expected rates of recidivism. In addition to overall risk for recidivism, other factors such as drug of choice, substance abuse severity,

and psychological problems are known to co-occur in ways that are associated with different patterns of criminal behavior, and may influence how participants respond to treatment. Because of this high degree of co-occurrence of psychopathology (characterized by criminality, externalizing behaviors such as aggression and inattention, and internalizing problems such as depression and anxiety) with substance use, it is possible that low intensity interventions that are effective in reducing substance use among individuals at moderate substance abuse risk could also be effective in reducing criminal recidivism, at least for some subgroups. However, despite efforts in the criminal justice field to tailor interventions to levels of risk and characteristics of individuals that influence responsiveness to treatment, interactions between individual and program characteristics are rarely tested in evaluations of intervention programs, due in part to methodological challenges that arise when testing them using variable-based approaches. Some of these challenges can be overcome by using person-centered approaches, which allow for comparisons to be made across classes of individuals that differ on several variables simultaneously. Research on the ecological predictors of crime, such as neighborhood disadvantage and alcohol outlet density, has also been limited by a lack of attention to interactions. These neighborhood-level factors are strong predictors of criminal behavior, yet little is known about whether they affect treatment outcomes. The present study used person-centered and ecological approaches to explore whether a moderate risk sample of clients receiving treatment for alcohol and/or drug abuse demonstrated lower levels of criminal and other externalizing behavior following treatment, and if so, whether their

outcomes differed depending on individual and neighborhood-level characteristics.

INDEX WORDS: Responsivity, Substance abuse, Motivational Interviewing, Ecological, Alcohol outlets, Latent class analysis

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

Increased recognition of the link between drug use and crime (Bennett, Holloway, & Farrington, 2008) has highlighted the potential of substance abuse treatment as an effective crime prevention strategy (Prendergast, Podus, Chang, & Urada, 2002). Accumulating evidence shows that substance abuse treatment is associated with reductions in both drug use and recidivism (Holloway, Bennett, & Farrington, 2006), however criminal behavior is rarely considered in outcome evaluations of substance abuse treatment programs, despite its significance both to the user and society at large (Tiffany, Friedman, Greenfield, Hasin, & Jackson, 2012). Substance abuse treatment has also been extensively integrated into rehabilitation programs delivered in the criminal justice system (Werb et al., 2016). There is evidence that such intensive intervention can be ineffective or even harmful for clients that are at relatively low or moderate risk for recidivism (Lowenkamp & Latessa, 2004), and recent research suggests that this group of individuals is likely to benefit from low-intensity, voluntary approaches based in the community instead of correctional settings (Reich, Picard-Fritsche, Rempel, & Farley, 2016). However, there remains a need for research on how client characteristics affect treatment response across a wider range of client and program types (Van Voorhis, Spiropoulos, Ritchie, Seabrook, & Spruance, 2013). There is also a gap in understanding between criminological research that has established the neighborhood-level predictors of crime (Shaw & McKay, 1942; Pratt & Cullen, 2005), and research from rehabilitative interventions that has focused largely on individual-level predictors. Research is beginning to show that neighborhood-level factors affect substance abuse treatment and rehabilitation program outcomes (Wright, Pratt, Lowenkamp, & Latessa, 2012; Mulia & Karriker-Jaffe, 2012). The present study focuses on a sample of 535 ED patients identified as being at low to moderate risk for substance-related harms and provided with a brief intervention focused primarily on reducing substance use. Following recommendations from Tiffany et al. (2012), this study examines whether a brief intervention for substance use contributes to reductions in externalizing symptoms (such as aggression and impulsivity), property crime (such as property destruction), and drug-related crime (such as selling drugs or driving under the influence). These outcomes, in addition to having relevance to public safety, are statistically and causally related to drug use (Bennett et al., 2008; Bennett & Holloway, 2009; Krueger et al., 2002). Importantly, these outcomes are also related to problems with impulsivity, an important mediator of substance abuse treatment outcomes (Kadden & Litt, 2011). Therefore, this study has the potential to highlight a common pathway by which interventions may affect change in both substance abuse and criminal behavior. This study examined the role of individual and neighborhood-level characteristics in affecting client response to treatment.

In a review of 30 studies, Bennett et al. (2008) found that drug users were four times more likely than non-users to commit a range of offenses, such as shoplifting and burglary. Much of this crime appears to be driven by the need for money to purchase drugs: longitudinal studies have found that rates of income-generating offending increase during periods of intense drug use (Gottfredson, Kearley, & Bushway, 2008). Clients entering substance abuse treatment programs often report engaging in recent criminal behavior

(Hayhurst et al., 2013), and treatment completion has been consistently associated with reductions in both drug use and crime (Basu, Paltiel, & Pollack, 2008; Campbell, Deck, & Krupski, 2007; Prendergast et al., 2002). These reductions in offending are at least partially due to reductions in drug use following treatment (Gossop, Marsden, Stewart, & Rolfe, 2000). For example, McIntosh, Bloor, and Robertson (2007) conducted 4 interviews over 33 months with 1,033 drug treatment clients, finding that drug consumption independently accounted for a significant portion of the variance in acquisitive crime. This research highlights the potential for substance abuse treatment to influence offending by helping clients cut down on or abstain from problem substance use.

One promising intervention for substance-related criminal behavior is motivational interviewing (MI), a person-centered approach that combines relational and cognitive elements (Miller & Moyers, 2015; Romano & Peters, 2016). MI's relational elements include a focus on empathic listening and maintaining a positive therapeutic alliance with the client, and cognitive elements involve helping clients focus on the discrepancy between their desired and actual behaviors, helping to resolve ambivalence, and encouraging commitment to change (Miller & Rose, 2009). Research supports these elements as important mechanisms of change: in a meta analysis of 19 studies, Apodaca and Longabaugh (2009) found consistent evidence that clients' change talk, intention to change, and experience of discrepancy were associated with better outcomes, whereas MI-inconsistent behavior on the part of the therapist was associated with worse outcomes. Copeland, McNamara, Kelson, and Simpson (2015) reached similar conclusions in a meta analysis of 37 studies, finding that motivation and MI spirit (e.g., collaborative approach and focus on client autonomy) were the most promising mechanisms of change in MI. MI is widely used to improve motivation and engagement in correctional rehabilitation programs (Austin, Williams, & Kilgour, 2011; McMurran, 2009), suggesting it is responsive to the needs and goals of criminally-involved clients, who often perceive correctional rehabilitation programs as unresponsive to their goals and concerns (Sturgess, Woodhams, & Tonkin, 2015).

MI has also demonstrated effectiveness for reducing problem drinking (Lundahl, Kunz, Brownell, Tollefson, & Burke, 2010; Rubak, Sandbæk, Lauritzen, & Christensen, 2005), suggesting it could be effective for reducing alcohol-related offending. For example, Beadnell, Crisafulli, Stafford, Rosengren, and DiClemente (2015) randomized 12,267 clients previously arrested for driving under the influence to standard care or an MI-based program, and found the MI condition was associated with lower rearrest rates. However, Hettema, Steele, and Miller (2005) noted in a meta-analytic review of 72 clinical trials that MI's effects seem to vary considerably depending on the characteristics of the study population and outcome targeted by the intervention (Lundahl et al., 2010; Burke, Arkowitz, & Menchola, 2003). For example, Bazargan-Hejazi et al. (2005) evaluated a randomized controlled trial of an ED-based brief MI intervention for risky alcohol use, finding at 3-month follow-up that treated patients with moderate alcohol use severity had decreased their risky use, while those with high severity showed no reduction. This indicates that MI may be most appropriate for clients whose risk for recidivism is too low to be appropriate for long-term programs, but who nevertheless engage in drug-related offending.

Variations in the effectiveness of treatment across individual characteristics are common in rehabilitation settings as well, playing a central role in the Risk-Need-Responsivity (RNR) framework, a widely-implemented set of principles that guide most programs delivered in correctional settings (Andrews & Bonta, 2010). RNR emerged during a time when there was a widespread consensus among criminologists that "nothing works" to reduce offending (Martinson, 1979) and rehabilitation was, at best, coercive and counterproductive (Gottfredson, 1979). Many policymakers were eager to end programs they saw as "coddling offenders", and accordingly policy began to shift towards an increased emphasis on punishment and deterrance through the use of long sentences and harsher criminal sanctions (Cullen & Jonson, 2011). Skeptical of this pessimistic view of rehabilitation, Andrews (1995) advocated for what became known as the principle of "general responsivity", which entails using behavioral and social learning approaches to target the individual-level risk factors associated with offending. The general responsivity principle also holds that approaches such as labelling, deterrance, and unstructured psychodynamic therapy will be ineffective because they fail to target major risk factors for offending. Instead, programs adhering to RNR match program intensity to client risk for recidivism, generally by delivering long-term treatment to high-risk clients (Andrews, Zinger, et al., 1990; Bonta & Andrews, 2007). Clients at high risk for recidivism have greater reductions in recidivism from these high-intensity, long-term programs than they do from low-intensity, voluntary, community-based approaches (Lowenkamp & Latessa, 2004), while those at low or moderate risk for recidivism might be harmed by such intensive interventions (Andrews & Dowden, 2005). However, researchers are increasingly questioning whether the interaction between program intensity and client risk for recidivism adequately captures the dynamics of treatment response (Taxman & Caudy, 2015; Ward, 2015). While the principle of specific responsivity is meant to capture these dynamics by taking into account client heterogeneity across characteristics such as learning styles, anxiety, and intelligence (Gendreau, 1996), Polaschek (2012) that the specific responsivity principle is understudied. Partially as a result, programs tend to rely heavily on manualized, one-size-fits all treatment approaches that may not be suitable for all clients.

One largely unexplored possibility is that the factors affecting treatment response for drug-involved clients differ compared with those affecting clients without drug involvement. For example, Wooditch, Tang, and Taxman (2013) examined how changes in individual-level factors affected changes in criminal behavior over time among 251 probationers. Over a 12-month period, they found that probationers who reported reduced alcohol use, increased work performance, and increased non-criminal social connections had the greatest reductions in crime, whereas those who increased their time spent in recreational/leisure activities were more likely to report reductions in drug use. Meta-analytic evidence also suggests that RNR-based programs may not be adequately addressing the substance abuse needs of clients. Prendergast, Pearson, Podus, Hamilton, and Greenwell (2013) reviewed 232 studies and found that programs adhering to RNR principles had larger reductions in recidivism than non-adherent programs, but adherence was not associated with reductions in substance abuse. While the adoption of RNR as the main approach to rehabilitation has resulted in an overall increase in program effectiveness, the precise cognitive and behavioral changes that underlie desistance from crime remain poorly understood (Serin, Lloyd, Helmus, Derkzen, & Luong, 2013), raising the possibility of enhancing program effectiveness by more carefully analyzing how individual-level factors affect recidivism outcomes, especially among drug-involved clients.

Previous research shows that drug use severity, type of drug used, and co-occurring psychological problems are associated with patterns of offending and substance abuse treatment outcomes, suggesting that they may be important factors for substance abuse treatment clients (Adamson, Sellman, & Frampton, 2009; Brorson, Arnevik, Rand-Hendriksen, & Duckert, 2013; Bradizza, Stasiewicz, & Paas, 2006). Under the RNR framework, the specific responsivity principle guides programs to respond to these factors by altering program content to address these issues (Sechrest, 1987). However, researchers have noted that the specific responsivity principle has not been explored as thoroughly as the risk and need principles (Van Voorhis et al., 2013), with most RNR-oriented studies focusing on the match between program intensity and overall risk for recidivism (Taxman & Caudy, 2015). Identifying these specific responsivity factors requires examining their potential role as moderators of treatment effects. However, detecting these interaction effects is difficult because they magnify error (Farrell, Henry, & Bettencourt, 2013). Furthermore, the co-occurrence of drug use severity, criminal behavior, and internalizing/externalizing problems among substance abuse treatment clients means that specific subgroups may respond differently to treatment, but since the higher-order terms suffer magnified error with each additional added, they are often impractical to test in practice (Cohen, Cohen, West, & Aiken, 2013). These problems increased interest in using person-centered approaches to examine treatment effects across subgroups (Rothman, 2013). Person-centered approaches use classification methods to divide the treated sample into subgroups that reflect heterogeneity across multiple variables (McCutcheon, 1987), and have been used across a variety of investigative contexts, such as examining variations in patterns of substance abuse and criminal behavior in studies of high-risk violent offenders (DeLisi, Vaughn, Salas-Wright, & Jennings, 2015), classification of addicted individuals based on symptoms of craving and impulsivity (Albein-Urios, Pilatti, Lozano, Martínez-González, & Verdejo-García, 2014), and identifying patterns of comorbidity in polysubstance abuse/dependence in epidemiological samples (Agrawal, Lynskey, Madden, Bucholz, & Heath, 2007). This approach offers a flexible alternative to variable-based methods for identifying subgroups that may respond differently to treatment by allowing the comparison of treatment effects between classes that differ across multiple individual-level characteristics.

1.1 A person-centered approach to investigating the responsivity principle

The risk principle holds that rehabilitation programs should adjust their intensity in response to variations in client risk for recidivism (Andrews, Bonta, & Hoge, 1990). However, researchers have questioned whether this approach properly captures variability in client response to treatment, noting that reducing client factors to an overall risk score undermines the conceptual link between program content and the cognitive and behavioral changes that lead to subsequent reductions in recidivism (Taxman & Caudy, 2015). Refining the explanatory power of RNR for substance-involved clients may require more sensitive assessment of risk that accounts for variation in drug of choice, drug abuse severity, and co-occurring psychological problems (Looman & Abracen, 2013). However, most available research on the effects of substance abuse treatment on recidivism lacks such a level of specificity in describing the nature of risk (Holloway et al., 2006). This section will provide an overview of how these factors are related to crime and substance abuse treatment outcomes, and argue that a person-centered approach will enhance our understanding of the specific responsivity principle.

Research supports the idea that variations in the severity of clients' substance abuse problems influence their response to treatment. Factors associated with substance abuse severity that may impact the treatment process include symptoms of dependence, cravings, and a lack of social support. In a meta-analytic review of alcohol treatment outcome studies, Adamson et al. (2009) found that the severity of alcohol dependence was one of the strongest patient-level predictors of treatment outcome. For high-intensity rehabilitation programs, increased problem severity tends to be associated with better outcomes. For example, Van Voorhis and Salisbury (2013) analyzed outcomes from a cognitive-behavioral intervention for offending and found that clients assessed as substance dependent at baseline had lower recidivism rates than those without dependence. MI-based interventions, in contrast, are often found to be most effective for those with moderate problem severity. For example, in a randomized controlled trial of an ED-based MI program targeting alcohol use, Bazargan-Hejazi et al. (2005) found the intervention was most effective for clients at moderate alcohol use severity, but ineffective those with high severity. Still, research suggests MI is a promising approach for reducing alcohol-related offending. Walton et al. (2010) examined outcomes from a randomized controlled trial of an MI-based intervention targeting violence and alcohol use in adolescents, finding the treated group significantly reduced aggression and violence-related consequences at three month follow-up.

Reductions in substance-related offending following intervention may also differ for users of different drugs. Alcohol use has been consistently linked with violent offending (Ito, Miller, & Pollock, 1996), however meta-analytic reviews have not supported a direct link between illegal drug use and violence (Boles & Miotto, 2003; Kuhns & Clodfelter, 2009). In contrast with alcohol use, illegal drug use has been associated most strongly with acquisitive crime such as burglary and shoplifting (Felson & Staff, 2017), and evidence suggests that reductions in crime following substance abuse treatment can largely be attributed to reduced drug use (McIntosh et al., 2007). For example, Gossop et al. (2000) analyzed crime and drug use outcomes for 753 substance abuse treatment clients, finding that reductions in heroin use were strongly associated with reductions in acquisitive crime. Gottfredson et al. (2008) analyzed within-person change among 157 criminally-involved substance abuse treatment clients, finding that reductions in cocaine and heroin use were associated with reductions in property crime. Some evidence shows that MI-based approaches are effective for reducing drug use. In a randomized controlled trial of 780 ED patients reporting recent drug use, Blow et al. (2017) found patients randomized to receive a brief MI reported fewer days using drugs and fewer days using marijuana at 90-day follow-up, compared with the enhanced usual care condition. Darker et al. (2016) randomized four addiction treatment centers serving opiate-dependent clients on methadone maintenance to deliver either brief MI or treatment as usual, finding that there was a significantly lower substance abuse severity score for the MI group than for the treatment as usual group at 3-month follow-up. It is clear that while interventions targeting alcohol and drug use can reduce crime, program effects may differ depending on the type of drug used by participants, and the type of crime analyzed as the outcome.

Externalizing behavior encompasses maladaptive behavior that is outwardly-directed, such as aggression and stealing (Achenbach & Edelbrock, 1978, 1984), and may be an important specific responsivity factor. One indicator of externalizing problems is impulsivity, which is a risk factor for both drug use and antisocial behavior (Perry & Carroll, 2008; De Wit, 2009), and is also associated with poorer outcomes in substance abuse treatment (Brorson et al., 2013; Loree, Lundahl, & Ledgerwood, 2015; Stevens et al., 2014). Personality characteristics associated with impulsivity, such as boredom proneness and sensation-seeking, may put clients with high levels of externalizing behaviors at particular risk for poor outcomes due to difficulty in exerting and maintaining the self-control in the face of stressors and temptations. Externalizing problems are also implicated in the etiology of co-occurring of drug use/dependence and criminal behavior

(Krueger et al., 2002). Individuals with externalizing behaviors are likely to experience drug abuse and addiction (Kotov, Gamez, Schmidt, & Watson, 2010; Ruiz, Pincus, & Schinka, 2008), with those at the severe end of the externalizing spectrum engaging in polysubstance use and other risky behavior (DeLisi et al., 2015). Therefore, while it is clear that externalizing behaviors affect substance abuse treatment outcomes, the co-occurrence between externalizing behavior and drug abuse severity indicates that both variables are likely to play an important role in drug-related offending outcomes.

Internalizing problems refer to maladaptive thoughts and behavior that are inwardly-directed, and associated with the development of mood and anxiety disorders (Krueger & Markon, 2006; Watson, 2005). Internalizing problems are associated with alcohol use. For example, Boden and Fergusson (2011)‘s meta-analysis found that presence of an alcohol use disorder was associated with depression. Epidemiological research also shows high levels of co-occurrence between drug use and internalizing disorders (Lai, Cleary, Sitharthan, & Hunt, 2015), with one meta-analysis of substance abuse treatment studies finding patients with co-occurring internalizing disorders had poorer outcomes than those without co-occurrence (Najt, Fusar-Poli, & Brambilla, 2011). Some evidence indicates that internalizing disorders influence patterns of substance use in ways that impact response to treatment. For instance, Anker, Kushner, Thuras, Menk, and Unruh (2016) analyzed outcomes of 218 alcohol disorder treatment clients with a co-occurring anxiety disorder, finding that those who reported drinking to cope with negative emotions had superior outcomes when randomized to cognitive behavioral therapy, compared to a control group that received progressive muscle relaxation therapy. However, for those not reporting drinking to cope with anxiety, outcomes were similar across both treatment conditions. These results suggest that internalizing problems may influence treatment response, and may be associated with different patterns of drug use than externalizing problems.

Research on how patterns of criminal behavior, substance abuse problems, and mental disorders coincide has produced some evidence that these patterns could influence an individual's response to treatment beyond the effect of risk for recidivism. However, while examining moderators of treatment effectiveness can be a productive way to specify the conditions under which treatment is successful (Rothman & Salovey, 2007), several difficulties face researchers attempting to draw meaningful conclusions from variable-centered moderation analysis. First, testing multiple interaction terms results in Type I error rate inflation (Farrell et al., 2013). Second, significance tests for higher-order interaction terms suffer from reduced power due to the multiplication of error terms for each variable, resulting in Type II error inflation (Cohen et al., 2013). Because drug use, psychological problems, and criminal behavior do have complex interrelationships, these challenges present significant barriers to performing the analysis required to refine the specific responsivity construct.

In response to these challenges, some researchers have turned to finite mixture modeling (FMM) approaches. Instead of assuming a homogenous study population, FMM is based on the assumption that population is composed of one or more subpopulations known as classes which are assumed to represent unobserved population heterogeneity

(McLachlan & Peel, 2004). Studies using FMM to classify individuals according to patterns of substance abuse and criminal behavior often find classes representing complex patterns that would be difficult to capture using variable-based approaches. For example, Vaughn et al. (2011) classified 43,093 psychiatric patients, finding that 5% of the sample had severe patterns of antisocial behavior and drug use, 8% had high substance abuse with moderate antisocial behavior, and 21% had low substance abuse with high antisocial behavior. Other research has revealed polysubstance use to be a particularly strong indicator of severe criminal behavior, with DeLisi et al. (2015) finding that 10.65% of a sample of seriously violent offenders endorsed polysubstance use and more severe criminal behavior than those with limited substance abuse or those who primarily used alcohol and cannabis. FMM studies have also begun to find interesting dimensions of drug use and co-occurring internalizing symptoms. In an international epidemiological study, Morley, Lynskey, Moran, Borschmann, and Winstock (2015) found individuals with anxiety disorders were more likely than others to belong to a class using cannabis and prescription drugs. Similar to DeLisi et al. (2015), Morley et al. (2015) also found that those endorsing violent behavior were more likely to belong to an "all-drugs" class representing a broad spectrum of polydrug use.

These studies show the potential usefulness of the FMM approach when examining the interactions between multiple variables, and researchers are increasingly advocating the use of FMM in analyzing the effects of prevention and treatment programs across classes of participants that vary across multiple interrelated dimensions (Lanza & Rhoades, 2013).

However, another potential source of variation in treatment response is neighborhood context. Neighborhood-level social and economic factors such as concentrated disadvantage are strongly linked with crime concentration (Shaw & McKay, 1942; Sampson, Raudenbush, & Earls, 1997; Pratt & Cullen, 2005; Lipton et al., 2013), and have been associated with variations in substance abuse treatment engagement (Stahler, Mennis, Cotlar, & Baron, 2009), attrition (Jacobson, 2004), and racial disparities in alcohol treatment outcomes (Jacobson, Robinson, & Bluthenthal, 2007). Additionally, research indicates that individual-level factors may interact with neighborhood-level variables to influence risk for reoffending (Lynam et al., 2000; Zimmerman, 2010). While criminology has a long history of attending to these community-level factors and their role in shaping geographic concentrations of crime, researchers have largely ignored the potential for interactions across ecological levels (Kubrin & Stewart, 2006). Given the strong effects of neighborhood factors on individual offending behavior (Pratt & Cullen, 2005), incorporating an ecological perspective into analyses of specific responsivity may help build a more detailed and explanatory account of individual variation in response to treatment. The following section will provide an overview of research on neighborhood-level effects on crime and examine how neighborhood factors might interact with individual-level factors to affect client outcomes.

1.2 Interactions between individual and contextual-level factors

Neighborhood contextual factors have wide-ranging impacts on mental and physical health outcomes (Leventhal & Brooks-Gunn, 2000; Pickett & Pearl, 2001). Early criminologists observed that the rapidly urbanizing environments were in a constant state of flux, with high levels of poverty and residential instability resulting in the breakdown of social norms against offending (Shaw & McKay, 1942). Disadvantaged communities also lack stable social and governmental institutions such as schools, police, and churches, limiting the ability of community residents to collectively regain control over social norms and reduce crime (Sampson et al., 1997). Disadvantage is a robust predictor of crime (Pratt & Cullen, 2005), but a meta-analysis of 34 studies concluded that the support for neighborhood disadvantage as a predictor of substance abuse was inconclusive: results tended to vary by characteristics of the sample such as gender and racial composition (Karriker-Jaffe, 2011). However, some evidence indicates that neighborhood disadvantage may be associated with substance abuse treatment outcomes. Jacobson et al. (2007) examined 2 years of discharge records from all publicly-funded alcohol treatment facilities in Los Angeles County, finding that neighborhood disadvantage accounted for 32.3% of the variance in racial disparities in treatment completion rates between African-American and white patients. With regard to criminal behavior, some evidence indicates that the effect of disadvantage depends partially on individual characteristics. In a longitudinal study of 1,191 twelve and fifteen-year-olds, Zimmerman (2010) found that the risk for offending was highest for those with high impulsivity who also lived in high SES neighborhoods, while there was no effect of impulsivity on offending in low-SES neighborhoods. This suggests that clients discharged from treatment into disadvantaged neighborhoods will be at elevated risk for recidivism compared to those returning to higher-SES areas. Neighborhood crime has also been associated with poor health outcomes, which Ross and Mirowsky (2001) found was mediated by fear. Other neighborhood-level factors such as alcohol outlet density play a role in excessive alcohol consumption (Campbell et al., 2009), alcohol-related crashes (Treno, Johnson, Remer, & Gruenewald, 2007), and engagement in substance abuse treatment (Stahler et al., 2007). The ways in which individual and contextual factors interact to influence offending is not well understood (Wikström & Sampson, 2003), however some research indicates individuals with traits such as impulsivity have a greater vulnerability to neighborhood factors (Lynam et al., 2000; Zimmerman, 2010). This section will examine the effects of neighborhood-level factors on crime, substance abuse, and treatment outcomes, while also considering how these effects might differ depending on individual characteristics.

Research also supports neighborhood-level crime as a predictor of individual-level substance abuse and criminal behavior. In a study of 228 former drug users, Yang, German, Webster, and Latkin (2011) found violent victimization was a significant predictor of relapse at 2-year follow-up. Ousey, Wilcox, and Schreck (2015) analyzed data from 3,000 tenth-grade students, finding that youth who experienced violent victimization were at higher risk of offending than youth who were not victimized, and that this effect was particularly strong for violent offending. Some studies have found that the criminal justice response in high-crime neighborhoods to be associated with negative outcomes. For example, using data from parolees across nine years, Chamberlain and Wallace (2016) found that the concentration of parolees in neighborhoods was associated with an increase in individual-level risk for recidivism. Clear (2009) proposed that the “churn” of offenders being removed and then re-entering the community disrupts social networks and contributes to area-level offending. Neighborhood crime may also contribute to fear, social withdrawal, and victimization, which could increase relapse risk for substance-using clients. In a 4-year longitudinal study of the link between neighborhood crime and psychological distress, Astell-Burt, Feng, Kolt, and Jalaludin (2015) found that increases in distress were associated with increases in neighborhood crime, especially for women. These findings indicate that neighborhood-level crime is an important factor in individual crime and substance abuse treatment outcomes.

Alcohol outlet concentration has been linked with crime (White, Gainey, & Triplett, 2012), including violent assaults (Gruenewald, Freisthler, Remer, LaScala, & Treno, 2006), as well as alcohol-related outcomes such as binge drinking (Xuan et al., 2015), alcohol-related injury (Campbell et al., 2009), and automobile crashes (Treno et al., 2007). Clients receiving treatment for alcohol abuse who reside in neighborhoods with a high concentration of outlets may have a more difficult time cutting down their drinking than those in neighborhoods with fewer outlets. Stahler et al. (2007) analyzed GIS, medical, and treatment utilization data on 271 patients discharged from a hospital inpatient unit to various outpatient substance abuse treatment providers, finding that patients residing within close proximity to two or more alcohol outlets were less likely to make their first appointment. These findings suggest that the association between alcohol outlets and recidivism outcomes following treatment may be stronger for individuals whose offending is primarily alcohol-related.

Some evidence suggests that some individuals are more vulnerable to criminogenic contexts (Hicks, South, DiRago, Iacono, & McGue, 2009; Zimmerman, 2010). For example, Zimmerman, Botchkovar, Antonaccio, and Hughes (2015) found that the link between low self-control and criminal behavior was stronger for individuals in neighborhoods that were more accepting of crime, but neighborhood SES and opportunities for crime did not moderate the link between self-control and offending. Additionally, in a study of justice-involved adolescents, Ray, Thornton, Frick, Steinberg, and Cauffman (2016) found that neighborhood disorder moderated the link between impulse control and substance abuse, such that individuals with low self-control were more likely to have severe substance abuse problems if they resided in neighborhoods with low levels of social and physical disorder. Conceptualizing interrelated individual-level variables using classes may help uncover the nature of interactions across ecological levels that would be difficult to detect using a variable-focused approach. For example, an individual whose aggressive behavior is classified as alcohol-related may be at elevated risk for engaging in violence in a neighborhood with a high concentration of alcohol outlets, driven partially by the contribution of the outlets to risk of relapse. However, the same individual may also be at risk of victimization by those with more severe criminal behavior, who may gravitate towards alcohol outlets as a source of targets for crimes such as robbery or carjacking. In such a scenario, variable-centric approaches aimed at identifying an interaction between alcohol abuse severity and outlet density would suffer from reduced power due to the unmeasured heterogeneity across the alcohol-using population.

1.3 Current study

The RNR framework has yielded valuable insights into how treatment should be delivered for clients at high risk for recidivism, leading to improvements in program delivery and client outcomes. However, there are three major gaps in the framework. First, the specific responsivity principle is not well developed, making it difficult to predict how different groups of clients, such as those engaging in drug-related crime, will respond to different types of treatment. Second, much of the research supporting RNR is based on samples of individuals at high risk for recidivism participating in long-term, intensive treatment. As a result, there is little information on effective treatment approaches for moderate-risk clients. Finally, research on the neighborhood-level predictors of crime is not well integrated with research on rehabilitation programs, so little is known about the role of contextual factors in the treatment process. The present study addressed these limitations by incorporating person-centered and ecological analytic approaches to explore heterogeneity of client outcomes following a brief intervention for substance abuse delivered to ED patients with moderate substance abuse severity. Specifically, the following hypotheses were tested:

1. Study participants assigned to receive brief intervention will have lower externalizing symptoms and criminal acts 6 months after study intake than assessment-only participants.

2. Study participants are predicted to belong to two or more latent classes, which reflect person-level variation in externalizing/internalizing symptoms, substance abuse severity, participation in crime and violence, and type of drug used.

3. For treated study participants, externalizing behaviors and criminal acts will differ depending on latent class membership. Specifically, better outcomes following treatment are most likely for classes representing moderate substance abuse severity, and low to moderate levels of co-occurring psychological problems, reflecting previous meta-analytic evidence that MI is generally most effective for clients with moderate problem severity. Participants assigned to an alcohol-only class are predicted to have better outcomes than participants assigned to other classes, as evidence for the effects of MI on illegal drug use is weaker than for drinking.

4. Treated participants who reside in neighborhoods with high levels of criminogenic risk factors, including concentrated disadvantage, crime, and alcohol outlet density, are predicted to have worse outcomes than those in neighborhoods with lower levels.

5. Class membership and neighborhood-level criminogenic risk factors will interact to influence patient outcomes. Specifically, participants assigned to a class with moderate to high levels of alcohol use severity, and moderate to high externalizing

symptoms and criminal behavior will have worse outcomes if they reside in census tracts with a high alcohol outlet density.

2 METHOD

The current study uses data gathered through The Georgia Brief Assessment, Screening, Intervention, and Continuum of Care System (Georgia BASICS) project, which was funded by the Substance Abuse and Mental Health Services Administration (SAMHSA). The project was conducted from 2009-2013 in the emergency departments of two urban medical centers, Grady Health Systems (GHS) in Atlanta and Medical Center of Central Georgia (MCCG) in Macon. Both facilities are level 1 trauma centers whose patients are often uninsured, homeless, or unstably housed. Institutional Review Boards at Georgia State University (GSU), MCCG, Emory University and the GHS Research Oversight Committee approved the research protocol.

Triage nurses delivered a brief screening tool to patients entering the ED. The screening tool was designed to detect harmful alcohol use, illicit drug use, and/or prescription drug misuse. Patients reporting any past-year binge drinking episodes, and/or any illicit or prescription drug misuse were considered screen positive. Patients who were jailed, institutionalized, or unable to communicate (e.g. under sedation or severely injured) were excluded from participation. Patients who provided written consent to participate in the 6-month follow-up were enrolled.

2.1 Participants

The sample used in the present study was drawn from patients recruitedenrolled in the GHS site of the into the Georgia BASICS study. Substance abuse severity was determined using scores from the Alcohol, Smoking and Substance Involvement Screening Test (ASSIST; Humeniuk et al. (2008), WHO ASSIST Working Group (2002)), which was administered to all patients who screened positive for harmful alcohol/drug use. In the larger study, patients with scores below a threshold of 10 points on the ASSIST for alcohol or other drug use (see measures section for further description of the ASSIST instrument), were regarded as being at relatively low risk and were not followed up. All patients scoring above that threshold were offered a brief intervention. In order to ensure a moderate risk sample for the current study, patients with an ASSIST score indicating high risk (such patients were offered more intensive services including multiple therapy sessions, detoxification, or residential treatment as needed) were excluded. BI-eligible patients from GHS (N= 599) were selected for inclusion. Macon patients were excluded because their location data was less reliable. Of the original 599 cases, 64 were removed due to missing location data. This resulted in a total sample of N = 535.

Intervention group. To obtain a random sample, only eligible patients with 30-39 as the last two digits of their Social Security number were approached for participation in the intervention phase of the study. Intervention patients received a Brief Intervention (BI), which is a 10-15 minute MI-based session delivered in the ED by a Health Education Specialist (HES; N = 283).

Comparison group. Before the initiation of SBIRT services, from February through April 2009, a comparison group provided written consent to participate in the follow-up. Comparisons were administered the ASSIST and other measures described below. These data were collected by HEs before they received MI training, and they provided comparisons that would be eligible for treatment a list of local substance abuse treatment resources (N = 252).

Follow-up. Six months after enrollment, study participants were administered a survey by telephone. This survey contained all measures that were assessed at baseline. Follow-up completion rates were maximized using periodic telephone check-ins, mailings, monetary incentives, and intensive tracking strategies (Gilmore & Kuperminc, 2014). Participants received $20 for completing the follow-up survey.

2.2 Measures

Treatment assignment. Treatment assignment was represented with a single dichotomous variable (1 = assigned to intervention group, 0 = assigned to comparison group).

Demographic control variables. Participants were asked their age, gender, race, and employment status. Age (in years) was measured as a continuous variable. A dichotomous indicator for race differentiated Black or African American patients (1) from patients of other races (0). Gender was coded dichotomously (1 = male, 0 = female). Employment status was coded dichotomously (full or part-time employment = 1; unemployed for any reason = 0).

Externalizing symptoms. Externalizing symptoms were assessed with items from the Externalizing Disorder Screener (EDScr), a five-item subscale of the GAIN Short

Screener (Dennis, Chan, & Funk, 2006). Previous research has shown the EDScr has good internal consistency (Cronbach's $\alpha = .76$), a high correlation with the Behavioral Complexity Scale from the full GAIN ($r = .88$; Dennis et al. (2006)) and loads on a single factor (Stucky, Edelen, & Ramchand, 2014). Questions measure symptoms of inattentive disorders, hyperactive/impulsivity disorders, and antisocial behavior occurring in the past 12 months. For each question, a response of "yes" was coded as 1, "no" was coded as zero, and the items were summed to create a count variable representing number of Externalizing symptoms (range: $0 - 5$; Cronbach's $\alpha = .66$).

Internalizing symptoms. Internalizing symptoms were assessed with items from the Internalizing Disorder Screener (IDScr), a five-item subscale of the GAIN Short Screener (Dennis et al., 2006). Previous research has shown the IDScr has good internal consistency (Cronbach's $\alpha = .74$), and is highly correlated with the Internal Mental Distress Scale from the GAIN ($r = .89$; Dennis et al. (2006)). Questions measure symptoms of somatic problems, depression, and anxiety/fear occurring in the past 12 months. For each question, a response of "yes" was coded as 1, "no" was coded as zero, and the items were summed to create a count variable representing number of internalizing symptoms (range: $0 - 5$; Cronbach's $\alpha = .76$).

Crime/violence involvement. Crime/violence involvement was assessed with the Crime/Violence Screener (CVScr), a five-item subscale of the GAIN Short Screener (Dennis et al., 2006). Previous research has shown the CVScr has good internal consistency (Cronbach's $\alpha = .72$), and a high correlation with the Crime and Violence Scale from the

GAIN ($r = .86$; Dennis et al. (2006)). Questions measure involvement in various illegal activity and violence, such as stealing, driving under the influence, and property destruction. For each question, a response of "yes" was coded as 1, "no" was coded as zero, and the items were summed to create a count variable representing number of symptoms (range: $0 - 5$; Cronbach's $\alpha = .57$).

Substance abuse severity. Substance abuse severity was assessed using the ASSIST version 2.0 (WHO ASSIST Working Group, 2002). The ASSIST contains seven questions each about ten substances: alcohol, cannabis, cocaine, tobacco, sedatives, hallucinogens, amphetamine-type stimulants, opiates, and an "other" category. Questions assess dimensions of substance use severity such as frequency of use, cravings, relationship problems, occupational consequences, and difficulty abstaining. Possible responses to each include: never, once or twice, monthly, weekly, and daily or almost daily. A validation study found high correlations between the ASSIST and other measures of substance abuse severity such as the Mini International Neuropsychiatric Interview (Sheehan et al. (1998), $r= .76$, $p< .01$) and measures of alcohol use severity such as the Alcohol Use Disorders Identification Test (Saunders, Aasland, Babor, De la Fuente, and Grant (1993), Humeniuk et al. (2008);$r= .82$, $p< .01$). A response of never is scored 0, and affirmative responses are given weighted scores ranging from 3 to 8 points. Substance-specific involvement (SSI) scores were calculated separately for alcohol, cannabis, and cocaine, which were then coded into three continuous variables (range $0 - 39$).

Neighborhood disadvantage. Neighborhood disadvantage was assessed using four variables from the 2010 Census of Population and Housing (U.S. Census Bureau, 2010): percent of female-headed households, percent of families receiving public assistance, the male unemployment rate, and the percent living below the poverty line. Previous research has shown that these variables load on a single factor (Sampson et al., 1997). Each variable was converted to sample-based Z scores, which were then summed to create a single variable representing neighborhood disadvantage.

Neighborhood crime. Neighborhood-level crime was assessed using the 2013 release of the CrimeRisk dataset (Applied Geographic Solutions, 2016). The CrimeRisk dataset contains estimates at the block-group level and higher for rates of personal crime (including murder, rape, robbery, and assault) and property crime (burglary, larceny, and motor vehicle theft). Based on FBI Uniform Crime Report (UCR) data, the CrimeRisk dataset was created to correct for a number of problems with the UCR data, including data entry errors, jurisdictional overlaps, and missing data. Missing data were handled using a model-based approach based on detailed jurisdictional data from 1990-1996, UCR data from 2005-2010, and 65 socioeconomic variables derived from the U.S. Census and American Community Survey. Individual crimes were grouped into personal and property crime, resulting in two continuous variables measuring the estimated number of neighborhood-level crimes per 100,000 residents.

Alcohol outlet density. Alcohol outlet density was measured using data from the Georgia Tax Center, which maintains a publicly-available database of alcohol outlets in the state (Georgia Department of Revenue, 2011). Address-level data from this database was geocoded to generate a set of geographic coordinates corresponding to each outlet. These coordinates were then plotted to a Census tract basemap. Alcohol outlet density was calculated at the tract level by computing the number of outlets per square mile. On and off-premises outlet density were computed separately, resulting in two continuous variables for the analysis (on-premises and off-premises alcohol outlets/square mile).

2.3 Plan of analysis

Analysis began with an examination of the data to assess each study variable for irregularities, such as non-normality, skew, outliers, and missing data. Normality and skew were assessed using histograms, and outliers were detected using scatterplots. Missing data were tested to determine whether the data are missing completely at random using Little's MCAR test (Little, 1988). Multiple imputation was performed in Mplus version 6.1 (Muthén & Muthén, 2010) to generate 50 data sets with ML estimates for the missing observations, using a model that included all variables to be used in subsequent analysis as dependent variables. Average results for analysis across the 50 sets are reported.

Fitting the classification model. Participants were classified based on their total substance abuse severity scores for alcohol, cannabis, and cocaine, and the sum of their responses to each of the GAIN-SS subscales (Externalizing, Internalizing, and Crime/Violence). These variables were regressed on the latent categorical variable representing class membership, beginning with a one-class solution and proceeding until the addition of classes failed to significantly improve model fit, as assessed by the bootstrapped likelihood ratio test, AIC, and BIC (McLachlan & Peel, 2004). Higher values of the log-likelihood and lower values of AIC and BIC indicated better fit (Celeux & Soromenho, 1996). Once the best-fitting classification model was chosen, the posterior probabilities of membership in each latent class were used to assign participants to the class for which they had the highest probability of membership. Class membership was then included in further analysis using a series of dummy-coded variables equal to the number of classes minus one (e.g., 1 = membership in Class A, 0 = not a member).

Propensity score matching. Because of the quasi-experimental nature of the participant assignment process, it was considered likely that the intervention and comparison groups would have significantly different baseline characteristics. Differences in variable means between treatment groups were assessed using dependent samples t-tests. Balance across all covariates was indicated by non-significance of these t-tests. Covariates where a significant difference was detected were included in a propensity score model, a logistic regression of treatment assignment on the unbalanced covariates. Based on the propensity score, a weight was computed in the R environment (R Core Development Team, 2013). The weight represented the inverse probability of assignment to treatment and was calculated as follows: $\frac{Z}{e} + \frac{1-Z}{1-e}$, where Z denotes intervention status (1 = BI, 0 = comparison) and e denotes the estimated propensity score.

Fitting the individual-level models. After weighting, two linear regression models were used to test for a significant main effect of treatment assignment on time 2 externalizing symptoms and time 2 crime/violence participation. Each model controlled for the time 1 predictor corresponding to the DV being tested, dummy-coded variables representing class membership, and other individual-level characteristics such as age, race, and gender. Next, the interaction of treatment assignment by class membership was tested by including product terms, one at a time, for each class variable. Significance of the interaction term indicated whether the effect of treatment assignment varied depending on class membership. Significant interaction terms were probed by estimating the main effect of treatment assignment controlling for its interaction with the reverse-coded class membership variable. This revealed differences in the size, direction, and/or significance of the treatment effect for class members compared with non-members. Once all interaction terms were tested, those that reached significance were incorporated into the final individual-level models.

Fitting the neighborhood-level models. Neighborhood-level predictors were modeled using multilevel linear regression, with individuals nested within census tracts. The main effect models regressed time 2 criminal behavior and externalizing symptoms on each level-2 IV, controlling for class membership, treatment assignment, and any class by treatment assignment interaction terms that were significant in the level-1 models. The cross-level interaction models added the product terms for each level-2 and latent class membership variable, with significant interactions probed following the same procedure as the individual-level models.

3 RESULTS

Excluded cases had a lower proportion of intervention participants than retained cases ($\chi^2(1) = 28.33, p < .05$), a higher employment rate ($\chi^2(1) = 9.04$, $p < .05$), and a lower proportion of Black participants $\chi^2(1) = 117.38$, $p < .05$). Excluded cases also had higher average levels of internalizing ($t(828.94) = 4.07$, $p < .05$) and externalizing symptoms ($t(852.12) = 3.13$, $p < .05$), but did not differ significantly from retained cases on crime/violence involvement, gender or age composition.

Attrition analysis was conducted by regressing followup status on each study variable. Participants who were reached for followup were older ($B = 0.03$, SE$= 0.01$, OR$= 1.03$, $p < .05$), had lower scores on the GAIN CrimeViolence scale ($B = -0.39$, SE$= 0.14$, OR$= 0.68$, $p < .05$), and were more likely to be in the intervention group ($B = 1.76$, SE$= 0.21$, OR$= 5.83$, $p < .05$) than cases that were lost to follow-up. To improve estimates of missing data, these variables were included in an unrestricted imputation model to generate 50 multiply imputed datasets in Mplus (Muthén & Muthén, 2010).

3.1 LCA

Latent class models ranging from two to six classes were fit to the imputed data. Models were screened based on overall fit statistics (-2LL, AIC, and BIC) and Entropy, to eliminate poorly performing models (see Figures 3.1 - 3.4). As expected, overall fit improved steadily with the addition of more classes to the model, however progression to five or more classes caused a noticeable drop in Entropy, suggesting redundancy across

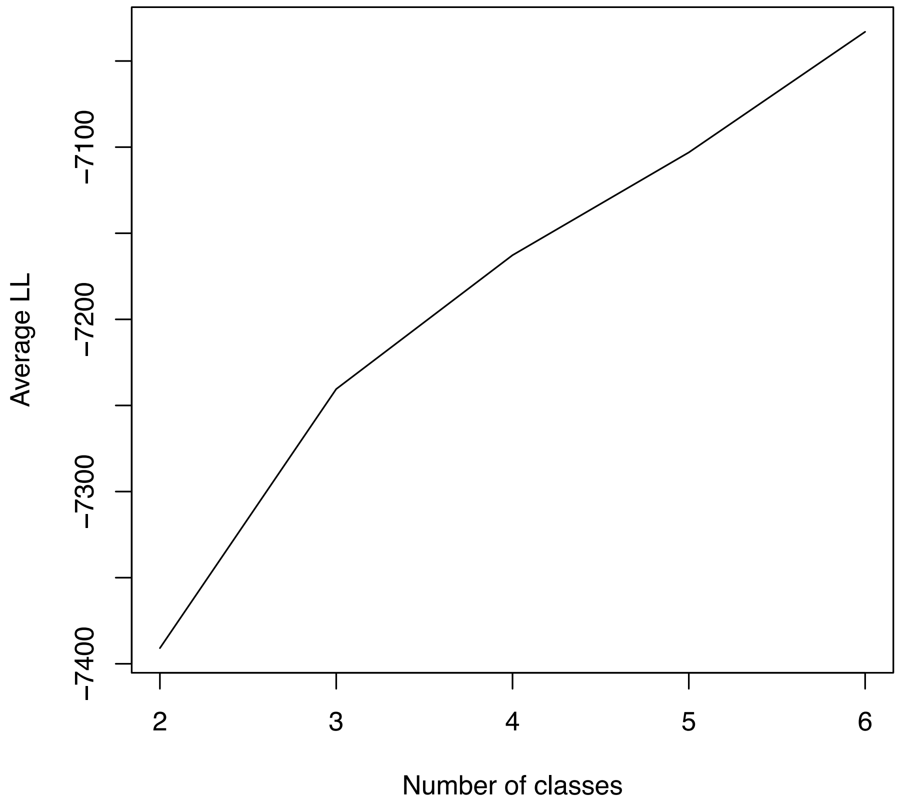

Figure 3.1. Loglikelihood by number of classes.

classes. While the two-class solution had high Entropy, it had substantially worse overall fit than the other models, so the two, five, and six class solutions were excluded from further consideration.

The four-class solution had better overall fit than the three-class solution, with lower BIC and AIC, and higher LL. Substantive comparison of the solutions was aided by plotting the Z-scores for each latent class indicator across latent classes (see Figures 3.5 and 3.6). Both three and four-class solutions had a low overall severity class and a high

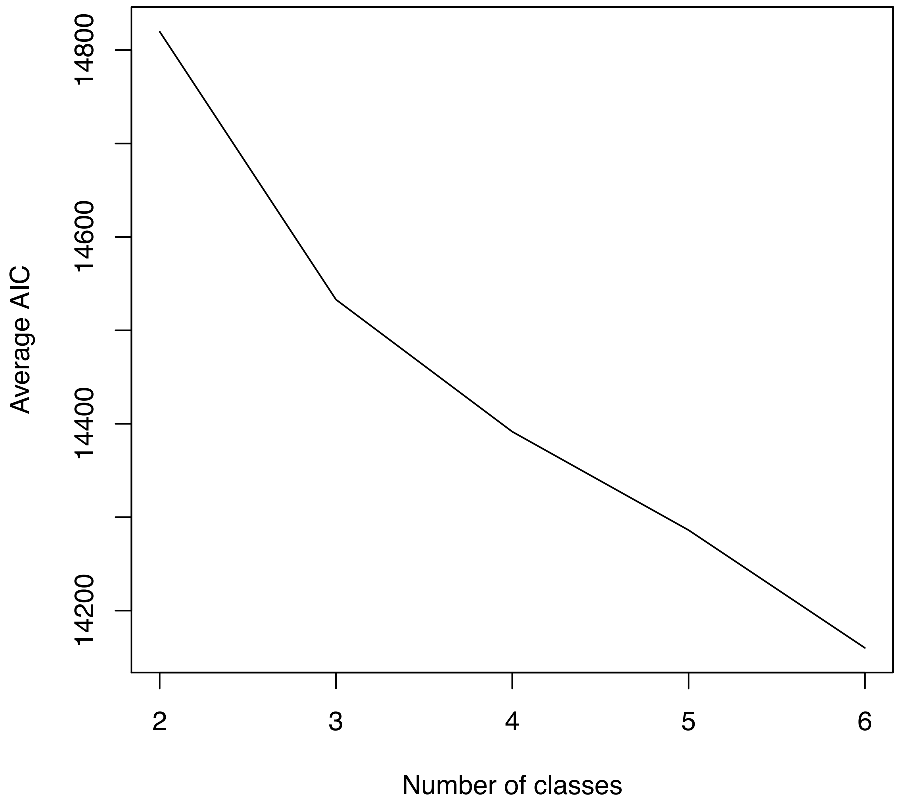

Figure 3.2. AIC by number of classes.

cocaine severity class, however they differed in the classification of patients with elevated crime/violence and co-occurring symptoms. In the three-class solution, these patients represented a single class with elevated cannabis use severity, while the four-class solution split these patients into two classes: one representing extensive criminal involvement and polydrug use, and the other showing cannabis use, minimal crime/violence involvement, and moderately high internalizing/externalizing symptoms. Thus, in addition to better fit, the four-class solution appeared to represent a more diverse profile of substance abuse and

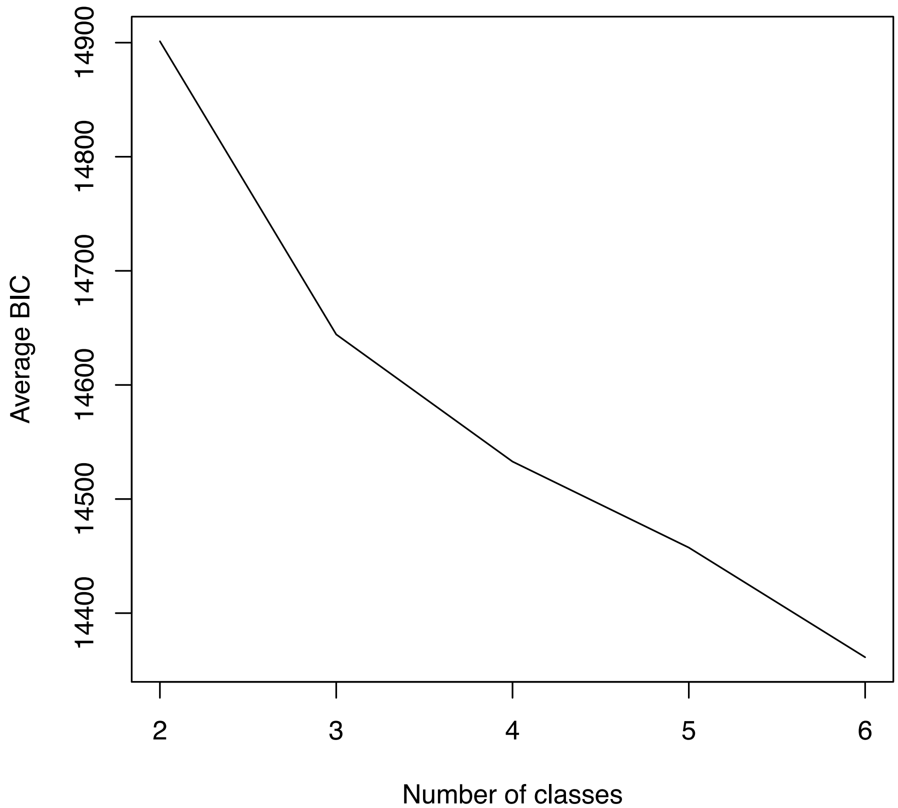

Figure 3.3. BIC by number of classes.

co-occurrence than the three-class solution. Given the objective of identifying classes representing different patterns of substance abuse, criminal involvement, and co-occurring symptoms, the four-class solution was judged to be more interpretable while also providing a better fit to the data. The four-class solution was retained as the final classification model. Analysis proceeded with the following labelled classes: Class 1: Normative (70.5%), Class 2: Psychopathology (13.9%), Class 3: Crime/polysubstance Use (4.2%), Class 4: Problem Cocaine Use (13.7%). See Table 3.1 for means and standard deviations by class

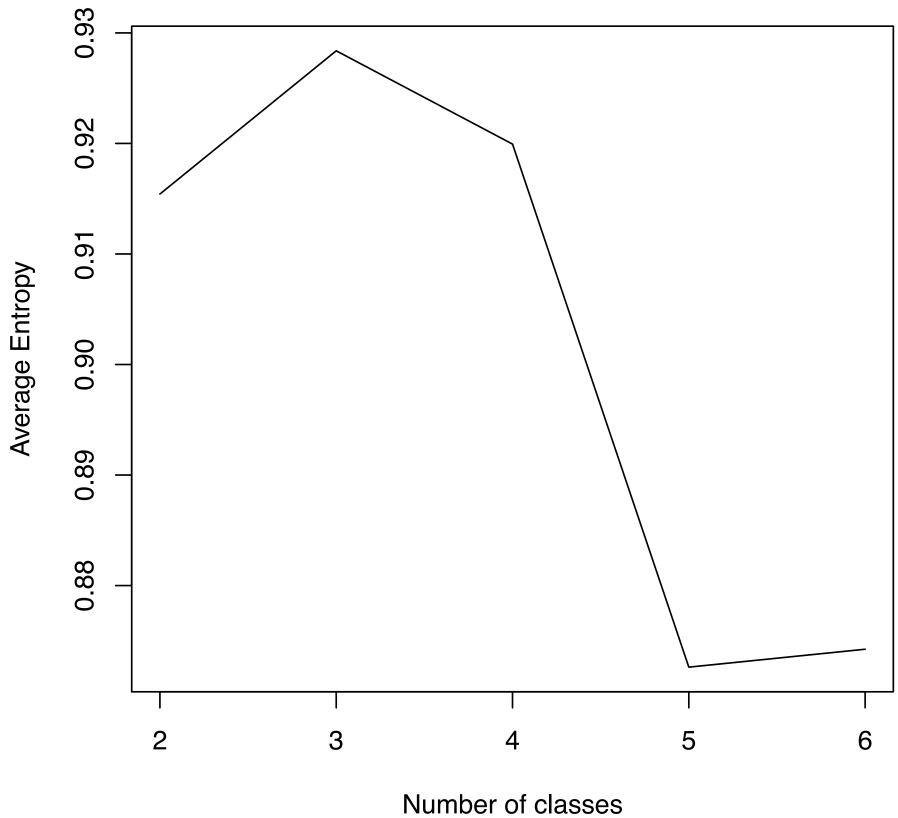

Figure 3.4. Entropy by number of classes.

membership.

Sensitivity analysis. A sensitivity analysis was conducted to determine whether variations across imputed datasets caused the classification models to converge to different solutions across imputed datasets. 10 sets of imputed data were generated, each with a different number of imputations (25-250 imputations/set, increasing by increments of 25), and the three and four-class solutions were tested on each dataset. To compare the solutions, a tolerance criterion was set representing the maximum allowable difference in

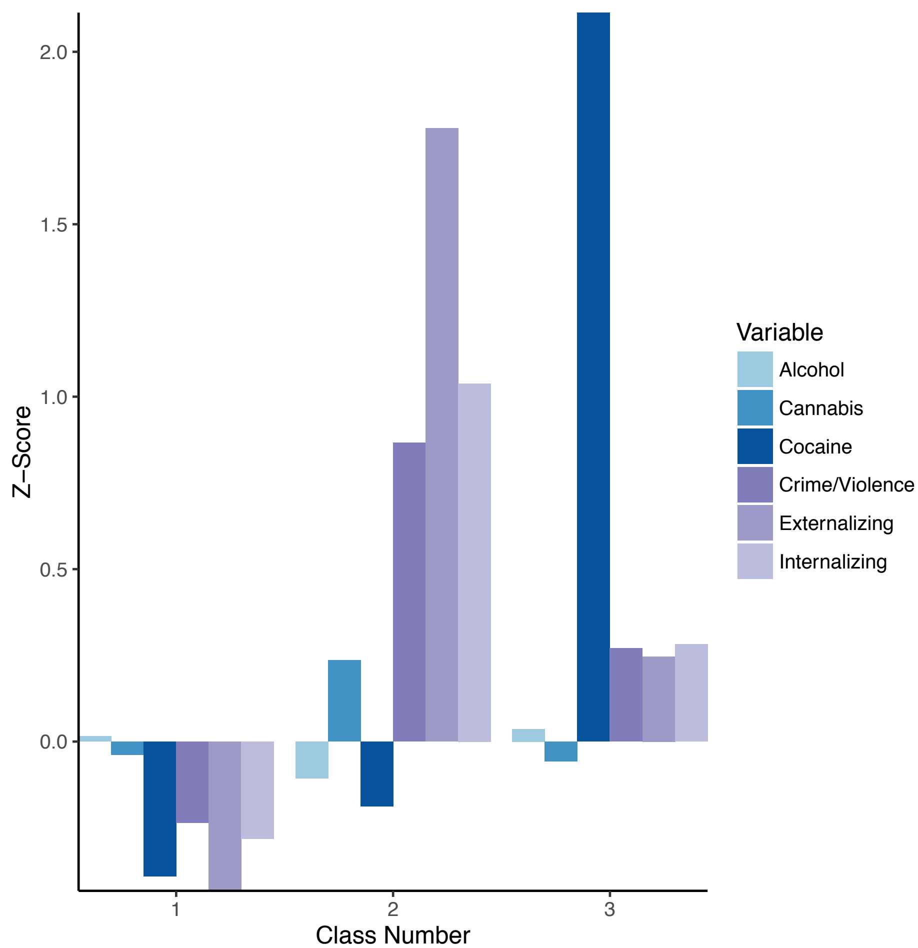

Figure 3.5. Z-scored means by latent class (3 class solution).

number of patients assigned to any one class between two datasets within the same solution. This value was set to 5 cases/class, allowing for slight variations in class assignment between solutions with a similar structure, while preventing the grouping of different solutions. After grouping the solutions based on tolerance, each solution was ranked by the number of datasets converging to it. The convergence rate of the top ranking solution was plotted across the range of imputation models (see Figure 3.7), indicating that the four-class solution was more stable than the three-class solution, with a convergence

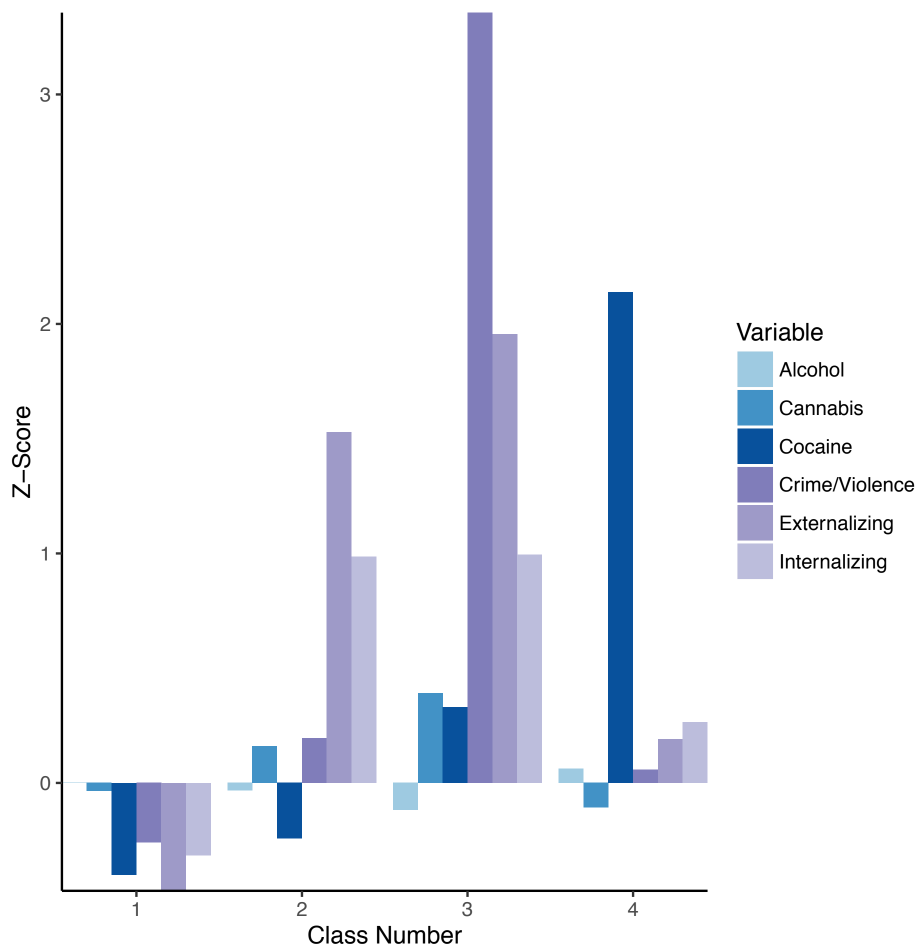

Figure 3.6. Z-scored means by latent class (4 class solution).

rate of over 95% across the entire range of imputed datasets. Based on these results, the four-class solution was retained and the dataset that failed to converge to the top ranked solution was excluded, leaving 49 of the original 50 datasets for further analysis.

3.2 Propensity score matching

To correct for imbalance across the treatment and comparison groups, a propensity score was calculated by fitting a logistic regression model of intervention status on a set of

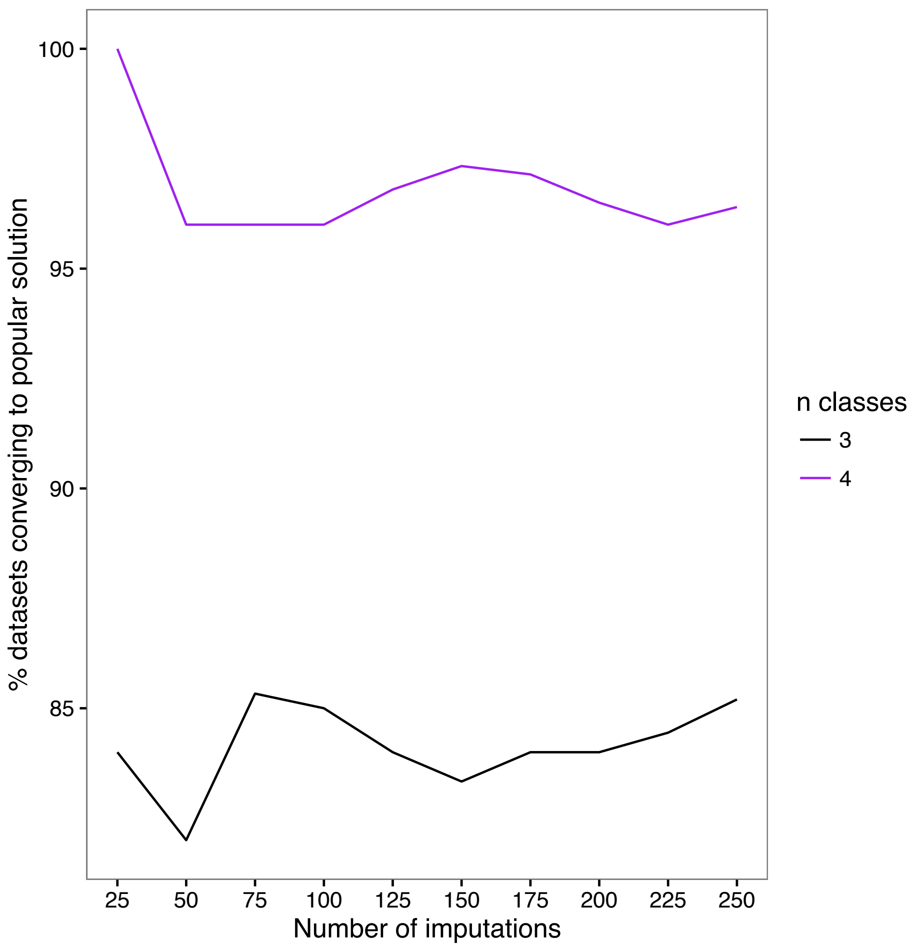

Figure 3.7. Convergence rate of the top-ranked solution by number of imputations and number of classes in the solution.

variables and recovering the fitted probability values for each participant. Variables were considered for inclusion in the model if they were imbalanced at baseline and were expected to be associated with the outcome, as these would be the variables most likely to bias estimates of the treatment effect (Austin, Grootendorst, & Anderson, 2007). A weight based on the inverse probability of treatment assignment was created based on these variables. Balance was assessed with and without the weights (see Figure 3.8), showing the weights improved balance compared to the unweighted data. In particular, variables used

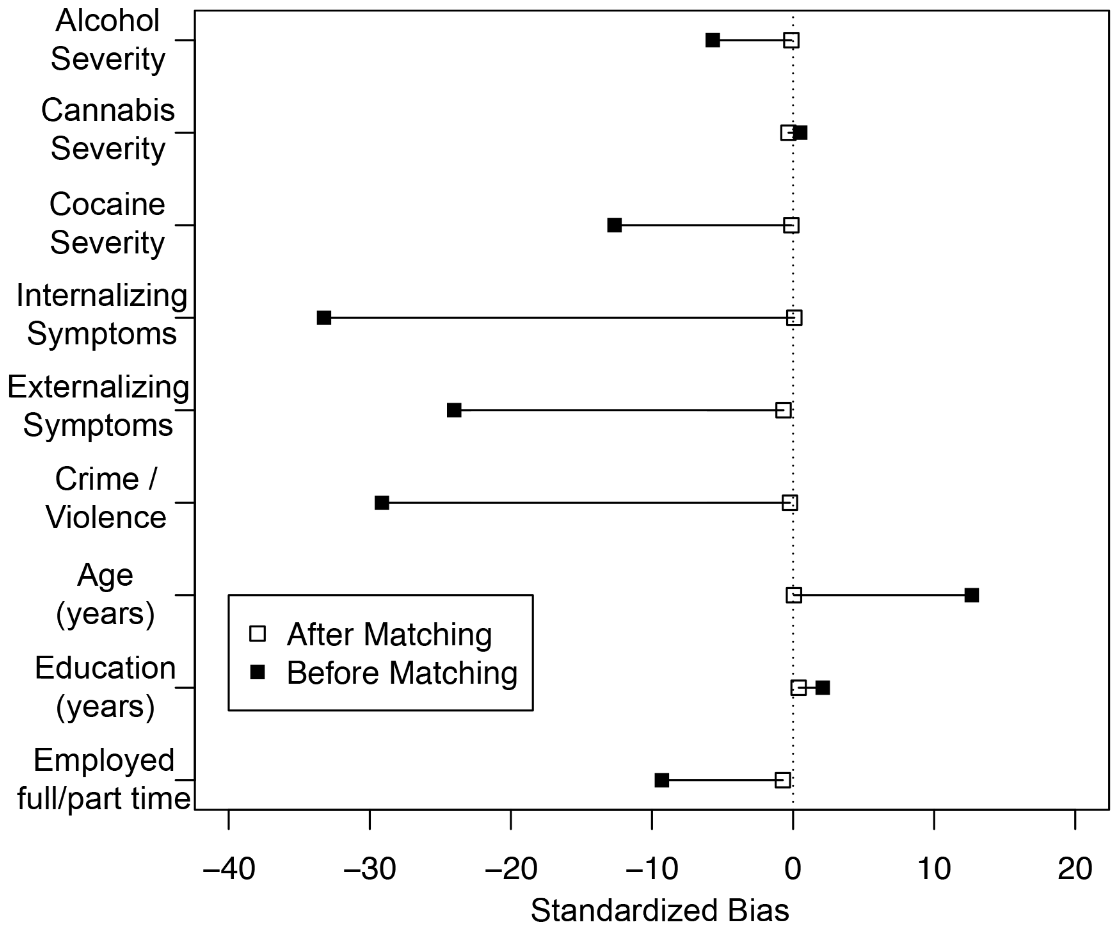

Figure 3.8. Standardized bias by variable and matching status.

in the classification model and in the outcome analyses were very well balanced, with estimates of bias near zero. The weights were then incorporated into the regression models. Tables 3.2 and 3.3 show the weighted correlations for level 1 and level 2 variables, respectively.

3.3 Intervention effects on externalizing symptoms and crime/violence involvement

Intervention effects were tested by regressing the outcome variables on intervention status, the baseline score on the DV, and demographic covariates, incorporating the stabilized weights generated by the propensity score model. Externalizing symptoms and crime/violence involvement at intake were positively associated with both outcomes at follow-up, and intervention status was not significantly associated with either outcome. Age was negatively associated with crime/violence, but not externalizing symptoms. Education was positively associated with crime/violence, but not externalizing symptoms.

3.4 Intervention effects across latent classes

Dummy-coded variables representing latent class membership were added to the model and time 1 status was removed due to overlap with the class membership variables. Membership in the Normative class was associated with lower scores on both outcomes at time 2. Membership in all other classes was associated with significantly higher scores on both outcomes. To test for interactions between intervention status and class membership, product terms were created and added to each model. There was a significant interaction between membership in the Crime/polysubstance Use class and intervention status on crime/violence. To probe for directionality, the class variable was reverse-coded, and the interaction term re-computed, revealing a significant negative association between receiving the intervention and time 2 crime/violence for members of the Crime/polysubstance Use class ($B = -0.93$, SE$= 0.39$, $p < .05$). For comparison patients, membership in the Crime/polysubstance Use class was positively associated with time 2 crime/violence ($B = 1.20$, SE$= 0.28$, $p < .05$). For both outcomes, no other treatment by class interactions reached significance (see Tables 3.4 and 3.5 for final models).

3.5 Neighborhood-level effects on outcomes

Participants were clustered by census tract, and neighborhood-level predictors were added to the intervention effect models (see Tables 3.6 and 3.7). Off-premises alcohol outlet concentration was associated with an increase in externalizing symptoms, while the other level-2 predictors were not significantly associated with either outcome. Each neighborhood-level predictor's interaction with each class membership variable was tested: these terms did not reach significance.

Table 3.1
Means and SDs by class

	Full sample	Class 1	Class 2	Class 3	Class 4
Variable	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
Age (years)	42.04 (12.75)	41.51 (12.99)	40.09 (12.94)	36.98 (12.2)	48.25 (9.25)
Education (years)	11.81 (1.88)	11.88 (1.78)	11.82 (1.82)	12.82 (1.7)	11.16 (2.26)
Employed (1 = full or part time)	0.28 (0.45)	0.33 (0.47)	0.16 (0.37)	0.27 (0.45)	0.19 (0.4)
Gender (1 = male)	0.71 (0.45)	0.72 (0.45)	0.64 (0.48)	0.69 (0.47)	0.74 (0.44)
Race (1 = Black/African-American)	0.93 (0.26)	0.94 (0.23)	0.88 (0.33)	0.87 (0.34)	0.92 (0.28)
ASSIST Alcohol	9.36 (5.68)	9.37 (5.74)	9.17 (5.65)	8.69 (4.61)	9.7 (5.79)
ASSIST Cannabis	6.62 (5.8)	6.41 (5.76)	7.55 (6.01)	8.88 (5.61)	6 (5.69)
ASSIST Cocaine	2.76 (5.02)	0.75 (1.95)	1.54 (2.6)	4.41 (6.02)	13.5 (3.14)
GAIN Crime/Violence	0.51 (0.91)	0.27 (0.53)	0.69 (0.78)	3.56 (0.84)	0.56 (0.79)
GAIN Externalizing	0.87 (1.2)	0.31 (0.52)	2.71 (0.82)	3.22 (1.28)	1.1 (1.13)
GAIN Internalizing	1.98 (1.68)	1.45 (1.44)	3.64 (1.27)	3.65 (1.53)	2.43 (1.66)
Off-premises outlets/sq mi.	3.1 (5.46)	3.14 (5.52)	2.97 (5.52)	3.58 (6.1)	2.9 (4.96)
On-premises outlets/sq mi.	2.05 (9.08)	1.86 (8.39)	2.06 (9.29)	4.66 (15.69)	2.2 (9.53)
Personal crimes/100k pop.	318.4 (268.73)	315.6 (269.28)	311.14 (262.92)	340.14 (261.47)	332.82 (278.38)
Property crimes/100k pop.	279.01 (225.68)	277.5 (225.62)	257.93 (213.72)	338.2 (217.51)	289.56 (240.71)
Neighborhood disadvantage	0.71 (3.01)	0.75 (3.02)	0.41 (2.81)	0.31 (2.55)	0.95 (3.30)
n	535	365	74	23	73

Note. Average results across 49 imputed datasets. n= 535. Class 1 labeled "Normative"; Class 2 labeled "Psychopathology"; Class 3 labeled "Crime/polysubstance Use"; Class 4 labeled "Problem Cocaine Use".

Table 3.2

Weighted correlations for level 1 variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Externalizing symptoms (Time 1)	–												
2. Crime/violence (Time 1)	45	–											
3. Externalizing symptoms (Time 2)	46	28	–										
4. Crime/violence (Time 2)	28	38	43	–									
5. Intervention status (1 = BI)	-12	-14	-10	-16	–								
6. Age (years)	-9	-15	-7	-25	6	–							
7. Employed (1 = full/part time)	-9	4	-13	8	-5	-10	–						
8. Gender (1 = male)	-9	2	-1	8	-3	6	1	–					
9. Race (1 = Black/African-American)	-9	-4	-5	-15	6	-2	-4	0	–				
10. Education (years)	4	9	3	15	1	-3	6	-7	-7	–			
11. Class 1 (Normative)	-69	-38	-34	-21	10	-6	14	3	9	5	–		
12. Class 2 (Moderate Antisocial)	61	8	24	8	-7	-6	-11	-7	-8	0	-59	–	
13. Class 3 (Severe Antisocial)	41	71	22	27	-6	-8	-1	-1	-4	11	-31	-8	–
14. Class 4 (Problem Cocaine Use)	8	2	9	5	-4	15	-8	3	-1	-14	-58	-16	-8

Note. Correlation coefficients multiplied by 100 to yield an integer. Correlations of 9 or higher are significant at $p < .05$.

Table 3.3

Weighted correlations for level 2 variables

	1	2	3	4	5	6
1. Externalizing symptoms (Time 2)	–					
2. Crime/violence (Time 2)	40	–				
3. Neighborhood disadvantage	7	18	–			
4. Off-premises outlets/sq mi	65	7	-6	–		
5. On-premises outlets/sq mi	29	-7	-23	71	–	
6. Personal crimes/100k pop.	36	1	12	59	40	–
7. Property crimes/100k pop.	5	-21	0	36	26	70

Note. Correlation coefficients multiplied by 100 to yield an integer. Correlations of 9 or higher are significant at $p < .05$. $k = 209$.

Table 3.4

Linear regression of time 2 crime/violence on treatment assignment, demographic covariates, class assignment, and treatment by class

Independent variable	*B*	SE	*B*/SE	*p*
Intervention status (1 = BI)	-0.08	0.09	-0.94	.35
Age (years)	-0.01	0.00	-4.05	.00
Education (years)	0.06	0.02	2.29	.02
Employed (1 = full/part time)	0.08	0.11	0.77	.44
Gender (1 = male)	0.14	0.09	1.55	.12
Race (1 = Black/African-American)	-0.24	0.16	-1.47	.14
Class 2 (Psychopathology)	0.25	0.12	2.16	.03
Class 3 (Crime/polysubstance Use)	1.20	0.28	4.26	.00
Class 4 (Problem Cocaine Use)	0.34	0.13	2.62	.01
Intervention*Crime/polysubstance Use	-0.84	0.38	-2.19	.03

Table 3.5

Linear regression of time 2 externalizing symptoms on treatment assignment, demographic covariates and class assignment

Independent variable	*B*	SE	*B*/SE	*p*
Intervention status (1 = BI)	-0.06	0.14	-0.45	.65
Age (years)	0.00	0.00	-0.92	.36
Education (years)	0.02	0.04	0.45	.66
Employed (1 = full/part time)	-0.26	0.17	-1.53	.13
Gender (1 = male)	0.02	0.13	0.14	.89
Race (1 = Black/African-American)	-0.02	0.26	-0.08	.94
Class 2 (Psychopathology)	0.81	0.18	4.54	.00
Class 3 (Crime/polysubstance Use)	1.10	0.39	2.85	.00
Class 4 (Problem Cocaine Use)	0.51	0.19	2.72	.01

Table 3.6

Multilevel linear regression of time 2 crime/violence

Level 1 model	*B*	SE	*B*/SE	*p*
Intervention status (1 = BI)	-0.10	0.09	-1.11	.26
Age (years)	-0.01	0.00	-4.13	.00
Education (years)	0.06	0.02	2.33	.02
Employed (1 = full/part time)	0.08	0.11	0.76	.44
Gender (1 = male)	0.15	0.09	1.74	.08
Race (1 = Black/African-American)	-0.33	0.17	-1.94	.05
Class 2 (Psychopathology)	0.25	0.12	2.15	.03
Class 3 (Crime/polysubstance Use)	1.20	0.28	4.23	.00
Class 4 (Problem Cocaine Use)	0.35	0.13	2.79	.01
Intervention*Crime/polysubstance Use	-0.73	0.37	-1.95	.05
Level 2 model				
Neighborhood disadvantage	0.01	0.01	0.55	.58
Off-premises outlets/sq mi.	0.01	0.01	0.72	.47
On-premises outlets/sq mi.	0.00	0.01	-0.66	.51
Personal crimes/100k pop.	0.00	0.00	0.49	.63
Property crimes/100k pop.	0.00	0.00	-0.86	.39

Note. Intraclass correlation= 0.06.

Table 3.7

Multilevel linear regression of time 2 externalizing symptoms

Level 1 model	*B*	SE	*B*/SE	*p*
Intervention status (1 = BI)	-0.09	0.14	-0.66	.51
Age (years)	-0.01	0.01	-1.47	.14
Education (years)	0.02	0.03	0.68	.50
Employed (1 = full/part time)	-0.24	0.17	-1.41	.16
Gender (1 = male)	0.03	0.13	0.20	.84
Race (1 = Black/African-American)	-0.07	0.25	-0.30	.76
Class 2 (Psychopathology)	0.82	0.18	4.63	.00
Class 3 (Crime/polysubstance Use)	1.18	0.37	3.19	.00
Class 4 (Problem Cocaine Use)	0.51	0.17	3.01	.00
Level 2 model				
Neighborhood disadvantage	0.00	0.02	0.12	.90
Off-premises outlets/sq mi.	0.04	0.02	2.32	.02
On-premises outlets/sq mi.	-0.01	0.01	-1.04	.30
Personal crimes/100k pop.	0.00	0.00	0.52	.60
Property crimes/100k pop.	0.00	0.00	-0.75	.44

Note. Intraclass correlation= 0.12.

4 DISCUSSION

RNR is a theoretical framework that has identified the major predictors of criminal behavior, and outlined best practices governing effective rehabilitation programs (Polaschek, 2012). The risk principle indicates that clients at high risk for recidivism are the most appropriate target population, the need principle outlines which individual risk factors should be targeted by treatment. The responsivity principle includes both general and specific components. General responsivity involves using treatment approaches appropriate for the offending population (such as cognitive-behavioral therapy), and specific responsivity entails tailoring program content to the specific needs of the client population (such as substance abuse; Andrews (1995)). Widespread adoption of the RNR framework has greatly expanded the understanding of "what works" to reduce offending (Latessa, Cullen, & Gendreau, 2002), however the specific responsivity principle remains underdeveloped (Andrews & Bonta, 2010), leaving the question of "what works for whom" largely unanswered (Polaschek, 2012). This question is especially important for clients at moderate risk for recidivism, who respond poorly to most RNR-based interventions (Lowenkamp & Latessa, 2004), but may be more responsive to low-intensity, voluntary treatment programs based in the community (Reich et al., 2016). This study addressed the needs of this group of clients by examining specific responsivity using a person-centered approach, hypothesizing that classes of patients sharing similar levels of substance abuse and co-occurring symptoms would emerge from the data, and that these classes would respond differently to a 15-30 minute BI for substance abuse delivered in an emergency department. Furthermore, it was hypothesized that neighborhood disadvantage, crime, and alcohol outlet density would negatively affect program outcomes, with patients in more severe classes more vulnerable to these effects. The hypothesis that intervention patients would have better outcomes in the overall sample was not supported. The classification hypothesis was supported. Classes emerged with distinct patterns of substance abuse and antisocial behavior. Specifically, substantial variation in substance abuse severity, type of drug used, co-occurring psychological problems, and criminal behavior was observed across classes. This is significant because drug of choice and polysubstance use are usually not considered in risk/need assessments in RNR-based programs. Furthermore, analysis of response to the intervention across classes revealed a significant reduction in crime/violence involvement for treated members of the Severe Antisocial class, supporting the hypothesis that classes would respond differentially to the intervention. The ecological hypotheses, which were designed to add contextual breadth to the analysis of risk and need, were partially supported. Off-premises alcohol outlet density was associated with externalizing outcomes in the overall sample, but other ecological predictors were not associated with outcomes. There were no significant differences in the ecological effects across classes. These findings contribute to the understanding of the risk and need principles by highlighting heterogeneity in a sample of clients with moderate substance abuse severity, many of whom would not be eligible to participate in an RNR-based program because their risk for recidivism would be considered too low. As will be discussed, this study joins existing efforts to refine and elaborate important aspects of the RNR framework and points to important directions for future research.

4.1 Person-centered approach to specific responsivity

Compared to the first two principles of RNR (i.e., risk and need) and the general component of the third principle, general responsivity, the specific responsivity principle has been underdeveloped, leading to an incomplete understanding of the effects of individual-level factors on program outcomes (Andrews & Bonta, 2010). In an appraisal of RNR's theoretical development using an adaptation of a metatheoretical framework developed by Ward and Hudson (1998), Polaschek (2012) characterized responsivity as a "catch-all category" and RNR itself as being at a pre-theory stage of development, more a framework than a theory. Perhaps as a result, RNR-based programs tend to focus on general responsivity by using manual-based cognitive-behavioral treatment approaches. However, the specific responsivity principle is relatively neglected in practice, with few programs adjusting treatment strategies to suit individual characteristics. Two findings from the present study suggest that an increased emphasis on the specific responsivity principle may be warranted for substance-involved clients. First, the response of the Severe Antisocial class to a brief MI-based intervention implies that interventions need not be cognitive-behavioral in approach to reduce offending among some drug-involved clients. Second, the classification model revealed substantial variation in substance abuse severity, co-occurrence, and criminal behavior in a sample of clients with moderate substance abuse severity, suggesting that the current practice of providing uniform interventions to all-drug involved clients may not be optimal. These findings raise the possibility that programs serving drug-involved clients could improve their outcomes by performing more in-depth assessments of clients' substance abuse severity, polysubstance use, and co-occurring psychological problems, and tailoring services to clients with different risk profiles.

In a meta-analytic review of the relevance of the RNR principles for drug-involved clients, Prendergast et al. (2013) found that clients in programs adhering to the general responsivity principle (i.e. using a cognitive-behavioral approach) did not have better substance abuse outcomes than clients in non-adherent programs. This suggests that drug-involved clients may be underserved by RNR-based programs, possibly because programs are not effectively tailoring treatment to the needs of clients with different patterns of drug-involved offending. The results from the person-centered analysis in the present study support this possibility, suggesting that the types of drugs used by clients, the presence of polysubstance use, and the severity of use are associated with different patterns of offending and in turn may be important specific responsivity factors. Specifically, although the Severe Antisocial class had lower cocaine abuse severity than the Problem Cocaine Use class, they had more externalizing symptoms and much higher crime/violence involvement. The Severe Antisocial class shares some similarities with classes that have emerged from epidemiological studies, supporting the reliability of the person-based approach for identifying heterogeneity among individuals involved in both drugs and crime. Like the "severe 5%" class detected in Vaughn et al. (2011) and the polysubstance abuse/dependence class in DeLisi et al. (2015), patients in the current study identified in the Severe Antisocial class used multiple illegal substances, engaged in the broadest range of criminal behavior, and were especially likely to commit violent offenses. Another similarity between Severe Antisocial clients in the present study and the Severe class members in Vaughn et al. (2011) was a high rate of co-occurring psychological problems: over three quarters of Severe Antisocial clients reported traumatic stress, and over half reported suicidal thoughts. Finally, in all of the studies just mentioned, these classes were the smallest, comprising approximately 5-10% of the total sample. Since the Severe Antisocial class responded well to an MI-based intervention, further research should investigate whether a similar class emerges in RNR-based programs. If so, analysis of their response to treatment should help clarify questions about the mechanisms of program-related change for drug-involved clients. A lack of response to these programs would imply that cognitive changes may be less important drivers of program-related change than motivation to change and/or reductions in substance abuse for this group of clients.

The reduction in criminal behavior for Severe Antisocial class members is consistent with the risk principle, which emphasizes the importance of targeting high-risk clients for program participation (Lowenkamp, Latessa, & Holsinger, 2006). However, these findings also highlight the limitations of the general responsivity principle, which says little about why a client with severe needs would respond well to an intervention that is brief, patient-directed, and lacking a cognitive restructuring component. RNR places heavy emphasis on long-term, structured, group-based interventions that target cognitive factors such as antisocial attitudes, values, and beliefs (Andrews & Bonta, 2010). However, if research continues to find MI-based interventions effective for reducing criminal behavior (McMurran, 2009; Anstiss, Polaschek, & Wilson, 2011), this emphasis may need to be adjusted to include factors relevant to other types of interventions like MI, such as motivation and readiness to change. While programs using the cognitive-behavioral approach are well-supported in terms of effectiveness (Andrews & Dowden, 2005), recent research suggests that cognitive changes may be less important to the rehabilitation process than previously thought. A recent meta-analysis tested whether cognitive changes mediate program effects, showing that while interventions were associated with reduced antisocial cognitions, these reductions were unrelated to subsequent reductions in recidivism (Helmond, Overbeek, Brugman, & Gibbs, 2014). Similarly, Wooditch et al. (2013) examined changes in several different risk/need factors over the course of a 12-month period, finding that alcohol use and a reduction in the number of criminally involved family members were the strongest predictors of recidivism, while antisocial cognitions were not significantly associated with change in criminal behavior. Further examination of responsivity across different program types should help clarify which mechanisms of change are most important for drug-involved clients.

Given the strong association between drug use and crime (Bennett et al., 2008), it is surprising that substance abuse is not well integrated into the specific responsivity construct. One reason may be a lack of well-validated measures. Risk/need assessments often use brief items or administrative data (such as lifetime use or a history of drug-involved offending) to determine clients' substance abuse needs. These measures may not be detailed enough to adequately characterize the treatment needs of substance-involved clients, in turn leading to difficulties tailoring program content to meet these needs. They also constrain the development of the specific responsivity principle by limiting the data collected and available for meta-analysis, an important tool that has been used to validate and refine the other principles of RNR. Another barrier to the development of specific responsivity has been the lack of attention to mediators of program-related change. Programs tend to aim for cognitive changes in their clients, but other potential mediators such as reductions in substance abuse are less well-examined. This study illustrates the importance of examining different treatment approaches to help determine which interventions work best for clients with different criminogenic needs. Overall, improving treatment for drug-involved clients will require more detailed assessment of the needs of substance-involved clients, evaluations of different types of interventions, and a careful examination of the mediators of program-related change.

4.2 Ecological analysis of program outcomes

Ecological factors including alcohol outlet density, neighborhood disadvantage, and neighborhood crime were hypothesized to affect program outcomes, and clients in different classes were hypothesized to respond differently to these factors, with those in more severe classes more vulnerable to these effects. Of the ecological effects tested, only off-premises alcohol outlet density was associated with externalizing outcomes, consistent with previous research showing that high neighborhood density of these venues are associated with elevated rates of violent crime (Lipton et al., 2013). Off premises outlets refer to retail businesses that sell alcohol but do not allow consumption (such as liquor or convenience stores), while on-premises outlets refer to locations that allow consumption (such as bars or night clubs). Spatial analyses by Gorman, Speer, Gruenewald, and Labouvie (2001) found the effect of outlet density was highly localized at the block group level, with limited effects on surrounding block groups, suggesting the criminogenic effect of these outlets may reflect social processes that occur in their immediate vicinity. Felson (1987) conceptualized retail areas such as off-premises outlets as crime attractors because they lack protective factors such as police guardianship and offer a concentration of potential targets for offending. Routine activities theory conceptualizes these characteristics as criminogenic for individuals that are ready/motivated to offend, increasing the likelihood that they will offend in that area (Cohen & Felson, 1979). If future research reveals that the effects of these outlets on program outcomes is highly localized around the outlets themselves, rather than reflecting broader social processes in the surrounding neighborhoods, programs may be able to help clients develop routines that avoid areas with high concentrations of these outlets.

In contrast, on-premises outlets were not associated with either outcome. While failing to support the hypothesis related to effects of on-premises alcohol outlets on criminality, the result is consistent with some research showing the strength of association between outlet density and assault is stronger for off-premises outlets (Pridemore & Grubesic, 2013), especially after controlling for indices of neighborhood disadvantage

(Snowden & Freiburger, 2015). These lack of linear associations linking density of on-premises outlets with criminality may actually mask interactions between these outlets and their surrounding social context. For example, Gruenewald et al. (2006) examined the effects of alcohol outlet density on hospital discharges for assault and found on-premises outlets were actually protective against crime in neighborhoods with high Hispanic immigrant concentration and high socioeconomic status, but criminogenic in low-income unstable neighborhoods and those that were more rural. Thus, while off-premises outlets may attract motivated offenders from other areas, on-premises offending may be driven more by the individual-level characteristics of the residents in the surrounding areas. Under that interpretation, on-premises outlets may have been less criminogenic for the current sample because no classes emerged with clearly alcohol-driven offending. Future research investigating the effects of on-premises outlets on recidivism outcomes should recruit samples with alcohol-related offending to examine the possibility that on-premises outlets are especially criminogenic for these clients.

Neighborhood disadvantage was not associated with either outcome, which is surprising due to the robust association in past studies between disadvantage and the geographical concentration of offending (Pratt & Cullen, 2005). However, some research suggests that the effect of disadvantage on outcomes is indirect for rehabilitation programs. For example, Wright et al. (2012) examined outcomes for 3,237 halfway house clients and a matched group of parolees, finding that the effects of neighborhood disadvantage on outcomes was strongly mediated by its effect on program quality. In other words, disadvantaged communities may lack the resources to provide high-quality treatment, which in turn affects program outcomes. While an analysis of program quality was outside the scope of the present study, future research should examine the possibility the disadvantage affects recidivism outcomes by undermining program quality.

The hypotheses that neighborhood personal and property crime rates would affect outcomes were not supported. Although the empirical link between victimization and offending is strong (Jennings, Piquero, & Reingle, 2012), Turanovic and Pratt (2013) noted that this link is not well integrated into criminological theory. One potentially relevant framework is general strain theory, which posits that antisocial behavior is a way some individuals cope with strains such as being unable to achieve financial or social success (Agnew, 1992). Under this interpretation, victimization may be a source of strain that could lead to an increase in offending. For drug-involved clients, another potentially relevant coping response to victimization may be self-medication and relapse. For example, Yang et al. (2011) found that past-year victimization was associated with increased risk for relapse at 2-year follow-up in a sample of former crack, cocaine, and heroin users. Increases in substance abuse in response to victimization-related strain could in turn contribute to elevated offending, but this pathway may have been less relevant for the moderate risk level of clients included in the present study because those with high substance abuse severity were excluded. Future research including clients with higher substance abuse severity should investigate the link between victimization, self-medication, and offending.

The hypothesis that ecological factors would affect the classes differently was not supported, illustrating a potential difficulty in analyzing cross-level interactions when combining person-centered and ecological approaches. While the person-centered approach highlights heterogeneity in the population, subsequent tests of cross-level interactions are limited by the patterns that emerge from the sample data. For example, alcohol outlets were hypothesized to affect clients with alcohol-related offending more strongly, however no clearly alcohol-related offending class emerged from the data. As a result, potential cross-level interactions between alcohol outlet density and alcohol-related offending could not be tested. On the other hand, since reliability is a strength of the person-centered approach, the class-invariant effect of off-premises outlet density may be interpreted with more confidence. Future research should test similar person by context interactions across different populations to see whether these results can be replicated in samples including drug dependent or alcohol-involved offending classes.

4.3 Theoretical implications

Returning to the link between drug use and crime can help clarify the potential mechanisms by which substance abuse treatment can lead to reductions in offending. Etiologically, the co-occurrence of drug use and crime is explained by an externalizing factor. In a hierarchical confirmatory factor analysis of the externalizing spectrum, Krueger, Markon, Patrick, Benning, and Kramer (2007) found that non-alcohol substance use and symptoms of impulsivity loaded on the general externalizing factor, while alcohol use and aggression loaded on both the general factor and separate sub-factors. This may help explain the elevated substance use problems and crime/violence in the Crime/polysubstance Use class. While the Psychopathology class also had elevated externalizing severity, the crime/violence involvement and polysubstance use observed in the Crime/polysubstance Use class suggest that members of this group may experience greater difficulties with impulse control. This is consistent with research by Vaughn et al. (2011), who found individuals with the most severe externalizing symptoms were also more likely to engage in risky behavior such as polysubstance use. Thus, one potential explanation for the lower rates of offending observed for treated Crime/polysubstance Use clients is that they were able to develop strategies for adaptive decision-making in the context of problematic impulses to use drugs or engage in criminal behavior.

Increasing motivation and self-efficacy for change may be one way MI is able to help clients dealing with impulsivity problems. Self-efficacy is a robust predictor and mediator of substance abuse treatment outcomes (Kadden & Litt, 2011), and may be especially important for clients with high levels of impulsivity. For example, in a study of 332 community-recruited women treated with MI, Hayaki et al. (2011) found that women with high impulsivity were more likely to use and abuse cannabis, and that this effect was mediated by lower self-efficacy to refuse cannabis. MI has been linked with greater improvements in self-efficacy than other treatments. For example, McKee et al. (2007) compared outcomes for 74 cocaine-dependent patients randomized to receive either CBT or CBT with an initial MI session, and found the patients in the MI+CBT condition had higher expectations for success in abstinence and greater treatment engagement than the

CBT only patients. Self-efficacy may be a particularly important mediator of substance abuse outcomes for cocaine using clients. In a study of the predictors of treatment outcomes for alcohol and cocaine users, McKay et al. (2005) found that perceived problem severity, self-efficacy, self-help group attendance, and lower social support for substance use were associated with better outcomes for alcohol using clients, but only self-efficacy was associated with better outcomes for cocaine users. Cocaine use is also associated with increases in impulsivity (Simon, Mendez, & Setlow, 2007), raising the possibility that treatment-related decreases in cocaine use may have helped reduce impulse-driven offending. Taken together with these studies, the present study illustrates that MI-based interventions may be well-suited to clients who use cannabis and/or cocaine and have problems with impulsivity, and that changes in substance use and impulse-driven offending could be mediated by improvements in self-efficacy.

4.4 Implications for practice

The lower rates of criminal behavior observed for treated Crime/polysubstance Use clients may also reflect reductions in income-generating offending to fund substance use. Income derived from crime has been closely linked with spending on illegal drugs (Collins, Hubbard, & Rachal, 1985; Johnson, Anderson, & Wish, 1988). These patterns of offending tend to rise during periods of heavy use and fall during periods of abstinence (Chaiken & Chaiken, 1990), supporting the effectiveness of substance abuse treatment for reducing both drug use and offending. This pattern of offending may also help explain why the

Crime/polysubstance Use class had lower crime/violence involvement, but not lower externalizing symptoms, following treatment. The externalizing measure used in the present study contained items on impulsivity and aggression, but not acquisitive offending, while the crime/violence scale contained items that past research has closely linked with acquisitive offending to purchase drugs (stealing and selling drugs). In a qualitative study on the causal connections between drug use and crime, Bennett and Holloway (2009) found that drug dealing, shoplifting, and robbery were the most commonly reported crimes used to fund drug use. These results suggest that reductions in substance abuse following treatment may in turn reduce acquisitive offending. However, because the present study was unable to examine mediators of treatment-related change or within-class differences in the effects of the intervention, further research is required to test these possibilities.

A central concern for the development of RNR is a movement towards an explanatory theory of change that incorporates both program and client-level characteristics, and describes their interplay. Despite a considerable body of evidence establishing the variables associated with recidivism and how client risk affects program response, the specific responsivity principle remains unelaborated. The practical result of the field's move towards RNR has been an increase in overall program effectiveness for high-risk clients. However, research to date has not offered results to inform an adequate understanding of the psychologically meaningful processes underlying reductions in recidivism. Before questions of process can be addressed, the relevant target population for these programs needs to be more fully characterized. Most RNR-based programs exclusively target individuals at high risk for recidivism, so few studies have examined responsivity among clients who fall below the high-risk threshold. The present study helps address this gap for drug-involved clients by excluding clients with high substance abuse severity and highlighting heterogeneity across the population of clients that may not meet the risk criteria for RNR-based interventions.

Current practice is to base program eligibility and treatment planning on clients' risk for recidivism, but the person-centered analysis used in the present study highlights the limitations of this approach. Despite receiving an intervention for substance abuse, treated clients in the Problem Cocaine Use class did not reduce their offending relative to controls, while Severe Antisocial class clients did show a reduction. Operationalization of offense and substance abuse severity as a single unidimensional risk index would probably have resulted in a failure to differentiate the Severe Antisocial class members from other participants. Basing program eligibility and treatment targets on overall risk for recidivism may make it more difficult for programs to respond to the heterogeneous needs of their substance-using clients. Results from the LCA used in the present study are consistent with similar analysis using epidemiological samples in finding that individuals with the most severe types of offending also show a different profile of substance use than those with less severe offending, in particular the use of stimulants and hallucinogens (Vaughn et al., 2011) and polysubstance abuse (DeLisi et al., 2015). They may also have different treatment-related needs than clients with different drug-related offending profiles, such as those with opioid dependence or alcohol-related offending. More completely characterizing the substance-using client population in terms of type of drug used, severity of use, and the presence of polydrug use may be an important next step in more precisely matching interventions to client characteristics.

Once the client population has been more accurately characterized, researchers can begin testing mediation hypotheses designed to reveal the mechanisms of program effects. Researchers are increasingly discovering that factors such as criminal thinking that are targeted extensively by RNR-based programs fail to mediate program effects, while factors such as substance abuse are responsive to intervention and mediate program effects on recidivism (Wooditch et al., 2013). Such findings highlight the need to move research on specific responsivity beyond the variables currently included in risk assessments: Factors that predict recidivism risk do not necessarily mediate treatment-related change. Furthermore, conceptualizing specific responsivity based on purely on risk fails to account for protective factors such as motivation that might also affect treatment response (Maruna & LeBel, 2002).

One approach to expanding conceptions of specific responsivity is to shift focus away from the predictors of recidivism and toward factors that can be operationalized in a way that is psychologically meaningful (Mann, Hanson, & Thornton, 2010). For substance-involved clients, the type of drug used, severity of use, and the presence of polysubstance use may all be psychologically meaningful for treatment response if they are linked with the individual's offending patterns. Currently, RNR-based programs see substance abuse as an additive factor contributing to overall risk for recidivism, but the results from the current study imply this may be an oversimplification of the link between substance use and offending. The Severe Antisocial class detected in the present study reported using both stimulants (cocaine/crack) and hallucinogens(cannabis) at sub-dependence severity. Cessation of stimulant and hallucinogen use does not cause the serious physical withdrawal symptoms associated with other drugs such as opiates, suggesting that it may be easier for these clients to reduce their substance use following an intervention. At the same time, meta analytic research has linked crack use with elevated rates of offending compared with heroin use (Bennett et al., 2008), suggesting that reductions in crack use may yield substantial reductions in offending. Future research investigating specific responsivity for substance-involved clients should combine the person-centered analytic approach with valid and reliable measures of substance abuse severity to avoid overgeneralizations about the role of substance use in clients' offending.

4.5 Limitations

Results of the present study should be interpreted with caution, in light of some limitations to internal and external validity. For estimates of the treatment effect, it is important to note that a lack of random assignment resulted in several differences between the intervention and comparison groups on baseline levels of substance abuse and crime/violence, with intervention participants generally at higher severity than controls. While a propensity score weight was effective in balancing the treatment and comparison groups on these variables and adjust the treatment effect estimates, it is not possible to account for unmeasured variables in the propensity score. For example, it is possible that HEs in the intervention phase of the study approached patients they perceived to be in greater need of an intervention. Future research would benefit from randomization, which would eliminate the potential for selection effects to bias estimates of the treatment effect.

A second threat to internal validity was the potential role of differential attrition. A significant number of participants could not be reached for the 6-month follow-up, resulting in missing data for the outcome variables. While multiple imputation was used to help account for missingness due to the observed covariates, those lost to follow-up could have worse outcomes than those retained, biasing estimates of the treatment effect. Future studies should seek to replicate these findings using intensive tracking procedures to help achieve a higher follow-up rate (Gilmore & Kuperminc, 2014).

Finally, these results may not be generalizable to clients in different types of programs. For example, most rehabilitation programs target individuals who have been charged or convicted of a crime, while the present intervention targeted ED patients. It is not clear whether the treatment effect observed for Severe Antisocial clients in the present study would apply to clients in these rehabilitation programs, who may have more severe substance abuse issues and/or criminal behavior. Future research on rehabilitation programs should collect more detailed information on the severity of the substance abuse needs and criminal behavior of clients in rehabilitation programs, so that results can be compared more easily across different types of interventions and target populations.

4.6 Conclusion

RNR has made a substantial contribution to the understanding and practice of rehabilitation for clients at high risk for recidivism. Still, gaps in the specific responsivity construct contribute to a lack of explanatory depth that has limited further development of the theory. The present study used person-centered methods to operationalize specific responsivity within a population identified as being at moderate risk for criminal behavior, resulting in the detection of a group with severe offending and polysubstance use that reduced their crime/violence following an intervention, relative to comparisons. Furthermore, analysis showed that off-premises alcohol outlets were associated with externalizing outcomes after controlling for individual characteristics, suggesting that incorporation of ecological variables into the conceptualization of treatment-related change could be important. In conclusion, researchers attempting to elaborate the specific responsivity principle more precisely can benefit from consideration of person-centered analysis that incorporates valid and reliable measures of substance abuse severity. The results of these analyses will help future studies make more informed hypotheses testing why and how different groups of participants respond to rehabilitative interventions.

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