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ORIGINAL ARTICLE

Recidivism Among Violent Offenders: Evaluating the Cumulative Impact of Psychological and Social Risk Factors

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Abstract

While the literature on criminal recidivism has extensively documented the role of independent risk factors, little is known about how these risk factors may co-occur to produce a cumulative effect. Such information would enhance understanding and be valuable for informing policy and programming. The current study uses data from a large sample of released violent offenders (*N*=38,097) to explore how two distinct cumulative risk indices, comprised of psychological and social risk factors, work to influence common recidivism patterns. Results across two multivariate modeling strategies consistently reveal linkages between the psychological and social indices and recidivism risk. Implications for research and practice are considered.

Keywords Cumulative risk · Recidivism · Psycho-social risk

Introduction

In the United States, more than half of individuals formerly incarcerated for violent crimes are rearrested within three years (Antenangeli & Durose, 2021). This rate of recidivism raises fundamental questions about the effectiveness of rehabilitation programs and societal reintegration efforts. Moreover, due to concerns for public safety, policymakers and academics concur that the correlates of recidivism among

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individuals incarcerated for a violent crime warrants significant research attention (Berg & Huebner, 2011; Reid et al., 2023; Visher & Travis, 2003). The empirical literature accumulated over the last few decades has focused primarily on the relationship between psycho-social risk factors and post-release criminal behaviors (Baay et al., 2012; Bonta et al., 1998; Nilsson et al., 2011; Reid et al., 2025; Rice & Harris, 1995; Stalans et al., 2004). However, much remains to be understood regarding the diversity of dynamics that underlie recidivism risk among this group of offenders.

One such understudied dynamic involves modeling the cumulative impact of multiple risk factors on recidivism. While the literature has generally focused on the effects of independent risk factors—such as how employment status or substance abuse relate to reoffending—it is also important to examine how multiple, co-occurring risk factors "stack up" to contribute to criminal behavior (Oliveira & Beaver, 2021; Reid et al., 2023; TenEyck et al., 2023). This approach—known as the cumulative risk approach—suggests that adverse life outcomes, including criminality, are not a product of isolated events or circumstances, but instead result from multiple events that work in tandem over time (Evans et al., 2013; Hatch, 2005; Nurius et al., 2015; Savolainen et al., 2018), which is in line with cumulative continuity or disadvantage processes proposed by life-course scholars (Moffitt, 1993; Sampson & Laub, 1993a). As risk factors accumulate, scholars argue the odds of criminal offending and recidivism will likely increase (Lawing et al., 2017a, b; Oliveira & Beaver, 2021; Reid et al., 2023; TenEyck et al., 2023).

The cumulative risk approach represents a distinct type of multiple-risk model. In this framework, risk is operationalized as an additive measure that captures the total number of risk factors a person has been exposed to throughout their life (Atkinson et al., 2015; LaNoue et al., 2020; Rutter, 1978). This approach allows researchers to explore how co-occurring risk factors affect a given outcome, enhancing understanding beyond the insights of single predictor models (Atkinson et al., 2015; Evans et al., 2013; Gest et al., 1999). Despite such benefits, empirical studies in the criminal justice sciences, particularly concerning recidivism, seldom use the cumulative risk framework for modeling risk (e.g., Lawing et al., 2017a, b; Reid et al., 2023).

The current study aims to narrow this void and contribute to the existing empirical work on recidivism by using long-term data from a large sample of individuals formerly incarcerated for violent crimes to evaluate how independent risk factors combine to influence common recidivism patterns. Exploring cumulative risk as it relates to criminal conduct fits suitably within the life-course perspective (Oliveira & Beaver, 2021; TenEyck et al., 2023), where adverse outcomes are explained by differential exposure to multiple bio-psycho-social risk factors (Crystal & Shea, 1990; Dannefer, 2003; Hatch, 2005; Sampson & Laub, 1997). This analysis will focus on psycho-social risk factors of criminal involvement using two distinct cumulative risk indices of prominent psychological and social variables for a two-pronged analysis. Specifically, we examine whether the cumulative effects of each index are similarly or uniquely associated with two different types of recidivism: reconviction for a new criminal offense and reconviction for a technical violation. We then explore how these cumulative psychological and social risk indices interact with each other to influence recidivism patterns among the cohort of released offenders. To ensure the robustness of our results and further contribute to the criminological literature on recidivism, we estimate recidivism patterns using two different survival modeling techniques. We compare traditional Cox Proportional Hazard model estimates with Accelerated Failure Time models, which, despite their statistical strengths, are rarely employed in criminological studies.

The following section highlights the conceptual factors generally associated with crime and recidivism, including a discussion of prominent psychological and social risk factors. Next, we outline the cumulative risk modeling framework and its application to the current study. We then detail the study's methodology and present findings from our analysis. The study concludes with a discussion of the implications of this work for life-course criminology, recidivism research, and re-entry programming.

Risk Factors for Recidivism

Levels of recidivism among individuals who commit violent crimes in the United States surpass those of individuals who commit non-violent crimes. According to the United States Sentencing Commission, almost two-thirds of violent offenders released from prison are rearrested within eight years, compared to about 40% of non-violent offenders (Hunt et al., 2019). Among the violent offenders who are rearrested, approximately 41% are reconvicted (vs. 23% of non-violent offenders), and 34% are reincarcerated (vs. about 18% of non-violent offenders).

For both individuals who commit violent and non-violent offenses, research has identified salient correlates of recidivism. For example, recidivism research has consistently affirmed that offender age remains one of the most salient predictors of desistance. The ubiquity of the age-crime curve suggests that it is typical for offenders to age out of crime (see Gottfredson & Hirschi, 1990), and indeed, research has found that older offenders are less likely to recidivate post-incarceration (Sampson & Laub, 1993a). Life-course and criminal careers research has suggested there are a small number of individuals who continue to participate in crime well into adulthood, accounting for a disproportionate amount of crime, including serious and violent crimes (Blumstein, 2005; DeLisi & Piquero, 2011; Farrington, 2015; Lynam et al., 1993; Zara & Farrington, 2016). Likewise, the recency of prior offending has been linked to future offending risk. Persons with more recent criminal activity are at greater risk of recidivating following release from prison (Huebner & Berg, 2011; Kurlychek et al., 2007).

A series of incarceration-related factors have also been shown to affect post-release criminal behavior. Research has found that factors such as length of incarceration (Loughran et al., 2009; Meade et al., 2013; Mears et al., 2016; Nagin et al., 2009; Rydberg & Clark, 2016), prison misconduct (Cochran et al., 2014; Cochran & Mears, 2017; Huebner & Berg, 2011), and participation in programming and visitation during incarceration predict recidivism outcomes (Mears et al., 2012; Nur & Nguyen, 2023; Turanovic & Tasca, 2022). However, beyond these correlates, scholars have also explored how various dynamic psychological and social risk factors may influence crime and general recidivism. Persistent offenders tend to be exposed to a higher number of psycho-social risk factors throughout their life-course, leading to a process of cumulative continuity. This process leads to fewer opportunities that may promote desistance from crime; thus, increasing these individuals' risk of continued participation in crime and of recidivism (Blokland & Nieuwbeerta, 2005; Huebner, 2005; Moffitt, 1993; Piquero et al., 2002a; Sampson & Laub, 1993a, b).

Psychological Risk Factors

The association between mental health and criminal engagement has been the subject of substantial debate. In comparison to the general population, there is an overrepresentation of individuals with mental health issues in the criminal justice system. Approximately half of the incarcerated population presents symptoms of a mental health disorder and around 20% experience symptoms of severe mental illness, compared to just 6% of the general population (Lafortune, 2010; Maruschak et al., 2021; Prins, 2014; SAMHSA, 2023). The pervasiveness of mental health disorders among the incarcerated has resulted in a widespread belief that the presence of mental health issues leads to increased violence and criminal involvement (Bagaric, 2016; Rueve & Welton, 2008; Teplin, 1990; Vreugdenhil et al., 2004).

This relationship between mental health and crime is a complex one, with empirical research findings being quite inconsistent, leading to much debate about the direction of this association and possible intervening factors. Specifically, some studies have suggested there is an association between certain psychopathologies and crime and/or violence, such as psychoses (including schizophrenia), paranoid ideation, clinical hostility, mania, and PTSD (Douglas et al., 2009; Douglas & Skeem, 2005; Fazel et al., 2010; Howard et al., 2017; Link & Stueve, 1994; McCabe et al., 2013; Nielssen et al., 2012) where a gradual progression of violent behaviors can occur after the onset of mental illness (e.g., Large & Nielssen, 2011). However, other scholars argue that mental illness, on its own, does not directly lead to criminal involvement (Rueve & Welton, 2008; Varshney et al., 2015), arguing instead that other factors mediate this association (e.g.,substance abuse, personality disorders, comorbidity issues, among others).

Indeed, many studies that find a positive association between mental health and crime do not control for the impact of substance use disorders as a comorbid factor, even though substance abuse has been identified as perhaps the most significant independent risk factor for overall criminal engagement and violence (Arseneault et al., 2000; Newman et al., 1998; Wittchen, 1996). Additionally, research has suggested the connection between mental health and crime can be primarily explained by the presence of personality disorders, specifically those associated with a lack of impulse control, low empathy, emotion deregulation, narcissism, and paranoid ideation (Lowenstein et al., 2016; Nestor, 2002), as these traits are more likely to increase the risk of engaging in violent and antisocial behaviors (Douglas & Skeem, 2005; Reid et al., 2025). Failing to control for these factors, therefore, can cause models to be mis-estimated, making it difficult to account for the independent effect of any given psychopathology on criminal involvement (Arseneault et al., 2000; Newman et al., 1998; Wittchen, 1996).

Irrespective of the association between mental illness and initial criminal involvement, violent incidents are limited to a small group of the population, and this is true for individuals with mental illness too, with a small number of individuals accounting for a large proportion of crime (Gardner et al., 1996; Monahan et al., 2001; Zara & Farrington, 2016). Research has indicated that individuals with mental disorders, especially with severe mental illness, are at higher risk for criminal recidivism (Cloyes et al., 2010; Grattet et al., 2008; Louden & Skeem, 2011; Wilson & Wood, 2014). Many authors have attributed this higher recidivism rate, at least in part, to the "revolving door" issue (those who have been in the system are more likely to return) as well as to the criminalization of mental illness that has taken place since the deinstitutionalization movement in the 1960's (Fisher et al., 2006; Messina et al., 2004; Raphael & Stoll, 2013; Teplin, 1984). This said, the association between mental illness and recidivism is a multifaceted and complex one that warrants further investigation.

Social Risk Factors

To further our understanding of recidivism, sociogenic explanations of criminal behavior must also be considered. These sociogenic explanations of criminal behavior, such as Sampson and Laub's (1993b) age-graded control theory of offending, have animated much of the 21st-century research on desistance and long-term offending patterns. This perspective argues that active involvement in prosocial institutions limits a person's opportunities to commit crime and can act as turning points, shifting antisocial trajectories toward more conventional, pro-social pathways.

Theorists suggest that stable employment, for example, provides significant structure to a person's daily routine and reduces situational motivations for crime, such as association with deviant peers (Sampson & Laub, 1993a; Warr, 1998) or the need to supplement income through illegal channels (Farrington et al., 2018; Loughran et al., 2017; Sampson & Laub, 1993a; Uggen, 2000b; Uggen & Staff, 2001). Empirical research on the role of employment as a turning point, however, has been mixed. Some studies have found that offenders with stable employment are less likely to reoffend (Farrington et al., 2009, 2018; Piquero, Macintosh et al., 2002; Reising et al., 2019; Uggen, 2000a), while others have found little support for this association (Andersen & Skardhamar, 2014; Giordano, 2013).

Another potentially important turning point identified in the literature is marriage, or a high-quality and stable relationship. A high-quality marriage or committed relationship can create stakes in conformity, increase one's social capital, limit access to criminal opportunities, and encourage desistance by being a source of informal social control (Sampson & Laub, 1993a, 2003). Research has generally provided support for quality marital relationships as an effective turning point (e.g., Barnes & Beaver, 2012; Blokland & Nieuwbeerta, 2005; Farrington & West, 1995; Larson et al., 2016).

The extant literature has also identified factors such as low educational attainment, gang involvement, and extensive criminal histories as salient risk factors for crime and recidivism. Offenders with lower educational attainment are at higher risk of recidivism because they tend to have lower social capital and are not exposed to the same level of informal social control as individuals who stay in school for more extended periods (Blomberg et al., 2012; Jacob & Lefgren, 2003; Moore & McArthur, 2014). Individuals with low educational attainment also have lower levels of marriageability and are less likely to find stable jobs and engaging careers. Likewise, research has found that individuals who have longer criminal histories, commit crimes at higher frequency and severity, and participate in gang activity are more likely to continue offending and thus, have higher rates of recidivism (DeLisi & Piquero, 2011; Dong & Krohn, 2016; Gilman et al., 2014; Gilman, 2018; Huebner & Berg, 2011; Piquero et al., 2003; Thornberry, 2003).

Overall, the extant evidence suggests that throughout the life course individuals are exposed to a myriad of social risk factors that increase their odds of criminal involvement and reoffending. Exposure to a high number of risk factors initiates a process of cumulative continuity or disadvantage that impacts individual trajectories and access to opportunities in the short term—essentially keeping offenders in environments, circumstances, or states where they are more likely to commit crime—which in turn influences long-term offending and recidivism (Arnett, 1998; Blokland & Palmen, 2012; DeLisi & Piquero, 2011; Moffitt, 1993; Piquero et al., 2002a; Sampson & Laub, 1993a). The current study aims to build on this notion of cumulative continuity by considering the additive impact of risk factors on recidivism patterns, as opposed to examining only the influence of individual risk factors.

The Cumulative Risk Framework

Based on the reality that individuals are characterized by diverse environments, experiences, and personal traits throughout their lives, the cumulative risk framework offers a compelling way to model and understand how multiple risk factors work in tandem to influence individual outcomes and life-course trajectories (Evans et al., 2013; Hatch, 2005; Nurius et al., 2015; Savolainen et al., 2018). This framework suggests that risk factors do not operate in a vacuum, but instead are overlapping contingencies that affect life outcomes; therefore, the number of risk factors an individual is exposed to shapes the likelihood of adverse life outcomes (Atkinson et al., 2015; Evans et al., 2013; LaNoue et al., 2020). Specifically, cumulative risk scholars suggest that no single risk factor (irrespective of magnitude, type, or time-ordering) will impact outcomes over the life course as much as an accumulation of the number of risk factors an individual is exposed to (Buehler & Gerard, 2018; Cuevas et al., 2019; Ettekal et al., 2019; Evans et al., 2013; Lawing et al., 2017a, b). From this perspective, cumulative risk is defined and constructed as an additive index encompassing the total number of risk factors individuals have experienced throughout their lives (Atkinson et al., 2015; Cuevas et al., 2019; LaNoue et al., 2020; Rutter, 1978).

Several recent studies have used this modeling strategy to examine recidivism among samples of young adult or youthful offenders. For example, Oliveira and Beaver (2021) examined the relationship between three separate cumulative risk indices (biosocial, psychopathological, and family risk indices) and long-term self-reported offending. Using a longitudinal sample of high-risk youths, the authors found that being exposed to more biosocial and family risk factors in early adolescence was related to more continued offending in late adolescence and early adulthood, whereas presenting more comorbid psychopathological symptoms was associated with less offending. TenEyck and colleagues (2023) employed a similar approach, using a single biopsychosocial cumulative risk index to assess its relationship with later offending in a sample of adolescents and young adults. The authors found that, unlike individual risk factors, which had weaker predictive power, the cumulative risk index was consistently associated with criminal behaviors over adolescence and early adulthood. Lawing and colleagues (2017) likewise found that a cumulative risk index created from a risk assessment actuarial tool effectively predicted recidivism in a sample of high-risk youths.

We identified only two studies that have used a cumulative risk framework to examine recidivism among adult samples. In the first study, Solomon and colleagues (2016) explored whether a cumulative risk index would help predict child maltreatment recidivism (i.e., parental/caregiver reoffending of child abuse and neglect). The authors developed a total risk index based on the number of family risk factors found in case files. Results from this study showed that a family's cumulative number of risk consistently predicted maltreatment recidivism by caregivers. The authors highlight the importance of understanding cumulative risks when developing recidivism prevention strategies. Despite the relevance of this study, it focused on a very different group of offenders and different measures of recidivism not linked to incarceration. In the second study, Reid and colleagues (2023) explored the association between two cumulative risk indices —social and mental health—and recidivism among a sample of homicide offenders. The authors used three measures of recidivism: reconviction for any reason, reconviction for a new crime, and reconviction for a technical violation. Findings revealed that while the cumulative disadvantage index (i.e. being exposed to more social cumulative disadvantage) consistently predicted all forms of recidivism across modeling strategies, the mental health index, which tapped into comorbid mental illnesses, was only related to recidivism for a technical violation but not for a new crime. Upon further exploration, the authors found that personality disorders were associated with reconvictions for a new crime. The authors underscored the importance of expanding this line of research using cumulative risk indices to explore risk of recidivism beyond homicide offenders. Notably, it is one of the few studies within this body of literature that examines post-incarceration recidivism as an outcome measure.

Cumulative risk models enable scholars to investigate how the co-occurrence of and differential exposure to risk factors influence a specific outcome, thereby expanding our knowledge base beyond the insights provided by single-predictor models (Atkinson et al., 2015; Evans et al., 2013; Gest et al., 1999). Given its usefulness, assessments of cumulative risk are common in disciplines such as psychology and health (e.g. Atkinson et al., 2015; Copeland et al., 2009; Evans et al., 2013; Lima et al., 2010; Prochaska et al., 2014; Santini et al., 2021; Seifer et al., 1992). However, it is a less typical approach in criminology. The limited number of studies that have used the cumulative risk framework have explored factors contributing to antisocial outcomes among adolescents (Murray et al., 2010; Stoddard et al., 2012; Thornberry, 2003), outcomes that follow antisocial or delinquent behaviors in adolescent samples (Craig et al., 2022; Lamela & Figueiredo, 2018; McGoron et al., 2020), as well as risk assessments in criminal justice (e.g., Walters, 2015). Even fewer studies have explored adverse outcomes, including reoffending and recidivism, not related to adverse childhood experiences (Lawing et al., 2017b; Oliveira & Beaver, 2021; TenEyck et al., 2023), and only two studies to our knowledge have used cumulative risk indexes to understand adult recidivism (Reid et al., 2023; Solomon et al., 2016).

Current Study

The current study aims to expand on these prior studies by exploring how prominent psychological and social variables are associated with recidivism patterns among a large sample of formerly incarcerated violent offenders (N=38,097). Due to public safety concerns—stemming from fear of violent victimization among the general public, as well as higher rates of recidivism among individuals who committed violent crimes (Antenangeli & Durose, 2021)—this population warrants additional empirical attention to better understand factors contributing to their behavior upon release from prison. Our study proceeds in two stages. First, we estimate the effects of a cumulative psychological risk factor index and a cumulative social risk factor index on the timing of recidivism. We then explore how our psychological and social indices interact with each other to affect the timing of recidivism among our sample. Previous researchers have noted the difficulty of defining recidivism (see generally, Bhati, 2023; Zara & Farrington, 2016). Reconvictions for new crimes reflect more persistent offending (e.g., Moffitt, 1993; Sampson & Laub, 1993a). However, technical violations—which often stem from offenses such as missing a meeting with a parole/probation officer, failing to follow curfew, or being unable to secure a job—reflect more on an inability to meet supervision requirements (Duwe, 2011). Essentially, reconvictions for a new crime relate more to the individual's offending behavior, while technical violations relate more to the supervision system and relatively minor behavioral misdeeds of the individual. To account for both outcomes and explore differences between them, this study measures recidivism in two different ways: (1) a reconviction for a new criminal offense, and (2) a reconviction for a technical violation. We further estimate recidivism outcomes using different survival modeling strategies to ensure a robust investigation. The findings that emerge from this analysis have direct implications for recidivism research, life-course criminology, and re-entry policy and programming, which are explored in the discussion section.

Data and Methods

Sample

The data used in this study comes from the Recidivism Database (Bales et al., 2014), which contains information collected from the Florida Department of Corrections, the Florida Department of Law Enforcement, and the Florida Department of Revenue. This database includes information for a cohort of 227,509 individuals released from Florida prisons between 2004 and 2011. Within this sample, 58,440 individuals were convicted of a violent crime, including homicide (N=4,323), aggravated assault and battery (N=15,464), robbery (N=16,587), sex crimes (N=9,758), or other violent offenses (N=5,077). The present study excludes offenders convicted of sex crimes, given the different nature, victimology, and risk of recidivism for this group of offenders (Gudjonsson & Sigurdsson, 2000; Przybylski, 2010; van der Put et al., 2020). The study also excludes women (N=4,557), given the qualitative distinctions in the etiology of offending and desistance between males and females (e.g., Bennett et al., 2005; Steffensmeier & Allan, 1996; Uggen & Kruttschnitt, 1998). This strategy left us with a total potential sample of 44,125 males convicted of a violent crime. Of these offenders, 40.2% were white, with a mean age was 30.4 years. Furthermore, most of the sample had a prior criminal history in the state of Florida (76.8%), did not have a high school diploma (73.4%), and were unemployed at the time of their arrest (40%). Descriptive statistics are presented in Table 1.

Dependent Variables

The outcome variables in this study include two separate measures of time to recidivism, measured in months after release. Specifically, in line with prior research (Zara & Farrington, 2016), we measure recidivism as time to reconviction for (1) a new criminal offense, and (2) a technical violation. The distinction between reconviction for a technical violation (individual fails to comply with the conditions imposed for post-release supervision—e.g., meeting with the probation/parole officer) and for a new crime (more serious than a technical violation, considered a substantive violation and individuals are charged with a new crime) is a crucial one to overcome challenges present in prior research where this distinction was not considered (Bhati, 2023; Zara & Farrington, 2016). To facilitate a survival analysis, we censor these variables at 60 months (or 5 years). Respondents who avoid a new conviction for 5 years are therefore considered not to have recidivated. These measures were extracted from the Florida Department of Corrections records, specifically the date of release, the date of recommitment, and the cause for recommitment.

Independent Variables

Prior research suggests that numerous overlapping factors work in tandem to shape behavior over the life course. The current study, informed by this understanding, adopts a cumulative risk approach to gain deeper insights into the risks that underlie recidivism among our cohort of released offenders. Our analysis focuses on risk domains related to psychological and social factors, and is based on prior literature suggesting the use of multiple risk domains (Evans et al., 2013). To that end, and consistent with recent work by Reid et al. (2023), we construct two additive indices: a cumulative mental illness index and a cumulative social risk index, each comprising variables identified in the literature as affecting the risk of crime and recidivism. Modeling risk using these additive indices, as proposed by the cumulative risk approach, enables a better understanding of how stacked risk factors are related to recidivism, while also incorporating a larger number of risk factors in the models without incurring multicollinearity issues. Research comparing several approaches to modeling risk has suggested that the cumulative risk approach may provide a more robust measure to predict outcomes of interest compared with modeling individual

Table 1 Descriptive statistics

Variable		Mean	SD	Min	Max
Reconviction - new crime					
	Reconvicted (5 years)	0.271	0.444	0	1
	Duration (months)	56.503	31.201	1	121
Reconviction - tech violation					
	Reconvicted (5 years)	0.091	0.287	0	1
	Duration (months)	64.846	31.661	1	121
Race/Ethnicity		0.686	0.625	0	2
	White	0.402	0.490	0	1
	Black	0.511	0.500	0	1
	Hispanic	0.088	0.283	0	1
Age at admission		30.389	10.428	13	81
Crime type		2.767	0.929	1	4
	Homicide	0.080	0.271	0	1
	Robbery	0.336	0.472	0	1
	Aggravated assault	0.322	0.467	0	1
	Other violent	0.262	0.440	0	1
Time served in months		37.280	44.716	0.067	421
Prison misconduct		4.614	9.457	0	269
Programming		0.507	0.500	0	1
	GED	0.089	0.285	0	1
	GED + vocational training	0.029	0.168	0	1
	Substance abuse	0.091	0.288	0	1
	Visitation	0.483	0.500	0	1
Social risk index		2.140	0.965	0	5
	No high school diploma	0.734	0.442	0	1
	Unemployed	0.400	0.490	0	1
	Gang member	0.041	0.198	0	1
	Priors violent	0.457	0.498	0	1
	Priors non-violent	0.179	0.383	0	1
	Youthful 1 st conviction	0.197	0.398	0	1
Mental health index		0.528	0.647	0	4
	Paranoid personality disorder	0.0004	0.019	0	1
	Schizoid personality disorder	0.0003	0.016	0	1
	Antisocial personality disorder	0.086	0.281	0	1
	Narcissistic personality disorder	0.0001	0.011	0	1
	Borderline personality disorder	0.005	0.073	0	1
	Psychosis	0.034	0.181	0	1
	Mood disorders	0.029	0.168	0	1
	PTSD	0.003	0.050	0	1
	Impulse control disorder	0.005	0.071	0	1
	Antisocial behavior	0.004	0.062	0	1
	Disruptive behavior	0.002	0.043	0	1
	Substance abuse	0.386	0.487	0	1
Total N		38,097			

Duration (months) variables include only individuals who were reconvicted during the observation period risk factors (Ettekal et al., 2019; Evans et al., 2013). These two indices comprise a total of 17 variables, with each variable dichotomized (0 = risk factor absent; 1 = risk factor present) prior to creating the additive indices. It is relevant to note that the cumulative risk approach uses additive indices that assess absolute exposure to risk factors; therefore, greater exposure to risk factors results in a higher value on the index. The composition of these indices is informed by theoretical expectations rather than measures of fit in the observed data (Oliveira & Beaver, 2021). However, supplemental analyses show that the risk-related variables included in the indices are significantly correlated in the expected directions (see supplemental files).

Social Risk Index

The social risk index is an additive index comprised of six variables. These dichotomized variables (0 = no risk; 1 = risk factor) include: not having completed high school, being unemployed, belonging to a gang, having a criminal history in the state of Florida (violent priors and non-violent priors), and having a youthful first conviction (before the age of 18). Although the highest potential score on this variable was 6, the highest observed score was 5. These variables were recorded by individual prisons and reported to the Florida Department of Corrections, or recorded by the Florida Department of Law Enforcement in criminal history files.

Mental Health Index

The mental health index is an additive index that includes 12 dichotomous variables (0 = no diagnosis; 1 = diagnosis). The index includes diagnoses for personality disorders (paranoid, schizoid, antisocial, and borderline personality disorders) and severe mental illnesses (psychosis, mood disorders, PTSD, impulse control disorder, antisocial, and disruptive behaviors)[1] derived from the literature (e.g., Arseneault et al., 2000; Bonta et al., 2014; Fazel & Danesh, 2002). Each of these diagnoses include DSM-IV axis I and axis II clinical diagnoses, completed by medical professionals at the most recent mental health assessment before release from prison[2]. In correctional settings, these assessments would only be made if individuals exhibit symptoms. Missingness on these items indicate the respondent was not given a mental health assessment, thus, these respondents were coded as having no mental health diagnoses. Finally, whether an individual has a substance use disorder (0 = no diagnosis; 1 = diagnosis) comes from information obtained from the Drug Simple Screening Instrument assessment (e.g. Scaggs et al., 2016; Reid et al., 2023, 2025). The total number of clinical diagnoses across these three domains were added up to create the

[1] The literature has generally evidenced that mental illness on its own is not a direct risk factor for offending (Rueve & Welton, 2008; Varshney et al., 2015), with a few studies noting that severe mental illness may be a risk factor when comorbid with substance abuse disorders (Arseneault et al., 2000; Newman et al., 1998; Wittchen, 1996).

[2] The pathologies and disorders selected for this project have been widely used in the literature and typically have an onset in late adolescence or early adulthood, remaining throughout the life course.

mental health index[3]. Although the highest potential score on this variable was 12, the highest observed score was 4.

Control Variables

To isolate the direct and interactive relationships of interest, we incorporate established correlates of recidivism as control variables (Cochran & Mears, 2017; Gottfredson & Hirschi, 1990; Huebner & Berg, 2011; Kurlychek et al., 2007; Mears et al., 2012, 2016; Sampson & Laub, 1993a; Turanovic & Tasca, 2022; Zara & Farrington, 2016). A total of eight control variables were included in our models: (1) age in years, (2) race (0 = white, 1 = Black, 2 = Hispanic), (3) primary offense type (0 = homicide, 1 = robbery, 2 = aggravated assault and battery, 3 = other violent crimes), (4) number of months incarcerated, (5) the number of recorded misconduct incidents during incarceration, and (6) the use of educational programming or receiving visits while incarcerated[4] (0 = no programming, 1 = some programming).

Plan of Analysis

The analyses for this study were conducted in several steps. First, we used Cox Proportional Hazard modeling to examine the survival time until reconviction for a new offense, with a focus on the effects of mental health and social disadvantage on recidivism. Second, we re-estimated the same model, adding an interaction term (multiplicative interaction) to explore potential moderation effects between the two risk indices (in line with suggestions by Douglas & Skeem, 2005). Third, we re-ran both analyses for the second outcome of interest, examining survival time until reconviction for a technical violation. Fourth, we re-ran all models using a second modeling strategy—Accelerated Failure Time (AFT) modeling—which allowed us to further test for the robustness of results. Finally, we ran several supplementary analyses to examine the robustness of our findings, which are discussed in the footnotes.

The first models we present in the results section are Cox Proportional Hazard Models. These survival analyses are a set of longitudinal regression methods used to estimate the average time until the event of interest—in this case recidivism—occurs (Allison, 2010; Despa, 2010). While Cox Proportional Hazard models are traditionally used in the social sciences to test for differences in survival time between two or more groups while considering covariates of interest (Cox, 1972; Despa, 2010), these models should only be used when the proportional hazards assumption has been met. For this study, this assumption was tested using the visual analysis of

[3] In supplementary analyses, we also examine the effects of these three disaggregated indices, separately referred to as the personality disorder index, the serious mental illness index, and the substance abuse disorder variable (which is dichotomous), respectively.

[4] In line with what has been done in previous research (e.g. Reid et al., 2023), we opted to combine visitation and educational programming into a single programming variable as these were not our primary variables of interest and to ensure parsimony of the statistical model. Although these variables might have differing causal mechanisms through which they influence later offending, they are both been associated with reductions in offending (Mears et al., 2012; Stickle & Schuster, 2023).

the survival curves as well as the more robust time-dependent covariate test (Bradburn et al., 2003; Cox, 1972; Ng'andu, 1997; Therneau & Grambsch, 2000). The time-dependent covariate test detects nonproportionality and is obtained by including interaction terms between the covariates and the (log)time, allowing the effect of relevant covariates to change with time (Bradburn et al., 2003; Therneau & Grambsch, 2000). Some researchers have proposed that violations of the proportional hazards assumption may be expected because covariates will have different effects on the outcome across time (Schemper, 1992; Stensrud & Hernán, 2020), and they suggest these models can still be used in these instances. Following their guidance, we began our investigation with these models.

However, because we saw evidence the model's assumptions were violated, we conducted a second set of analyses using the more robust Accelerated Failure Time (AFT) models as proposed by Cox (Allison, 2010; Cox, 1972; Therneau & Grambsch, 2000) to explore if a violation of the proportionality assumption would severely impact the findings. AFT models are parametric survival models where the effects of the covariates act multiplicatively on the survival time. Rather than looking at time to failure, like Cox models, these AFT models look at time to success, or how long the individual goes without recidivating. In sum, we ran all models, including both main effects and interaction models, using both Cox Proportional Hazard models (Tables 2 and 3) and AFT LogNormal models (Tables 4 and 5).

Akaike's information criterion (AIC), Bayesian information criterion (BIC), and Log Likelihood Ratio (−2 Log Likelihood) were used to determine the best-fitting models (best fit determined by lower fit indices) (Allison, 2010; Faruk, 2018; Materu et al., 2023). All analyses were conducted using SAS Analytics Software 9.4. Multicollinearity and heteroskedasticity assessments were conducted for all analyses

Table 2 Cox proportional hazard models predicting reconviction for a new offense

	Model 1				Model 2			
	(Main Effects)				(Moderation)			
	Coeff.	Sig.	S.E.	Hazard Ratio	Coeff.	Sig.	S.E.	Hazard Ratio
Age	−0.035	***	0.001	0.966	−0.035	***	0.001	0.966
Race (ref. White)								
Black	0.098	***	0.021	1.103	0.098	***	0.021	1.103
Hispanic	−0.238	***	0.038	0.788	−0.238	***	0.038	0.788
Primary offense (ref. Homicide)								
Robbery	0.249	***	0.043	1.283	0.249	***	0.044	1.283
Aggravated assault	0.059		0.046	1.061	0.059		0.046	1.060
Other violent	0.053		0.047	1.055	0.053		0.047	1.054
Time served in prison	−0.007	***	0.000	0.993	−0.007	***	0.000	0.993
Prison programming	−0.145	***	0.020	0.865	−0.145	***	0.020	0.865
Misconduct	0.015	***	0.001	1.015	0.015	***	0.001	1.015
Social risk index	0.147	***	0.010	1.158	0.150	***	0.013	1.162
Mental health index	0.035	*	0.014	1.035	0.050		0.038	1.051
Social disadvantage X mental health	--		--	--	−0.006		0.014	0.994

*$p < .05$; **$p < .01$; ***$p < .001$; ± $p < .1$; N= 38097

Table 3 Cox proportional hazard models predicting reconviction for a technical violation

	Model 1 (Main Effects)				Model 2 (Moderation)			
	Coeff.	Sig.	S.E.	Hazard Ratio	Coeff.	Sig.	S.E.	Hazard Ratio
Age	0.049	***	0.002	1.050	0.049	***	0.002	1.050
Race (ref. White)								
Black	0.409	***	0.037	1.506	0.410	***	0.037	1.506
Hispanic	−0.121		0.076	0.886	−0.122		0.076	0.885
Primary offense (ref. Homicide)								
Robbery	0.756	***	0.071	2.129	0.754	***	0.071	2.125
Aggravated assault	0.772	***	0.075	2.165	0.770	***	0.075	2.159
Other violent	0.513	***	0.078	1.671	0.510	***	0.078	1.666
Time served in prison	0.010	***	0.000	1.010	0.010	***	0.000	1.010
Prison programming	−0.221	***	0.037	0.802	−0.221	***	0.037	0.802
Misconduct	−0.011	***	0.002	0.990	−0.010	***	0.002	0.990
Social risk index	0.314	***	0.019	1.369	0.337	***	0.023	1.400
Mental health index	0.016		0.025	1.016	0.121	±	0.070	1.129
Social disadvantage X mental health	--	--	--	--	−0.043		0.026	0.958

*$p < .05$; **$p < .01$; ***$p < .001$; ± $p < .1$; N= 38097

Table 4 Accelerated failure time (AFT) regression model predicting reconviction for a new offense

	Model 1 (Main Effects)			Model 2 (Moderation)		
	Coeff.	Sig.	S.E.	Coeff.	Sig.	S.E.
Intercept	4.205	***	0.064	4.205	***	0.067
Age	0.031	***	0.001	0.031	***	0.001
Race (ref. White)						
Black	0.246	***	0.037	0.246	***	0.037
Hispanic	−0.078	***	0.021	−0.078	***	0.021
Primary offense (ref. Homicide)						
Robbery	−0.266	***	0.043	−0.266	***	0.043
Aggravated assault	−0.031		0.045	−0.031		0.045
Other violent	−0.044		0.046	−0.044		0.046
Time served in prison	0.007	***	0.000	0.007	***	0.000
Prison programming	0.165	***	0.021	0.165	***	0.021
Misconduct	−0.021	***	0.001	−0.021	***	0.001
Social risk index	−0.144	***	0.010	−0.144	***	0.013
Mental health index	−0.029	±	0.015	−0.028		0.038
Social disadvantage X mental health	--	--	--	0.000		0.015
Scale	1.490		0.011	1.490		0.011

*$p < .05$; **$p < .01$; ***$p < .001$; ± $p < .1$; N= 38097

Table 5 Accelerated failure time (AFT) regression model predicting reconviction for a technical violation

	Model 1 (Main Effects)			Model 2 (Moderation)		
	Coeff.	Sig.	S.E.	Coeff.	Sig.	S.E.
Intercept	17.229	***	0.300	17.339	***	0.309
Age	-0.117	***	0.004	-0.118	***	0.004
Race (ref. White)						
Black	0.206		0.149	0.209		0.149
Hispanic	-0.859	***	0.078	-0.860	***	0.078
Primary offense (ref. Homicide)						
Robbery	-1.760	***	0.154	-1.754	***	0.153
Aggravated assault	-1.893	***	0.161	-1.885	***	0.161
Other violent	-1.354	***	0.165	-1.345	***	0.165
Time served in prison	-0.026	***	0.001	-0.026	***	0.001
Prison programming	0.535	***	0.077	0.534	***	0.077
Misconduct	0.034	***	0.005	0.034	***	0.005
Social risk index	-0.703	***	0.040	-0.753	***	0.051
Mental health index	-0.060		0.054	-0.278	±	0.143
Social disadvantage X mental health	--	--	--	0.091		0.056
Scale	3.864		0.055	3.863		0.055

*$p < .05$; **$p < .01$; ***$p < .001$; ± $p < .1$; N= 38097

and no issues were found. Due to missingness on some variables, the analytical sample was reduced to 38,097, which represents approximately 14% missingness. Listwise deletion was prioritized in the main analyses, but supplementary analyses (not presented here) were conducted with alternative single-item imputation strategies to examine and confirm the robustness of findings.

Results

Cox Proportional Hazard Models

To examine the effects of mental health and social disadvantage on recidivism amongst newly released violent offenders, we begin with an examination of Table 2. Table 2 presents two sets of Cox Proportional Hazard models, both of which predict the likelihood that an offender receives a reconviction for a new offense. In the first model, the control variables and the two risk indices are included. Results show that mental health and social disadvantage were both significantly associated with increases in the likelihood of being reconvicted for a new offense[5]. Each additional risk factor on the social risk index was associated with a 15.8% increase in the

[5] In supplementary analyses that examine three separate mental health indices (personality disorders index, severe mental illness index, dichotomous indicator for a substance abuse disorder), we find that all three were associated with significant increases in the hazard of being recommitted for a new offense. Each additional personality disorder diagnosis made an offender 9.5% more likely to be recommitted, each additional severe mental illness diagnosis increased an offender's likelihood of being recommitted by 9.9%, while having a substance abuse disorder decreased the hazard of reconviction by 4.4%.

likelihood of reconviction for a new crime. Furthermore, each additional mental health diagnosis increased the hazard of reconviction for a new crime by 3.5%. We also find that older offenders were less likely to be reconvicted. White offenders were more likely to be reconvicted than Hispanic offenders, but less likely to be reconvicted than Black offenders. When looking at the effects of crime type, robbery offenders were more likely than homicide offenders to be reconvicted for a new crime, but no significant differences emerged between other types of offenders. Individuals who were incarcerated longer and those who attended programming were less likely to recidivate; however in-prison misconduct was associated with an increased likelihood of recidivism. The second model in Table 2 includes all the same variables from the main effects model, plus an interaction term between social disadvantage and mental health. The interaction did not significantly predict reconviction for a new crime[6]. We can also see the effects of the other variables were consistent with those observed in Model 1, but the mental health index was no longer significant on its own.

Table 3 also displays Cox Proportional Hazard models, this time predicting the likelihood of reconviction for a technical violation. The first model once again shows the main effects of each of the independent variables and controls, without any interaction terms included. The social index was associated with a significantly higher likelihood of recommitment for a technical violation. Each additional risk factor on the social risk index was associated with a 36.9% increase in the likelihood of reoffending[7]. The mental health index was not significantly associated with reconviction for a technical violation. We also find that younger offenders and white offenders (compared to black offenders) are significantly less likely to be reconvicted for a technical violation. Robbery offenders, aggravated assault offenders, and other violent offenders were all significantly more likely than homicide offenders to be reconvicted for a technical violation. Time served increases the likelihood of reconviction, while both participation in prison programming and participation in in-prison misconduct lowered one's risk of recidivating. In Model 2, we once again included a multiplicative interaction term between the two risk factor indices. This interaction term was not significant[8]. Furthermore, the effects of two social risk indices and the control variables were consistent with those displayed in Model 1. However, in Model 2 we see the mental health index becomes only marginally significant (p<.10), with each additional mental health diagnosis associated with a 12.9% increase in the likelihood of recidivism.

[6] In supplementary analyses, we also examined interactive effects between each of the three disaggregated mental health indices and the social risk index. Only the interaction term for social disadvantage and the severe mental illness index was significantly associated with reconviction for a new crime. The coefficient was negative, and the main effects associated with each variable were positive, indicating that each of the main effects is lessened by increases in the other, i.e. the likelihood of reconviction for a new crime was lower for individuals with higher scores on both indices.

[7] When looking at the 3 separate mental health indices, we find here that only the personality disorders index was associated with a higher likelihood of reconviction for a technical violation, with each additional diagnosis increasing recommitment likelihood by 37.9%.

[8] When looking at the three separate mental health indices, only the interaction between social disadvantage and personality disorders was significant for reconviction for a technical violation. The coefficient was negative, while the main effects associated with each variable were positive, indicating that each of the main effects is lessened by increases in the other, i.e. the likelihood of reconviction for a technical violation was lower for individuals with higher scores on both indices.

When using Cox Proportional Hazard Models, the proportionality assumption needs to be met. This assumption can be tested in several ways; in the current study we chose to test this assumption using the test for homogeneity of survival curves. When we observed overlap between curves for both outcomes of interest, we further tested the proportionality assumption by using time variant covariates. Once again, we observed a violation of the assumption as several interactions between predictors and the log of time were significant (see Table A5 supplemental files). These significant interactions were especially problematic in the reconviction for a new offense model, where the hazard ratios for several variables substantially increased or decreased. Additionally, these changes in hazard ratios were impactful enough to change the directionality of the coefficient for race and primary offense. We therefore followed the recommendations in the literature (Allison, 2010; Cox, 1972) and replicated the analyses using AFT models.

Accelerated Failure time Models

In the following set of analyses, we replicated the first set of models that were conducted with Cox Proportional Hazard models, but here use the more robust Accelerated Failure Time models to compare our findings across modeling strategies. In Table 4, we can see the effects of most variables are quite similar to those from the Cox models. For example, robbery offenders (as compared to homicide offenders), those who spend longer in prison, those who participate in prison programming, and those who have less in-prison misconduct all have longer survival times. The effects of race are different here than in the Cox models presented in Table 2, with White offenders being reconvicted faster than Black offenders but slower than Hispanic offenders. The effect of the social risk index is substantively similar across modeling strategies, with individuals with additional risk factors being more likely to be reconvicted for a new crime. Each additional social risk factor present shortens the individual's survival time by 13.4%[9]. Unlike in the original Cox models predicting reconviction for a new offense, the mental health index is not significant in the AFT models[10], even though it marginally approximated significance (p=.057). In the second model with the moderator variable, the effects of the control variables are consistent. Here, too, we see that only the social risk index was significant, with individuals with more social risk factors exhibiting a shorter time until reconviction for a new offense. Each additional social risk factor is associated with a 13.4% shorter time until reconviction. Neither the mental health index nor the interaction term was significant[11].

Table 5 displays the AFT models predicting reconviction for a technical violation. The first model once again shows the main effects of each of the independent variables and controls, without any interaction terms included, and the second model

[9] The percentage is calculated based on the following formula: [1-EXP(coeff.)]*100 (Allison, 2010).

[10] In supplementary analyses including the three disaggregated mental health indices, we find that personality disorders and severe mental illness were significantly associated with lower average survival times while a substance abuse disorder predicted longer average survival times.

[11] When looking at the three separate mental health indices, the interaction between severe mental illness and social disadvantage was significant and positive for reconviction indicating increases in the survival time for a new crime.

includes the interaction term. In Model 1, social risk was significantly associated with a shorter survival time until reconviction for a technical violation, with each additional risk factor reducing survival time by 50.5%. Mental health, however, was only marginally significant ($p<.10$)[12].We also find that younger offenders and white offenders (compared to Hispanic offenders) had significantly longer survival time. Robbery offenders, aggravated assault offenders, and other violent offenders all had shorter survival times than homicide offenders. Time served in prison increased one's likelihood of reconviction, while prison programming and prison misconduct both increased the survival time. These patterns were consistent across Model 2, which included the interaction term. In this model, each additional social risk factor shortened time to a new technical violation reconviction by 52.9%. The main difference in Model 2 was that the mental health index once again reached only marginal significance, with individuals with more mental health issues exhibiting less time until reconviction for a technical violation (24.3% decrease in survival time, $p<.10$). The interaction term was, once again, non-significant[13]. When comparing these findings with those from the Cox models presented in Table 3, we notice some differences again with the race variables. Specifically, while the Cox models showed significant differences between Black and White offenders, this finding was not replicated in the AFT models; furthermore, in the AFT models there is a significant difference between White and Hispanic offenders that is not present in the Cox models.

When comparing the fit of both the AFT and Cox Proportional Hazard models for the two outcomes of interest (Faruk, 2018; Materu et al., 2023), the AFT models presented much lower values on all the fit indices, namely Akaike's information criterion (AIC), Bayesian information criterion (BIC), and Log Likelihood Ratio (−2 Log Likelihood), indicating it is the best fitting model for this data (see Table A5 of the supplementary files). The findings across these models were substantively similar, although we saw some variations in the significance of race and the mental health index. Given the violation of the proportional hazards assumption and the better fit statistics associated with the AFT models, we believe the results from this modeling strategy (i.e., those displayed in Tables 4 and 5) should be prioritized. Regarding our indices of focus, this means that the cumulative social risk index did predict recidivism, while the cumulative mental health risk index did not have consistent effects.

Discussion

There is a large body of research on recidivism exploring how individual risk factors may impact the odds of reoffending. This body of research has provided invaluable knowledge and insights on recidivism; however, it is fundamental to consider

[12] When looking at the three separate mental health indices, we find here that neither having severe mental illness diagnoses nor having a substance abuse disorder had an effect on recommitments for technical violations. Personality disorders were associated with a higher likelihood of recommitments.

[13] When looking at the three separate mental health indices, the intereaction between personality disorders and social disadvantage was significant and positive for reconviction indicating increases in the survival time for a technical violation.

how multiple co-morbid risk factors can impact recidivism. The present study used a cumulative risk approach to study the role of additive psychosocial risk factors on recidivism among offenders convicted of violent crimes in Florida.

Several key findings emerged from this study. First, the social disadvantage index consistently predicted both reconviction for a new offense and reconviction for technical violations. This effect was also evidenced across modeling strategies, regardless of whether it was predicting time to failure or survival time. This finding is in line with life-course research focusing on the process of cumulative disadvantage, and aligns with the limited research using cumulative risk indexes and their influence on criminal recidivism (Lawing et al., 2017a, b; Moffitt, 1993; Reid et al., 2023; Sampson & Laub, 1997), highlighting the benefit of using these indices to account for multiple, often co-occurring risk factors within an individual's social environment. Specifically, this finding aligns with Reid and colleagues' (2023) examination of adult homicide offenders, where cumulative social risk also consistently predicted reconviction for both a new crime and a technical violation. These findings are also in line with those reported by Lawing and colleagues (2017), Oliveira and Beaver (2021), and TenEyck and colleagues (2023), who found that cumulative risk indices predicted continued self-reported offending over time in youth samples.

Second, the mental health index had inconsistent effects across models. We found that cumulative mental health issues only increased the likelihood of recidivism in some models, specifically in the main effects of the Cox model for a reconviction for a new offense, and the interaction models for technical violations. These inconsistent findings on the effects of mental health on recidivism are in line with the body of research on the role of mental health in criminal justice system processing. Specifically, some studies have shown that mental health issues increase the risk of recidivism (Chang et al., 2015; Honebein, 1996), while others have found that mental health does not increase the risk of recidivism (Bonta et al., 1998; Reid et al., 2023; Rueve & Welton, 2008; Varshney et al., 2015). In supplementary analyses that assessed disaggregated indices, we observed that both personality disorders and severe mental illness consistently predicted reconviction for a new crime. However, only personality disorders predicted a reconviction for a technical violation, which is expected given that prior research indicates that personality disorders are more strongly related to criminal offending than mental illness on its own (Lowenstein et al., 2016; Nestor, 2002). The relationship between cumulative mental health risk and recidivism might be further complicated by the comorbidity of mental health issues and substance abuse (e.g., Baillargeon et al., 2010; Wilson & Wood, 2014), which could not be disentangled in the present study due to data limitations.

Another plausible explanation for the inconsistencies of these effects may be that offenders may have limited to no access to mental health or substance abuse treatment after they leave prison (Alsan et al., 2023; Browne et al., 2022a, b; Mallik-Kane & Visher, 2008). The loss of these supports might contribute to greater reoffending risk, but we could not control for whether the offenders had access to community-based treatment after release. It is also possible that mental health conditions may differentially influence criminal justice responses, regardless of the individual's specific offending behavior. For example, a respondent with a mental health issue may have a higher likelihood of being detected by law enforcement or may be more likely to plead guilty or be found guilty in trial proceedings (Brown, 2019; Hall et al., 2019; Peterson & Heinz, 2016). Similarly, it is possible that we observed a higher risk of technical violations for individuas with personality disorders due to a higher discretionary power and possible bias among parole officers, especially when dealing with individuals frequently considered to be "difficult." Prior research has indicated that supervision officers have a relatively high level of discretion on how they respond to technical violations, with responses ranging from verbal warning to full revocation (individual re-incarcerated for the remainder of the sentence) (Bonta et al., 2008; Ruhland & Scheibler, 2022). Some research has further suggested that these responses by parole officers may be prone to biases based on the probationers race (e.g. Jannetta et al., 2014; Saunders & Midgette, 2023) and gender (e.g. G.E. Browne et al., 2022a, b), and they may be more common in cases where officers are overworked or have limited resources (Saunders & Midgette, 2023). In this way, it is plausible to consider that similar biases may occur towards individuals with personality disorders, who present as difficult to manage, especially when supervision officers lack the training or access to adequate resources to support these individuals. Future research should further explore these mechanisms to better understand, one the one hand, the complex relationship between mental health and recidivism among similar samples of adult violent offenders, and on the other, to better explore the role that probationary discretion may have on recidivism measured as a technical violation for individuals with personality disorders.

Finally, the multiplicative interaction between the social risk index and the mental health index did not significantly predict recidivism across modeling strategies. Prior research using the cumulative risk approach has either added up different types of risk factors (e.g. TenEyck et al., 2023) or explored the effects of different types of cumulative indices on outcomes of interest (e.g., Oliveira & Beaver, 2021; Reid et al., 2023, 2025). However, to the best of our knowledge, no prior research has explored if or how these cumulative additive indexes interact with each other. In the present study, the two separate risk factor indices were predictive of recidivism, but in a multiplicative interaction their effects appeared to wash out or dissipate. We recommend future research further explores potential interactions between different risk indices vs. creating one overarching risk index and compare outcomes of these analyses[14].

Findings from these analyses support the need to continue exploring and modeling the cumulative effects of being exposed to multiple risk factors. As previously noted, the cumulative risk approach provides unique insights by analyzing how the presence of multiple risk factors predicts outcomes of interest, in this case recidivism, allowing for more robust estimates of cumulative disadvantage processes (Ettekal et al., 2019). This said, it is relevant to note this method has its limitations, as it does not allow

[14] In the supplementary analyses with disaggregated indices (footnotes 45,7,10, and 12), the interaction between social disadvantage and severe mental illness was significant for reconviction for a new offense. Similarly, the interaction between social disadvantage and personality disorders was significant for reconviction for technical violations. In both cases this indicated that likelihood of reconviction was lower for individuals with higher scores on both indices. These findings suggest that individuals with comorbid mental illnesses or personality disorders and with high number of social risk factors are less likely to recidivate. This is contrary to our expectations further highlighting the need to explore how various cumulative risk factors interact with one another.

researchers to model the magnitude or time ordering of risk factors, which have been demonstrated to be relevant in prior research (Basto-Pereira et al., 2025; LaNoue et al., 2020). The study is further limited by the dichotomous nature of the mental health measures, which lack the nuance to capture the respondents' symptoms severity, impact, and treatability. Future research should replicate and expand on this study by using more integrative methodologies that enable more nuanced measurement of both the cumulative effect and the magnitude of individual risk factors (Ettekal et al., 2019; LaNoue et al., 2020).

These findings have important implications for theory and research. An important direction for future research is to continue to use cumulative indices, which allow us to control for co-occurring risk factors. Not only do these indices allow us to account for multicollinearity issues between highly correlated risk factors, but they also allow us to theoretically and empirically examine numerous factors that tend to impact individuals concurrently. Research consistently finds that individuals who are exposed to multiple risk factors may behave differently than those who are exposed to only a few (Sampson & Laub, 1993a). Other important risk factors to examine through a cumulative risk approach would include risk factors related to things like family life, neighborhood, and re-entry supports (or the lack thereof). Additionally, future research should seek to further examine potential interactions between cumulative risk factors. Although our study did not find evidence of any interaction between these two indices, it is plausible that other types of cumulative disadvantage might interact in ways that still warrant further exploration, as notes in our anxiliry analyses.

Unfortunately, most criminal justice data is limited in its ability to measure some of these factors. Data taken from traditional jail and prison intake surveys often focus on recent offending, criminal history, and the offender's immediate social context (like recent employment). However, very little data is collected on information related to social or family support, histories of victimization or other traumas, or other important environmental domains that might influence reoffending (Zara & Farrington, 2010). Our current study was also limited by the lack of post-release data. Specifically, the reoffending measures in this dataset only included whether individuals were reconvicted for a new offense (but no information about what that offense was or if an offense was effectively committed) or for a technical violation. We did not have access to any measures related to self-reported offending, arrests that did not lead to reconvictions, or changes in attitudes or beliefs toward offending. Although we did have a measure of whether the offenders attend in-prison programming, we had limited information about the programs they attended, whether they completed programs, or their perceptions of those programs. Further, we lacked information on continued programming, as well as mental health and substance abuse status after release. Future data collection efforts to study recidivism should seek to incorporate more information about an offender's social context and background, include more in-depth measures capturing in-prison experiences, and examine various post-release measures impacting re-entry success. Finally, although beyond the scope of the present study, future research should explore the differential gendered effects and the specific effects of these social and mental health indexes with female samples.

Finally, our study incorporated multiple modeling techniques to examine how these risk factors influenced the outcomes under examination. Although Cox Proportional Hazard models have been widely used in criminology, the proportional hazard assumptions that underlie these models are often not met with criminological data. In the past, researchers merely noted that violations of the proportional hazards assumption are expected, as covariates have different impacts on individuals across time (Schemper, 1992; Stensrud & Hernán, 2020). However, based on the findings from this paper, we do not consider these violations to be negligible. Although the findings for most main predictors remained identical across modeling techniques, we did observe a change in the directionality of some variables within models, which can have substantial impacts on the interpretation of findings and implications derived. In this study, we observed that the AFT parametric models were more robust and a better fit than the semi-parametric Cox models, and we recommend that future researchers incorporate AFT parametric models in similar studies.

These findings also have several implications for policy and practice. First, we find that attending in-prison programming significantly improves recidivism outcomes, even after accounting for the social and mental health risk factors that offenders carry with them. Additional studies that examine the efficacy of various forms of programming are needed to provide more nuanced suggestions about the types of programs that are most worthy of investment. However, these initial findings are supportive of these interventions overall.

We also found that homicide offenders were less likely to be reconvicted of a technical violation than the other types of violent offenders, and they were less likely to be reconvicted for a new offense than robbery offenders. Re-entry-focused interventions might, therefore, also be targeted toward other groups of violent offenders—those who are at higher risk of reoffending and are more likely to be released from prison—especially those convicted of offenses like aggravated assault. Future research could examine the interaction effects between violent offense type and prison programming to better untangle the particular interventions that might be most effective for each group.

Our supplementary findings highlight the importance of in-prison programming that focuses on diagnosing and providing continued support for individuals with mental illness. Research shows that mental illness is overrepresented among prison populations (Maruschak et al., 2021; SAMHSA, 2023), and we find here that this risk factor, along with personality disorders, can further increase reconviction for a new crime. Researchers have identified that having access to some form of health insurance or benefit alongside evidence-based programming targeting individual needs can reduce the odds of recidivism, and we echo their calls to both implement and examine these programs in prison and reentry settings (for reference, see SAMHSA, 2023). Given the strong impact that social disadvantage also had in predicting recidivism, it would be relevant to develop more reentry support programming targeted at these forms of dynamic social factors to help reduce offender recidivism risk after release.

In sum, we find that cumulative social disadvantage consistently predicts recidivism across models, and while cumulative mental health issues do not seem to impact the risk of reconviction for a new crime, the disaggregated mental illness and personality disorder indexes also predicted reconviction for a new crime across modeling strategies. Based on these core findings, we conclude that it is crucial to focus on adequate programming and support for individuals being released from prison to help with the challenges of reentry and promote long-term desistance for these individuals. Specifically, focusing on dynamic risk factors linked to cumulative disadvantage—such as offering vocational training or support in securing stable employment upon release—may help individuals succeed. Further, providing continued mental health support and treatment for those individuals diagnosed and receiving treatment in prison may help reduce reconvictions for this group of individuals.

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Declarations

Competing interests The authors report there are no competing interests to declare.

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