Title
Straight from the Source: Using Client Strengths and Risks to Predict Future Supervision Violations

Author
Hunnicutt, Kayleigh

Publication Date
2017

UNIVERSITY OF CALIFORNIA

Santa Barbara

Straight from the Source: Using Client Strengths and Risks to Predict Future Supervision Violations

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Counseling, Clinical, and School Psychology

by

Kayleigh Lynne Hunnicutt

Committee in charge:

Dr. Jill Sharkey, Lecturer with Security of Employment, Chair

Professor Merith Cosden

Professor Michael Furlong

June 2018

The dissertation of Kayleigh Lynne Hunnicutt is approved.

Michael Furlong

Merith Cosden

Jill Sharkey, Committee Chair

August 2017

Straight from the Source: Using Client Strengths and Risks to Predict Future Supervision Violations

by

Kayleigh Lynne Hunnicutt

ACKNOWLEDGEMENTS

There are many people that were critical to the completion of my dissertation and progression through my doctoral journey. My advisor and mentor, Dr. Jill Sharkey, has been one of the biggest contributors to my success, and I could not ever express my gratitude toward her in ways that words could accurately capture. Her support, guidance, compassion, brilliance, integrity, understanding nature, and advocacy have been parallel to none that I have ever experienced. It has been a true blessing to work under her mentorship for the last five years, and one that I am thankful for every day. The support I have received from my other committee members – Dr. Merith Cosden and Dr. Mike Furlong – have also been key elements in my doctoral journey. I have had the pleasure of working with Dr. Cosden on other projects, to which her calm and positive demeanor and expert knowledge in criminal justice-involved populations has provided me with invaluable experiences that I draw from and build upon in my research to this day. Similarly, the extremely engaging and brilliant academic knowledge of Dr. Furlong in strengths-based work has allowed me to broaden my understanding of related topics and concepts, some of which became the foundation for my dissertation and my passion for study in the field of psychology. My committee members have helped guide me through multiple unexpected data challenges, with the right mixture of support, confidence in my abilities, and constructive feedback that allowed me to overcome these barriers. Thank you all for your belief in me and your unwavering support.

My family. Those two words are about all I can say. Without their compassion, unconditional love, and support I wouldn't have even a small dose of the motivation and drive that I do. I wouldn't be able to persevere or see the light at the end of the tunnel. They have spent the last 12 years cheerleading me through my long post-secondary educational journey, never tiring or wearing thin in their strong belief that I was on the "right" path and was going to do great things with my future. In my line of research, I'm well aware of what a commodity this is. Thank you to my Mom, my sister Brianna, my sister Shayna, my sister Carys, Mike, Anita, my aunt Mary, Jimmy (for the inspiration and personal knowledge), and to my co-parent. To my many other immediate and extended family members in the Tursich and Fisher families; all of you have impacted my life and helped guide my journey in some way. I love you all. Thank you for all that you have done to get me to the finish line.

To my friends, new and old, those that are present and those that are not. Every person in my life has played a critical piece in this experience. I am grateful for all of you. Dan and Kami, Kelly, Michelle, and Jennifer – thank you for the incredible lengths you have gone to provide me with support and love over the last (for some of you) decade(s). Taking any of you out of the picture would have removed a critical piece in my foundation. To my colleagues at the university that have supported me through the twists and turns of graduate school life, particularly Kate, Cecile, and Danielle, I cherish you and thank you for just being you.

Most of all, in the last four years, my biggest inspiration has been my beautiful daughter. Even before she was born, she changed my life, my approach to my work, and my awareness that I still needed to become the person I was designed to be. Not a day goes by that my life isn't filled with joy and happiness, that I don't strive to be better and have more humility, that I don't cherish every single moment… because of her. I love you, Hayden. You are my inspiration every single day. I dedicate this work to you, and in hopes that I can

make positive contributions to the world we live in so that you can live the most fulfilling life possible.

VITA OF KAYLEIGH LYNNE HUNNICUTT
August 2017

EDUCATION

Bachelor of Science in Psychology, California Lutheran University, 2007 (cum laude)
Master of Arts in General-Experimental Psychology, California State University, Northridge, 2012 (with distinction)
Master of Education in Counseling, Clinical, and School Psychology, University of California, Santa Barbara, 2015
Doctor of Philosophy in Counseling, Clinical, and School Psychology, University of California, Santa Barbara, 2018 (expected)

PROFESSIONAL EMPLOYMENT

2010-2012: Graduate Research Assistant, California State University, Northridge
2010-2014: Research Assistant, Ventura County Behavioral Health
2012-present: Graduate Research Assistant, University of California, Santa Barbara
2014-present: Independent Research Consultant, Ventura County Behavioral Health
2017-present: School Psychologist Intern, Carpinteria Unified School District

PUBLICATIONS

Lenzi, M., Sharkey, J., Furlong, M. J., Mayworm, A., Hunnicutt, K., & Vieno, A. (in press). School sense of community, teacher support, and students' school safety perceptions. American Journal of Community Psychology.

Mayworm, A. M., Sharkey, J. D., Hunnicutt, K. L., & Scheidel, K. C. (2016). Teacher consultation to enhance implementation of school-based restorative justice. Journal of Educational and Psychological Consultation, 26(4). doi:10.1080/10474412.2016.1196364

Sharkey, J. D., & Hunnicutt, K. (2015). Discipline: School and classroom. In W. G. Scarlett (Ed.). The SAGE Encyclopedia of Classroom Management. (259-262). Thousand Oaks, CA: Sage

Sharkey, J. D., Hunnicutt, K. L., & Furlong, M. J. (2015). Adolescent homicide. In T. P. Gullotta, R. W. Plant, & M. A. Evans (Eds.), Handbook of Adolescent Behavioral Problems: Evidence-Based Approaches to Prevention and Treatment–Second Edition. (515-537). New York: Springer

Sharkey, J. D., Hunnicutt, K. L., Mayworm, A. M., Schiedel, K. C., & Calcagnotto, L. (2014). Effective yard supervision: From needs assessment to customized training. Contemporary School Psychologist. 18, 103-116.

Seegan, P., Welsh, K., Plunkett, S. W., Merten, M. J., & Sands, T. (2012). Neighborhood, parenting, and individual qualities related to adolescent self-efficacy in immigrant families. Family and Consumer Sciences Research Journal, 40(4), 348-360.

AWARDS

Graduate Research Mentorship Fellowship, University of California Santa Barbara, 2014

Best Paper in Human Development and Family Studies, Family & Consumer Sciences Research Journal, 2013

Outstanding Research Article in 2012, Family & Consumer Sciences Research Journal, 2013

William Wilsoncroft Award, California State University Northridge, 2012

Honorable Mention Applicant award recipient, California Pre-Doctoral Program, 2011

Poster Award Finalist, American Psychological Association (APA) Division 5 – Evaluation, Measurement, and Statistics, 2011

FIELDS OF STUDY

Major Field: Counseling, Clinical, and School Psychology

Studies in risk, resilience, and at-risk and criminal justice involved populations with Dr. Jill Sharkey

Studies in adult criminal justice involved populations and criminal justice processes with Dr. Merith Cosden

Studies in resilience, risk, and strengths-based methods with Dr. Michael Furlong

ABSTRACT

Straight from the Source: Using Client Strengths and Risks to Predict Future Supervision Violations

by

Kayleigh Lynne Hunnicutt

The number of individuals convicted of crime in the United States is large, and re-conviction rates among these individuals is even higher. Criminal conviction and recidivism rates are concerning for a variety of reasons, most of which are related to the various deleterious outcomes found to be associated with criminal justice involvement. The extant literature on factors related to recidivism focus primarily on unalterable risk factors and alterable risk factors; however, there is still a dearth of research on which alterable strength factors are associated with recidivism, and how patterns of risks and strengths relate to recidivism. The present research addresses some of these gaps by investigating: (a) if established strengths-based internal assets scales are internally reliable for use with criminal justice-involved populations; (b) if classes of clients can be ascertained on a number of alterable strengths (i.e., twelve-step support, self-efficacy, cognitive reappraisal), alterable risks (i.e., difficulty with: transportation, housing, employment, substance use), and an unalterable risk measure (i.e., a standardized risk assessment score derived from prior convictions and personal history; *Recidivism Risk* from the COMPAS); (c) if ethnicity

functions as a significant covariate between emerging classes; and (d) if the emerging classes significantly predict recidivism (i.e., supervision violations) within three-months post-completion of the initial survey. The initial sample for the reliability analyses consisted of $N = 333$ clients serving time under community supervision at a probation agency in California, due to primarily substance-related convictions. Clients were all identified as male, 58% were identified as Hispanic and 42% White, $M = 39$ years old. After variables were selected for use in the LCA and observations with missing data were eliminated, the final sample utilized in the LCA was $N = 262$.

The internal reliability analyses revealed very high internal reliability statistics (α = .91 to .95) on the internal asset scales examined (self-efficacy, self-awareness, cognitive reappraisal, self-regulation). This is an important contribution due to the limited number of studies that examine strengths-based and internal asset scales with criminal justice-involved populations; future research would benefit from continuing to explore these measures and their utility with this population. Next, the LCA analyses revealed strong fit indices for a three-class model that was delineated as representing: *Low Strengths, High Risks* (45%); *High Strengths, Low Risks* (29%), and *Very Low Strengths, Low Risks* (26%). Of note was that the unalterable risk factor (i.e., Recidivism Risk) was not a notable factor in distinguishing class membership. In the covariate analysis, class membership was not found to be divergent by ethnicity. When recidivism (i.e., acquisition of supervision violations within three months of post-completion of the survey) was added as a distal outcome to the three-class solution, significant differences between the three classes emerged on the probability of whether or not an individual was likely to acquire supervision violations. Specifically, the *Low Strengths, High Risks* population was significantly more likely to acquire supervision violations than the other two classes of clients (*High Strengths, Low Risks*; *Very Low Strengths, Low Risks*).

The research suggests that clients may be able to be screened by use of alterable risk and alterable strengths in preventing or identifying propensity toward recidivism. Based on the lack of discriminant ability of the unalterable risk factor (based largely on criminal history), it is unclear now what the utility of an unalterable measure may be in such a screening tool. The use of LCA in this study provides an innovative way to bridge research into practice, in that practitioners and individuals in direct contact with similar criminal justice-involved clients could utilize results of these analyses to develop client profiles to intervene or provide additional supports to clients, in an effort to prevent recidivism. This research has important implications due to the various gaps in the literature; the potential for this research to be immediately useful and applicable for practitioners, policymakers, and researchers; and the general lack of strengths-based approaches used with criminal-justice involved populations that may help to better understand factors related to recidivism, and thus help deter the various negative outcomes that are associated with continued criminal justice involvement.

TABLE OF CONTENTS

1. Introduction

Lifetime criminal conviction rates for the average American are estimated to be approximately 1 in 3 (Vallas & Dietrich, 2014). Furthermore, once individuals are convicted of a crime, their likelihood of being arrested for another crime substantially increases (e.g., 68% within three years; Durose, Cooper, & Snyder, 2014). This occurrence of criminal re-offending is referred to as *recidivism*, and it has been a topic at the forefront of criminal justice research, policy, and treatment for the last several decades. Criminal conviction and recidivism rates are concerning for a variety of reasons, most of which are related to the various deleterious outcomes found to be associated with criminal justice involvement at various levels of impact (i.e., individual, familial, community, economy). In response to this dilemma, researchers have attempted to examine which factors are associated with recidivism. The initial result was a plethora of research primarily focused on unalterable risk and demographic factors (e.g., prior criminal history, racial background), followed by a shift toward alterable risk factors. While this research has yielded informative results, there is a dearth of research on the association of recidivism with another potentially impactful set of variables – alterable strength factors.

The present study contributes to recidivism research by examining recidivism from mixed strengths- and risk-based approaches, using supervision violations as a proxy for recidivism. The data for this study were derived from a population of individuals in central California who are under community supervision as part of their criminal sentence for primarily substance-related convictions under the Public Safety Realignment Act (PSRA). A latent class analysis (LCA) was performed to determine if groups of clients emerge from the study variables based on similar client patterns of responses on measures of alterable strengths, alterable risks, and unalterable risk. The emerging classes of clients were then examined in terms of how they differ based on ethnicity (covariate), as well as differences in the proportion of clients within each class that go on to obtain supervision violations within three-months post-completion of the initial survey.

The alterable risks and internal assets were chosen due to their ability to be intervened upon within the lives of criminal justice-involved clients[1], while recognizing that other combinations of variables and factors may yield stronger results. The intention is to see if viewing recidivism from this approach can provide more information on how dynamic factors relate to clients' continued criminal justice involvement. This is an important line of research due to the growing and ongoing struggle with reoffending that many individuals in the United States encounter daily. This research is also innovative in that it takes a new approach to examining recidivism in terms of: (a) providing information on how clients can be grouped into classes that directly translate to profiles of clients, as well as how these classes relate to recidivism; (b) how clients who recidivate are different from those who are not, in a practical way (i.e., direct comparison of client mean scores); and (c) utilize supervision violations as a proxy for recidivism. These approaches can be directly useful for practitioners, as they do not require advanced statistical knowledge to apply the knowledge gleaned, but rather provide easily usable profiles of clients to better identify clients that are at risk of recidivating. This research has important implications due to: the overall lack of understanding of alterable factors related to recidivism within the literature, policy, and treatment settings; the general absence of literature on strengths-based approaches to researching client recidivism; the lack of information on classes of clients as they relate to

[1] From this point forward, the term "criminal justice-involved clients" is shorted to "clients."

recidivism; and the general lack of knowledge as to how clients who recidivate and clients who do not recidivate are different in relation to mean strength and risk scores.

2. Recidivism

Recidivism is a phenomenon of concern due to the deleterious outcomes that have been documented in the literature as being associated with criminal justice involvement. If an individual is incarcerated due to their criminal charge or subsequent recidivism, the potential negative impacts are extended to the individual, their families, the victims, and the community. For example, at the individual level, people who are incarcerated have been found to experience a reduced ability to secure employment (Apel & Sweeten, 2009; Pager, 2003), significantly less earnings than pre-conviction (Waldfogel, 1994), smaller lifetime wage growth compared to that of non-convicted counterparts (Western, 2002), high rates of various marital struggles (Siennick, Stewart, & Staff, 2014), housing instability (Geller & Curtis, 2011), and trauma symptoms (i.e., from coercion witnessed and experienced in prison; Johnson Listwan, Colvin, Hanley, & Flannery, 2010). Having a household member who has ever been to prison has been an identified risk factor for traumatic impacts for minor children, as evidenced by the inclusion of this risk factor into the Adverse Childhood Experiences (ACE) inventory (Felitti et al., 1998). Other researchers have also suggested a likely relation between having a parent in prison and negative outcomes for children (see Akesson et al., 2012 for a review of these assertions), and emerging research is confirming these assertions (e.g., Kopak & Smith-Ruiz, 2016). Crime victims are also negatively impacted by criminal justice involvement, due to the re-traumatization that occurs during criminal justice proceedings of the prosecution of the crimes that victimized them (e.g., Parsons & Bergin, 2010). Lastly, economic impacts of criminal justice involvement are exorbitant; costs associated with the criminal justice system have been cited as being over $270 billion annually (e.g., in 2012; Council of Economic Advisors, 2016). Over $80 billion of this money is spent on incarceration (Council of Economic Advisors, 2016), with research finding little deterrent impact of incarceration on recidivism (e.g., Chalfin & McCrary, 2017; Johnson & Raphael, 2012; Liedka, Piehl, & Useem, 2006), and that incarceration is often related to an increased likelihood of recidivism (and thus, increased criminal justice costs; Council of Economic Advisors, 2016). Thus, to avoid deleterious outcomes for individuals, their families, their communities, and the economy, it is important to identify factors that are related to reducing the probability of recidivism for individuals with prior convictions.

A. Defining Recidivism

There are numerous definitions and methods of measuring of recidivism in the literature and in policy. Each of these methods has their own utility, importance, and implications in the literature. The criminal justice literature often refers to recidivism as engaging in further criminal behavior after initial criminal behavior has been perpetrated; a background of the history of the word *recidivism* suggests that the literal root meaning of recidivism is a “relapse” of criminal behavior (Peirson, 2016).

One common measure of recidivism is a “return-to-prison” statistic (e.g., Cartier, Farabee, & Prendergast, 2006; California Department of Corrections and Rehabilitation, 2016). This statistic refers to crimes in which individuals return to prison for their criminal offenses, and is not considered to be a global measure of recidivism (i.e., any commission of further crimes of a lesser degree). This statistic has been useful in more broad analysis, such as when comparing progress between and across states (e.g., Durose et al., 2014) and counties within states (e.g., California Department of Corrections and Rehabilitation, 2016).

Recidivism has also been measured by way of any new felony convictions (e.g., Mears, Cochran, Bales, & Bhati, 2016), supervision violations (e.g., Hendricks, Clark, Johnson, Faintaine, & Cropsey, 2014), re-arrest (Durose et al., 2014), or even self-admission of reoffending (e.g., Cartier et al., 2006). Recidivism definitions can also vary based on time frames examined; three-year recidivism rates appear to be most commonly reported (e.g., California Department of Corrections and Rehabilitation, 2016; Mears et al., 2016; Scott, Grella, Dennis, & Funk, 2014), although one-year (Cartier et al., 2006) and five-year (Durose et al., 2014) recidivism rates have also been reported.

B. Measuring Recidivism

The wide variability in definitions and measurement of recidivism has made specific statistics related to recidivism difficult to generalize across studies and findings. However, the statistics that are available paint an alarming picture. The national lifetime conviction rates within the United States are abysmal; the lifetime criminal conviction rates for the average American are estimated to be approximately 1 in 3 (Vallas & Dietrich, 2014), which equates to an estimation of between 70 and 100 million Americans with a criminal history (Bureau of Justice Statistics, 2014; Vallas & Dietrich, 2014). This statistic is critical when considering the phenomenon of recidivism because, by definition, in order to recidivate an individual must first have a criminal history. Furthermore, once an individual has been convicted of a crime, their likelihood of committing another crime substantially increases; statistics on individuals who are released from prison and re-convicted of future crimes within a three-year period are estimated to be around 68% nationally (Durose et al., 2014). These statistics suggests that the multitudinous negative impacts of criminal justice involvement are occurring to many Americans, and are re-occurring regularly for those with prior criminal justice involvement. Researchers with a desire to target recidivism may benefit from taking a nuanced look at the recidivism issue in their geographic region of interest due to significant variation in rates by state. As such, the present study is concerned with recidivism specific to California.

Recidivism trends in California over the last 20 years have appeared promising, but interpretations have been tainted by recent changes in state-wide legislation that upend the ability to compare statistics over time. For example, the available recidivism rates in California have indicated a recent and dramatic decrease; the return-to-prison recidivism rate (i.e., recidivism within three years of release from incarceration) hovered from between 64-68% between the years 2002 and 2008, before dropping to 45% in 2011 (California Department of Corrections and Rehabilitation, 2016). However, the passage of a new state legislation in 2011 (Public Safety Realignment Act [PSRA]; Beard et al., 2013; Criminal Justice Alignment, 2011ab) has complicated these statistics in immeasurable ways. The PSRA legislation intended to: (a) move supervision of a subset of clients released from prison from being supervised by state parole to being supervised local probation departments (clients are referred to as Post-Release Community Supervision; PRCS), and (b) has re-routed another subset of clients to spend time in local jail for their criminal conviction versus state prisons, many of whom are also sentenced to a period of community supervision by local probation departments (clients are referred to as 1170[h]). Both subsets of individuals reflect clients that possess a constellation of criminal history factors[2] and whose current offense is a felony and is primarily substance-related, as defined by PSRA legislation criteria.

[2] For example, for the latter group (1170[h])), these clients also must possess a criminal history being non-serious, non-violent, and non-sexual in order to be eligible to serve time under the legislation. These same criteria are not necessarily applied in the identification of clients to be released under the legislation for the former group (PRCS).

Both groups also can involve community supervision under local probation agencies; PRCS mandates community supervision for all clients released back into the community and 1170(h) provides a pathway where a jail only sentence is served (1170[h][a]) and another pathway where a jail sentence is served followed by a period of community supervision (1170[h][b]). Because state reporting on California's return-to-prison rates are on a five-year lag time, the impact of PSRA legislation, particularly the aspect re-routing clients through local jail versus prison, has yet to be reflected in available statistics on California's overall return-to-prison rates.

Local evaluation reports have suggested that, while the return-to-prison rate may not be high for individuals sentenced under this legislation since 2011, the overall rate of re-offending (i.e., conviction of any subsequent crime locally) within three-years post-release of incarceration is extremely high for some local populations subsumed under this legislation. For example, Hunnicutt, Sharkey, Cosden, Meskunas, and Janes (2017b) reported that locally there was an aggregate 25% return-to-prison rate during a post-release supervision period for clients released from state prison, between 2011-2015, reflecting the same trending decline in return-to-prison rates in California overall. However, re-conviction rates for *any* crime — regardless of whether or not that included a return to state prison to serve out their sentence — was much higher; within one year post-release 11-38% of these individuals released from state prison to local supervision between 2011-2015 were convicted of any new crime, and within two years between 40-53% were convicted of any new crime[3]. Thus, the drop in the return-to-prison rate observed in California in 2011 may reflect re-routing individuals into

[3] Rates were calculated by cohort year and thus reflect a range of possible percentages. Also note that conviction rates of *any* new crime can include those captured in the prior return-to-prison statistic.

the local jail system and not necessarily a decrease of recidivism itself. This is an important observation to make, in that it would be remiss to conclude that recidivism is not an issue for California or that the problem is being ameliorated. Furthermore, these rates indicate that the issue of recidivism with criminal justice-involved populations is of concern within the local community.

i. Supervision violations. While this paper is focused on utilizing supervision violations as a proxy for recidivism, I assert that, for many reasons, the criminal justice research community may benefit from utilizing supervision violations as a better outcome measure of a recurrence of engagement in criminal behavior. In the present paper data on incarceration for supervision violations was utilized as a measure for recidivism in the present analyses. Although unconventional, this measure was chosen over jail bookings for new recidivism events as well as the use of criminal conviction data, which is the standard measure of recidivism. The rationale for this is seven-fold:

(1.) it is unclear to what extent data on jail bookings would adequately capture new recidivism (compared to the ability of new criminal behavior to be captured using supervision violation data);

(2.) latency times for obtaining criminal conviction data within the court system can be lengthy, thus impeding the ability to provide real-time information on client progress, whereas supervision violation data are available immediately;

(3.) criminal conviction data can rarely be easily and definitively tracked to prior bookings that would indicate when the actual alleged crime occurred, and would instead provide a measure of when clients were convicted of the crime, which can be several months after the crime was actually committed (and thereby skewing the results and interpretability of the data), while supervision violation data is often a reflection of more recent behavior;

(4.) acquiring supervision violations is highly correlated with acquiring criminal convictions;

(5.) supervision violations can occur for a variety of reasons, including the acquisition of new charges, but also in relation to violation of probation terms, such as substance use or possession, of which may or may not result in future criminal charges;

(6.) supervision violations can potentially account for local criminal justice system responses to clients' out-of-county recidivism events, which are not captured in local booking or conviction data but can result in supervision violations due to out-of-county recidivism; and

(7.) recidivism itself represents too broad of a term that can encompass numerous meanings across many years after initial offense, which is not likely to accurately capture how current influences in the client's life affect their propensity toward engagement in criminal behavior.

These points are discussed in more detail below.

(1.) Jail bookings and recidivism. First, it is unclear to what extent a client may be charged with a crime but not be booked into the County jail for the subsequent crime, including for low-level crimes or crimes that result in the issuance of a citation. A preliminary analysis of this variable also suggested very low rates of new bookings within three-months post-completion of the survey, suggesting it to be an unstable variable to utilize in advanced statistical analyses. However, supervision violation data indicated nearly three

times as many data points on clients, suggesting supervision violations to be more robustly capturing client engagement in antisocial or criminal behavior.

(2.) Long latency times of criminal conviction data. Secondly, the utilization of criminal conviction data would require long latency times as clients move through the criminal justice system and acquire both convictions and sentences for their convictions. This delays the ability to provide real-time results on client behavior by several years, at which time client trends of behavior and needs may no longer be relevant or most accurate. On the contrary, supervision violation data is maintained by the overseeing probation department and is not affected by latency times.

(3.) Convictions not easily traced to the original offending behavior. Third, criminal conviction data provides data on when crimes were *convicted* versus when they were *committed*, and data points that would provide information on the actual crime commission date are often difficult to pinpoint and not easily forthcoming for data analyses. Thus, utilizing criminal conviction data can often skew results when they are linked within specific short time frames (i.e., three months, as in the present study) in that they can be reflective of behavior that occurred prior to the time frame in question. Conversely, supervision violations are often linked to recent behavior, or ongoing noncompliant behavior that has recently culminated and resulted in a probation response to that behavior; supervision violations are not typically administered in relation to *only* events that occurred months prior.

(4.) Violations and convictions are correlated. Fourth, acquiring supervision violations has been significantly associated with acquiring new criminal convictions in the local population being studied over several years of evaluation data (Hunnicutt, Dougherty, Sharkey, & Cosden, 2015; Hunnicutt et al., 2017b), suggesting that this is an appropriate

proxy for investigating recidivism in lieu of waiting out the latency time to receive client recidivism data.

(5.) Breadth of behavior captured in violations. Fifth, supervision violations can occur for a variety of reasons, including the acquisition of new charges, but also in relation to violation of probation terms, such as substance use or possession. The latter of these noncompliant behaviors could normally result in criminal convictions if clients were not under supervision, but for clients under supervision this may instead result in higher supervision levels, including increased supervision, treatment, or case management. Thus, supervision violations may be able to capture recidivist-like behavior that is not directly captured within the recidivism data.

(6.) Violations might account for out-of-county events. Lastly, supervision violations are likely to be the best source of accounting for clients' out-of-county recidivism events, which are not captured in local booking or conviction data. However, client recidivism out-of-county can result in supervision violations locally when the supervising department becomes aware of these events, further making supervision violations a strong measure to use as a proxy to recidivism.

(7.) Recidivism is a broad term that doesn't accurately capture impacts of current influences. The term recidivism itself represents too broad of a concept that can encompass numerous and conflicting meanings, with many recidivism definitions including time lengths that are many years after the initial offense. Report on data several years after an initial offense is not likely to be reflective of the true impact of any treatment modalities, interventions, or strength/risk factors on clients while they were being implemented or experienced.

It is important to note that many of these points will apply to most counties' data and procedures, making their applicability to other counties in California, as well as across the country, wide-spread. Because recidivism has been reported in the same way over a long period of time there may be resistance to altering the focus on how to collect better real-time data on recidivism in terms of utilizing supervision violations. This may occur particularly within probation departments that feel "spread too thin" and as if they are lacking the resources to implement supervision violations as often as they feel they should occur. However, this is more reason to utilize supervision violations as a measure of recidivism; it would thus provide support for criminal justice departments that need additional funding to keep their communities and clients safe. Based on the points outlined above, it is clear that the current focus on recidivism as strictly a conviction statistic is largely and inherently flawed, in favor of other potential methods for more accurately capturing the root of the word "recidivism" itself as a re-engagement of criminal behavior.

C. Models for Addressing Recidivism

There have been many theories on how to address criminal behavior in clients. In recent decades, the reigning theory has been the Risk-Needs-Responsivity (RNR) model (Andrews & Bonta, 2017; Looman & Abracen, 2013). This model examines criminal justice interventions from the perspective that three main elements should be evaluated and addressed for criminal behavior (and subsequently, recidivism) to be reduced among clients; client risks, client needs, and characteristics that enhance client to responsivity to intervention (Andrews & Bonta, 2017). The risk factor represents the idea that clients should receive intervention commensurate with their risk level, such that high-risk clients should receive more intensive interventions than low-risk clients (Andrews & Bonta, 2017; James, 2015). The needs factor asserts that an assessment of clients' criminogenic needs is critical, and that interventions should target the identified criminogenic needs. The needs factor further states that treatment should steer away from addressing factors in treatment that are related to noncriminogenic needs (e.g., self-esteem, distress), as they are not considered within the theory to be able to decrease recidivism (Andrews & Bonta, 2017; James, 2015). Finally, the responsivity factor suggests that clients' ability levels and personal characteristics be considered when providing treatment, otherwise treatment is likely to be less effective (Andrews & Bonta, 2017). The responsivity factor also favors cognitive-behavioral interventions and interventions that are consistent with social learning theories (Andrews & Bonta, 2017). The risk and needs factors assessed in the RNR model are history of antisocial behavior, antisocial personality patterns, antisocial cognitions, antisocial associates, family/marital factors, school/work, leisure/recreation, and substance abuse.

Research has generally supported the use of the RNR model with criminal justice involved populations. Multiple metanalyses of treatment studies have found that targeted interventions versus punitive reactions to client misconduct has resulted in better client outcomes (Dowden & Andrews, 1999, 2000), with interventions that embraced the RNR model demonstrating the largest effects for treatment (Andrews et al., 1990; Dowden & Andrews, 1999,; Hanson et al., 2009). While many modern risk assessment tools assess for risk and needs factors, the RNR model goes a step further than the mere assessment and demands that service delivery address these factors on an individual basis (James, 2015). However, criticisms to this model have included the idea that the RNR model is deficit-based and denies the importance of embracing strengths-based factors within its approach to clients (Ward & Stewart, 2003). Even among RNR proponents there has been recent acknowledgement that the RNR model as it stands may not be sufficient (Looman & Abracen, 2013), though these proponents suggest further examination of clients' risk factors, such as trauma and mental health disorders.

More recently, strengths-based models have been explored in terms of addressing clients' criminal behavior. Strengths-based approaches examine the way in which clients' strengths can promote resilience in the face of adversity (Pulla, 2012). Researchers have suggested that strengths-based approaches clarify client outcomes when working with criminal justice involved populations, such as within the context of social work (e.g., Peck, 2013), working with clients with prior sexual offenses (e.g., Ward & Stewart, 2003), and working with clients re-entering the community from prison (Hunter, Lanza, Lawlor, Dyson, & Gordon 2016). However, the use of strengths-based models with adult criminal justice involved populations is not widely occurring. Researchers have recently begun making calls to action for include strengths-based approaches in the assessment of criminal justice involved clients (e.g., Hunter, 2016), with some of the research suggesting an almost entirely strengths-based approach with these clients overall (e.g., Ward & Laws, 2010) and others calling for an integration of strengths with risks (e.g., Hunter, 2016). Criticisms of strengths-based models are often the inverse of those for risk-based models such as RNR; it is that the predominantly strengths-based models give the appearance of ignoring the importance of client risk factors (Loomans & Abracen, 2013).

The research on the RNR model and the potential for inclusion of strengths-based variables within client assessments in the criminal justice system seem to suggest that there is room for improvement upon and integration of these respective theories. However, a cohesive theory that integrates strengths and risks into an understanding of client recidivism

— and particularly with clients with primarily substance-related crimes — is nonexistent. Given that there is research to support the use of both types of models in work with clients in general, the present research was conducted in hopes of providing additional stimuli for the construction of a framework that would integrate both risk and strengths effectively.

D. Factors Related to Recidivism

Identifying factors related to a decreased probability of recidivism is important due to these deleterious and cyclical associations of an individual's involvement in the criminal justice system. This sense of urgency is apparent in the voluminous amount of research examining factors related to recidivism that has been amassed in the last few decades. While some of the available research examines factors related to recidivism from a traditional research standpoint (i.e., analyzing a hypothesized association between variables), there is also a large amount of research borne out of (or as a result from) the push to design tools such as risk assessments that can provide information on an individual's probability of recidivating and recommended supervision levels for clients who will be supervised in the community. These tools vary in scope (i.e., type of variables examined) and nature (e.g., predicting general recidivism or violent recidivism), but are distinct from other forms of scales or assessments that may be utilized with criminal justice involved populations in that they are also intended to be linked to supervision and/or treatment decisions (Hochstetler, Peters, & DeLisi, 2016).

Despite the proliferation of risk assessment tools, much of the research on recidivism and risk assessment tools has been focused on select factors, making much of the available research condensable. The literature on recidivism has suggested three overarching themes regarding factors associated with or predictive of recidivism: (a) *unalterable risk factors* are related to an increased likelihood of recidivism; (b) *alterable risk factors* are related to increased likelihood of recidivism; and (c) *alterable strengths factors* are related to a decreased likelihood of recidivism. Within this context, *risk factors* for recidivism are factors that increase the likelihood of reoffending and *strength factors* are factors that decrease the likelihood of reoffending (Cuervo & Villanueva, 2015; Farrington, Loeber, & Ttofi, 2012). *Unalterable factors* refer to variables that are stable and not possible to intervene upon, and generally include variables such as demographics or historical variables; conversely, *alterable factors* are variables that have the potential to be changed or altered in some fashion, and are not inclusive of historical and/or irreversible factors.

A review of these themes and concepts below outlines the common characteristics found throughout the literature on criminal recidivism; however, this is not an exhaustive review. It is also important to note that, while the findings outlined below represent generalized themes within the literature of variables that are related to recidivism (i.e., unalterable risks, alterable risks, alterable strengths), there is often crossover in studies between the different themes described below. For example, research regarding the Level of Service Inventory–Revised (LSI:R; Andrews & Bonta, 1995) risk assessment tool often includes an examination of what is referred to as risks (i.e., unalterable risks) and needs (i.e., alterable risks) that are inherent within the scores provided by that tool (e.g., Caudy, Durso, & Taxman, 2013). Similarly, the Structured Assessment of Violence Risk in Youth (SAVRY; Borum, Bartel, & Forth, 2006) risk assessment tool is comprised of social factors (i.e., alterable risks), historical factors (i.e., unalterable risks), and strengths (Shepherd, Luebbers, Ogloff, Fullam, & Dolan, 2014); research that involves this tool may cross over in multiple themes, as well. Thus, studies on recidivism — and particularly on risk assessment tools — are often not conducted in isolation of one type of factor examined. This suggests that some findings are already incorporating the variance accounted for by other types of factors; for example, a study on the SAVRY that finds unalterable risks not to be predictive of recidivism may be in part due to the SAVRY also accounting for variance in alterable risks and strengths that better account for the data.

i. Unalterable risk factors. Early research on recidivism was largely focused on unalterable factors that were related to an increased probability of recidivism, such as prior criminal history or racial background. Over time research on recidivism has taken a more varied approach to inclusion of other types of factors in predicting recidivism; however, research on unalterable risk factors has generally found large predictability of recidivism. For example, one of the most consistently examined unalterable risk factor is an individual's criminal history, with research generally demonstrating that aspects of an individual's prior criminal history are linked to an increased likelihood to recidivate (Caudy et al., 2013; Linn, Nochajski, & Wieczorek, 2016; Olson, Stalans, & Escobar, 2016; Silver & Chow-Martin, 2002). Aspects of an individual's criminal history that have been linked to increased recidivism have included variables examining the nature, extent (Olson et al., 2016), or mere presence of (Silver & Chow-Martin, 2012) an individual's prior criminal history; in terms of whether or not prior crimes occurred within a specific time frame (e.g., prior two years, or within a juvenile record; Silver & Chow-Martin, 2002), or in terms of total prior lifetime rates (Olson et al., 2016); and in terms of arrests (e.g., Silver & Chow-Martin, 2002) or incarcerations for new convictions (e.g., Olson et al., 2016). Other unalterable factors that have been generally linked to recidivism have included younger age (Gendreau, Little, & Goggin, 1996; Piquero, Jennings, Diamond, & Reingle, 2015), substance use history, gender

(Silver & Chow-Martin, 2002), childhood trauma, prior mental health treatment (Håkansson & Berglund, 2012; Olson et al., 2016), having certain mental health diagnosis (Guebert & Olver, 2014), and not having custody of minor children (Scott et al., 2014).

While various combinations of these unalterable risk factors have amounted to providing in some case upward of 95% accuracy in predicting recidivism among clients (Silver & Chow-Martin, 2002), there has been much criticism to this approach. Such approaches seem to reduce an individual to their history and prior circumstances without accounting for any individual variance that might occur within more fluid or change-related aspect of a person (Gendreau et al., 1996; Glazebrook, 2010). Furthermore, recent research on risk assessment tools that have incorporated other factors (i.e., alterable risks, alterable strengths) has suggested that, when these other important factors are considered, unalterable risks are no longer significant predictors of recidivism (Lodewijks, de Ruiter, & Doreleijers, 2010). These points beg the question of whether a high reliance on factors that are unable to be intervened upon is the best approach to identifying all possible factors — including the most relevant factors — related to recidivism.

ii. Alterable risk factors. New approaches of examining recidivism eventually arose after the emergence of the early stages of recidivism research and research on treatment for criminal justice-involved clients. Many of these approaches focused on including alterable risk factors (referred to as dynamic risks or criminogenic needs in much of the criminal justice literature; Andrews & Bonta, 2003; Bergeron & Miller, 2013) in their analyses of recidivism outcomes (Duwe, 2014). The intention of including alterable risk factors is to identify factors that can be intervened upon and inform treatment interventions (Genderau et al., 1996).

The terminology used to describe these alterable risk factors has often been inconsistent. Much of the criminal justice literature uses the word “dynamic” to describe criminogenic and/or internal characteristics (e.g., Andrews & Bonta, 2017; Gendreau et al., 1996; van der Put, Creemers, & Hoeve, 2014) that are related to recidivism, while others consider a more inclusive definition of dynamic to extend to such ecological variables as relationships with others and employment (e.g., Hunter et al., 2016; Piquero et al., 2015). Some researchers use the word without providing their operationally defined interpretation of the meaning (e.g., Singh et al., 2014), further adding to the confusion and inconsistency. Regardless, an overarching theme found within the recidivism literature is that *any* alterable risk factor has the potential to decrease the likelihood of recidivism; thus, the term *alterable* is used in this study to cohesively describe those factors. A review of the relevant literature has found that alterable risk factors linked to recidivism have included specific internal risk characteristics, substance use, and ecological factors.

Many studies of alterable risk factors for recidivism have focused on intra-individual change (Serin, Lloyd, Helmus, Derkzen, & Luong, 2013). One of the most heavily researched of these is criminal thinking (or antisocial attitudes). Criminal thinking measures have suggested a strong and positive relationship with recidivism (Banse, Koppehele-Gossel, Kistemaker, Werner, & Schmidt, 2013; Guebert & Olver, 2014; Serin et al., 2013), and have been a focus of several evidence-based treatment interventions for clients (e.g., Moral Reconation Therapy; Little & Robinson, 1988). Other internal and alterable risk factors related to recidivism have included aggression and negative affect (Linn et al., 2016).

Substance use is another alterable risk factor strongly linked to recidivism. This is particularly relevant when measured broadly, such as in terms of general use, frequency, or symptom presence (Guebert & Olver, 2014; Scott et al., 2014; Serin et al., 2013; van der Put et al., 2014). Substance use has also been found to be a significant indicator of recidivism even after controlling for various risk and protective factors (van der Put et al., 2014). However, research on more specific types of substance use variables, such as drug type, with recidivism has yielded less consistent or informative results (e.g., Håkansson & Berkglund, 2012; Hendricks et al., 2014). Thus, indicators of general substance use appear to have the most reliable qualities for predicting recidivism within the literature.

Alterable risk factors in an individual's ecology have also been found to be highly predictive of recidivism. Socially, an individual's association with antisocial or negative peer groups (Jung & Rawana, 1999; Serin et al., 2013) and lack of social support in general (Serin et al., 2013) have demonstrated significant relations to recidivism. Similarly, lack of employment (Jung & Rawana, 1999) and residing in urban areas (Silver & Chow-Martin, 2002) have been found to be positively associated with recidivism; conversely, having a job has been found to be negatively associated with recidivism (Silver & Chow-Martin, 2002). While some ecological variables — such as employment and type of city residing in — are less amenable to traditional approaches to intervention with clients, these variables are still able to be intervened upon and are thus considered to be alterable risk factors.

iii. Alterable strength factors. The third common thread within the recidivism research is found within the emerging research on alterable strength factors. Strengths (also referred to as protective factors) within the recidivism literature generally refer to factors that are related with a decreased probability of re-offending (Cuervo & Villanueva, 2015; Farrington et al., 2012). While the definitions of risk and strength factors appear to suggest mutual exclusivity, this is not necessarily the case. These two types of variables (i.e., risk, strength) often represent related but independent approaches to a variable (Cuervo & Villanueva, 2015; Farrington et al., 2012), such that the absence of a risk does not always imply the presence of a strength, and vice versa. In some cases, the absence of a risk may in fact imply the presence of a strength (e.g., a dichotomous variable of having either abstained from or used an illicit substance); however, the available research on strengths-based approaches, as well as the literature on strengths in recidivism, suggest that these two sets of variables be treated as separate.

Generally, the literature appears to suggest that having more and/or higher levels of strength factors is negatively associated with recidivism. For example, an analysis of alterable risks and strengths (using the Structured Assessment of Violence Risk in Youth [SAVRY]) on violent recidivism in a sample of Dutch juvenile clients revealed that strengths significantly and negatively predicted violent recidivism, while alterable risks were not significantly related to recidivism at all when considered in the same model as strengths (Lodewijks et al., 2010). Furthermore, these authors found that prediction of recidivism could be explained by a combination of alterable risk and protective factors, but unalterable risk factors did not contribute at all to predicting recidivism when all three types of variables were considered within the model. Interestingly, similar findings were obtained using the same instrument in a sample of Australian juvenile clients; the protective factors subscale had the most significant association with and prediction of recidivism in this population of clients, for males, females, and the overall population combined, above and beyond alterable and unalterable risk subscales included in the model (Shepherd et al., 2014). Another study examined Spanish juvenile clients, comparing those who recidivated and those who did not on protective factors (Cuervo & Villanueva, 2015). The authors found that the recidivist group had significantly lower mean scores on each of the protective factors included in the model than the non-recidivist group (i.e., positive family influences, vocational achievement, positive peer relationships, abstaining from substance use, hobbies, prosocial behavior and attitudes). Total number of protective factors has also been found to significantly predict desistence from recidivism in juvenile populations (Rennie & Dolan, 2010). Lastly, self-control has been linked to recidivism in a sample of adult offenders (Malouf et al., 2014).

The findings suggest a stable predictive power of alterable strengths in predicting recidivism in juvenile offending populations. While it is unclear to what extent these findings would generalize to adult criminal justice-involved populations, it would be remiss to ignore alterable strengths in any consideration of how to account for adult recidivism. Furthermore, these findings provide further context to conflicting research regarding alterable risk factors in predicting recidivism; researchers have found that the addition of alterable risks did not improve prediction of recidivism in a baseline model of unalterable risk factors predicting recidivism (Caudy et al., 2013), but when researchers have incorporated both alterable risks and alterable strengths they have found that both types of factors were significant predictors of recidivism, with the strengths being predictive above and beyond unalterable risks (Lodewijks et al., 2010; Shepherd et al., 2104). This suggests that the predictability of recidivism is enhanced consistently when alterable strengths and risks are included with static risks, and may even account for variance in explaining the impact of unalterable risks. This may occur via the following mechanism: an individual's prior experiences with unalterable risks (e.g., prior criminal justice involvement, exposure to traumatic experiences, growing up in poverty) may in turn influence their current state of functioning (and thus, their current and alterable strengths and risks). Without intervention or if otherwise unchanged, these alterable internal and ecological factors (i.e., strengths and risks) continue to manifest in a circular fashion, continuing to perpetuate the same prior result that was achieved (i.e., offending). The findings taken together suggest that examining alterable strengths is a more fruitful and powerful approach to predicting client recidivism than by models of unalterable and alterable risk factors alone.

Several considerations remain in the examination of client strengths in relation to recidivism. First, the research on recidivism is notably absent of a focus on unalterable strength factors; while little research does exist, a much stronger focus has been placed on alterable strengths. Second, the research on client strengths within the recidivism literature is not nearly as vast as the work on client risks (Cuervo & Villanueva, 2015), and that most of the known research on strengths is within the context of examining both risks and strengths together (and thus, not in models with strengths alone). Third, much of the available literature on alterable strengths and recidivism has been conducted with juvenile populations, making generalizations to the adult client populations tenuous. Lastly, the recent focus on alterable strengths in relation to recidivism is likely born out of coinciding recent calls to approach criminal justice populations in a strengths-based way, including in the examination of re-offending (Hunter et al., 2016); the recency of this movement is likely part of the reason for the dearth of available literature of alterable strengths with adult populations. The present study seeks to help fill some of these gaps by conducting research on criminal justice involved adult populations that implements an examination of both risk and alterable strength factors in relation to client outcomes.

3. The Current Study

The recent research focus on alterable risk factors has significantly expanded upon prior recidivism research that primarily focused on unalterable and historical variables. However, the extant literature on alterable and unalterable risk factors have indicated conflicting results as to whether they provide enough information to robustly predict recidivism. For example, in one study, adding alterable risks to an existing model that used unalterable risks to predict recidivism did not significantly increase the predictability of recidivism (Caudy et al., 2013), while other studies have found that alterable risks have been significantly predictive of recidivism (e.g., Banse et al., 2013; Guebert & Olver, 2014; Linn et al., 2016; Serin et al., 2013). The research on recidivism has found that the inclusion of *alterable strengths* significantly bolsters the prediction of recidivism in statistical models (Lodewijks et al., 2010; Shepherd et al., 2014), suggesting that it is important to include such variables in recidivism research, and that these variables may account for conflicting results when only risks are accounted for. Lastly, the research on strengths-based variables and recidivism — and particularly with adult clients — is sparse, despite many recent calls for more investigation of strengths-based approaches to address recidivism.

The present study contributes to addressing several of these gaps in the literature by investigating recidivism within the context of a mixed strengths and risk-based approach, using supervision violations as a proxy for recidivism. Latent class analysis was utilized to determine the presence of distinct patterns of alterable strengths, alterable risks, and unalterable risks among a population of adult criminal justice-involved clients in California. The inclusion of all three types of variables (i.e., alterable strengths, alterable risks, unalterable risks) is due to the review of the literature indicating that all three types of variables are independently significantly related to recidivism, as well as the intention of providing further evidence of the importance of strengths when all three types of variables are included. The study also examined how any emerging patterns (i.e., classes) of client responses relate to client recidivism (i.e., acquisition of supervision violations).

Lastly, the present study hopes to provide a starting point from which strengths-based factors outside of the current variables in known risk assessment tools are evaluated, as I suspect that other strengths than the small subset of ones that have previously been examined may have predictive validity of recidivism. I do not assert that the ones in the present study are the only important strengths variables to consider, but they are intended to be ones from which a foundation for future studies to examine strengths with client populations can be built upon.

A. Covariate

Ethnicity was controlled for in the present study. This covariate was chosen due to its unalterable nature and the large body of literature suggesting that ethnicity contributes to explaining variance in criminal justice research outcomes. For example, ethnic disparities in convictions and incarceration rates are well-documented (e.g., Carson, 2015; Nellis, 2016), with individuals of minority racial and/or ethnic backgrounds being more likely to be arrested, receive longer sentences, (Hartney & Vuong, 2009) and be incarcerated (Carson, 2015; Nellis, 2016) than individuals of the dominant White culture. This is part of a larger conversation regarding the intersection between criminal justice and social justice concerns and initiatives, and is beyond the scope of the present study to review. However, ethnicity was controlled for to more accurately assess the relation between recidivism and risk and strengths variables.

B. Research Questions

The specific research questions that were examined are:

1. Are strengths-based measures reliable for use with criminal justice involved populations and normally distributed?
2. Which alterable risk, alterable strengths, and unalterable risk factors are related to recidivism?
3. Are there classes of clients based on the factors identified as significant in R2?
4. Do any resulting classes from R3 relate to recidivism?

i. Research Question #1: Are strengths-based measures reliable for use with criminal justice involved populations and normally distributed? The literature is lacking in information about the use of strengths-based measures in adult criminal justice involved populations. The extant literature on the use of such measures within juvenile populations suggests that strengths-based measures are reliable and important indicators of future criminal justice-related outcomes (e.g., Lodewijks et al., 2010; Shepherd et al., 2104). The present study first examined reliabilities of strengths-based measures to ensure that they are reliable for use with an adult criminal justice population and report on these reliabilities prior to proceeding to the subsequent analyses. Cronbach's alpha was utilized to assess reliability. It was hypothesized that the strengths-based scales would yield strongly reliable statistics for use with the present population, which would subsequently assist in ensuring accuracy of analyses, insomuch as reliability is a factor. Additionally, the scales were analyzed for normality of distribution of mean scores to determine the extent to which "ceiling effects" may exist within the average scale means.

ii. Research Question #2: Which alterable risk, alterable strength, and unalterable risk factors are related to recidivism? There are varying amounts of information on unalterable risk factors, alterable risk factors, and alterable strength factors, and how each type of variable has been found to relate to recidivism. The present study seeks to add to the body of literature that exists for each of the three types of factors by examining whether variables representative of each are related to recidivism. This was done by dichotomizing survey and background information from criminal justice involved individuals and comparing each individual item by whether a significant proportion of clients who endorsed that item recidivated within three-months post-completion of the survey. Because most of the variables examined within this study have not been thoroughly explored within the recidivism literature, this exploratory analysis was conducted to help identify a subset of those that would be helpful in developing profiles related to recidivism.

iii. Research Question #3: Are there classes of clients based on the factors identified as significant in R2? There is a lack of available research examining the interplay of unalterable risks, alterable risks, and alterable strengths within criminal justice involved populations. Additionally, one of the biggest drawbacks to the current state of recidivism literature is the lack of immediately applicable research findings for practitioners and professionals working on the "front lines" with criminal justice involved populations. The present study employed a latent class analysis (LCA) to provide more accessible information on what profiles of clients look like within similar criminal justice involved populations, based on item responses on unalterable risks, alterable risks, and alterable strengths. LCAs lend toward results that are graphically depicted in in a functional way, such that they can be visually interpreted even to those unfamiliar with advanced statistical knowledge. They provide profiles of client responses to dichotomized items, so that the likelihood of clients endorsing each item within the identified profiles (i.e., "classes" in LCA) is depicted. The

LCA in this study used a small number of items for the analysis, which means that only a small number of items would need to be translated into a screening tool for practical and immediate use.

Using an LCA is also superior to solely relying on cut off scores to determine client classifications into groupings, as it does not force clients into one specified group or another, which often occurs when using cutoff scores (Nylund et al., 2007). This means that client patterns can freely cross over into multiple potential grouping domains, and are not identified as being solely representative of one group. In the present study, it allows us to examine the extent to which clients may endorse risks and strengths at the item level, which would allow for clients to report experiencing any of several combinations of relations between these variables; whereas with cutoff scores, clients are forced into groupings and then scores on those groupings are compared or used to determine other associations.

iv. Research Question #4: Do any resulting classes from R3 relate to recidivism? Using the classes identified in Research Question #3, the intention was to then see how well these classes predicted recidivism (i.e., supervision violations within three-months post-completion of the survey) to provide a method for classifying which alterable/unalterable risk factors and alterable strengths may be contributing to a client's propensity toward recidivism. Within the context of the present study, practitioners can use the results to determine if a client in their office is likely to engage in criminal behavior in the next three months, based on their responses to a limited number of items that are examined in the LCA. It also allows for practitioners to identify the unique strengths and risks of the client that could be targeted for various interventions, versus a blanket statement that they are "at risk," or by identifying their likelihood of noncompliance based on one item only. This can provide a cost-effective and research-based way to disseminate agency resources, which are often limited across programs that work with criminal-justice involved populations, and in turn, this could reduce client propensity toward recidivism.

4. Method

A. Procedures

Data for the present study were derived from data collected from a California Probation Departments' internal client survey, as well as the Probation Department's client background and jail booking data. The internal survey includes items on demographics, treatment participation, treatment perceptions, logistic difficulties while on community supervision, and internal assets (i.e., strengths). Background data include demographic information, and recidivism data include booking information into local County jail.

The clients were mandated to complete the internal survey during the check-in process for appointments with their probation officers, as part of the client's supervision terms. Clients completed the survey on a computer-based kiosk in the front office of the probation department. Clients were informed that their answers would remain confidential (i.e., they would not be sent to their Probation Officers and would only be kept on file for internal departmental evaluation purposes). Surveys were provided in both English and Spanish; however, due to the small number of Spanish surveys ($N = 15$), only English surveys were included in the present analyses. Clients completed the survey one time during their supervision period, with these time periods varying across clients; the survey administration was part of a pilot data gathering program and as such clients were administered the survey as quickly as possible upon survey initiation, which resulted in this wide variation among clients. Data in this study reflect surveys administered to clients from

December 2015 through February 2017 for all clients who reported to their probation officer as part of their PSRA supervision terms during this time frame.

Data were collected, stored, secured, and maintained by the probation department of origin. De-identified data were provided for the purposes of evaluating program statistics and for research purposes, which were subsequently coded, stored, and analyzed by trained research assistants at our institution.

B. Sample

All participants had received felony criminal convictions that fell under the auspices of the Public Safety Realignment Act, which denotes clients being released from state prison or County jail for eligible non-violent and primarily substance-related crimes. All clients had been released from incarceration for their convictions and were serving out supervision terms as a condition of their release from incarceration. The exact length of time since clients had been released from incarceration was unavailable. This was due to two factors: (1) all clients on community supervision were administered the survey once, with the administration occurring based on a survey "roll out" time frame and not based on when the clients entered community supervision; and (2) data on client release from incarceration for other prior or current crimes were unavailable from the agency that housed these data.

To provide generalizable and accurate results, only data on male clients who identified as Hispanic or White were examined. Research has consistently shown that criminal justice involvement (e.g., Carson, 2015) and substance use (the primary motivation of this study's population of clients; e.g., Center for Behavioral Health Statistics and Quality, 2016) are extremely divergent between genders. The low number of female client responses available (47 out of 417) also suggested that there would not be enough power to conduct stable analyses or comparisons between male and female clients; thus, female clients were excluded to strengthen the interpretation and generalizability of results. Additionally, only data on Hispanic and White clients were analyzed, due to the very small number of clients endorsing ethnicities outside of these two categories (and thereby limiting generalizability of results to these populations). Of the $N = 417$ initial survey responses, 47 (11%) clients were identified as female and 43 (10%) identified as Black, Other, or had missing ethnicity data. These data points were deleted in order to maximize generalizability of study results, leaving $N = 333$ data points (note that these two demographics do not represent mutually exclusive data points; clients could have been grouped within both categories, and thus the difference did not exactly equate to $N = 333$). Of the $N = 333$ sample, 194 (58%) of clients were identified as Hispanic and 139 (42%) were identified as White. The average age of clients at the time of the survey was 39 years old. While age is considered a potential influential factor, the Recidivism Risk score uses age to assist in calculating the risk variable (Northpointe, 2015b), and thus is captured within this variable in the analyses.

C. Measurement

Both established measures and one-item measures created for the internal survey were used in the present analyses.

i. Strengths. Six strengths were examined within the present study, including two forms of program support (i.e., twelve-step support, treatment support) and four internal assets (i.e., self-efficacy, self-awareness, cognitive reappraisal, self-regulation). All strengths were self-reported by the client as part of the internal survey administered by Probation. The latter four internal asset scales are derived from Social Emotional Health Survey — Higher Education edition (SEHS-HE; Furlong, You, Shishim, & Dowdy, 2017); self-efficacy and self-awareness are derivative from the *belief in self* factor, and self-regulation and cognitive reappraisal are derivative from the *emotional competence* factor. Some of the items were slightly modified to present questions in a way that the present population could access and understand. Most modifications were minor in nature, usually involving omitting a single word or replacing one a more complex word or phrase with a simpler one (see Table 1); the nature of the questions and the intention of the constructs remained the same. The internal assets scales were chosen for examination due to their ability to be altered within the objectives of available treatment modalities within the community, as well as their well-documented and sound psychometric properties and significant relations to a wide variety of individual outcomes. Lastly, two different forms of program support (i.e., twelve-step support and treatment support) were also examined due to the documented importance of treatment in assisting clients with criminal histories in being successful in avoiding recidivism in the future (e.g., Serin et al., 2013). Both types of program support (twelve-step support, treatment support) were examined separately due to the separate nature of their program types.

Twelve-step support. As part of the internal survey, clients were asked to indicate which treatment modalities that they have participated in (i.e., "Which programs have you participated in? [CHECK ALL THAT APPLY]") out of a list of different drug and alcohol and mental health treatment services. Clients who clicked on the box that stated "AA/NA – I attend and I DO have a sponsor" were coded as having indicated that they receive twelve-step support (i.e., *Yes* = 1, *No* = 0). A separate box was available for endorsement that read "*AA/NA – I attend and I do NOT have a sponsor,*" but was not coded for endorsement of twelve-step support due my hypothesis that clients would differ based on whether they attend meetings only, versus go the extra step to obtain a sponsor and work on their "step work" in the twelve-step program. This item was created for the internal survey.

Treatment support. As part of the internal survey, clients were asked to indicate which treatment modalities that they have participated in (i.e., "Which programs have you participated in? [CHECK ALL THAT APPLY]") out of a list of different drug and alcohol and mental health treatment services. Clients who clicked on any of these boxes were coded as having obtained *treatment support*: "Groups (Other than AA/NA)" under the Drug and Alcohol Treatment list of services, "Individual therapy/counseling" under the Mental Health Treatment list of services, or "Group therapy" under the Mental Health Treatment list of services. Clients were coded as having indicated that they receive treatment support dichotomously (i.e., *Yes* = 1, *No* = 0). The treatment support item is intended to reflect treatment support received by a treatment program separate from 12-step group participation. This item was created for the internal survey.

Self-efficacy. Self-efficacy was assessed by examining client responses to the questions, "Generally, I think I can handle problems," "I will be able to achieve most of the goals that I have set for myself," and "I will be able to successfully deal with many problems." Items were assessed using a four-point scale 1 = *Not at all true*, 2 = *A little true*, 3 = *Pretty much true*, and 4 = *Very true.* Items were averaged to obtain a scale mean score. The self-efficacy subscale has demonstrated adequate reliability with college-aged students (i.e., r = .83; Furlong et al., 2017). Reliability of this construct within the population utilized in the LCA in the present study yielded a high reliability for the self-efficacy scale (r = .94).

Self-awareness. Self-awareness was assessed by examining client responses to the questions, "I am able to identify the reasons behind my actions," "I understand my moods and feelings," and "I have a good sense of why I have certain feelings most of the time." Items were assessed using a four-point scale 1 = *Not at all true*, 2 = *A little true*, 3 = *Pretty much true*, and 4 = *Very true.* Items were averaged to obtain a scale mean score. The self-awareness subscale has demonstrated adequate reliability with college-aged students (i.e., r = .76; Furlong et al., 2017). The reliability for the self-awareness scale in the present study for the population utilized in the LCA was high (r = .94).

Cognitive reappraisal. Cognitive reappraisal was assessed by examining client responses to the questions, "When I feel down, I try to focus on the positives," "I can lift my mood by changing my thoughts to positive ideas," and "I am able to think about the other options to a problem in hard situations." Items were assessed using a four-point scale 1 = *Not at all like me*, 2 = *A little like me*, 3 = *Like me*, and 4 = *Very like me.* Items were averaged to obtain a scale mean score. The cognitive reappraisal subscale has demonstrated adequate reliability with college-aged students (i.e., r = .74; Furlong et al., 2017). The cognitive reappraisal scale for the population utilized in the LCA of the present study yielded a high reliability for this construct (r = .94)

Self-regulation. Self-regulation was assessed by examining client responses to the questions, "I think about possible results before I act," "I can wait for what I want," and "I think before I act." Items were assessed using a four-point scale (1 = *Not at all true*, 2 = *A little true*, 3 = *Pretty much true*, and 4 = *Very true*). Items were averaged to obtain a scale mean score. The self-regulation subscale has demonstrated adequate reliability with college-aged students (i.e., r = .67; Furlong et al., 2017). The self-regulation scale for the overall population in the present study for the population utilized in the LCA yielded a high reliability for this construct (r = .93)

ii. Alterable risks. Five risk factors were examined within the present study; four represent struggles that clients experience in managing the logistics of everyday life, and one reflects struggles with substance use. The logistic risk factors include transportation to appointments/job, employment, housing, and financial obstacles. These factors were chosen for examination due to their ability to be altered by engagement with various resources and treatment services in the community, as well as their well-documented relationships to a wide variety of individual outcomes.

All items were measured by way of an overarching question stem that asked the client to rate "Have you had any of these problems while on supervision?" Four of the five risk factors (i.e., "Housing," "Employment," "Financial," and "Substance use") were then presented on their own line, with possible client responses reflected on a five-point scale (1 = *Never*, 2 = *Occasionally*, 3 = *Sometimes*, 4 = *Often,* and *5 = Always*). Thus, each individual risk was measured in one-item. Two items represented the risk factor of difficulty with transportation (i.e., "Transportation to appointments," "Transportation to a job,"), both represented on the same 5-point scale as the other items above. For this item, the largest response number from either of the transportation items was taken to measure the risk factor of *transportation.*

One-item measures have been found to be valid for use across a variety of measures, including alcohol and drug use (e.g., McNeely et al., 2015) and perceived safety (e.g., Lester & Cross, 2015; Milam et al., 2010; Nijs et al., 2014). Dichotomous one-item counts of risks and strengths are also routinely used in various risk assessment tools for recidivism, such as the SAVRY when coded by clinicians for the presence/absence of a strength/risk for the cumulative index (e.g., Shepherd, Luebbers, & Ogloff, 2016). These outcomes are also not representative of latent or internal constructs, but rather the frequency with which the client encounters barriers in these arenas. Thus, one-item measures of these risk factors are presumed to be valid for use in the present study.

iii. Recidivism risk. Recidivism Risk was derived from the COMPAS scale (Northpointe, 2015a, 2015b), and is reflective of an unalterable risk factor. The COMPAS is a risk and needs assessment tool for use with clients involved in the criminal justice system, and is the assessment tool utilized by the participating probation agency in determining their clients' risk for recidivism. The Recidivism Risk subscale of the COMPAS utilizes information regarding a client's criminal history in combination with other demographic factors to provide a single quantifiable number that corresponds with a risk level of that person recidivating in the future. Examples of factors that are accounted for within Recidivism Risk include: information on prior offenses (both adult and juvenile), history of substance use, and peer associations (Northpointe, 2015b). Algorithms built into the COMPAS software use this information to provide a risk level in the form of a number from 1-10, from lowest risk to highest risk of recidivism. Risk levels are delineated by the following groupings: 1-4 is considered low risk of recidivism, 5-7 is considered medium risk of recidivism, and 8-10 is considered high risk of recidivism (Northpointe, 2015b). Affiliates with COMPAS have reported within the peer-reviewed literature acceptable reliabilities for the various subscales (e.g., Brennan, Dieterich, & Ehret, 2009), as well as findings that the COMPAS is an adequate tool in predicting recidivism (e.g., Brennan, Dieterich, & Oliver, 2007). However, reliability for the Recidivism Risk scale in the present study was unable to be calculated, due to protection over this variable and algorithm by Northpointe.

iv. Supervision violations. New bookings into the local county jail for supervision violations (i.e., flash incarcerations, revocations) were utilized as a measure of whether an individual recidivated. Flash incarcerations are short duration incarceration terms (1-10 days) and revocations are long-term incarceration terms (up to 180 days) that are administered to clients in response to noncompliant behavior(s) while on supervision (Hunnicutt et al., 2015, 2017b). Revocations differ from flash incarcerations in that revocations terminate the remainder of the supervision, whereas flash incarcerations return clients back to the community and under community supervision after the completion of the incarceration.

Supervision violations were utilized as a proxy for recidivism due to the factors outlined in the section *Proxy for Recidivism*. Any individual who completed the consumer survey and was booked into County jail on a flash incarceration or revocation within three-months post-completion of the survey were considered to have recidivated. Individuals without any supervision violation information were not considered to have recidivated.

v. Ethnicity. Ethnicity was obtained through intake records at the local probation agency. The present study removed cases for individuals whose ethnicity was reported as neither White nor Hispanic. Prior local reports have failed to demonstrate consistent differences between ethnicities and other variables (i.e., Hunnicutt et al., 2015, 2017a, 2017b); however, due to the lack of prior examination of ethnicity in terms of strengths, ethnicity is included within the present analyses as a potential covariate.

D. Data Analytic Plan

This section outlines the various approaches taken to research the study questions. Additionally, this section outlines the way variables were coded for each research question analysis; the variables in the present study were coded differently depending on which analyses and research question was being answered.

i. Data cleaning. Data were cleaned by addressing cases without complete information. Clients with at least two valid cases (out of three) on any of the scales that require mean scores were included within the present study; however, clients without information on any of the one-item scales were excluded from analyses due to the inability to calculate these scores from other data. While Mplus can estimate data points for data with missing observations using Full Information Maximum Likelihood estimation, this estimation is only efficient when data are assumed to be missing completely at random; it was expected that at least one of the responses (i.e., *Substance Use*) would yield patterned responses of data that were not missing completely at random, which would have the potential to drastically skew interpretations and results (Asparouhov & Muthén, 2010). Thus, data were only considered for clients with full data available on all data points. Mischievous responding was not examined within the present analyses; it was hypothesized that there may be more untruthful reporting within criminal justice-involved populations than in other populations that are often studied, and as such it was believed that the scores they report are important to examine for professionals working with them to be able to accurately respond to the patterns that are presented by these clients (truthful or otherwise).

ii. Correlation table. Although not included within a specific research question, a correlation table displaying the association of study variables was created as part of the analyses, which also includes means and standard deviations (see Table 2). Bivariate correlations of all study variables were examined for assessing the strength and direction of variable associations, and were also assessed for any indications of multicollinearity (i.e., at *r*

>.80; Farrar & Glauber, 1967; Field, 2013). The correlation table displays correlations between all study variables their original item format.

iii. Research question #1. All internal asset strengths were analyzed in their original format (as described within the Measurement section) for the reliability and normal distribution analyses set forth by the first research question (*Are strengths-based measures reliable for use with criminal justice involved populations and normally distributed?).* Reliabilities of all internal assets scales (i.e., self-efficacy, self-awareness, cognitive reappraisal, self-regulation) were examined to determine if the scales were adequate for use in the present study and with the present population, using Cronbach's alpha. Cronbach's alpha is a reliability measure, specifically one that measures how well a set of given items group together (i.e., internal consistency; Tavakol & Dennick, 2011). Additionally, normality of distribution was examined for these scale means using skewness and kurtosis testing (Field, 2009); however, Field warns that for samples that exceed 200 observations, skewness and kurtosis testing can be irrelevant and visual inspections are often more informative.

iv. Research question #2. The intention of the second research question (*Which alterable risk, alterable strength, and unalterable risk factors are related to recidivism?)* was to identify variables for the LCA analysis in the third research question. This was an exploratory effort to determine which variables would be most likely to differentiate classes and be related to recidivism within the later research questions.

The second research question was analyzed using a series of chi-square analyses conducted on dichotomized study variables. Dichotomized variables were utilized to mimic the format in which they would appear within the LCA, and LCAs require the use of categorical item formats (Muthén, 2001); if variables were significant in *t*-test analyses (i.e., by utilizing their original measurement structure) but not significant within the chi-square analyses, the LCA would also likely not yield informative results on such variables.

Chi-square analyses were determined to be the most appropriate analysis for comparing the variables, given their dichotomous format. Chi-square analyses compare the distributions of populations in groups of discrete variables (Tabachnick & Fidell, 2007), and thus make it easy to assess the association between multiple dichotomous variables. Chi-square outcomes were evaluated utilizing the Pearson chi-square statistic and its associated *p*–value for statistical significance. Significance levels were not adjusted to prevent a Type 1 error that can occur within the data when multiple analyses are utilized on the same data set, as this was exploratory and intended to inform the items to be included in the subsequent LCA analyses; the individual significance of each chi-square test was not interpreted within any other context within this study other than for this purpose.

Dichotomizing items. The scale measures (i.e., the internal assets) were dichotomized by using a cutoff score of 3.67 for the scale means (3.67 > = Strength, 3.67 < No strength). The cutoff point for the 3-item strength scale means is derived from an examination of the scale anchors (1 = *Not at all true*, 2 = *A little true*, 3 = *Pretty much true*, and 4 = *Very true*) both quantitatively and qualitatively. Qualitatively, an average score of “4” (i.e., “very true”) represents the ideal and highest score an individual can achieve. While an average score of “3” (i.e., “pretty much true”) implies the presence of the strength in question to some degree, it also leaves the individual on the cusp of the next anchor below it (i.e., “a little true”), which is not indicative of high quantities of that strength. Thus, by using an average of 3.67, an individual can indicate two items as a “4” (i.e., “very true”) and one item as a “3” (i.e., “a little true”) and be considered to possess the strength. This allows for some differences in interpreting anchor points — particularly in the case of "pretty much true" as being indicative of the presence of a strength — while still retaining a strong focus on the highest anchor point (i.e., 4; "very true").

For the alterable risks, all one-item measures were dichotomized from their original five-point scale (1 = *Never*, 2 = *Occasionally*, 3 = *Sometimes*, 4 = *Often,* and *5 = Always*). Specifically, a response of *1 = Never* for each of the items was counted as indicating the absence of that risk factor, and all other responses (2 = *Occasionally*, 3 = *Sometimes*, 4 = *Often,* and *5 = Always*) was coded as indicating the presence of that risk factor.

For the unalterable risk factor (i.e., Recidivism Risk), the variable was dichotomized into a "High Recidivism Risk" variable. This was conducted by taking the "high-risk" cutoff point (a score of 8, 9, or 10 out of a possible score range of 1-10) and indicating that a client was "high risk" if they exhibited any scores at or above the cutoff point. All lower scores were indicated as having an absence of a "High Recidivism Risk" profile.

v. Research question #3. To answer the third research question (*Are there classes of clients based on the factors identified as significant in R2?)*, the dichotomized item format was utilized for the LCA classification analysis; LCAs require dichotomized items within their classification systems (Muthén, 2001). Latent class analysis (LCA) is a statistical method that utilizes categorical (usually dichotomous) data to group observations on indicators into latent classes (Magidson & Vermunt, 2004). At the outset of an LCA the number of classes is unknown, but the assumption exists that there is only one true class membership for each observation. These classes are defined by their similarity of patterned responses to the chosen indicators within the analysis, which in turn provides a tangible profile of observations that would typically reside within each class. (Muthén, 2004; Nylund, Asparouhov, & Muthén, 2007). Thus, the level of similarity is often an aspect used to determine how good of model fit there are between the different number of classes explored.

LCA was employed in this study to provide information on classes of clients in terms of the variables that were found to most strongly relate to recidivism outcomes. The intention was to identify the variables that are of most importance for practitioners within this local population in intervening upon or preventing recidivism, and then provide information on which classes were most at risk for recidivism. Additionally, ethnicity was explored as a potential covariate to class membership.

*Power analysis***.** Unlike most other forms of statistical analyses, a uniform method for conducting power analyses for latent variable modeling does not currently exist (Berlin, Williams, & Parra, 2014). Power in LCAs can be sufficient in very low sample sizes (i.e., 30, Lubke, 2010), or require as many as hundreds or thousands of participants (Lubke, 2010; Nulund, Asparouhov, & Muthén, 2007). This is often because power in LCAs is specific to the type, number, and psychometric properties of the variables being utilized (Muthén & Muthén, 2002). Thus, the analyses in the second research question were conducted to aid in reducing the number of indicators utilized in an effort to also improve the power of the LCA analyses.

*Determining LCA classes***.** First, an LCA was conducted to determine if reliable latent classes could be extracted from the data. During the LCA process, models are examined starting with a one-class model, up through the last class where model fit is acceptable or desirable (Masyn, 2013; Nylund et al., 2007). After the analyses were completed, log likelihood convergence, fit statistics (i.e., BIC, BLRT, LMRT, VLMR, BF, cmP) and entropy were examined in deciding upon the number of classes (if any) that would be retained for subsequent analyses.

Log likelihood values were examined as a precursor to examining further fit statistics. Replication of log likelihood values across multiple starts indicates that the model is stable enough to proceed with (Asparhouhov & Muthén, 2012). Next, the Bayesian Information Criterion (BIC) was evaluated. The BIC is calculated utilizing log functions of the number of parameters and observations in the model (Masyn, 2013). The BIC favors models of classes with the lowest value on this index (Magidson & Vermut, 2002; Masyn, 2013; Muthén, 2001). The BIC is analyzed both by numeric examination of the lowest number (Masyn, 2013), as well as visual examination of the BIC values (Muthén, 2001).

Next, the bootstrapped likelihood ratio test (BLRT), Lo-Mendell-Rubin Test (LMRT), and the Vuong-Lo-Mendell-Rubin (VLMR) test were examined to aid in class determinations. These three tests are evaluated using different statistical mechanisms, but all are evaluated in the same manner; interpretations are conducted by way of examining the significance associated with the respective test statistics, which is computed by comparing statistics from class k against class k - 1 (i.e., the preceding class; Asparouhov & Muthén, 2012). A significant p-value indicates that class k is superior in classifying observations than the preceding class (k - 1; Asparouhov & Muthén, 2012; Masyn, 2013; Nylund et al., 2007). Thus, the class with the last and most significant p-value is the class suggested for retention by each of these tests.

The Bayes Factor (BF) is another statistic that can be used to evaluate model fit of the various latent classes. Like many of the statistics discussed above, this statistic computes a value that compares to parallel classes to one another (Masyn, 2013). The BF uses the following criteria to determine which class demonstrates the best model fit: if BF is between the values one and three, the model is suggested to demonstrate weak model fit; if the BF is between three and 10, the model is suggested to demonstrate moderate model fit; if the BF is above 10, the model is suggested to have strong model fit (Masyn, 2013; Quirk, Nylund-Gibson, & Furlong, 2013).

The final fit statistic being considered is the correct model probability (*cmP*). The *cmP* assumes that, across the classes being investigated, the correct model is among them (Masyn, 2013). The *cmP* provides the probability of each of these classes as being the correct model, adding up to 1.0. Thus, the *cmP* indicates that the most superior number of classes is that in which the highest *cmP* value is observed.

Entropy values were also considered when determining how many classes to retain. Entropy provides a measure of how precise each model is in predicting class membership for the overall model (Magidson & Vermunt, 2004; Masyn, 2013). Values of entropy are essentially a summary of the posterior probabilities for every class within each model; posterior probabilities are the measure of how well each class in a model assigns people into classes (Magidson & Vermunt, 2004; Masyn, 2013). Resulting entropy values range from 0 to 1, with lower entropy suggesting insufficient membership prediction. Entropy is recommended to be above .80 to retain a model specification, otherwise it is likely that the model is not classifying class membership well enough (Clark & Muthén, 2009). However, entropy in and of itself is not intended to be a fit statistic measure, and is only used to aid in determining if a model is sufficiently differentiating class memberships (Masyn, 2013).

Ethnicity as a covariate to class membership. After the model was determined to have converged upon stable class configuration and a class model was retained, the model was then run with the covariate *e*. Within LCA analyses, covariates are included as a regression analysis, whereby classes are regressed against the covariate to determine if classes differ by their likelihood of being grouped by the covariate *ethnicity* (Asparouhov & Muthén, 2014a, 2015). In this case, this means that ethnicity was examined insomuch as it significantly predicts group membership into any of the classes. LCA analyses utilize dichotomous indicators and ethnicity is also utilized presently as a dichotomous indicator (Hispanic = 1; White = 0); thus, the form of regression utilized for this part of the analysis was logistic regression (Quirk et al., 2013).

vi. Research question #4. This research question (*Do any resulting classes from R3 relate to recidivism?)* utilizes the resulting classes from R3 and adds in a dichotomous distal outcome — recidivism. In this case, recidivism is analyzed in terms of its original form; a dichotomous variable indicating the presence or absence of recidivism. LCA analyses were conducted utilizing the DCAT 3-step command (Asparouhov & Muthén, 2014b, 2015; Lanza et al., 2013). Per authoritative recommendations (Lanza et al., 2013), the distal outcome in the present study was analyzed as if it were a study covariate, due to this being the superior method of evaluating binary distal outcomes. Furthermore, the DCAT command has been found to work well when the distal outcome is categorical and does not suffer the same propensity toward class shifts that invalidate the prior step of initial classification of observations (versus often occurs with the Lanza method with continuous variables; Asparouhov & Muthén, 2015).

5. Results

Results of the analyses for the present study follow this sequence below: (a) examination of variable correlations; (b) examination of scale reliabilities for adequate psychometric properties of internal assets scales; (c) examination of normality of distribution for internal asset scales; (d) *t*-tests and crosstabulations of variables related to recidivism; and (e) latent class analysis (LCA) of variables among criminal justice involve clients, including impacts of ethnicity as well as using the LCA to predict recidivism as a distal outcome.

A. Bivariate Correlations

Attending *AA with a sponsor*, *treatment support,* and *ethnicity* were not significantly correlated with nearly any of the study variables; while the remaining internal assets, logistic risks, substance use, and Recidivism Risk were all strongly correlated with most of the study variables (see Table 2). Multicollinearity was observed between the variables *self-efficacy* and *self-awareness*, as well as between *self-regulation* and *cognitive reappraisal* ($r > .80$; Farrar & Glauber, 1967; Field, 2013). This was not surprising, given that *self-efficacy* and *self-awareness* have been identified as belonging to a larger second-order factor of *belief in self*, and *self-regulation* and *cognitive reappraisal* have been identified as belonging to the second order factor *emotional competence* (Furlong et al., 2017). The variables *self-efficacy* and *cognitive reappraisal* were also found to be multicollinear, with the remaining combinations of the four internal assets displaying near-multicollinear reliabilities ($r = .71$-.78).

B. Scale Reliabilities

The reliability analyses suggested that the internal asset scales (i.e., self-efficacy, self-awareness, cognitive reappraisal, self-regulation) demonstrated high internal validity for the overall sample as well as for both of the ethnicities included in the study (Hispanic, White; see Table 3). This suggests that these scales are internally reliable for use with criminal justice involved populations.

C. Scale Distributions

Z-scores for skewness and kurtosis indicated non-normal data for internal assets scores; scale means were all significantly negatively skewed, and *self-awareness* and *self-regulation* were significantly kurtotic (see Table 4 and Figure 1 to 4). A visual inspection of these data points, as recommended by Field (2009), confirmed the statistical findings that the internal asset scores were all dramatically skewed. The distributions of these data points are not surprising; high scale scores for these same internal assets were reported with college-age populations (Furlong et al., 2017), suggesting that these constructs may be ones that regularly experience ceiling effects.

D. Chi-Square and Variables Chosen for LCA

The results of the chi-square analyses indicated that most of the variables demonstrated significantly correlated distributions with whether they recidivated (i.e., acquired supervision violations) within three-months post-completion of the survey (see Table 5). Three logistic risk variables (i.e., *housing, employment, transportation)*, all four of the internal assets (i.e., *self-efficacy, self-awareness, cognitive reappraisal, self-regulation*), *substance use*, and *AA with a sponsor* were all significantly correlated with recidivism in the chi-square analyses. The variables *transportation* and *AA with a sponsor* were correlated at $p = .06$ but were retained for the LCA analyses due to the close significance displayed to the standard $p < .05$ cutoff. The remaining variables were correlated at $p < .05$ or stronger.

Due to the strong correlation within the *belief in self* internal asset variables (i.e., *self-efficacy, self-awareness*) and within the *emotional competence* internal asset variables (i.e., *cognitive reappraisal, self-regulation*), it was decided that only one variable representative of each of the two domains would be necessary for the subsequent LCA analyses. The variable *self-efficacy* was chosen to represent the *belief in self* domain, due to its much larger predictive validity in the chi-square analysis. The variable *cognitive reappraisal* was chosen to represent the *emotional competence* domain, due to its stronger internal reliability index across all populations (see Table 4), and in the absence of notable differences within the chi-square analysis between these two variables on recidivism.

Thus, in total, the following variables were chosen from these exploratory analyses to be included within the subsequent LCA: *housing, employment, transportation, substance use, AA with a sponsor, self-efficacy,* and *cognitive reappraisal.* Missing data were deleted prior to data analysis, in order to most accurately capture descriptive information and to avoid variable imputation that may occur in Mplus (see rationale for this in *Data Analytic Procedures* section). Of the $N = 333$ cases that represented the overall population, the following cases were deleted due to missing data, in this order: two cases missing data on *self-efficacy* and *cognitive reappraisal*, two cases missing data on *Recidivism Risk*, 54 cases missing data on *substance use*, 10 cases missing data on *housing*, and three cases missing data on *employment*. Note that deletions occurred within that order; additional cases could have exhibited missing data on cases that were deleted in the prior variable deletion, and thus the numbers reported above are not representative of the total number of cases missing data on each variable, but rather the number that remained with missing cases at that step in the deletions. This resulted in $N = 262$ cases to be analyses for the LCAs.

E. Latent Class Analysis (LCA)

LCA was employed to answer research question three (*Are there classes of clients based on the factors identified as significant in R2*). Bivariate correlations of the binary LCA variables can be found in Table 6; multicollinearity was not observed between any of the dichotomously coded variables for the LCA analyses. All LCA analyses were conducted using the statistical software M*plus* (Version 7.4; Muthén & Muthén, 2015). All cases with missing data had been removed in the prior step; thus, missing data were not handled within this portion of the analyses. Analyses were run for five classes within the present data (see Table 7).

i. Fit statistics and related information. Log likelihood values were replicated for all five classes, with the same log likelihood being replicated for all random starts for all classes examined. The BIC favors models of classes with the lowest value on this index (Magidson & Vermut, 2002; Masyn, 2013; Nylund, et al., 2007); in the LCA analysis, the BIC indicated the three-class model as having the best model fit (BIC = 2443.843; see Figure 5). The BLRT, LMRT, and VLMR favor the class with the last and most significant *p*-value is the class suggested for retention by each of these tests (Asparouhov & Muthén, 2012; Masyn, 2013; Nylund et al., 2007); in the present analysis the BLRT indicated that the four-class model demonstrated the most superior fit, the LMRT indicated that the three-class model demonstrated the most superior fit, and the VLMR indicated that the three-class model demonstrated superior fit, all as indicated by the respective classes having the last (and lowest) significant value prior to significance values increasing in later class models. According to the BF statistic, the first class that demonstrated strong model fit was for the three-class model (BF = 10.974). Lastly, in the present analysis, no *cmP* value above zero was observed, and therefore this statistic was unable to be used in model fit evaluation. Entropy was also considered within the class determinations. Entropy for the two-class model was .89, for the three-class model was .95, for the four-class model was .94, and for the five-class model was .86.

ii. Number of classes retained. Given the information above, the fit indices appeared to uniformly suggest a three-class model as the superior fit (i.e., BIC, LMRT, VLMR, BF), aside from two fit indices (i.e., BLRT, *cmP*). Specifically, the BIC value was the lowest for the three-class model (BIC = 2443.843), the MLRT and VLMR values were significant ($p < .001$) up through the three-class model and then became insignificant ($p > .05$), and the BF value first became ≥ 10 at the three-class model (BF = 10.974). Additionally, entropy for this model was high (.945), and the entropy for the three-class model was higher than the other models examined. The posterior probabilities and average classification probabilities for the three-class mimic the entropy and suggest that, in general, clients have a 97-98% chance of being classified in the most appropriate class (see Table 8). Thus, the three-class model was retained for the remaining interpretation and analyses.

iii. Class interpretations. The three-class model can be shown depicted in Figure 6, and item probabilities for each class can be found in Table 8. Interpretations on classes were based on the probability scores of clients within in each class on the various strengths and risks included in the model. The class with the highest proportion of clients in it was Class 2 (45% of the sample). This class was labeled as *Low Strengths, High Risks*, and was delineated as such due to their low probability for endorsing most of the alterable strength items (i.e., internal assets), and their high probability for endorsing the various alterable risks (i.e., all logistic risks, substance use). Class 1 had the next highest proportion of clients within it (29%) and was labeled the *High Strengths, Low Risks* group due to the extremely high proportion of clients endorsing most of the alterable strengths within this population (i.e., internal assets) and their low probability of endorsing any of the alterable risk items (i.e., logistic risks, substance use). Finally, Class 3 contained 26% of the sample and was labeled the *Very Low Strengths, Low Risks* population.

It is important to note that two items were not extremely discriminant between the classes: *AA with a Sponsor* and *High Recidivism Risk.* The variable *AA with a Sponsor* appeared to contain nearly equal proportions of clients from all three classes within this item, and thus did not aid in any interpretations that differentiated the three classes. Additionally, *High Recidivism Risk*, the unalterable risk variable, resulted in moderate to low differentiation between the groups; clients in Class 1 had a 50% chance of being designated as High Risk, clients in Class 2 had a 73% chance, and clients in Class 3 had a 58% chance (see Table 9). While Class 2 exhibited a higher probability of having this classification than the other groups, it does not appear that groupings based on this variable lend toward extremes or easily identifiable ways of using this variable for screening purposes. This is interesting given the large body of literature emphasizing this risk characteristic as being salient in profiling criminal justice-involved populations.

iv. Ethnicity as a covariate to class membership. Next, ethnicity was examined as it pertained to class membership, with Class 1 (*High Strengths, Low Risks*) being used as the reference class (see Table 10). The results indicated that class membership was not significant divergent by ethnicity; this held true regardless of which class was used as the reference class. Thus, there did not appear to be an association between ethnicity and class membership.

v. Recidivism as a distal outcome. Lastly, recidivism (i.e., *supervision violations*) was evaluated as a distal outcome to class membership (see Figure 7). A visual survey of Figure 7 reveals that Class 1 (*High Strengths, Low Risks*) and Class 3 (*Very Low Strengths,* *Low Risks*) had a lower probability of acquiring new supervision violations than the overall population altogether, and Class 2 (*Low Strengths, High Risks*) had a higher probability. Between classes, the overall test of significant difference of distributions between classes was significant, $\chi^2 = 10.615$, $df = 2$, $p < .01$, indicating that classes significantly differed based on the proportion of clients who went on to acquire supervision violations. Class 1 (*High Strengths, Low Risks*) and Class 2 (*Low Strengths, High Risks*) displayed significantly different proportions of acquiring new supervision violations within three-months post-completion of the survey (18.9% versus 41.8%, respectively; $\chi^2 = 10.360$, $df = 1$, $p < .01$. Class 2 (*Low Strengths, High Risks*) also displayed a higher probability of acquiring new supervision violations (41.8%) than Class 3 (*Very Low Strengths, Low Risks*; 27.8%), though this difference fell just outside of the significance range, $\chi^2 = 3.709$, $df = 1$, $p = .05$. There were not any significant differences between the probability of clients in Class 1 (*High Strengths, Low Risks*) and Class 3 (*Very Low Strengths, Low Risks*) who acquired new supervision violations, 18.9% and 27.8%, respectively; $\chi^2 = 1.401$, $df = 1$, $p > .05$.

6. Discussion

The present study sought to investigate if discernable patterns of alterable strengths, alterable risks, and unalterable risk can be ascertained from a population of criminal justice-involved clients in California with primarily substance-related convictions under community supervision. This line of research is important due to the numerous deleterious impacts associated with criminal justice involvement and recidivism. To date, the extant literature on factors associated with recidivism primarily focuses on unalterable risk factors and alterable risk factors. However, strengths-based factors are emerging as important variables to be considered within recidivism prediction models, though there is a pervasive lack of research examining strengths-based factors in relation to recidivism, and particularly in adult populations. The present research addressed some of these gaps by providing information on internal reliability of strengths-based internal assets scales for use with adult criminal justice-involved populations, investigating if classes of clients could be ascertained through latent class analysis (LCA), and how any emerging classes fare in predicting future supervision violations.

A. Use of Strengths-Based Internal Asset Scales

Internal reliability statistics and normality distributions were examined for the strengths-based internal assets (i.e., *self-efficacy*, *self-awareness*, *cognitive reappraisal*, *self-regulation*) as part of the first research question. Examination of data normality suggested that most of the internal asset mean scores were skewed, which was also found when these scales were used with college-aged populations (Furlong et al., 2017). Additionally, all four of the internal assets were found to be highly reliable within the overall sample and for both ethnicities individually (i.e., Hispanic, White). This is an important contribution due to the limited number of studies that examine strengths-based and internal asset scales with adult criminal justice-involved populations, combined with emerging findings suggesting that strengths-based variables play an important role in the outcomes of criminal justice-involved clients (e.g., Cuervo & Villanueva, 2015; Lodewijks et al., 2010; Rennie & Dolan, 2010; Shepherd et al., 2014).

B. Latent Class Analysis of Strengths and Risks

The second through fourth research questions were examined through conducting latent class analyses (LCA) of client strengths and risks. Of the original study variables, those found to be related to future supervision violations and that were not multicollinear with other study variables were retained in the LCA analyses: *housing, employment, transportation, substance use, AA with a sponsor, self-efficacy,* and *cognitive reappraisal.* The LCA indicated strong fit indices in support of a three-class model. The class with the highest proportion of clients was defined as a *Low Strengths, High Risks* group (45%), followed by a *High Strengths, Low Risks* group (29%), and finally a *Very Low Strengths, Low Risks* group (26%). These classes of clients make intuitive sense, and were not found to co-vary as a function of ethnicity. The classes were also found to significantly predict acquisition of supervision violations within three-months post-completion of the survey; the *High Strengths, Low Risks* and the *Very Low Strengths, Low Risks* classes exhibited significantly lower probabilities of acquiring new supervision violations than the *Low Strengths, High Risks* class, with the *High Strengths, Low Risks* group demonstrating the lowest probability of future violations. The results of the LCA suggest that classes of clients can be clearly delineated based on alterable strength and alterable risk measures, with moderate distinction observed on unalterable risk (i.e., *Recidivism Risk*), and negligible distinction on the treatment support variable (*AA with a Sponsor*). The examination of alterable strengths, alterable risks, and unalterable risk variables within a population of adult criminal justice-involved clients is novel, and in utilizing these variables within the context of an LCA.

Several other interesting findings also emerged. First was regarding the observed hierarchy of the classes in terms of which classes were more/less likely to acquire new supervision violations. Not surprisingly, the *High Strengths, Low Risks* clients were at the lowest likelihood for acquiring new supervision violations within three months of the survey; this group of clients endorsed high protective factors and low risk factors, which would suggest that they would have more positive influences and resources to address any life challenges that may arise. This was followed by the *Very Low Strengths, Low Risks* group, which is a group that is more at-risk for future supervision violations than the *High Strengths, Low Risks*, and is differentiated by their dramatically different pattern of endorsement of strengths factors, namely that they are nearly nonexistent. This group may not be acquiring new supervision violations at higher rates due to the low endorsement of risk factors present in their lives, but also may be lacking the internal assets to ameliorate any future risks, should they arise. The emergence of similar patterns of responding has been found in other areas of literature examining strength and risk factors. For example, the universal screening literature that suggests that students that have absent psychosocial assets (without the presence of extreme risks) may be effectively *languishing* (Furlong et al., 2017; Keyes, 2002); they are not displaying the worst outcomes but they do not have the resources to overcome future adversities if presented with them. These types of clients are likely to be overlooked in traditional assessment tools that focus solely on risks, as such tools do not consider the importance of the absence of strengths; a misnomer is that the absences of risk is the presence of strengths, which is statistically and theoretically false (see Cuervo & Villanueva, 2015 and Farrington et al., 2012 for reviews on strengths and risk variables). Finally, the *Low Strengths, High Risks* group displayed the highest risk for future supervision violations, and also comprised almost half of the clients in the study; this demonstrates the large scale and ongoing struggles that clients in the criminal justice system face as they re-enter the community and attempt to re-integrate. Furthermore, the downward progression from the *Very Low Strengths, Low Risks* group to the *Low Strengths, High Risk* group; is evident here in this latter group, the strengths continue to be low but the risks switch to being very high.

This class hierarchy also provides further support for the assertion that the *Very Low Strengths, Low Risks* may be truly languishing, and “hanging by a thread” in terms of their ability to manage obstacles as they occur. The findings also highlight the importance of building strengths within these populations of clients.

Second, the research findings appear to confirm emerging research trends suggesting the statistical importance and significant predictability of strengths in predicting client outcomes for criminal justice involved clients (Lodewijks et al., 2010; Shepherd et al., 2014). At present, clear class hierarchies were found based on patterns of strengths and risks with client strengths being a huge factor in delineating classes of clients. Furthermore, the only group that endorsed high strengths (*High Strengths, Low Risks*) was the group that demonstrated the lowest likelihood of acquiring new supervision violations. Lastly, as previously mentioned, the class hierarchies suggest interplay between strengths and risk factors that indicate that both types of factors should be considered apart from one another and help to distinguish outcomes best when differentiated between each other (e.g., versus treating absence of risk or strengths as the presence of the other type of factor). All of these findings provide support for the recent calls to action of researchers to integrate a strengths-based lens into the consideration of risk factors with clients in general (e.g., Peck, 2013) and criminal justice-involved clients specifically (e.g., Hunter, 2016). The findings suggest that, without the addition of strengths-based factors, the full picture of client potential and needs are not in focus.

Third, two items in the present analyses were not extremely discriminant between the classes: *AA with a Sponsor* and *High Recidivism Risk.* The variable *AA with a Sponsor* appeared to contain nearly equal proportions of clients from all three classes within this item, and thus did not aid in any interpretations that differentiated the three classes. This was also mimicked in the general lack of significant correlations of the treatment support variables (including *AA with a Sponsor*) that were observed in the overall population prior to the identification of appropriate variables for the LCA, despite most of the other variables (i.e., internal assets, logistic risks) being found to be significantly correlated with the study outcome (i.e., supervision violations). This may suggest that individuals working with criminal justice involved populations may benefit from soliciting more information about clients' internal states and ecological challenges versus their mere treatment attendance in attempts to support these clients. It also suggests the potential for targeted needs assessments with criminal justice-involved populations to utilize internal assets and logistic risks as additional variables to consider when working with these populations, as they may have stronger associations with client outcomes than when considering treatment-related variables in isolation. This is congruent with the research on the RNR model that suggests that the greatest treatment gains are observed when clients' individual needs are linked to treatment (Andrews et al., 1990; Dowden & Andrews, 1999, 2000; Hanson et al., 2009), and with the various modern risk assessment tools used with adult clients in the criminal justice system that do assess for ecological risk factors (e.g., LSI:R; Andrews & Bonta, 1995). However, neither the RNR model nor modern risk assessment tools explicitly include strengths. The strengths variables in the present study were observed to be extremely important in classifying clients, further supporting the assertion that these tools (i.e., RNR model, risk assessments) may significantly benefit from inclusion of strengths-based variables within their programming. Additionally, the present study did not directly examine the difference in variance explained by the different types of variables, and thus these assertions would benefit from further exploration in future research.

Additionally, the *High Recidivism Risk* variable (i.e., the unalterable risk variable) resulted in moderate to low differentiation between the groups within the LCA classes. While some differentiation was observed, *High Recidivism Risk* did not appear to provide the dramatic and extreme difference in grouping the classes of clients that was observed in most of the other variables (i.e., all of the other variables than *AA with a Sponsor*). Thus, groupings based on this variable did not lend toward easily identifiable ways of using this variable for screening purposes. This is interesting given the large body of literature emphasizing this risk characteristic as being salient in profiling criminal justice-involved populations. However, the *High Recidivism Risk* probabilities mimicked the class hierarchies of acquiring new supervision violations; the *High Strengths, Low Risks* class demonstrated the lowest probability of having a *High Recidivism Risk* status, followed by the *Very Low Strengths, Low Risks* class, followed by the *Low Strengths, High Risks* class. This same pattern was observed within the probabilities of acquiring new supervision violations; the same class order was observed from least- to most-likely to acquire supervision violations. The results suggest that a *High Recidivism Risk* designation may not differentiate the classes as well as other alterable strength and alterable risk measures, though it does appear to differentiate the classes to some degree. This is consistent with emerging research suggesting that, when alterable strengths and alterable risks are accounted for within statistical models, the unalterable risk factors become less predictive of client outcomes (e.g., Lodewijks et al., 2010; Shepherd et al., 2104). The present study contributes to this new body of literature that highlights the importance of studying alterable factors – both strengths and risks – in assessing client outcomes, and suggests that measures that are not accounting for alterable strengths and alterable risks within their assessment models may be lacking in their ability to accurately measure client needs, functioning, and outcomes.

C. Clinical and Practice Implications

The results of the present analyses are important for treatment and supervision efforts for multiple reasons. First, the results suggest that client recidivism may be able to be prevented if client risks and strengths are accurately identified and treated in a timely fashion; in the present analyses, recidivism was examined within a three-month span, providing sufficient time for client outcomes to be addressed to some degree if addressed early enough, and thereby recidivism could potentially be prevented. It is also important to note that this short-term temporal relationship between data points was possible in large part due to the outcome measure utilized (i.e., supervision violations versus criminal conviction data).

Second, practitioners can easily apply these results to their work with clients and identify clients at-risk for future engagement in criminal behavior. One of several options are available to interested practitioners in order to accomplish this. Practitioners could screen for the presence of risk factors and the absence of internal assets without abiding by any specific algorithm, as the present research has indicated that either of these scenarios are likely to increase the propensity toward future criminal behavior. The major implication of the present research is that strengths need to be increased (when they are low), and risks need to be decreased (when they are high); identifying whether or not clients fit within a particular class is not necessary for practical and efficient application of study results. Practitioners could use their knowledge of their clients or in gathering simple information from their clients;

alternatively, professionals interested in formalized methods of data collection and procedural identification could utilize measures from the present study to identify their clients, or even use information from screening or risk assessment tools that they already have access to. If using the present screening tool, the cutoff marks for indicating the presence or absence of alterable strengths and risks could be utilized (see Table 11 for an example of how these can be easily calculated). If using existing risk assessment tools, examining internal assets should also be considered; practitioners may already have access to information on clients' logistic risks. From there, practitioners could work with clients identified as high risk for recidivating by helping them to address their needs and build their strengths. However, it is important to note that regardless of the method, professionals working with similar populations of clients need to consider the role that *alterable strengths* play versus merely examining the presence of risks; furthermore, they would benefit from an examination of *alterable risks* specifically, with less of an emphasis on *unalterable risks* when linking clients to appropriate interventions and considering risk of engaging in criminal behavior.

Third, this method for identifying the most at-risk clients for recidivism would allow for a more streamlined method of resource allocation, in that clients who are truly at highest risk of recidivism are provided with targeted intervention for their multifaceted needs. Supervision levels and decisions on treatment referrals and intensity are often highly dependent on indicators provided by unalterable variables such as *Recidivism Risk*, which emerging research has indicated is not the only important factor to consider in predicting recidivism. Being able to pinpoint only a few client needs that have high predictive validity and that are strongly linked to client outcomes – such as was done in the present analyses –

may be a more efficient way of identifying clients who are most at risk and targeting them for more intensive intervention or resource allocation than identifying clients for intensive intervention due to criminal history factors alone. The results of the present analyses also provide strong evidence for the use of supervision violation data versus the use of criminal conviction as a measure of future engagement in criminal behavior (i.e., recidivism data), due to benefits of using data with short turn-around time, which supervising agencies are likely to have easy access to.

The results of the present study provide further evidence for the need to consistently screen criminal justice involved clients for the presence of dynamic strength and risk factors. This suggestion is consistent with literature in other fields of social sciences, such as in the literature on conducting universal screenings in the schools with children and adolescents. Universal screenings in the schools are conducted at regular intervals to capture students who endorse areas of concern (e.g., high risks, low strengths) that could be addressed through targeted intervention (Levitt, Saka, Romanelli, & Hoagwood, 2007). Ideally, students are then linked to interventions that match their level of need, in hopes that this can improve their functioning in the domain of interest. Screenings are then conducted again at regular intervals to continue capturing students who might be exhibiting areas of concern that had not been in the prior screening, and also before students are in need of triage or extensive intervention. The idea is to address these areas of concern in a method of prevention or intervention, before adversely negative outcomes have a chance to manifest, and ideally to assess for their presence on a *regular basis* to ensure that the concerns are identified in a timely manner.

Conversely, a common practice of many criminal justice-serving agencies is to administer risk assessment tools – the most commonly used form of "screening" clients – inconsistently or at irregular intervals, or at time points that coincide with other procedural events (e.g., identifying or re-assessing supervision levels). Using risk assessment tools often for screening purposes can be costly for the treating agency, as well as arduous for both client and practitioner (as they are often lengthy tools). However, using a brief, free screener (e.g., with items similar to the ones in this study) at regular intervals with criminal justice involved clients may help to ameliorate this issue. Not only would it be quick and easy to administer and interpret, but clients could be identified within minutes as to whether or not their constellation of risk and strength factors put them at risk for engagement in criminal behavior within the next three months. In this way, it would mimic the universal screening procedure of providing prevention or early intervention to clients before adversely negative outcomes have a chance to manifest. The items can also be specifically linked to services and interventions that individual jurisdictions can immediately provide to address their clients' needs. Furthermore, utilizing an on-the-spot screening tool that elicits the engagement of both the client and the practitioner in evaluating the results could help to foster a stronger working alliance between the practitioner and the client; this would allow both to spend time acknowledging the state of the clients current risks and strengths levels, while also providing an opportunity for the practitioner to gain insight into the clients' interior and exterior world that they may have otherwise been unaware of. In this way, the client may feel more invested in the relationship and the practitioner can help to provide assistance in addressing the clients' needs that might ultimately prevent the undesired future behavior. Furthermore, this is in line with more contemporary theories of recidivism, such as the RNR model, which suggests that clients' needs be addressed in an individualized fashion (Andrews & Bonta, 2017; Looman & Abracen, 2013), but also adds a strengths-based component that is currently lacking from the present RNR model.

In terms of linking clients to interventions, the results suggest that there is a need to focus on how to link clients to interventions when an absence of strengths is discovered. In the present study, the absence of strengths indicated the absences of self-efficacy and cognitive reappraisal; this indicated a lack of belief in themselves and a lack of belief in their ability to monitor and alter negative emotional states (respectively). Ways that these strengths can be built include individual therapy and cognitive-behavioral therapy (CBT) related techniques. While CBT-related lessons are often inherent in some programming that criminal justice involved clients often received (e.g., Moral Reconation Therapy), most criminal justice involved clients receive these types of interventions in a group and without individualized attention toward their specific level of perceived proficiency in these areas. Thus, clients who are criminal justice involved may benefit from more individualized and intensive services to help build their strengths and may include a direct focus on building the strengths (versus avoiding risks, which is common practice in may group settings for this population).

It is worth noting that social desirability may have played a part in the responding of client patterns that emerged. It may be that clients who are more untruthful in their responding might have emerged in separate classes, if there were a larger population of clients from which to conduct the analyses; the present sample size was sufficient for identifying smaller classes of clients that exist within the data, but would not likely have lent toward being able to identify larger numbers of classes, should they truly exist within these populations of clients. However, a strong likelihood exists that some clients were not truthful in their responding (e.g., 18% of the clients in the *High Strength, Low Risk* group still did acquire new supervision violations), and future research would benefit from conducting similar research among larger populations of criminal justice involved clients to attempt to address, identify, and ameliorate this issue.

D. Study Strengths

The present research contributes to the body of knowledge on criminal justice involved clients, particularly in helping to address gaps related to: the inclusion of strengths-based measures in analyses of client recidivism, the inclusion of strengths-based measures utilized in research on adult criminal justice-involved populations, utilization of a constellation of variables that have not been examined in concert with one another in the adult offender literature, and the identification of internally reliable strengths-based measures for use with adult criminal justice-involved population. The present research also includes variables that are temporally different from one another (i.e., client survey data at Time 1 predicting recidivism at Time 2), providing stronger evidence for the predictive utility of the strength and risk factors examined than cross-sectional data alone.

The present research exhibits significant strength in its ability to provide maximum applicability in practice. LCAs were used to classify clients, which provide an innovative way to bridge research into practice; practitioners and individuals in direct contact with similar criminal justice-involved clients could utilize results of these analyses to develop client profiles to intervene or provide additional supports to clients, in an effort to attempt to prevent recidivism. Furthermore, the research variables focused on *alterable* risk and strength factors, which are factors that could be intervened upon in the lives of individuals involved in the criminal justice system. This is a departure from much of the literature focusing on historical and demographic factors (which cannot be intervened upon, and therefore contribute less to our knowledge on how to advance our work with these populations), which is an additional contribution to the literature, as well. Lastly, the research design presented here is replicable for future researchers, and includes access to measures that do not require subscriptions to software or survey material (e.g., as occurs with traditional risk assessment tools).

E. Study Limitations

The findings of this study cannot be generalized to larger populations without further replication in outside samples; the study sample was drawn from small and specific populations within a small locale (i.e., Hispanic or White, under community supervision as outlined by the Public Safety Realignment Act for primarily substance-related crimes, in California). Similarly, this population of criminal justice involved clients were under an intentionally more robust form of supervision focused on treatment and rehabilitation and as such, results might only be transferable to criminal justice involved populations under similarly intensive forms of supervision; more variability in supervision violation rates may exist within criminal justice involved populations under less intensive forms of supervision, as their engagement in future criminal behavior might not be as likely to be caught by supervision officers under less intensive supervision methods. The logistic risk items were one-item scales that do not have an established research base and were constructed for internal use at the probation agency from which the data were derived. There is also a possibility that social desirability bias was present in client responding to survey items; this could have emerged within the LCA as a separate class of respondents, but the study may also not have exhibited enough power for fit indices to support higher-class models. It is unclear if results differ based on the amount of time that clients had been in the community after release from incarceration, which should be examined further. The alterable strengths and alterable risks examined in the present study are not reflective of the only potential strengths and risks that could delineate classes of clients who are involved in the criminal justice system; future research will need to determine if these variables are sufficient or require significant modifications. Lastly, item presentation to clients was not controlled for or randomized, and this could have demonstrated a test bias in client responding such that they were not fully attending to questions presented to them and thus results could present a skewed picture based on this.

F. Future Directions

This study indicates a strong ability to predict recidivism (i.e., supervision violations) by using latent class analyses. Future research might benefit from expanding the results of the study into clinical applicability, by utilizing the classes discovered as a method for screening clients and assigning resources based on the profiles of strength/risk identified. This would further validate the use of LCA as a potential method for identifying and classifying clients into groups based on risk, while doing so from a largely alterable variable perspective. This in turn has the potential to improve rehabilitation efforts for clients in the community and thus reduce recidivism.

The present research could also benefit from further exploration of a wider range of variables within the arenas of alterable risks and strengths (e.g., social support, family support, motivation, psychological states) in similar statistical models (i.e., latent variable analyses), and within the context of client recidivism, in an effort to better inform supervision and treatment efforts with criminal justice-involved populations. Research would also benefit from examining the variance that is explained by alterable strengths, alterable risks, and unalterable risks when all of these types of variables are included within a statistical model, in an effort to determine importance of these types of variables in adult recidivism among criminal justice involved populations. Future research would benefit from further identification and examination of *unalterable strengths* within the context of client outcomes; the only strengths-based variables that are currently examined within the literature on criminal justice-involved populations is on *alterable strengths*. Additionally, the internal reliabilities reported in this study were even higher than those reported by Furlong et al. (2017) within college-age populations, suggesting that future research may benefit from continuing to examine the utility of these measures with criminal justice involved populations, including within the context of the complete *covitality* survey from which these measures were derived (SEHS-HE; Furlong et al., 2017) and how they relate to client outcomes.

Similarly, future research may benefit from examining if the number of strengths and risks are more important indicators than the specific risks and strengths themselves, versus researching these factors in terms of the specific items themselves. Research within adolescent populations has found that the *number* of strengths (across multiple domains of life) are significantly predictive of substance use, with the authors suggesting that the actual strengths and risks themselves may not be as important as the *quantity* and *variety* of types of strengths an individual posses (Lenzi, Dougherty, Furlong, Sharkey, & Dowdy, 2015), In the present study, only a couple of internal assets were examined, as well as several logistic risks, making the variety of these variables limited in scope. Research building upon the present study and the work by Lenzi et al. (2015) could account for better variety of variables and in a quantified (versus individual item) manner, to determine if this is also a viable and efficient method for classifying clients into groups and predicting future outcomes.

Social desirability biases were unable to be examined in the present study, within client responses. It may be that clients who are more untruthful in their responding might emerge in separate classes, if there were a larger population of clients from which to conduct the analyses (and thus identify them from the majority of the class they are currently grouped into); future research could address this by using larger samples of clients involved in the criminal justice system. Similarly, utilization of recidivism outcomes that are more typically reflected within the recidivism literature (e.g., convictions, jail bookings for new offenses) may also be of interest for future research within similar analyses, should the frequencies of such variables allow for accurate measurement of statistical models. Longitudinal data may assist in pinpointing specific time frames post-release from incarceration when these traits are particularly salient for clients, and may help to track the trajectory of these variables over time as a function of recidivism. Finally, future research would likely benefit from exhibiting more control over item presentation to clients, per best practices in survey administration, such as items presented one at a time and in random order.

G. Conclusions

The current state of research on recidivism within adult populations of clients involved in the criminal justice system is limited in scope, with a primary focus on risk factors and unalterable factors. However, emerging research suggests that focusing on alterable risk factors *and* alterable strength factors provides more robust information on client outcomes. Furthermore, common practices in the supervision and treatment of these clients, in an effort to deter recidivism, are based on risk assessment tools with complex administration and data collection, costly subscriptions, and unknown psychometric properties (i.e., that are consistently demonstrated independent of the authors). One method for addressing these issues is in employing a more straightforward statistical method that provides easily accessible profiles of clients and their coinciding propensity toward recidivism (i.e., via LCA), that is based on client risks and strengths, with low monetary cost, and specifically tailored toward the needs displayed by the population of interest. The present study offers a starting point for utilizing LCAs in research on criminal justice involved clients, and providing initial client profiles of strengths and risks and how they relate toward future propensity toward recidivism. Future research is warranted to replicate, expand, and improve upon this design.

References

Akesson, B., Smyth, J. M., Mandell, D. J., Doan, T., Donia, K., & Hoven, C. W. (2012). Parental involvement with the criminal justice system and the effects on their children: A collaborative model for researching vulnerable families. *Social Work and Public Health, 27*, 148-164.

Andrews, D. A., & Bonta, J. (1995). *The Level of Service Inventory - Revised*. Toronto, Canada: Multi-Health Systems.

Andrews, D. A., & Bonta, J. (2003). *The psychology of criminal conduc*t (3rd ed.). Cincinnati, OH: Anderson.

Andrews, D. A., & Bonta, J. (2017). *The psychology of criminal conduct* (6th ed.). NY: Routledge.

Andrews, D. A., Zinger, I., Hoge, R. D., Bonta, J., Gendreau, P., & Cullen, F. T. (1990). Does correctional treatment work? A clinically relevant and psychologically informed meta-analysis. *Criminology, 28,* 369-404.

Apel, R., & Sweeten, G. (2009). *The effect of criminal justice involvement in the transition to adulthood*. Report prepared for the U.S. Department of Justice. Retrieved from https://www.ncjrs.gov/pdffiles1/nij/grants/228380.pdf

Asparouhov, T., & Muthén, B. (2010). *Weighted least squares estimation with missing data.* Retrieved from https://www.statmodel.com/download/GstrucMissingRevision.pdf

Asparouhov, T., & Muthén, B. (2012). *Using Mplus TECH11 and TECH14 to test the number of latent classes: Mplus web notes, No. 14.* Retrieved from https://www.statmodel.com/examples/webnotes/webnote14.pdf

Asparouhov, T., & Muthén, B. (2014a). *Appendices for auxiliary variables in mixture modeling: 3-step approaches using Mplus.* Retrieved from https://www.statmodel.com/download/AppendicesOct28.pdf

Asparouhov, T., & Muthén, B. (2014b). *Auxiliary variables in mixture modeling: 3-step approaches using Mplus, Mplus web notes, No. 15, Version 8.* Retrieved from https://www.statmodel.com/download/webnotes/webnote15.pdf

Asparouhov, T., & Muthén, B. (2015). *Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary secondary model, Mplus web notes No. 21, Version 2.* Retrieved from https://www.statmodel.com/examples/webnotes/webnote21.pdf

Banse, R., Koppehele-Gossel, J., Kistemaker, L. M., Werner, V. A., & Schmidt, A. F. (2013). Pro-criminal attitudes, intervention, and recidivism. *Aggression and Violent Behavior, 18*, 673-685.

Beard, J. A.,Toche, D., Beyer, B., Babby, W., Allen D., Grassel, K., … Maxwell, D. (2013). *Realignment report: An examination of offenders released from state prison in the first year of Public Safety Realignment*. Sacramento, CA: California Department of Corrections and Rehabilitation.

Bergeron, C. L., & Miller, H. A. (2013). Tracking change through treatment with the inventory of offender risk, needs, and strengths. *Psychological Assessment, 25*(3), 979-990.

Berlin, K. S., Williams, N. A., & Parra, G. R. (2014). An introduction to latent variable mixture modeling (part 1): Overview and cross-sectional latent class and latent profile analyses. *Journal of Pediatric Psychology, 39*(2), 174-187.

Borum, R., Bartel, P., & Forth, A. (2006). *Structured Assessment of Violence Risk in Youth (SAVRY)*. Lutz, FL: Psychological Assessment Resources.

Brennan, T., Dieterich, W., & Ehret, B. (2009). Evaluating the predictive validity of the COMPAS risk and needs assessment system. *Criminal Justice and Behavior, 36*(1), 21-40.

Brennan, T., Dieterich, W., & Oliver, W. (2007). *COMPAS: Correctional offender management for alternative sanctioning. Technical manual and psychometric report (V. 5.01).* Traverse City, MI: Northpointe Institute for Public Management.

Bureau of Justice Statistics (2014). *Survey of state criminal history information systems, 2012.* U.S. Department of Justice. Retrieved from https://www.ncjrs.gov/pdffiles1/bjs/grants/244563.pdf

Criminal Justice Alignment, Chapter 15 Statues of 2011. (2011a).

Criminal Justice Alignment, Chapter 39, Statues of 2011. (2011b).

California Department of Corrections and Rehabilitation (2016). *2015 outcome evaluation report: An examination of offenders released in fiscal year 2010-11.* Sacramento, CA: CDCR Office of Research.

Carson, E. A. (2015). Prisoners in 2014. *Bureau of Justice Statistics*. Retrieved from https://www.bjs.gov/content/pub/pdf/p14.pdf

Cartier, J., Farabee, D., & Prendergast, M. L. (2006). Methamphetamine use, self-reported violent crime, and recidivism among offenders in California who abuse substances. *Journal of Interpersonal Violence, 21*(4), 435-445.

Caudy, M. S., Durso, J. M., & Taxman, F. S. (2013). How well do dynamic needs predict recidivism? Implications for risk assessment and risk reduction. *Journal of Criminal Justice, 41*, 458-466.

Center for Behavioral Health Statistics and Quality. (2016). *2015 National Survey on Drug Use and Health: Detailed Tables.* Substance Abuse and Mental Health Services Administration: Rockville, MD.

Chalfin, A., & McCrary, J. (2017). Criminal deterrence: A review of the literature. *Journal of Economic Literature, 55*(1), 5-48.

Clark, S. L., & Muthén, B. (2009). *Relating latent class analysis results to variables not included in the analysis.* Retrieved from https://www.statmodel.com/download/relatinglca.pdf

Council of Economic Advisors. (2016). *Economic perspectives on incarceration and the criminal justice system.* Retrieved from https://obamawhitehouse.archives.gov/sites/whitehouse.gov/files/documents/CEA%2BCriminal%2BJustice%2BReport.pdf

Cuervo, K., & Villanueva, L. (2015). Analysis of risk and protective factors for recidivism in Spanish youth offenders. *International Journal of Offender Therapy and Comparative Criminology, 59*(11), 1149-1165.

Dowden, C., & Andrews, D. (1999). What works for female offenders: A meta-analytic review. *Crime & Delinquency, 45*(4), 438-452. doi:10.1177/0011128799045004002

Dowden, C., & Andrews, D. A. (2000). Effective correctional treatment and violent reoffending: A meta-analysis. *Canadian Journal of Criminology, 42*, 449-468.

Durose, M. R., Cooper, A. D., & Snyder, H. N. (2014). *Recidivism of prisoners released in 30 states in 2005: Patterns from 2005 to 2010.* Washington, DC: Bureau of Justice Statistics. Retrieved from https://www.bjs.gov/content/pub/pdf/rprts05p0510.pdf

Duwe, G. (2014). The development, validity, and reliability of the Minnesota Screening Tool Assessing Recidivism Risk (MnSTARR). *Criminal Justice Policy Review, 25I*(5), 579-613. doi:10.1177/0887403413478821

Farrar, D. E., & Glauber, R. R. (1967). Multicollinearity in regression analysis: The problem revisited. *The Review of Economics and Statistics, 49*(1), 92-107. doi:10.2307/1937887

Farrington, D., Loeber, R., & Ttofi, M. (2012). Risk and protective factors for offending. In B. C. Welsh & D. P. Farrington (Eds.), *The Oxford handbook of crime prevention* (pp. 46-69). Oxford, UK: Oxford University Press.

Felitti, V. J., Anda, R. F., Nordenberg, D., Williamson, D. F., Spitz, A. M., Edwards, V., … Marks, J. S. (1998). Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults: The adverse childhood experiences (ACE) study. *American Journal of Preventative Medicine, 14*(4), 245-258. doi:10.1016/s0749-3797(98)00017-8

Field, A. (2009). *Discovering statistics using SPSS* (3rd ed.). London, UK: SAGE.

Field, A. (2013). *Discovering statistics using IBM SPSS Statistics* (4th ed.). Los Angeles, CA: SAGE.

Furlong, M. J., You, S., Shishim, M., & Dowdy, E. (2017). Development and validation of the Social Emotional Health Survey–Higher Education version. *Applied Research in Quality of Life, 12*, 343-367.

Geller, A., & Curtis, M. A. (2011). A sort of homecoming: Incarceration and the housing security of urban men. *Social Science Research, 40*, 1196-1213. doi:10.2139/ssrn.1632578

Gendreau, P., Little, T., & Goggin, C. (1996). A meta-analysis of the predictors of adult offender recidivism: What works! *Criminology, 34*(4), 575-607.

Glazebrook, J. S. (2010). Risky business: Predicting recidivism. *Psychiatry, Psychology and Law, 17*(1), 88-120.

Guebert, A. F., & Olver, M. E. (2014) An examination of criminogenic needs, mental health concerns, and recidivism in a sample of violent young offenders: Implications for risk, need, and responsivity. *International Journal of Forensic Mental Health, 13*, 295-310.

Håkansson, A., & Berglund, M. (2012). Risk factors for criminal recidivism – a prospective follow-up study in prisoners with substance abuse. *BMC Psychiatry, 12*, 111-118.

Hanson, R. K., & Morton-Bourgon, K. E. (2005). The characteristics of persistent sexual offenders: A meta-analysis of recidivism studies. *Journal of Consulting and Clinical Psychology, 73,* 1154-1163. doi:10.1037/0022-006X.73.6.1154

Hartney, C., & Vuong, L. (2009). Created equal: Racial and ethnic disparities in the U.S. criminal justice system. *National Council on Crime and Delinquency.* Retrieved from http://www.nccdglobal.org/sites/default/files/publication_pdf/created-equal.pdf

Hendricks, P. S., Clark, C. B., Johnson, M. W., Fontaine, K. R., & Cropsey, K. L. (2014). Hallucinogen use predicts reduced recidivism among substance-involved offenders under community corrections supervision. *Journal of Psychopharmacology, 28*(1), 62-66.

Hochstetler, A., Peters, D. J., & DeLisi, M. (2016). Classifying risk development and predicting parolee recidivism with growth mixture models. *American Journal of Criminal Justice, 41*, 602-620.

Hunnicutt, K. L., Carter, D., Sharkey, J., & Cosden, M. (2017a). *Santa Barbara County Annual Report: Public Safety Realignment Act (October 2011-December 2016)*. University of California Santa Barbara.

Hunnicutt, K. L., Dougherty, D., Sharkey, J., & Cosden, M. (2015; revised 2016). *Santa Barbara County Annual Report: Public Safety Realignment Act (October 2011-December 2014).* University of California Santa Barbara.

Hunnicutt, K. L., Sharkey, J., Cosden, M., Meskunas, H., & Janes, L. (2017b). *Santa Barbara County Annual Report: Public Safety Realignment Act (October 2011-December 2015).* University of California Santa Barbara.

Hunnicutt, K. L., & Sharkey, J. D. (2015). *Female adolescent substance use and Maslow's hierarchy of needs*. Unpublished manuscript.

Hunter, B. W., Lanza, A. S., Lawlor, M., Dyson, W., & Gordon, D. M. (2016) A strengths-based approach to prisoner reentry: The fresh start prisoner reentry program. *International Journal of Offender Therapy and Comparative Criminology, 60*(11), 1298-1314.

James, N. (2015). Risk and needs assessment in the criminal justice system. *Congressional Research Service.* Retrieved from https://fas.org/sgp/crs/misc/R44087.pdf

Johnson, R., & Raphael, S. (2012). How much crime reduction does the marginal prisoner buy? *Journal of Law and Economics, 55*, 275-310.

Johnson Listwan, S. Colvin, M., Hanley, D., & Flannery, D. (2010). Victimization, social support, and psychological well-being: A study of recently released prisoners. *Criminal Justice and Behavior, 37*(10), 1140-1159. doi:10.1177/0093854810376338

Jung, S., & Rawana, E. P. (1999). Risk and need assessment of juvenile offenders. *Criminal Justice and Behavior, 26*(1), 69-89.

Keyes, C. L. M. (2002). The mental health continuum: From languishing to flourishing in life. *Journal of Health and Social Behavior*, 43, 207-222. doi:10.2307/3090197

Kopak, A. M., & Smith-Ruiz, D. (2016). Criminal justice involvement, drug use, and depression among African American children of incarcerated parents. *Race and Justice, 6*(2), 89-116.

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling, 20*(1), 1-26. doi:10.1080/10705511.2013.742377

Lenzi, M., Dougherty, D., Furlong, M. J., Sharkey, J., & Dowdy, E. (2015). The configuration protective model: Factors associated with adolescent behavioral and emotional problems. *Journal of Applied Developmental Psychology, 38*, 49-59.

Lester, L., & Cross, D. (2015). The relationship between school climate and mental and emotional wellbeing over the transition from primary to secondary school. *Psychology of Well-Being, 5*(9). doi:10.1186/s13612-015-0037-8

Levitt, J. M., Saka, N., Romanelli, L. H., & Hoagwood, K. (2007). Early identification of mental health problems in schools: The status of instrumentation. *Journal of School Psychology, 45*(2), 163-191.

Liedka, R. V., Piehl, A. M., & Useem, B. (2006). The crime-control effect of incarceration: Does scale matter? *Criminology & Public Policy, 5*(2), 245-276.

Linn, B. K., Nochajski, T., & Wieczorek, W. (2016). Relationship of aggression, negative affect, substance use problems, and childhood delinquency to DWI recidivism. *The American Journal of Drug and Alcohol Abuse, 42*(1), 48-55.

Little, G. L., & Robinson, K. D. (1988). Moral reconation therapy: A systematic step-by-step treatment system for treatment resistant clients. *Psychological Reports*, 62, 135–151.

Lodewijks, H. P. B., de Ruiter, C., & Doreleijers, T. A. H. (2010). The impact of protective factors in desistance from violent reoffending. *Journal of Interpersonal Violence, 25*(3), 568-587.

Looman, J., & Abracen, J. (2013). The risk need responsivity model of offender rehabilitation: Is there really a need for a paradigm shift? *International Journal of Behavioral Consultation and Therapy, 8*(3-4), 30-36. doi:10.1037/h010098

Lubke, G. H. (2010). Latent variable mixture modeling. In G. R. Hancock & R. O. Mueller (Eds.), *The reviewer's guide to quantitative methods in the social sciences.* New York, NY: Routledge.

Magidson, J., & Vermunt, J.K, (2004). Latent class models. In D. Kaplan (Ed.), *The Sage handbook of quantitative methodology for the social sciences* (pp. 175-198). Thousand Oaks: Sage.

Malouf, E. T., Schaefer, K. E., Witt, E. A., Moore, K. E., Stuewig, J., & Tangney, J. P. (2014). The brief self-control scale predicts jail inmates' recidivism, substance dependence, and post-release adjustment. *Personality and Social Psychology Bulletin, 40*(3), 334-347.

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In T. D. Little (Ed.), *The Oxford Handbook of Quantitative Methods* (pp. 551–611). New York, NY: Oxford University Press.

McNeely, J., Cleland, C. M., Strauss, S. M., Palamar, J. J., Rotrosen, J., & Saitz, R. (2015). Validation of self-administered single-item screening questions (SISQs) for unhealthy alcohol and drug use in primary care patients. *Journal of General Internal Medicine, 30*(22), 1757-1764.

Mears, D. P., Cochran, J. C., Bales, W. D., & Bhati, A. S. (2016). Recidivism and time served in prison. *Journal of Criminal Law and Criminology, 106*(1), 81-122.

Milam, A. J., Furr-Holden, C. D. M., & Leaf, P. J. (2010). Perceived school and neighborhood safety, neighborhood violence and academic achievement in urban school children. *The Urban Review, 42*, 458-467. doi:10.1007/s11256-010-0165-7

Muthén, B. (2001). Latent variable mixture modeling. In G. A. Marcoulides & R. E. Schumacker (Eds.), *New developments and techniques in structural equation modeling* (pp. 1-33). Mahwah, NJ: Erlbaum.

Muthén, B. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed.), *Handbook of quantitative methodology for the social sciences* (pp. 345–368). Newbury Park, CA: Sage.

Muthén, L. K., & Muthén, B. O. (2002). How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling, 9*, 599–620.

Muthén, L. K., & Muthén, B. O. (2015). *Mplus: Statistical analysis with latent variables* (Version 7.4) [Computer software]. Los Angeles, CA: Muthén & Muthén.

Nellis, A. (2016). The color of justice: Racial and ethnic disparity in state prisons. *The Sentencing Project: Washington, D.C.* Retrieved from http://www.sentencingproject.org/wp-content/uploads/2016/06/The-Color-of-Justice-Racial-and-Ethnic-Disparity-in-State-Prisons.pdf

Nijs, M. M., Bun, C. J. E., Tempelaar, W. M., de Wit, N. J., Burger, H., Plevier, C. M., … Boks, M. P. M. (2014). Perceived school safety is strongly associated with adolescent mental health problems. *Journal of Community Mental Health, 50*, 127-134. doi:10.1007/s10597-013-9599-1

Northpointe Inc. (2015a). *Measurement and treatment implications of COMPAS Core Scales* [Computer software manual]. Traverse City, MI.

Northpointe. (2015b). *Practitioner's guide to COMPAS core*. Retrieved from http://www.northpointeinc.com/downloads/compas/Practitioners-Guide-COMPAS-Core-_031915.pdf

Nylund, K. L., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling. A Monte Carlo simulation study. *Structural Equation Modeling, 14,* 535-569. doi: 10.1080/10705510701575396

Olson, D. E., Stalans, L. J., & Escobar, G. (2016). Comparing male and female prison releases across risk factors and post prison recidivism. *Women & Criminal Justice, 26*(2), 122-144.

Pager, D. (2003). The mark of a criminal record. *American Journal of Sociology, 108*(5), 937-975. doi:10.1086/374403

Parsons, J., & Bergin, T. (2010). The impact of criminal justice involvement on victims' mental health. *Journal of Traumatic Stress, 23*(2), 182-188.

Peck, M. J. (2013). Building safe communities: Teaching social work students about the importance of comprehensive strengths-based approaches of offender rehabilitation. *Social Work in Action, 25*(4), 221-231.

Peirson, R. P. (2016). Locking away "recidivism." *Administration Policy and Mental Health, 43*, 479-481.

Piquero, A. R., Jennings, W. G., Dianmond, B., & Reingle, J. M. (2015). A systematic review of age, sex, ethnicity, and race as predictors of violent recidivism. *International Journal of Offender Therapy and Comparative Criminology, 59*(1), 5-26.

Pulla, V. (2012). What are strengths based practices all about? In V. Pulla, L. Chenoweth, A. Fancis, & S. Bakaj (Eds.), *Papers in strengths based practice* (pp. 51-68). New Delhi: Allied Publishers.

Quirk, M., Nylund-Gibson, K., & Furlong, M. (2013). Exploring patterns of Latino/a children's school readiness at kindergarten entry and their relations with Grade 2 achievement. *Early Childhood Research Quarterly, 28*, 437-449.

Rennie, C., & Dolan, M. (2010). The significance of protective factors in the assessment of risk. *Criminal Behaviour and Mental Health, 20*, 8-22.

Scott, C. K., Grella, C. E., Dennis, M. L., & Funk, R. R. (2014). Predictors of recidivism over 3 years among substance-using women released from jail. *Criminal Justice and Behavior, 41*(11), 1257-1289.

Serin, R. C., Lloyd, C. D., Helmus, L., Derkzen, D. M., & Luong, D. (2013). Does intra-individual change predict offender recidivism? Searing for the Holy Grain in assessing offender change. *Aggression and Violent Behavior, 18*, 32-53.

Shepherd, S. M., Luebbers, S., Ogloff, J. R. P., Fullam, R., & Dolan, M. (2014). The predictive validity of risk assessment approaches for young Australian offenders. *Psychiatry, Psychology and Law, 21*(5), 801-817.

Shepherd, S. M., Luebbers, & S., Ogloff, J. R. P. (2016). The role of protective factors and the relationship with recidivism for high-risk young people in detention. *Criminal Justice and Behavior, 43*(7), 863-878.

Siennick, S. E., Stewart, E. A., & Staff, J. (2014). Explaining the association between incarceration and divorce. *Criminology, 52*(3), 371-398. doi:10.1111/1745-9125.12040

Silver, E., & Chow-Martin, L. (2002). A multiple models approach to assessing recidivism risk: Implications for judicial decision making. *Criminal Justice and Behavior, 29*(5), 538-568.

Singh, J. P., Desmarais, S. L., Sellers, B. G., Hylton, T., Tirotti, M., & Van Dorn, R. A. (2014). From risk assessment to risk management: Matching interventions to adolescent offenders' strengths and vulnerabilities. *Children and Youth Services Review, 47*, 1-9.

Tabachnick, B. G., & Fidell, L. S. (2007). Experimental design using ANOVA. Belmont, CA: Duxbury.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education, 2*, 53-55.

Vallas, R., & Dietrich, S. (2014). One strike and you're out: How we can eliminate barriers to economic security and mobility for people with criminal records. *Center for*

American Progress. Retrieved from https://cdn.americanprogress.org/wp-content/uploads/2014/12/VallasCriminalRecordsReport.pdf

van der Put, C. E., Creemers, H. E., & Hoeve, M. (2014). Differences between juvenile offenders with and without substance use problems in the prevalence and impact of risk and protective factors for criminal recidivism. *Drug and Alcohol Dependence, 134*, 267-274.

Waldfogel, J. (1994). The effect of criminal conviction on income and the trust “reposed in the workmen.” *The Journal of Human Resources, 29*, 1, 62-81. doi:10.2307/146056

Ward, T., & Laws, D. R. (2010). Desistance from sex offending: Motivating change, enriching practice. *International Journal of Forensic Mental Health, 9,* 11-23. doi:10.1080/14999011003791598

Ward, T., & Stewart, C. A. (2003). The treatment of sex offenders: Risk management and good lives. *Professional Psychology: Research and Practice, 34,* 353-360. doi:10.1037/0735-7028.34.4.353

Western, B. (2002). The impact of incarceration on wage mobility and inequality. *American Sociological Review, 67*, 526-546. doi:10.2307/3088944

Table 1

Item Modifications from Their Original Format For Use With The Present Criminal Justice Involved Population

Original Item	Current Item
Self-Efficacy	
1. Generally, I feel capable of overcoming obstacles.	1. Generally, I think I can handle problems.
2. I will be able to achieve most of the goals that I have set for myself.	2. I will be able to achieve most of the goals that I have set for myself.
3. I will be able to successfully overcome many challenges.	3. I will be able to successfully deal with many problems.
Self-Awareness	
1. I am able to identify the motivations behind my actions.	1. I am able to identify the reasons behind my actions.
2. I recognize my moods and feelings.	2. I understand my moods and feelings.
3. I have a good sense of why I have certain feelings most of the time.	3. I have a good sense of why I have certain feelings most of the time.
Cognitive Reappraisal	
1. When I feel down, I try to focus on the positives.	1. When I feel down, I try to focus on the positives.
2. I can lift my mood by redirecting my thoughts to positive ideas.	2. I can lift my mood by changing my thoughts to positive ideas.
3. I am able to think about the alternatives to a problem under stressful situations.	3. I am able to think about the other options to a problem in hard situations.
Self-Regulation	
1. I think about potential consequences before I act.	1. I think about possible results before I act.
2. I can wait for what I want.	2. I can wait for what I want.
3. I think before I act.	3. I think before I act.

Table 2

Variable Correlations For All Original Study Variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. AA/Spons	-													
2. TreatSup	.00	-												
3. SelfEffic	-.03	.00	-											
4. SelfAwar	-.05	-.02	**.84**	-										
5. CogReap	-.02	.04	**.81**	**.78**	-									
6. SelfReg	-.02	.03	**.77**	**.71**	**.87**	-								
7. Transp	-.04	-.02	**-.13**	-.10	**-.15**	**-.14**	-							
8. Housing	-.04	.08	**-.16**	**-.14**	**-.17**	**-.16**	**.62**	-						
9. Employm	-.07	.03	**-.17**	**-.17**	**-.18**	**-.22**	**.67**	**.64**	-					
10. Financial	-.03	.07	**-.12**	**-.14**	**-.19**	**-.21**	**.68**	**.60**	**.79**	-				
11. SubUse	-.03	-.03	**-.20**	**-.14**	**-.26**	**-.29**	**.41**	**.45**	**.50**	**.42**	-			
12. Ethnicity	**-.16**	-.02	.00	-.01	-.01	-.01	-.03	-.05	-.03	**-.14**	.04	-		
13. RecRisk	.09	.02	**-.20**	**-.17**	**-.24**	**-.25**	**.10**	.06	**.14**	**.08**	**.27**	**.13**	-	
14. Vios	-.11	.02	**-.17**	**-.17**	**-.21**	**-.19**	**.12**	**.18**	**.16**	**.12**	**.21**	.07	**.17**	-
M	0.23	0.48	3.27	3.32	3.11	3.07	2.28	2.05	2.15	2.56	1.76	0.57	7.63	0.36
SD	0.42	0.50	0.83	0.80	0.86	0.87	1.46	1.44	1.42	1.49	1.16	0.50	2.53	0.48

Note. Variables correlated at $p < .05$ are in bold; variables correlated at $p < .01$ are bolded and underlined; the remaining pairs of variables were not significantly correlated. For the variable Ethnicity, Hispanic = 1 and White = 0; for the variable Vios, having acquired flash incarcerations/revocations = 1 and not having acquired any = 0.

Table 3

Descriptive Statistics And Reliabilities For The Internal Asset Variables Included In The Study, By Ethnicity And Total Sample

	Hispanic Sample				White Sample				Total Sample			
Scale	*M*	SD	N	α	*M*	SD	N	α	*M*	SD	N	α
Self-efficacy	3.28	0.83	193	.95	3.26	0.82	138	.94	3.27	0.83	331	.94
Self-awareness	3.31	0.82	193	.95	3.32	0.77	138	.93	3.32	0.80	331	.94
Cog. reappraisal	3.10	0.88	193	.95	3.13	0.85	138	.94	3.11	0.86	331	.94
Self-regulation	3.06	0.90	193	.94	3.08	0.82	138	.91	3.07	0.87	331	.93

Table 4

Normality Tests for Internal Asset Scales Using Skewness and Kurtosis

	Skewness			Kurtosis		
Scale	Statistic	St. Error	*Z*-Score	Statistic	St. Error	*Z*-Score
Self-efficacy	-1.062	0.134	-7.93***	0.450	0.267	1.69
Self-awareness	-1.148	0.134	-8.57***	0.801	0.267	3.00**
Cog. Reappraisal	-0.724	0.134	-5.40***	-0.327	0.267	-1.22
Self-regulation	-0.604	0.134	-4.51***	-0.531	0.267	-1.99*

Note. Significance of *Z*-scores are as follows: *$p < .05$ when $z \geq 1.96$; **$p < .01$ when $z \geq 2.58$; ***$p < .001$ when $z \geq 3.29$ (Fields, 2009). For skewness and kurtosis, z – values are considered in terms of their absolute value.

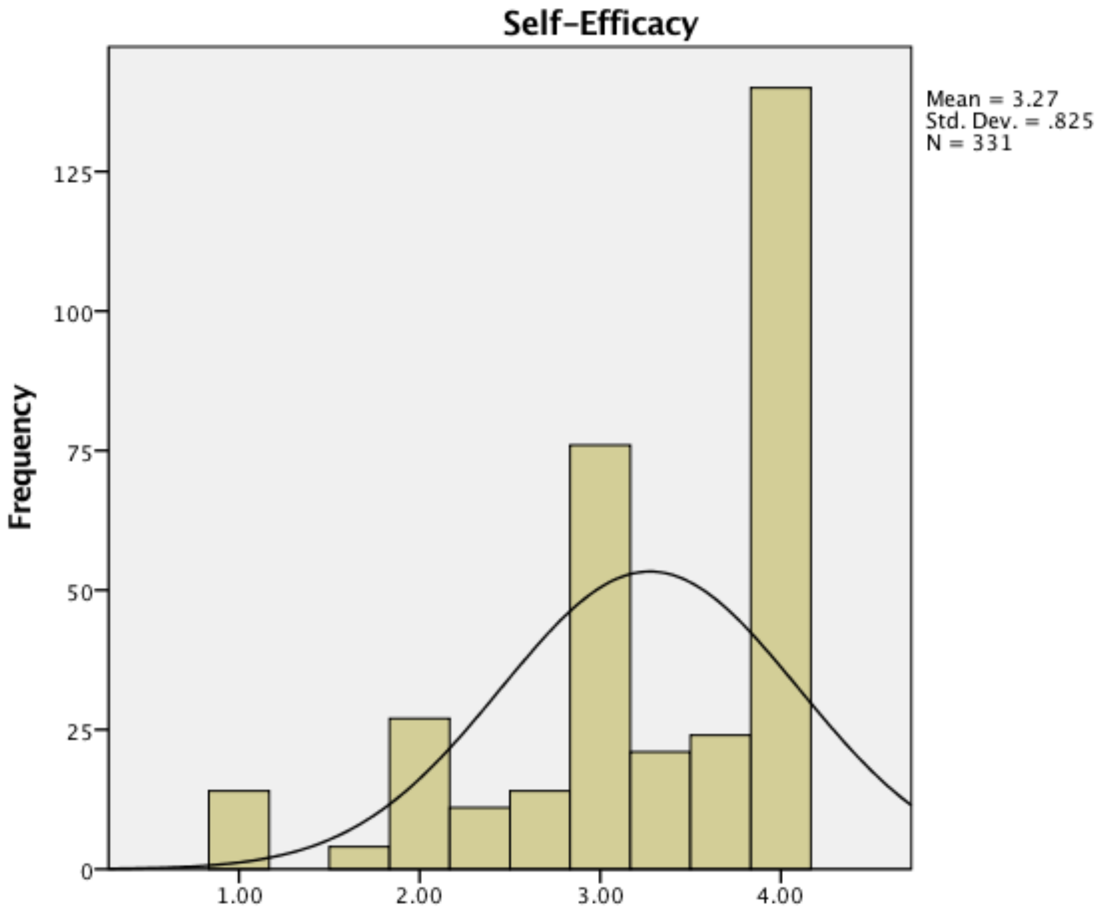

Figure 1. The distribution of the self-efficacy variable against the normal curve projection.

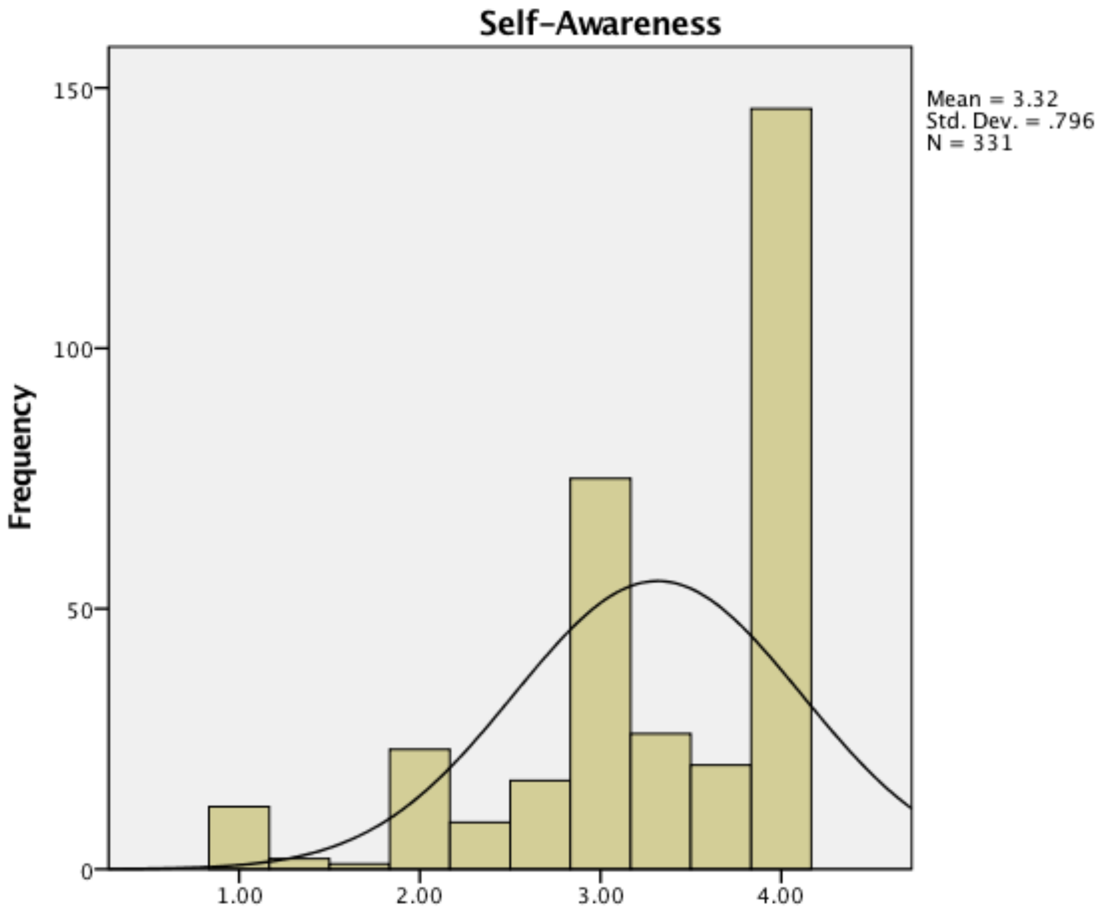

Figure 2. The distribution of the self-awareness variable against a normal curve projection.

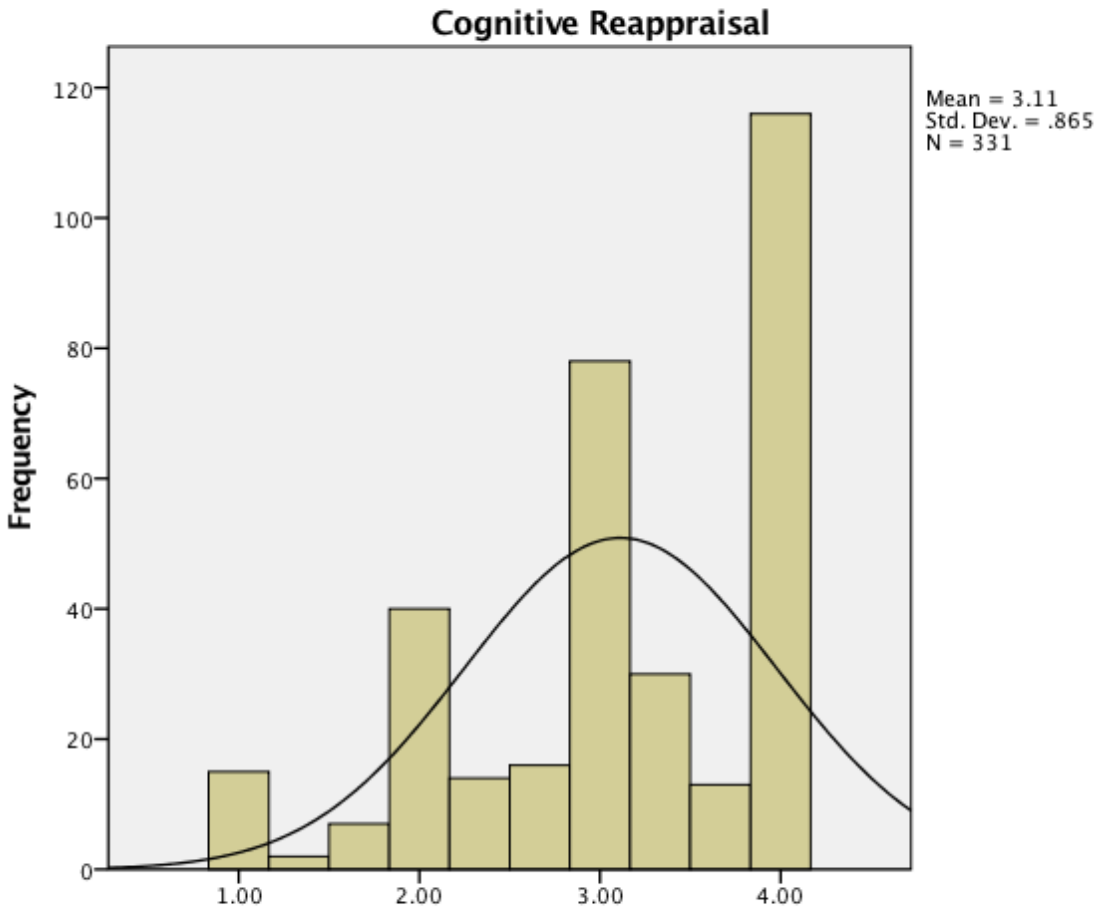

Figure 3. The distribution of the cognitive reappraisal variable against the normal curve projection.

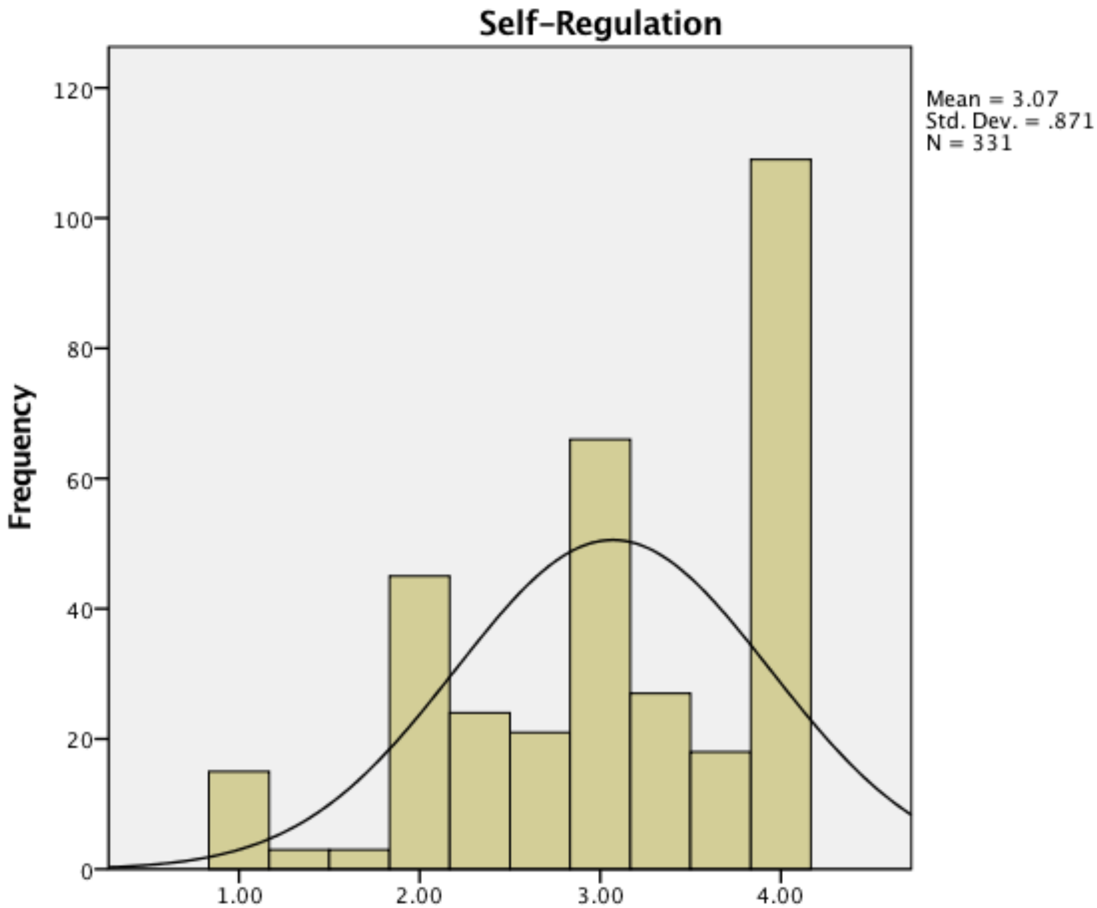

Figure 4. The distribution of the self-regulation variable against the normal curve projection.

Table 5

Chi-square analyses of Supervision Violations by Various Predictor Variables

Predictor Variables	Supervision Violations No	Supervision Violations Yes	χ^2	N
Housing Difficulties				
No	122 (63%)	45 (47%)	6.741**	290
Yes	72 (37%)	51 (53%)		
Employment Difficulties				
No	108 (56%)	42 (43%)	4.330*	289
Yes	84 (44%)	55 (57%)		
Financial Difficulties				
No	78 (40%)	34 (36%)	0.392	289
Yes	117 (60%)	60 (64%)		
Transportation Difficulties				
No	107 (53%)	44 (42%)	3.654†	308
Yes	95 (47%)	62 (58%)		
Substance Use Struggles				
No	126 (67%)	44 (49%)	8.736**	277
Yes	61 (33%)	46 (51%)		
AA with a Sponsor				
No	158 (74%)	99 (83%)	3.805†	333
Yes	56 (26%)	20 (17%)		
Treatment Support				
No	113 (53%)	60 (50%)	0.174	333
Yes	101 (47%)	59 (50%)		
Self-Efficacy				
No	95 (45%)	72 (61%)	8.186**	331
Yes	118 (55%)	46 (39%)		
Self-Awareness				
No	96 (45%)	69 (58%)	5.457*	331
Yes	117 (55%)	49 (42%)		
Cognitive Reappraisal				
No	121 (57%)	81 (69%)	4.473*	331
Yes	92 (43%)	37 (31%)		
Self-Regulation				
No	122 (57%)	82 (69%)	4.791*	331
Yes	91 (43%)	36 (31%)		

Note. Numbers in parentheses indicate column percentages.
†p <.06. *p < .05. *p < .01. *p < .001.

Table 6

Variable Correlations for Binary LCA Study Variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. SelfEff	-									
2. CogReap	**.65**	-								
3. AASpons	-.02	-.02	-							
4. Housing	**-.17**	**-.17**	.02	-						
5. Employm	**-.16**	**-.21**	.03	**.68**	-					
6. Transp	**-.19**	**-.20**	.01	**.62**	**.69**	-				
7. SubUse	**-.21**	**-.25**	-.02	**.46**	**.48**	**.43**	-			
8. HighRisk	-.09	**-.13**	.08	**.16**	**.17**	.09	**.24**	-		
9. Hispanic	.01	.00	**-.17**	-.07	.01	.01	.05	**.18**	-	
10. Vios	**-.19**	**-.13**	-.05	**-.14**	**.14**	.12	**.18**	**.17**	.11	-
M	.51	.42	.25	.39	.47	.48	.37	.63	.56	.32
SD	.50	.49	.43	.49	.50	.50	.48	.48	.50	.47

Note. Variables correlated at $p < .05$ are in bold; variables correlated at $p < .01$ are bolded and underlined; the remaining pairs of variables were not significantly correlated.

Table 7

LCA Class Fit Statistics

# of Classes	Log Likelihood	BIC	BLRT *p*-value	LMRT *p*-value	VLMR *p*-value	*BF*	*cmP*	Class Prevalence
1	-1388.952	2822.451	-	-	-	< .001	< .001	1.00
2	-1194.224	2483.111	< .001	< .001	< .001	< .001	< .001	.43, .57
3	-1149.533	**2443.843**	< .001	**< .001**	**< .001**	**10.974**	< .001	.29, .45, .26
4	-1126.871	2448.634	**< .001**	.299	.292	104977.361	< .001	.31, .14, .27, .28
5	-1113.375	2471.757	.013	.061	.059	-	< .001	.24, .17, .23, .10, .26

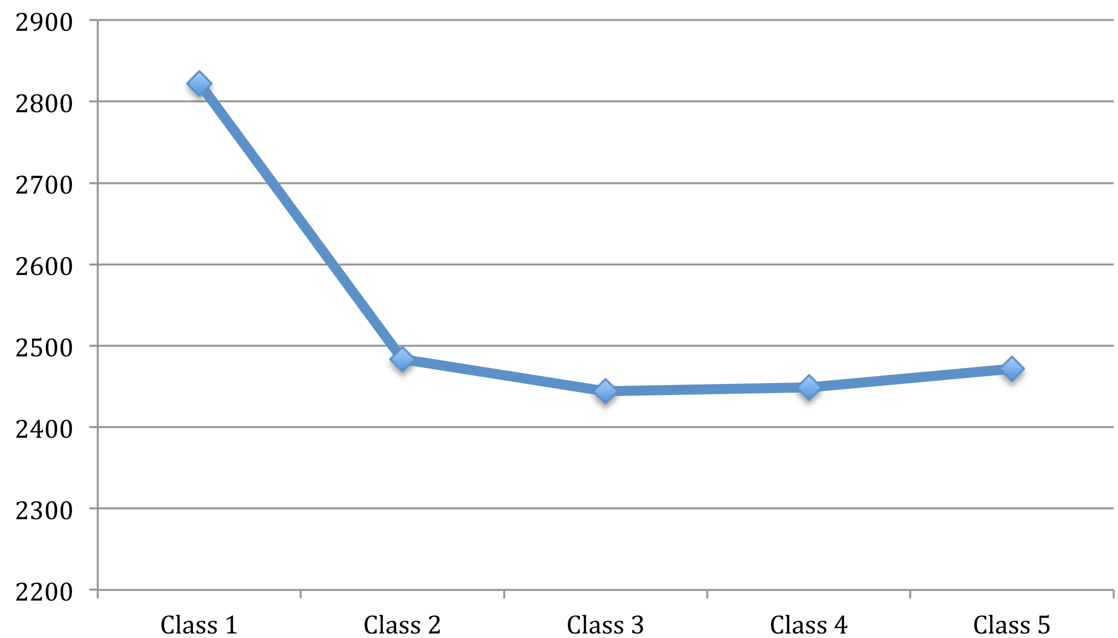

Figure 5. Scree plot of the BIC statistic for the class models examined in the present study.

Table 8

Classification Probabilities for the Most Likely Latent Class Membership (Column) by Latent Class (Row), for the LCA 3-Class Solution

		Most Likely Latent Class Membership		
		1	2	3
Latent Class	1	.977	.023	.000
	2	.015	.976	.009
	3	.000	.018	.982

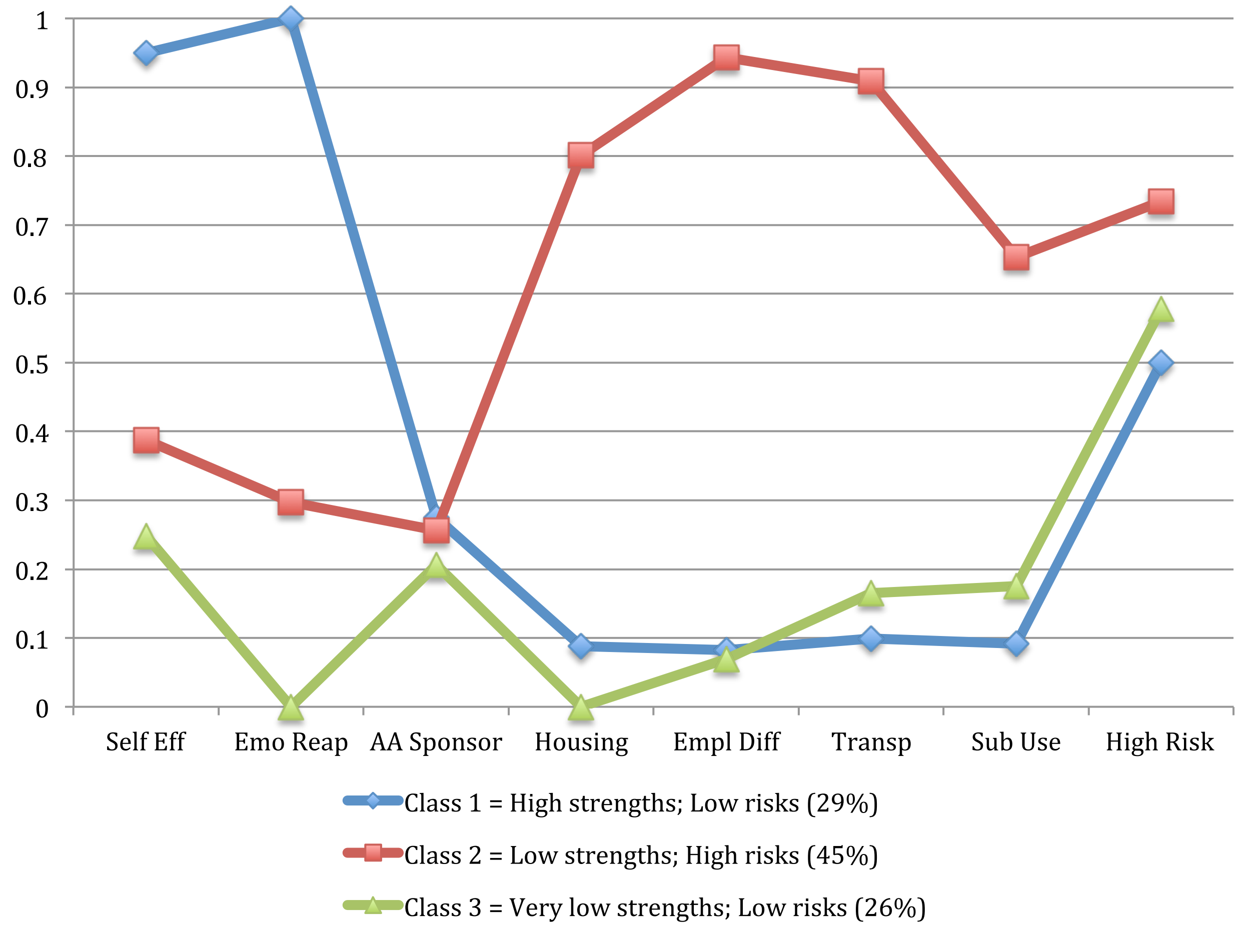

Figure 6. The LCA 3-class solution depicted graphically.

Table 9

Item Probabilities for Each Class within the LCA 3-Class Solution

Variable	Class 1 = High strengths; Low risks (29%)	Class 2 = Low strengths; High risks (45%)	Class 3 = Very low strengths; Low risks (26%)
Self-Efficacy	0.950	0.387	0.248
Emotional Reappraisal	1.000	0.297	0.000
AA with a Sponsor	0.275	0.256	0.206
Housing	0.088	0.801	0.000
Employment Diff.	0.082	0.943	0.069
Transportation Diff.	0.099	0.909	0.165
Substance Use	0.092	0.653	0.175
High Recidivism Risk	0.500	0.734	0.578

Table 10

Logistic Regression Output for Regressing Ethnicity (Covariate) Onto the LCA 3-Class, using Class 1 (High Strengths, Low Risks) as the Reference Group

Class	Logit	*SE*	*t*	Odds Ratio
Low Strengths, High Risks	0.126	0.309	0.407	0.684
Very Low Strengths, Low Risks	0.431	0.346	1.245	0.213

Note. *p < .05. **p < .01.

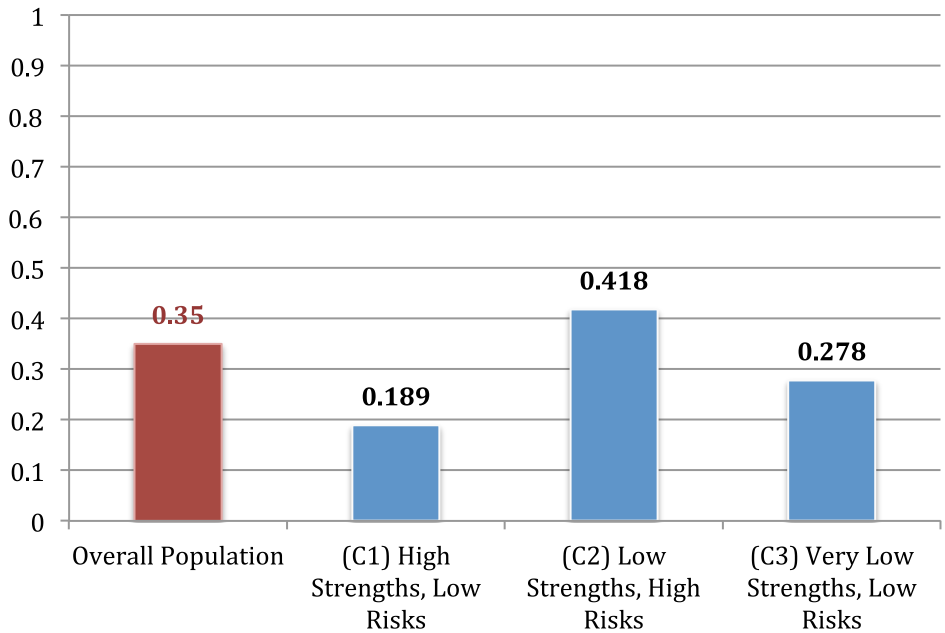

Figure 7. The probability of obtaining supervision violations by class designation, as compared to the probability of obtaining supervision violations across the overall study population.

Table 11

Sample Cutoff Points for Practitioners in Determining the Presence of Risks or Absence of Strengths

Variable	Range of All Possible Scores	Use Scale Means or Item Scores?	Score Range for Strength/Risk
Strengths			
Self-Efficacy	**1 – 4** (1 = *Not at all true*, 2 = *A little true*, 3 = *Pretty much true*, and 4 = *Very true*)	**Scale mean**	**3.67>=Strength**
Cognitive Reappraisal	**1 – 4** (1 = *Not at all true*, 2 = *A little true*, 3 = *Pretty much true*, and 4 = *Very true*)	**Scale mean**	**3.67>=Strength**
AA with a Sponsor	**0 (No), 1 (Yes)**	**Item score**	**1 = Strength**
Risks			
Employment	**1 – 5** (1 = *Never*, 2 = *Occasionally*, 3 = *Sometimes*, 4 = *Often,* and *5 = Always*).	**Item score**	**2>=Risk**
Housing	**1 – 5** (1 = *Never*, 2 = *Occasionally*, 3 = *Sometimes*, 4 = *Often,* and *5 = Always*).	**Item score**	**2>=Risk**
Transportation	**1 – 5** (1 = *Never*, 2 = *Occasionally*, 3 = *Sometimes*, 4 = *Often,* and *5 = Always*).	**Item score**	**2>=Risk**
Substance Use	**1 – 5** (1 = *Never*, 2 = *Occasionally*, 3 = *Sometimes*, 4 = *Often,* and *5 = Always*).	**Item score**	**2>=Risk**

Appendix A
Original Survey Items

Variables: Twelve-step Support, Treatment Support
Which programs have you participated in? (CHECK ALL THAT APPLY)

Drug and Alcohol Treatment
- ☐ AA/NA - I attend and I do NOT have a sponsor
- ☐ AA/NA - I attend and I DO have a sponsor
- ☐ Groups (Other than AA/NA)
- ☐ Detox
- ☐ Residential treatment/clean and sober housing

Mental Health Treatment
- ☐ Individual therapy/counseling
- ☐ Group therapy
- ☐ Medication

Variables: Logistic Risks, Substance Use Struggles

Have you had any of these problems while on supervision?						
Problem	**1=Never**	**2= Occasionally**	**3= Sometimes**	**4= Often**	**5= Always**	
Transportation to appointments	1	2	3	4	5	
Transportation to a job	1	2	3	4	5	
Housing	1	2	3	4	5	
Employment	1	2	3	4	5	
Financial	1	2	3	4	5	
Childcare	1	2	3	4	5	I do not have children
Substance Use	1	2	3	4	5	

Variables: Self-Efficacy, Self-Awareness

How well do you think the following sentences describe you?				
Question	**1=Not at all true**	**2=A little true**	**3=Pretty much true**	**4=Very true**
Generally, I think I can handle problems.	1	2	3	4
I will be able to achieve most of the goals that I have set for myself.	1	2	3	4
I will be able to successfully deal with many problems.	1	2	3	4
I am able to identify the reasons behind my actions.	1	2	3	4
I understand my moods and feelings.	1	2	3	4
I have a good sense of why I have certain feelings most of the time.	1	2	3	4

Variables: Cognitive Reappraisal, Self-Regulation

How well do you think the following sentences describe you?				
Question	**1=Not at all like**	**2=A little like**	**3=Like me**	**4=Very like me**

	me	me		
When I feel down, I try to focus on the positives.	1	2	3	4
I can lift my mood by changing my thoughts to positive ideas.	1	2	3	4
I am able to think about the other options to a problem in hard situations.	1	2	3	4
I think about possible results before I act.	1	2	3	4
I can wait for what I want.	1	2	3	4
I think before I act.	1	2	3	4