The Impact and Fidelity of the Structured Decision Making Framework (SDMF) In California Board of Parole Hearings (CBPH) Decisions

by

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A Thesis submitted to the Faculty of Graduate and Postdoctoral Affairs in partial fulfillment of the requirements for the degree of

Master of Arts

In

Psychology

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Abstract

While California has one of the largest state incarceration rates in America, the state has recently observed the greatest increase in the use of parole nationwide (Carson, 2020; Oudekerk & Kaeble, 2021). The purpose of the present study was to investigate whether the implementation of a new guide, the SDMF (Serin, 2019), has led to differences in parole decisions in California. Retrospective reports and case files of parole applicants were rated using the SDMF to come to a new parole decision, which was then compared to the original California Board of Parole Hearings (CBPH) decisions to evaluate fidelity. Results showed that denial rates significantly differed between pre- and post-implementation. Furthermore, SDMF-based decisions and CBPH decisions did not significantly differ, except for low-risk cases, suggesting commissioners may be considering extraneous information. Furthermore, the SDMF as a whole significantly predicted CBPH grants, with Release Plan and offender risk individually predicting these decisions.

Keywords. SDMF, parole, decision-making
Acknowledgements

First and foremost, I would like to thank my supervisor, Dr. Ralph Serin, for taking me on as a student and allowing me to work on such an interesting and important topic. Thank you for your exceptional support and advice throughout this project and this degree. I would also like to extend my gratitude to my committee members, Dr. Shelley Brown and Diana Majury, for providing such helpful and thoughtful recommendations on ways to improve this project.

To my fellow lab mates in the Criminal Justice Decision Making Laboratory, thank you for providing me with such helpful advice and encouragement. Specifically, I want to thank Danielle Reiger for sharing her extensive knowledge and experience in statistics and for offering to help with IRR coding. I would also like to thank Mackenzie Dunham for his support and wisdom throughout the graduate school process.

To my closest friends, you have all helped me throughout this degree in different ways and I will be forever grateful to have each of you by my side. To my parents, thank you for your undying support throughout these past two years and encouraging me to pursue what I am passionate about.

Lastly, I would like to thank my grandma Jan for always being my #1 fan and supporter. I truly could not have made it this far without you and your faith in me.
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Despite the fact that the crime rates in California are now lower than the national average (National Institute of Corrections, 2019), the State of California has one of the highest incarceration rates in America (Carson, 2020). In recent years, however, incarceration in California has been continually declining (Carson, 2020). Simultaneously, California has observed the greatest increase in the use of parole nationwide (Oudekerk & Kaebel, 2021). Between 2018 and 2019, the number of parolees in California increased by 31.2%, indicating a potential state-wide shift toward community supervision (Oudekerk & Kaebel, 2021). This shift corresponds with the recent implementation of a more structured decision-making process by the California Board of Parole Hearings (CBPH). Implemented in 2019, the Structured Decision Making Framework (SDMF; Serin, 2019) has aided CBPH decision makers in releasing eligible individuals within the state correctional system to serve the rest of their sentence in the community. This increase in individuals on supervised release reduces the financial and infrastructural strain on California’s correctional institutions, while also reducing the likelihood of recidivism. The benefits of community supervision, however, are only beneficial if the individuals being released are both suitable and prepared for return to the community. Thus, the release of individuals from correctional institutions warrants further investigation.

Literature Review

A prevalent concern of criminal justice systems in the Western world is the re-entry of individuals who have been incarcerated back to the community (Serin et al., 2016). In Canada, specifically, individuals within correctional institutions are increasingly released to be supervised in the community prior to warrant expiry (Public Safety Canada, 2019). Similarly, the United
States has experienced a slight increase in the number of individuals on parole (Kaeble & Alper, 2020). Encouragingly, as the number of individuals on conditional release has increased, so have their success rates. In fact, between 2012 and 2018, Canadian revocation rates for individuals on day parole, full parole, and statutory release decreased, suggesting at least some success with community supervision (Public Safety Canada, 2019). This increasing success for individuals under community supervision is promising, however, revocation while under conditional release still represented approximately one third of admissions to the Canadian federal jurisdiction (Public Safety Canada, 2019). Additionally, according to the Bureau of Justice Statistics, approximately 25% of individuals exiting parole in the United States between 2017 and 2018 returned to incarceration (Kaeble & Alper, 2020). Such failures under community supervision bring scrutiny to the decision-making process for granting conditional release and how it can be improved.

The Growing Need for Parole

The purpose of incarceration is to protect the public from potentially harmful individuals until such individuals are deemed safe to return to the community. However, recent studies have found that incarceration is ineffective at preventing violence or deterring crime once individuals who have been incarcerated are released (Cochran et al., 2014; Cullen et al., 2011; Harding et al., 2019; Petrich et al., 2021). For example, in a recent study of over 100,000 individuals who were criminally sentenced in the United States, Harding and colleagues (2019) found that imprisonment and serious punishment were ineffective at reducing recidivism once the individual returned to the community. Furthermore, a recent meta-analytic review of 116 studies found that custodial sanctions such as imprisonment not only have no effect on reoffending—
they actually have the potential to slightly increase the likelihood that an individual will reoffend (Petrich et al., 2021).

Evidence suggests that imprisonment may exacerbate issues related to recidivism (Harding et al., 2019; Petrich et al., 2021). According to Harding and colleagues (2019), imprisonment can contribute to new or worsening mental health concerns or negative coping skills, aid in the development of negative internal dispositions toward the law, erode positive social networks, and create obstacles in finding housing, employment, and health services upon release. These consequences of imprisonment can increase an individual’s risk to reoffend, as demonstrated in research conducted by Jolliffe and Hedderman (2015). In a study of 5,500 British individuals who criminally offended, Jolliffe and Hedderman (2015) found that individuals who had been incarcerated for their index offense were significantly more likely to commit another offense once released, when compared to individuals matched on offense type and risk who were supervised in the community. Similarly, through propensity score matching analyses of individuals who criminally offended in Florida, Cochran and colleagues (2014) found that placement in prison—compared to traditional and intensive probation and jail—was associated with an increase in recidivism. Such findings highlight the need for a shift from incarceration to alternative strategies to reduce recidivism.

In addition to incarceration’s contributions to recidivism, the costs associated with housing inmates across North America has led to interest in reducing the populations in correctional institutions (Serin et al., 2016). Between 2016 and 2017, the average cost of keeping an inmate incarcerated in Canada was $116,473 per individual (Public Safety Canada, 2019). With 114 inmates per 100,000 people in Canada, the country spends millions of dollars on a form of crime reduction that is not necessarily effective at reducing recidivism. The high costs of
incarceration are also evident in the United States, with 655 inmates per 100,000 people, which costs an average of about $36,299 annually per inmate (Bureau of Prisons, 2018). Community supervision practices offer a more fiscally responsible approach to corrections (Serin, et al., 2020). From 2016 to 2017, the average cost of supervising a federal offender in the community was $30,639 in Canada and $4,392 in the United States (Public Safety Canada, 2019; United States Courts, 2017). The cost of incarceration is generally much higher than the cost of community supervision, as evidenced by fiscal reports by both Canada and the United States. Thus, both the iatrogenic influence that imprisonment has on recidivism and the higher costs associated with incarceration have contributed to the increased use of community supervision. This trend has become increasingly prevalent since the beginning of the COVID-19 pandemic.

The high incarceration rates in Canada, and more significantly, the United States, have contributed to substantial overcrowding in correctional institutions, making these institutions epicenters for the COVID-19 virus (Heard, 2020). When the COVID-19 pandemic was declared in 2020, the World Health Organization urged countries to address infection control inside prisons, warning that rapidly increasing transmission of COVID-19 within these institutions would amplify the effect of the epidemic (WHO, 2020). In response to this warning, governments worldwide aimed to reduce prison populations where possible. These reductions included the consideration of release for people near the end of their sentence, those sentenced for minor crimes, and those who would not compromise public safety (Heard, 2020). In the United States, various justice reform organizations noted a 30% drop in jail populations between March 2020 and May 2020 and an 8% drop in prison populations between March and June 2020 (Widra & Wagner, 2020; Sharma et al., 2020). With more individuals within correctional institutions being released into the community due to costs of incarceration and the current
climate surrounding COVID-19, it is in the interest of public safety to ensure that the release is granted to those who are unlikely to reoffend when they return to the community.

Along with addressing the present issues facing correctional systems, post-release community supervision practices like parole have been widely used in Western societies since the late nineteenth to early twentieth century (Burke, 2011; Hoffman, 2003). Parole continues to contribute to public safety by allowing individuals who have been incarcerated to re-enter the community while having access to aftercare and support (Serin et al., 2020). The structure and support provided by supervision can contribute to the individual’s success in the community (Chadwick et al., 2015). Individuals being supervised in the community are less likely to reoffend once released compared to their incarcerated counterparts (Jolliffe & Hedderman, 2015; Harding et al., 2019; Ostermann, 2015; Petrich et al., 2021; Solomon et al., 2005), which may be attributed to the fact that these individuals no longer face the same risk-related challenges created by incarceration (Harding et al., 2019; Petrich et al., 2021).

Unlike individuals who have been incarcerated, those in the community have access to a wider range of mental health and healthcare services, have the ability to maintain positive social networks, and can access assistance for both housing and employment, all of which can mitigate recidivism (Harding et al., 2019). As parole contributes to the rehabilitation and structured reintegration of individuals who have been incarcerated and is aimed at reducing recidivism, it serves as a way to maintain public safety. Indeed, parolees appear to have recidivism rates approximately 4% lower when controlling for various criminal risk indicators (Solomon et al., 2005) and even more when simply comparing outcomes for parolees and end-of-sentence cases (Wardrop et al., 2019). However, public safety is only maintained by parole if the individuals being released by decision makers are good candidates for being managed in the community
(Serin et al., 2020). Thus, there are a variety of different factors that must be taken into account when considering the possibility of release.

**Releasing Authorities and Parole Decision-Making**

The determination of who makes release-related decisions can vary based on jurisdictional practices and sentencing structure. Releasing authorities typically follow either determinate sentencing frameworks, indeterminate sentencing frameworks, or a combination of both. Jurisdictions that follow a determinate sentencing framework use mandatory sentences, in which individuals who are sentenced for a crime receive fixed sentences and are automatically released once they have reached the end of their sentence (Ruhland et al., 2017). For some jurisdictions, the release date is legislated, but the paroling authority may assign supervision conditions. On the other hand, jurisdictions that follow indeterminate sentencing frameworks typically enforce discretionary sentences. In these jurisdictions, there is no absolute release date for individuals who have been sentenced and releasing authorities have some discretion in release-related decisions. In these discretionary release cases, paroling authorities consider and weigh policies and the potential risk the individual poses to the community to make an informed decision on whether the individual is suitable for parole and when they should be released.

The type of sentencing framework used varies by country and by individual state. Canada and some U.S. States follow discretionary practices, giving releasing authorities the discretion to make release decisions (Ruhland et al., 2017). Some states have presumptive release in that the paroling authority must show that an individual poses undue risk to the community to prevent release, otherwise the individual will be released. Overall, jurisdictions that follow indeterminate or presumptive sentence frameworks place the responsibility of determining whether and when to release individuals who have been incarcerated in the hands of paroling authorities.
Thus, in jurisdictions following an indeterminant or discretionary sentencing framework, paroling authorities have the responsibility of releasing individuals who have criminally offended into the community without putting public safety at undue risk. In order to ensure public safety, parole decision makers must identify possible factors within each parole application that indicate the likelihood of recidivism and suitability for release. To do this, decision makers typically utilize various sources such as risk assessments, criminal history, and release plans to help inform their release decision (Mooney & Daffern, 2013). Additionally, they may also consider information from victims, families, correctional staff, district attorneys, judges, and law enforcement (Ruhland et al., 2017). Risk factors that have historically been found to be influential in parole decisions include criminal history, institutional behaviour, offender mental health, victim input, and case-specific factors (Caplan, 2007). However, not all of these factors are empirically relevant to recidivism (Serin, et al., 2016). Collective works by Serin and colleagues have since identified criminal history, ability to control behaviour, programming, institutional behaviour, offender change, release plan, and case-specific factors as areas that should be considered in parole decisions (Serin, et al., 2016).

When considering whether an individual is suitable for parole, decision makers must also distinguish between risk factors and policy factors (Serin et al., 2020). Risk factors are related to parole decision making because they are empirically linked to an individual’s likelihood of reoffending once released. Policy factors, on the other hand, must be considered to meet legislative or policy requirements, but do not necessarily contribute to an understanding of an applicant’s risk (Serin et al., 2020). For example, victim input statements and input from sentencing judges may sometimes be considered in a parole decision but are not empirically validated risk factors. Furthermore, in cases where the crime was heinous in nature or received
notoriety via the media, decision makers may deny release in order to maintain public trust in paroling authorities (Serin et al., 2020). Hence, parole authorities must take many different factors in consideration when making decisions related to parole.

Significant pressure is therefore placed on parole decision makers to identify and differentiate individuals who are likely to succeed in the community from those who are unsuitable for release and likely to reoffend. Parole authorities must weigh public safety concerns against the civil liberty concerns of extended incarceration (Naylor & Schmidt, 2010). Releasing an individual who presents a risk of recidivism puts public safety at risk. On the other hand, keeping an individual who has demonstrated change, is legally eligible for release, and has the potential to succeed in the community is neither defensible nor ethical (Naylor & Schmidt, 2010). Furthermore, as previously discussed, keeping an individual incarcerated may increase, rather than decrease, their likelihood of offending once returned to the community (Cochran et al., 2014; Jolliffe & Hedderman, 2015; Petrich et al., 2021). Decision makers must negotiate between the possibility that they may make false positive errors in an effort to avoid false negative errors (Serin et al., 2020). Paroling authorities are most concerned about false negatives and reflect on the impact of such community failure as distinct from the likelihood of failure (Serin et al., 2020). Indeed, these decision errors are not viewed as equal by different stakeholders in the criminal justice system. Further, despite the fact that the individuals released on parole succeed more frequently than fail in the community (Serin et al., 2020; Solomon et al., 2005), paroling authorities are often faced with criticism and public distrust, due to 20-20 hindsight. An important strategy to mitigate such criticism is the utilization of a standardized and validated decision process.
Issues Related to Parole Decision Making

One of the most notable issues related to parole decision making is the accuracy of the board’s decisions. When a paroling authority grants an individual parole and that individual reoffends (false negative), it reflects poorly on both the effectiveness of conditional release practices and the credibility of paroling authorities. Parole success, then, cannot be separated from the fidelity and efficacy of community supervision (Bonta et al., 2008). Unsurprisingly, the media tends to sensationalize such parole failures, reducing public trust in releasing authorities and undermining the legitimacy of parole (Serin et al., 2020). However, from a rehabilitative perspective, parole allows for a more structured and supported reintegration into the community compared to release at expiration of sentence. Denying an individual parole when they were likely to succeed in the community (false positive) can negatively impact that individual and increases the cost of corrections.

Another criticism of parole decision making has been the lack of empirical support for the factors weighed most heavily in release decisions. Past studies have found that parole decision makers may rely on information or place inappropriate weight on certain factors that are not necessarily relevant to recidivism. For example, Caplan (2007) reported that the mental health of the applicant and victim input were influential factors considered in parole decisions, despite evidence suggesting that they do not necessarily predict recidivism. Work by Bonta, Blais, and Wilson (2014) asserts that the presence of mental health concerns is not empirically validated as a risk factor for recidivism. Furthermore, since acknowledging victim impact has not been proven to improve empathy in forensic populations (Jackson & Bonacker, 2006), and empathy does not necessarily reduce recidivism (Gottschall et al., 2014), it should not be heavily weighted in decision making. The influence of risk factors that do have empirical relevance to
risk can also be weighted disproportionately in decision making. For example, in studies of both 
American parole decision makers (Turpin-Petrosino, 1999) and a sample of Canadian students 
(Lloyd, 2005), the type of offense committed predicted release decision more so than risk level. 
These studies found that despite that the individuals who were incarcerated were at similar levels 
of risk to reoffend, participants placed greater weight on the type of offense when making 
decisions.

Decision makers’ use of decisional heuristics and reliance on the input of other 
professionals may also negatively impact decisional accuracy (Gobeil & Serin, 2009). The 
increase in caseloads for paroling authorities has resulted in time pressure for decision making. 
Lack of sufficient time can lead decision makers to rely on decisional heuristics or mental 
shortcuts to allow them to make quick decisions. Lack of time being related to a tendency to 
simplify and overlook information in a given case (Gobeil & Serin, 2009; Hawkins, 1983). 
Shortcuts, simplification, and missing information related to parole applications can influence 
the accuracy of the decision being made and the lack of attention to the details of an application 
does not provide parole applicants a just chance at parole. Decision makers may also place 
unwarranted importance on input from other individuals. Parole board members decisions have 
been found to be heavily influenced by the suggestions of case analysts, correctional staff, and 
judges (Carroll et al., 1982; Carroll & Burke, 1990; Ruhland et al., 2017). When decision makers 
rely on information that is not empirically supported, their decisions lack sufficient support and 
cannot be defended or explained to stakeholders. This further adds to criticisms of paroling 
authorities, as such decision-making processes lack transparency.

A major criticism by the public is the apparent lack of transparency and mutual 
understanding of the parole decision-making process. Parole applicants who are denied parole do
not always receive a sufficient explanation of the reason for the denial (Schwartzapfel, 2015). Transparency can also vary by jurisdiction. In the United States, twenty-seven parole boards hold open hearings, fourteen hold closed hearings, and three make decisions without a hearing at all (Kinnevy & Caplan, 2008). The lack of inclusion of parole applicants in decision making has created skepticism related to the fairness and transparency of parole decisions. Furthermore, with the public and the parole applicants often being unaware of the information reviewed for parole decisions, discrepancies between what individuals believed is influential information and what board members actually consider may result in further distrust and frustration (Serin et al., 2020).

As the factors that are influential to final parole decisions can vary across decision makers, releasing authorities have faced pressure to adjust their policies and practices to make decision making more structured and consistent.

The overarching criticism that has begun to be addressed by paroling authorities is the lack of structure in the decision-making process, which potentially results in inconsistent, inaccurate, and seemingly arbitrary parole decisions (Serin et al., 2020). Without sufficient structure or guidelines for paroling authorities to follow, decision makers may use their subjective professional judgement, personal biases, and other empirically irrelevant factors to make decisions that are inaccurate or not reflective of the parole applicants’ potential for success (or failure) in the community. Furthermore, unstructured approaches can lead to inconsistent decisions that cannot be empirically supported or defended (Serin, et al., 2020). Structured decision making has been proven to improve the consistency and predictive accuracy of release decisions (Rhine, 2017; Serin et al., 2020; Wardrop, et al., 2019). In recent years, a tool has been developed to address these criticisms that paroling authorities face by offering a structured, transparent, and empirically supported template that can aid in the decision-making process.
The Structured Decision Making Framework (SDMF)

The SDMF is a structured, evidence-based, and transparent template to guide parole decision makers through the decision-making process. The SDMF was developed to address the inconsistencies in the factors contributing to parole decisions and the lack of empirically based approaches to decision making. A thorough review of the literature on risk assessment, institutional adjustment, correctional programming, mental health, violence, and release planning aided in the development of the SDMF as a face valid structured professional judgment (SPJ) approach (Serin et al., 2016).

The SDMF incorporates statistical risk estimates to guide decision making in order to contribute to more accurate decisions based on the likelihood each individual will reoffend (Serin et al., 2016). Different scales are utilized for different populations (e.g., individuals who have sexually offended, Indigenous individuals) to ensure that each individual is accurately and appropriately represented in terms of risks and needs. To address criticisms related to a focus on factors irrelevant to risk of recidivism, literature on recidivism and parole outcomes was broken down into specific domains that empirically inform decisions (Serin et al., 2016). Thus, the presence of extraneous information that could influence the accuracy of the decision is limited. The decision-making process of the SDMF is intended to reduce bias, as it can be applied to all cases, regardless of gender or ethnicity. Empirically relevant dynamic factors, such as offender change, were included in the SDMF and group-based risk information was bridged with case-specific information to further ensure decisions were empirically related to risk but also applicable to each unique offender (Serin et al., 2016). In essence, two individuals with the same crime, same sentence, and same risk score could receive different, albeit defensible, parole
decisions. In this manner, risk is a key consideration but not the only consideration when arriving at a parole suitability decision.

The Framework is also transparent in that the final decision can be explained by the ratings of each domain and in the context of the individual’s risk level. The authors ensured that it would be easily understood by board members and defensible to various stakeholders. Finally, the SDMF provides the structure and consistency to paroling authorities that previous decision-making practices were lacking. The SDMF follows a structured professional judgment approach that acts as a template for decision makers to follow and address all relevant areas to be considered before making a final parole decision. The SDMF provides a holistic analysis of the combination of domains to yield a transparent rational for determining an applicant’s suitability for release. Identified areas of concern also potentially provide applicants with information to improve their suitability for subsequent reviews.

The Framework

**The Comprehensive Risk Assessment (CRA)**

The essential first step in the SDMF and in considering whether to release an individual on parole is the Comprehensive Risk Assessment (CRA). The CRA, when available, serves as an analysis of the offender’s current risk (low, moderate, or high). In California the risk rating is based on the structured professional judgment of a forensic clinical psychologist concerning the individual’s risk of future violence. Any additional information about the individual that is provided in the subsequent steps of the SDMF is considered in the context of the initial risk estimate that the CRA provides.
Domains

Next, the SDMF requires a review and rating of seven domains related to an individual’s risk to reoffend, four additional policy factors, and any discordant information. The seven domains include Criminal and Parole History, Self-Control, Programming (Responsivity), Institutional Behaviour, Offender Change, Release Plan, and Case-Specific Factors. Each domain is assigned a rating related to recidivism: aggravating (+), mitigating (-), or neutral. Aggravating factors are those that appear to increase the risk of recidivism, while mitigating factors are those that purport to decrease recidivism. A domain is considered neutral or to have no impact if the factor is similar to the general offender population and thus does not discriminate regarding expected outcome. A detailed user manual and training curriculum are provided to paroling authorities to assist in implementation. In California, this now includes a competency-based e-learning curriculum.

Criminal and Parole History. An individual’s histories of criminal activity and criminal justice experiences are important to consider when determining the likelihood of their success in the community. Research related to recidivism has indicated that one of the strongest predictors of future criminal behaviour is criminal history (Gottfredson & Gottfredson, 1986; National Research Council, 2008). This domain considers information regarding risk-related components of criminal behaviour such as the age of onset, density, escalation, severity, and breaches. Literature on criminal history and recidivism indicates that earlier onset of criminal behaviour, shorter time between arrests and more crimes committed, an increase in the severity of offenses, more serious crimes and criminal histories, and prior failures on community supervision are strongly related to reoffending (Serin, 2019). Criminal and Parole History is an aggravating factor if the individual had an early onset of criminal behaviour, multiple crimes with little time
in between, crimes that escalated in seriousness, or multiple parole violations or revocations. This factor is rated as mitigating if the individual had no previous criminal history or only minor infractions. A neutral rating in this domain indicates that the individual may have a history of minor crimes, no escalation in severity, and long periods between them.

**Self-Control.** This domain considers the impulsivity of an offender in determining the likelihood that they will inhibit any antisocial or criminal behaviour in the community. Previous research has determined that low self-control is related to engagement in criminal or antisocial behaviours (Hirschi & Gottfredson, 2020). Factors such as negative peer pressure, anger, jealousy, rejection, anxiety, substance use, threat perception, intelligence, impulsivity, sexual deviance, callousness, and criminal attitudes are related to how well an individual regulates their behaviour, and thus, should be considered in the decision-making process. Individuals who exhibit poor self-control as indicated by one or more of said Self-Control factors receive a rating of aggravating in the self-control domain. Those rated mitigating exhibit long-term goals, can explain the consequences of their actions, and demonstrate pro-social and self-regulatory behaviours. A rating of neutral is given to individuals who neither indicate a serious lack of self-control nor demonstrate an ability to maintain self-control based on the relevant Self-Control factors.

**Programming.** Through review of the offender’s CRA, decision-makers must identify whether there are any currently relevant risk factors and whether these risk factors have been addressed through correctional programming. Program intensity and dosage should be consistent with the offender’s risk/need level and program style should be consistent with their abilities or learning style (Andrews & Bonta, 2016). Programming that follows the risk-need-responsivity model and matches an individual’s relevant risk level, criminogenic needs, motivations, and
learning style are more successful at reducing recidivism upon release (Andrews & Bonta, 2010). If the CRA identifies currently relevant risk factors and the individual has not completed correctional program corresponding to that risk, they are rated as aggravating for the Programming domain. If there are no currently relevant risk factors identified or relevant risk factors have been addressed through active participation and completion of required RNR-based programming, Programming is rated as mitigating. The domain is rated neutral if the CRA identifies currently relevant risk factors and the individual has completed some programming in response to those risk factors, but some criminogenic needs have not been addressed and/or the dosage is insufficient given the risk level.

**Institutional Behaviour.** As poor institutional behaviour is related to post-release recidivism, parole-decision makers must consider the applicant’s performance while incarcerated (Cochran et al., 2014). For this domain, decision makers must consider the individual’s compliance with institutional rules and regulations, work performance, and recent misconducts (Serin, 2019). Institutional Behaviour is considered aggravating if the offender demonstrated serious misconduct at any point during the current period of incarceration or any recent misconduct of any severity. An absence of misconduct or the presence of meritorious behaviour while incarcerated is rated as a mitigating factor. Institutional Behaviour is considered a neutral factor if the offender demonstrates no misconduct plus basic rule compliance, or, in the case of California, if the misconduct is minor or occurred more than 5 years ago.

**Offender Change.** Changes in thinking, decisions, and behaviours are the most important factor in predicting individuals’ post-release outcomes (Wardrop et al., 2019). Any evidence that the offender has benefited from programming or experienced changes in their thought processes, decision-making, and behaviour is important to this domain. Indicators of pro-social thinking,
decisions, and behaviour in individuals who have committed an offense include the acceptance of responsibility for crime and crime-related behaviour; an ability to explain the consequences of their behaviour; the use of cognitive skills to make decisions and consider consequences; and pro-social behaviours, including having a pro-social support group and the avoidance of ‘trigger’ situations. Evidence of changes in motivation, changes from pro-criminal to pro-social identity, increased agency, and having redemptive considerations are encouraging indicators of offender change (Serin, 2019). An individual who rejects the need for change, refused programming, or was kicked out of programming due to non-compliance is given a rating of aggravating in Offender Change. If there is evidence of change in the individual, regardless of program completion, offender change is rated as mitigating. Offender Change is considered neutral if the individual demonstrates some evidence of change since commission of the crime, but that change is not substantial, clear, or consistent enough over time to suggest reduced risk.

**Release Plan.** Having a specific and realistic release plan for an individual who is to be released is related to their ability to discontinue criminal behaviour in the community (Dickson et al., 2013). Community stability factors included in the release plan, such as stable housing, stable employment, the presence of pro-social support, access to treatment programs and support services, a difference in situation or setting since previous criminal behaviour, and specific plans to manage high risk situations are all related to an individual’s success in the community and are important to consider in parole decisions (Serin, 2019). A rating of aggravating in this domain indicates that the applicant lacks a concrete and realistic parole plan and there is a connection between the lack of plan and the individual’s current risk. An individual with a concrete, realistic parole plan that addresses the community stability factors is rated as mitigating. Release Plan is rated neutral if the parole applicant has concrete, realistic parole plans, but several community
stability factors are not adequately addressed and the individual does not have specific strategies to manage their risk factors. Of note, the CBPH provides stable housing to all Lifers released on parole in California.

**Case-Specific Factors.** These factors are not otherwise accounted for in other domains that are still relevant to the decision-making process. Case-Specific Factors can include medical/physical limitations, mental health concerns, developmental disabilities, prior physical or sexual abuse, and more. These unique Case-Specific Factors are considered aggravating if they increase the individual’s current level of dangerousness and mitigating if they reduce the individual’s current dangerousness. If there are no unique Case-Specific Factors that affect the parole applicant’s dangerousness, this domain is rated neutral.

**Long-Term Offender Considerations.** Literature regarding considerations for long-term offenders in decision-making have been incorporated into the SDMF for use in California. For each SDMF domain, there is a discussion of its relevance to the likelihood of recidivism in long-term offenders. These considerations will assist decision-makers in making more evidence-based decisions that are appropriate to the parole applications of Lifers.

**Additional Factors and Discordant Information.** Any additional factors that may be relevant to the parole decision are considered in this domain. Specific to California, victim or District Attorney information, youth factors, elderly parole considerations, intimate partner battering considerations are statutorily required to be reviewed. As well, any discordant or incongruent information are important for paroling authorities to consider prior to making a release decision. Victim or District Attorney information is rated as aggravating if the victim, the victim’s next of kin, or the prosecutor expressed verifiable issues of safety or current dangerousness of the parole applicant. Youth factors are to be considered and given great weight
when making release decisions. Youth are found suitable for parole unless there is reliable and relevant evidence that the youth remains a current and unreasonable risk to public safety. As recidivism typically decreases with age, the individual’s age, long-term confinement, and any evidence of diminished physical condition are given special consideration in the decision-making process for elderly parolees. Any information or evidence that at the time of the commission of the crime, the individual had experienced intimate partner violence is also considered in the parole decision. Finally, any discordant information, discrepancies in information provided to the panel, or discrepancies between the risk rating and panel decisions are to be considered here. Any inconsistencies must be supported by a rationale for particular decisions.

There is no total score or absolute decision produced by following the Framework. Rather, the SDMF provides decision makers with a holistic analysis to make an informed and empirically supported final release decision that is easily defensible and transparent (Serin et al., 2020). As visualized in Figure 1, the process of decision making with the SDMF begins with the review of risk-relevant information about the justice involved person and the subsequent rating of each domain using this information. Then, decision makers must take into consideration the CRA risk rating, domain ratings, and any additional factors and discordant information and come to a release decision using structured professional judgement. Rather than a summative total score that is then compared to a cut-off to determine release decisions, the SDMF allows for decision makers to use their own discretion and weigh information in the context of each unique applicant. New decision rules (discussed below) have now been incorporated in some jurisdictions, which will make the weighing of information more empirically based and consistent.
The Structured Decision Making Framework – A Roadmap of the Process

Note. CRA = Comprehensive Risk Assessment.

The SDMF was validated using retrospective case file information (Gobeil & Serin, 2005). Cases were reviewed and coded following SDMF protocols and a hypothetical parole decision was made. The decision derived from using the SDMF was compared with the original decision and eventual outcome for each case (Gobeil & Serin, 2005). The same methodology was then applied to larger random samples of representative cases, cases serving shorter sentences, Board of Investigation cases of sensational violent parole failures, and a sample of cases of Indigenous individuals (Serin et al., 2016). When the SDMF was applied to these retrospective cases, there was a 2.5-6% increase in decision accuracy compared to the original decisions, with acceptable inter-rater reliability (intraclass correlation coefficient [ICC] = 0.82) for a SPJ approach (Serin et al., 2016). Furthermore, these studies demonstrated that the use of the SDMF reduced the number of false positives and false negatives compared to original

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1 Coders were blind to the final parole decision.
decisions. Not only did the SDMF improve decision accuracy, but it was also able to identify
cases of individuals who were initially denied parole but succeeded upon release (false positives)
and those who were initially granted release and subsequently reoffended (false negatives; Serin
et al., 2016).

Given the success of the SDMF at improving the decision-making process, it is now
implemented federally in Canada. In addition, the SDMF has now been implemented throughout
the United States in Ohio, Kansas, Connecticut, South Dakota, Kentucky, and Utah. Serin and
Gobeil (2014) evaluated the use of the Framework in three U.S. states: Ohio, Kansas, and
Connecticut. The SDMF was used to make parole decisions for 100 retrospective case files per
state. These retrospective parole decisions were then compared to the actual parole decision that
was made by the relevant parole board, along with parole outcome data. Preliminary results from
Ohio, Connecticut, and Kansas demonstrated that cases that were denied parole exhibited more
aggravating domains on the SDMF compared to those granted parole (Serin & Gobeil, 2014). In
Connecticut specifically, summed ratings on the Framework were found to adequately
differentiate between justice involved individuals who recidivated and those who did not (AUC=
.68).

In a follow-up study of the SDMF in Connecticut, Wardrop et al. (2019) examined the
domain ratings and release decisions of 4,966 parole applicants. Domain ratings on the
Framework were once again found to be related to release decisions, with more aggravating
ratings associated with parole denial. Furthermore, recidivism data indicated that Framework
domains, specifically Offender Change, Programming, and Release Plan, were significantly
predictive of revocation. Overall, ratings on the SDMF were once again able to differentiate
between individuals who reoffended and those who did not (Wardrop et al., 2019). Interestingly,
in the year following the implementation of the SDMF in Connecticut there was a reduction in recidivism for both new offenses (22.6% to 6.6%) and technical violations (29.9% to 18.3%; Wardrop et al., 2017). Given the previous success of SDMF implementation in these states, the SDMF has been implemented in the state of California by the California Board of Parole Hearings (CBPH).

**Parole in California**

The CBPH is responsible for making parole decisions for individuals who have been incarcerated under the jurisdiction of the California Department of Corrections and Rehabilitation (CDCR). As previously mentioned, individuals in some U.S. States serve indeterminate sentences. However, the state of California uses both determinate and indeterminate sentencing practices. Those serving a determinate sentence in California are sentenced to a fixed duration of time and then released on parole when that fixed duration is met. Alternatively, those serving indeterminate sentences are typically serving life sentences with or without the possibility of parole (MacKay, 2019). Individuals serving indeterminate life sentences with the possibility of parole can become eligible for parole and assessed for parole suitability once they have reached a Minimum Eligible Parole Date (MEPD; MacKay, 2019).²

The focus of the present study is on the release decisions of those serving indeterminate life sentences with the possibility of parole in California.

The duties of the CBPH include conducting parole suitability hearings, parole reviews for nonviolent cases, medical parole hearings, hearings for applicants with a mental health disorder, and reviews of sexually violent predators (California Department of Corrections and

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² MEPD is determined based on the length of the minimum statutory term for the life offense minus pre-sentence credits and institutional good-conduct credits (MacKay, 2019).
Rehabilitation, 2021). The CBPH is comprised of the Executive Office and five divisions, each with specific responsibilities related to parole and parole decisions. The CBPH workforce includes 17 full-time commissioners and 50 deputy commissioners who are responsible for conducting parole suitability and reconsideration hearings and parole eligibility consultations (California Department of Corrections and Rehabilitation, 2021). In 2020, the CBPH held 7,684 parole hearings. Of these hearings, the CBPH granted parole to 16% of cases and denied parole 29% (State of California Board of Parole Hearings, 2020). The remaining hearings resulted in stipulations (5%), voluntary waivers (12%), postponements (34%), or continued/cancelled hearings (4%).

As California has observed an increased number of individuals on parole (Kaeble & Alper, 2020), the workload of CBPH members has also increased (Board of Parole Hearings, 2020). In 2020 alone, the CBPH experienced a 27% increase in case load since the previous year (State of California Board of Parole Hearings, 2020). According to the CBPH, this increase was due to both changes in legislation and the COVID-19 pandemic. Between 2019 and 2020, changes to the Penal Code and Proposition 57 required that the Board increase the number of scheduled hearings for determinately sentenced parole applicants with youth considerations and indeterminately sentenced individuals who are nonviolent, as to not exclude these populations from parole opportunities (State of California Board of Parole Hearings, 2020). Prior to 2020, only indeterminately sentenced persons were eligible for a parole hearing after reaching their MEPD (Shaffer, 2021).

Now, both determinately and indeterminately sentenced individuals may be eligible for a parole hearing after serving the minimum term imposed by the court or after serving 15, 20, or 25 years if eligible for a parole hearing for youth considerations, elderly parole hearing, or a
nonviolent case hearing (Shaffer, 2021). Furthermore, the COVID-19 pandemic resulted in the postponement of 2,138 hearings, adding to the already increasing workload. The implementation of the SDMF in California allowed the CBPH to streamline the hearing process and increase consistency in decision-making (State of California Board of Parole Hearings, 2020). Along with decreasing the length of parole hearings, the implementation of the SDMF in California has also led to lower failure rates for indeterminately sentenced individuals on parole (State of California Board of Parole Hearings, 2020; Kusaj, 2020).

**Implementing the SDMF in California**

The State of California has one of the largest populations of adults on parole in the United States (Kaebble & Alpher, 2020). Due to their determinate sentencing practices allowing individuals to be automatically released upon sentence expiry, the State also observed fairly high recidivism rates. In fact, at one point in time, California’s recidivism rate within three years of parole release was 66%, which was 26% higher than the national average at the time (Grattet et al., 2009). Since then, policy changes that move away from strictly mandatory sentencing have led to decreasing recidivism rates. According to Kusaj (2020), despite an 800% increase in parole grants since 2007, California has not observed an increase in recidivism in parolees. Specifically applied to cases involving indeterminate sentencing, the SDMF has provided decision makers in California with a tool to ensure that those who become eligible for release are actually suitable for community living.

Since the implementation of the SDMF to indeterminately sentenced cases in April 2019, the CBPH has observed an increase in grant rates, more concise reports, and improved decision accuracy (Kusaj, 2020). In 2018, prior to the implementation of the SDMF, the CBPH granted parole to 27.5% of applicants ($N=2647$). In the year following the implementation of the SDMF,
the CBPH granted parole to 29.5% of applicants (N=2832)—a 2% increase—and denial rates increased by 4%. The use of the SDMF has also helped to reduce the average length of parole hearings in California by thirty minutes (Serin et al., 2020). A recent preliminary study found no difference between grant and denial rates between actual CBPH decisions and decisions made by an external rater explicitly following the SDMF (Vettesse, 2021). These preliminary findings suggest that the CBPH is following the recently implemented Framework at least to some degree. However, the sample used for this particular study was not considered representative in terms of risk-level or decision. That is, there were equal number of low and moderate risk cases and an equal number of cases were granted and denied release. In consideration of these limitations, the current study will examine a random sample of CBPH decisions to further examine the utility of the SDMF in California.

**Implications of the Present Research**

The present study will expand on past SDMF research and examine the impact of the SDMF on parole decision making for indeterminate cases in California. This study will differ from previous SDMF research in a few ways. First, the SDMF has now been fully implemented in California and now reflects recent adaptations for long-term offenders (Lifers). Lifers typically have different risks and needs than younger offenders, meaning that determining their suitability for being managed in the community needs to be considered in the context of their unique circumstances. These considerations will be applied throughout the decision-making process in the current study.

Second, new Decision Rules have been created for credentialing through training. This will assist decision makers using the SDMF in considering all of the relevant mitigating and aggravating factors related to the individual’s suitability for release (in the context of their risk
level) to make a final decision. These rules reflect relevant policies and statutes and indicate the specific combinations of SDMF ratings and risk levels in which parole should be granted or denied for each risk group (low, moderate, or high). Of note, while CBPH members have access to the relevant policies, statutes, and literature that have contributed to the creation of these Decision Rules, they do not have access to the explicit Rules themselves. Thus, the present study is different from previous research—and from CBPH parole decisions—in that it will incorporate these explicit Decision Rules in the decision-making process. This improvement in decisional accuracy will permit a more robust examination of the utility of the SDMF in California.

Finally, the present study will use a random sample of CBPH CRA files to ensure that the findings are reflective of a typical CBPH caseload in terms of applicant risk and parole decisions. Previous studies used only low and medium risk cases and ensured that there was an equal proportion of parole grants and denials. However, the distribution of the risk levels of parole applicants in California is not even. In 2020, 22% of examinees were classified as Low Risk, 45% were classified as Moderate Risk, and 33% of examinees were classified as High Risk (Kusaj, 2020). To better reflect the typical distribution of risk levels in CBPH cases, the present study will use a random sample of the approximately 349 CBPH cases reviewed in the calendar month of June 2021. This methodology will ensure that the proportion of CBPH grants, denials, and applicant risk is random and more representative of parole reviews in California.

The present study aims to identify whether the incorporation of the SDMF in California has led to changes in parole decisions by CBPH. Such changes have implications for parole applicants, the public, and paroling authorities and should provide important insight for decision-making research and practice. Accurate decision-making ensures that only those who are ready and equipped for life in the community are released, thus preventing parole failure and
reincarceration. Consequently, accurate decision-making also protects the public by ensuring that individuals who are likely to reoffend are denied release and the public is protected from potential victimization. Furthermore, a lack of parole failures gives the impression that paroling authorities are making correct decisions and potentially protecting them from public scrutiny. On the other hand, inaccurate decision making can contribute to the false positive error rate whereby cases are denied release who would have succeeded if released. Therefore, it is important to ensure that not only are those who are unlikely to succeed denied parole, but also those who can be successful are given the opportunity to re-enter the community. Overall, any changes to decision-making that are accurate and predictive of parole success have positive implications for the field of corrections and should be further investigated to allow for increased implementation in other jurisdictions.

The Current Study

The goal of the present research is to examine the utility of the SDMF in two ways: first, by comparing parole decisions in California made pre-implementation of the SDMF with decisions made post-implementation, and second, by comparing CBPH parole decisions against parole decisions made by explicitly following the SDMF. The comparison of decisions pre- and post-implementation will inform us of any changes in parole decisions since the introduction of the SDMF in California in 2019. Following rigorous training on the use of the SDMF and using decision rules endorsed by CBPH, the second study will use a more specific and informed approach to decision-making with the SDMF than was done in previous studies. Using a sample of indeterminately sentenced individuals in California, the second study seeks to determine whether CBPH actual decision rates differ from SDMF-based decision rates.
Essentially, I will determine whether the incorporation of the SDMF in California has led to changes in parole decisions by CBPH board members. These changes will be reflected in the discrepancies in grant and denial rates across implementation years and in the differences in the number of cases who are granted or denied parole by the CBPH versus the number of cases granted or denied parole through SDMF ratings. In addition, the present study will investigate whether a holistic total score of the Framework or any individual domains predict the final parole decision. This will allow me to identify whether specific domains or the Framework overall are predictive of the actual parole decision, given the use of a more representative sample, new decision rules, and Lifer considerations incorporated into the decision-making process. Overall, the current study will help indicate whether the incorporation of a more structured and evidence-based decision-making tool like the SDMF has led to changes in decisions by paroling authorities in California.

**Study 1: The Impact of SDMF Implementation on Parole Decisions in California**

**Purpose**

The purpose of Study 1 was to compare parole decisions made by the CBPH across SDMF implementation years. Rates of parole grants and denials between 2018 (pre-implementation) and 2020 (post-implementation) will inform us of any differences in decision rates and for which populations of applicants (e.g., low, moderate, and high risk cases) these changes have occurred.

**Hypotheses**

1. Grant and denial rates will differ prior to and after the implementation of the SDMF (2018 to 2021).
Method

Sample

Based upon the CBPH reports, the sample of cases pre-implementation (2018) were predominantly moderate risk (47%), with 26% of applicants identified as low risk and 27% identified as high risk. In 2018, parole applicants were mostly men ($n=2877, 95\%$) and the majority of applicants had already spent 21 to 30 years incarcerated ($n=1473, 49\%$). Similarly, parole applicants in the 2020 calendar year were predominantly moderate risk (45%), with 22% of applicants being labelled as low risk and 33% of applicants identified as high risk. Of the 2020 applicants, 97% identified as men and 3% identified as women. Reports from 2020 indicated that most applicants had already spent 10 to 20 ($n=1290, 32\%$) or 21 to 30 ($n=1964, 48\%$) years incarcerated.

Materials

Board of Parole Hearings Report of Significant Events. The first study used decision statistics provided by the CBPH. Each year, the CBPH presents an annual report of descriptive statistics of grant and denial rates, applicants’ risk ratings, and other operational information relevant to the previous calendar year. These descriptive statistics were utilized in the present study to evaluate the differences in grant and denial rates overall and across the different risk levels between 2018 and 2020. The SDMF was implemented in California in 2019, thus, report data from 2018 was operationalized as pre-implementation. To ensure that the proper allotment of time for the tool to be fully incorporated by California decision-makers, data from the year of implementation (2019) was not included. Rather, decision data from the 2020 report was operationalized as post-implementation.
Procedure

Study 1 involved compiling report data from pre- and post-implementation of the SDMF and comparing decision rates between 2018 and 2020. Grant and denial rates between pre- and post-implementation were compared across parole applicant risk levels using statistical analyses.

Analyses

Study 1 used chi-square tests to compare grant and denial rates between 2018 and 2020. First, these decision rates were compared by year (2018 versus 2020). Then, decision rates in California were compared by year and across low, moderate, and high risk cases.

Results

The CBPH granted parole to 728 individuals in 2018 (27.5% of applicants) and 836 in 2020 (29.5% of applicants). In terms of denials, the CBPH denied parole to 1511 (57.1%) individuals in 2018 and 1738 (61.4%) individuals in 2020. As can be seen in Table 1, while grants and denials increased by 2% and 4.3% respectively, these increases were not statistically significant, $\chi^2 (1) = 0.0007, p = .979$. Table 2 presents the differences between pre- and post-implementation for low and moderate risk cases for parole grants and parole denials. A chi-square test of independence revealed that the differences in grant rates between low and moderate risk cases between pre-SDMF implementation and post-SDMF implementation were not statistically significant, $\chi^2 (1) = 1.12, p = .290$. However, denial rates were significantly different between pre- and post-implementation between low, moderate, and high risk cases, $\chi^2 (2) = 12.87, p < .01$. While denial rates decreased by 4% for low risk cases between 2018 and 2020, denial rates for high risk cases increased by 4%. Denial rates for moderate risk cases remained at 57%.
Table 1

*Chi-Square Test of Independence of Grant and Denial Rates Pre- and Post-SDMF Implementation*

<table>
<thead>
<tr>
<th>Decision</th>
<th>Pre-Implementation (2018)</th>
<th>Post-Implementation (2020)</th>
<th>$\chi^2$</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grant</td>
<td>728 (27.5%)</td>
<td>836 (29.5%)</td>
<td>0.0007</td>
<td>0.979</td>
</tr>
<tr>
<td>Deny</td>
<td>1511 (57.1%)</td>
<td>1738 (61.4%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Hearings resulting in stipulation and post-postponements were not included.
Table 2

Grant and Denial Rates by Risk Level between Pre- and Post-Implementation of the SDMF

<table>
<thead>
<tr>
<th>Risk Level</th>
<th>Grant Pre-Implementation</th>
<th>Grant Post-Implementation</th>
<th>Deny Pre-Implementation</th>
<th>Deny Post-Implementation</th>
<th>( \chi^2 )</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>459 (63%)</td>
<td>544 (65%)</td>
<td>271 (18%)</td>
<td>243 (14%)</td>
<td>1.12</td>
<td>.290</td>
</tr>
<tr>
<td>Moderate</td>
<td>269 (37%)</td>
<td>285 (34%)</td>
<td>862 (57%)</td>
<td>991 (57%)</td>
<td>12.87</td>
<td>.002**</td>
</tr>
<tr>
<td>High</td>
<td>0 (&lt;1%)</td>
<td>7 (&lt;1%)</td>
<td>377 (25%)</td>
<td>504 (29%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note. Hearings resulting in stipulations and postponements were not included. Percentages may not add to 100 due to rounding. Chi-square analysis for grant rates did not include high risk cases, as there were too few high risk grants (one cell was less than 1). * \( p<.05 \), ** \( p<.01 \), *** \( p<.001 \).*
Study 2: The Fidelity of CBPH Board Members to the SDMF

**Purpose**

The purpose of Study 2 was to determine the fidelity of CBPH board members in using the SDMF when making parole decisions.

**Hypotheses**

2. Notwithstanding implementation of the SDMF, it is hypothesized that actual CBPH decisions will differ from SDMF-derived decisions, as Commissioners likely unconsciously consider factors outside the SDMF domains when making release decisions.

3. The greatest difference between SDMF-derived decisions and CBPH decisions will be observed in moderate risk cases, as Commissioners are likely risk averse, but there will be no difference for low risk or high risk cases.

4. The SDMF will moderately predict CBPH decisions.

5. Since offender change is considered to be the most important factor in predicting an offender’s post-release outcome, it is expected that the offender change domain will be the most predictive domain regarding CBPH decisions.

**Method**

**Sample**

The present study utilized CRA files from a sample of 78 cases of indeterminately sentenced Lifers being assessed for parole suitability by the CBPH in June of 2021. Reportedly, the CBPH reviews approximately 349 parole hearings per month. Thus, the present sample was a random selection of 78 parole cases from the over three hundred cases seen in June 2021. Every case in the present sample involved an individual who was both serving an indeterminant
sentence in the State of California and eligible for a parole hearing that month. The 78 cases were random in terms of the risk level and the final parole decision received by each individual in the sample. In other words, unlike previous studies, the present study did not explicitly exclude high risk cases or guarantee equal proportions of risk levels or decision outcomes. Rather, the proportions of low, moderate, and high risk cases in the present sample were representative of a typical monthly caseload of the CBPH, in which risk level and other individual characteristics are random and solely based on the parole eligibility date of each case. Similarly, the actual CBPH parole decision for each individual in the sample was unknown, therefore, the proportion of parole grants and denials in the present sample was completely random. Overall, only those suitable for a parole hearing in June of 2021—regardless of risk or parole decision—were included in the present sample.

**Materials**

**Comprehensive Risk Assessment (CRA).** As previously stated, the CDCR provided 78 CRA files for the present study. All CRA files were completed by a licensed CBPH forensic clinical psychologist through interviews with each parole applicant. These interviews resulted in an in-depth evaluation of each applicant’s risk of future violence based upon the structured professional judgement of the evaluator. The CRA case files provided a wide range of information about risk-related factors most relevant to the likelihood that an applicant would reoffend in the community.

The risk-related information provided in the CRAs was divided into psychosocial development, criminal history, clinical assessments, assessments of risk for violence (HCR-20), other risk considerations, and case formulations. The *psychosocial development* information provided insight into the individual’s childhood and adolescent development (e.g., experiences
growing up, home life, family dynamics, etc.) and adult development (e.g., relationships, employment, etc.). The criminal history section of the CRAs included information related to juvenile criminal records, adult criminal records, and any available information related to prior performance while on supervised release. Clinical assessments included a review of prior psychological exams or risk assessments, a mental status examination, the individual’s history of substance abuse and related disorders, and the identification of any mental health or personality disorders and related treatment. In addition, the clinical assessment section of the CRAs provided in-depth considerations of the individual’s institutional behavior, including educational or vocational training, work placements, program participation, and any instances of institutional misconduct. This section also included the individual’s plans for parole, revealing their plans for housing, employment, social support, programs, and risk management strategies upon their return to the community.

The assessment of risk for future violence used the HCR 20-V3 (Douglas et al., 2013), an analysis of the individual’s historic and current risk factors, to discuss the factors that would be most influential to the individual’s success (or failure) in the community. In addition to the HCR 20-V3, statistical risk estimates provided by the Static-99 (Hanson, 1999) and PCL-R (Hare, 1980; Hart et al., 1991) were included where relevant. Finally, based upon the aforementioned information of the CRA and the structured professional judgement of the evaluator, the case formulations provided a summary of all relevant risk and protective factors and a final determination of the individual’s risk level—either low, moderate, or high risk. The CRAs were used in the present study to inform the use of the SDMF, in combination with the aforementioned Decision Rules, to arrive at a release decision for each case.
Structured Decision Making Framework (SDMF). As previously discussed, the SDMF is a structured approach to guide the parole decision making process. The SDMF has been validated with different samples and has been implemented both federally in Canada and in several U.S. states (Serin & Gobeil, 2014; Wardrop et al., 2019). The use of the Framework is informed by the CRA (when available) and relevant correctional information sources. The SDMF involves the review and rating of seven risk-related domains that are empirically relevant to recidivism. The domains include Criminal and Parole History, Self-Control, Programming (responsivity), Institutional Behaviour, Offender Change, Release Plan, and Case-Specific Factors. Four additional policy factors, including victim and district attorney considerations, youth factors, elderly parole considerations, and intimate partner battering considerations are to be reviewed along with any discordant information that is present. Each domain or additional factor is given a rating of either aggravating, mitigating, or neutral, based on its potential to influence the individual’s likelihood of recidivism. Factors that appear to increase the applicant’s risk of recidivism are rated as aggravating, while factors that appear to decrease this risk are rated as mitigating. Informed by SDMF domain ratings and the initial statistical risk estimates provided in the CRA, parole board members can make empirically informed and transparent decisions about releasing an individual into the community. In the present study, the SDMF was used to make parole decisions using retrospective CRA files. All SDMF ratings and subsequent parole decisions in the present study were informed by extensive training and relevant SDMF resources.

SDMF Training. The coding process was informed by the SDMF User Guide, online training for the CBPH, and Decision Rules applicable to parole decision making. The SDMF User Guide (Serin, 2019) is an information manual created for the CBPH. The User Guide
includes relevant legal information about parole decisions and an overview of how to follow the Framework to come to a final parole decision. The document outlines each domain to be rated while following the SDMF, the CRA information to be used to rate each domain, and the appropriate rating for each domain based upon this information. To aid in decision making, the User Guide provides questions and factors that should be considered by decision makers when rating; examples of aggravating, mitigating, or neutral ratings; sample questions for decision makers to ask applicants; and long-term offender considerations for each domain. In the current study, the SDMF User Guide was used to aid in rating each domain of the Framework and come to a final decision for each of the 78 cases.

The coding process was also informed by a rigorous online SDMF training course that is utilized by the CBPH to train commissioners on parole decision-making. The SDMF course discusses general lessons on crime and parole, how to use and rate each domain of the SDMF, and how to make accurate and informed parole decisions. Quizzes throughout the course ensure that SDMF users are aware of the most important components of release decision-making. Furthermore, the course uses randomized case studies to assess users’ ability to rate the SDMF domains and make a final parole decision. This training helps to ensure that decision-makers are following an empirically informed and structured process to make their decisions.

**CBPH Decision Rules for the SDMF.** The present study used the newly developed Decision Rules to convert SDMF ratings to a new final parole decision. These rules were developed for the CBPH and are essentially instructions on how to consider the nexus of statistical risk estimates and domain ratings to inform whether to grant or deny parole. Once the CRA files were rated using the SDMF, the decision rules, in combination with the CRA risk
level and the ratings for each domain of the SDMF, were followed to make a new parole decision. The CBPH Decision Rules are as follows:

1. No high-risk cases granted parole unless all domains are rated mitigating, except self-control which can be aggravating and criminal history which can be neutral. Note: Criminal history can be mitigating even with capital crime.

2. High risk case can be granted parole if elderly offender domain confirms physical incapacitation such as stroke.

3. For moderate risk cases, mitigating domains must outweigh aggravating and offender change must be mitigating.

4. For low risk cases, number of mitigating domains outweigh (equal or greater than) aggravating domains and offender change is not aggravating.

5. For low risk cases, number of mitigating domains outweigh aggravating domains and institutional misconduct is not aggravating.

6. For low risk cases, number of mitigating domains outweigh aggravating domains and release plan is not aggravating.

7. Low or moderate risk and elderly offender issues apply (mitigating).

8. Low or moderate risk and youth offender issues apply (mitigating).

9. Any reliable (independently corroborated through investigation) evidence of current victim concerns for safety results in a denial.

The Decision Rules were derived from relevant policy and legal statutes in California, ensuring that parole decisions are being based upon the most risk- and policy-relevant factors. The Rules themselves were developed to refine the e-learning curriculum for the SDMF, which involves making parole decisions for a variety of case studies. It is important to note that while
Commissioners have access to the SDMF as well as the relevant policy and statute information that is reflected in the Decision Rules, they do not yet have access to the Rules themselves. Thus, the present study benefited from explicit direction when negotiating domain ratings, risk level, and policy considerations, to which Commissioners and previous SDMF researchers did not have access.

**Decision Information.** Since all cases included in the present study were retrospective, the CDCR provided the final parole decision that was made by the CBPH for each case in the sample. Individuals included in the current sample were either granted parole and released to be supervised in the community or denied parole and remained incarcerated. The present study compared these actual parole decisions made by the CBPH to new (hypothetical) parole decisions made by the author. For the present study, the actual CBPH decisions were referred to as *CBPH Decision* and the hypothetical decisions made for the present study were referred to as the *New SDMF Decision*.

**Procedure**

After completing all available training on the SDMF, consensus coding was completed on ten cases to assess inter-rater reliability. Once consensus was met, I coded the remaining 68 cases. I examined each CRA file and used the SDMF to code each domain and additional factor, while being blind to the original outcome of each case. Based on the statistical risk estimate (low, moderate, or high) provided by the CRA and my ratings for each of the seven domains (aggravating, neutral, or mitigating), I applied the Decision Rules to arrive at the New SDMF Decision. The CBPH and New SDMF Decisions were then compared through statistical analysis.
Analyses

The first hypothesis for Study 2 posited that CBPH Decisions would significantly differ from the New SDMF Decisions that were derived from explicitly following the Framework. To address this hypothesis, I conducted a cross-tabulation chi-square test, which compared the frequency of grants and denials between CBPH Commissioners and myself. Similarly, cross-tabulation chi-square tests were used to assess the second hypothesis, which predicted that the greatest difference in grant and denial rates between the two decision-making parties would be observed for moderate risk cases. Since there were no high risk cases in the present sample, I compared the grant and denial rates between the CBPH decisions and the New SDMF Decisions across low and moderate risk cases.

The final two hypotheses were addressed using binary logistic regression. In my fourth hypothesis, I predicted that my SDMF ratings would moderately predict CBPH decisions. Furthermore, my fifth hypothesis posited that of all of the SDMF domains, offender change would be the most predictive of CBPH decisions. The outcome variable in the present analyses was parole decision, which is binary in nature (grant vs. deny). Since the outcome variable in this case is binary, a binary logistic regression was the most appropriate method to determine which factors were the most predictive of the final parole decision. The SDMF domains of criminal and parole history, self-control, institutional behaviour, programming, offender change, release plan, and case-specific factors were all input as predictors. In addition to the domains, a weighted total score of the SDMF was calculated for each case and input as an additional predictor variable.

SDMF Total Score

As previously mentioned, the SDMF is not an actuarial instrument. While the domain ratings provide numeric values from -1 (aggravating) to 1 (mitigating), these values are not
reflective of the relative importance of each domain to the final parole decision and should not be summed to get a total score. However, it is of interest to determine whether the SDMF as a whole can predict parole decisions. Using the newly developed Decision Rules, I developed a new “Total” Score for the SDMF. Thus, this Total Score will be reflective of a combination of the individual risk level of the applicant and the ratings on domains that are the most influential to recidivism. The new Total Score was developed using SPSS syntax computations and aligns with the Decision Rules, allowing for a scoring system through which a decision can be made to grant or deny parole based on cut-off scores. This score was then included in the binary logistic regression to determine whether the SDMF holistically could predict the parole decisions of the CBPH.

Results

Sample Demographics

As reflected in Table 3, the sample of 78 parole cases provided by the CDCR was predominantly male-identifying individuals applying for parole \( (n = 72) \).\(^3\) The age of the applicants identified in the CRA files ranged from 32 to 85 years old \( (M = 50.55, SD = 13.07) \) and of the cases which specified the applicant’s ethnicity \( (n = 49) \), the majority were Hispanic \( (n = 24) \). As previously stated, each individual in the sample was serving a life sentence. The average amount of time served for the present sentence was 21.55 \( (SD = 9.44) \) years. The most common index offence among the present sample was homicide-related (e.g., murder, attempted murder, etc.) and 5% of individuals in the sample were serving a life sentence as a result of their third strike offence.

\(^3\) Of the 78 case, \( n = 6 \) participants identified as female.
Table 3

Sample Demographics (N=78)

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Proportion of Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% (n)</td>
</tr>
<tr>
<td>Gender</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>92.3 (72)</td>
</tr>
<tr>
<td>Female</td>
<td>7.7 (6)</td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>30.8 (24)</td>
</tr>
<tr>
<td>White</td>
<td>15.4 (12)</td>
</tr>
<tr>
<td>Black</td>
<td>11.5 (9)</td>
</tr>
<tr>
<td>Asian</td>
<td>2.6 (2)</td>
</tr>
<tr>
<td>Black/Hispanic</td>
<td>1.3 (1)</td>
</tr>
<tr>
<td>Indigenous</td>
<td>1.3 (1)</td>
</tr>
<tr>
<td>Not Specified</td>
<td>34.6 (27)</td>
</tr>
<tr>
<td>Offence Type</td>
<td></td>
</tr>
<tr>
<td>Homicide-Related</td>
<td>73.1 (57)</td>
</tr>
<tr>
<td>Sexual-Related</td>
<td>11.5 (9)</td>
</tr>
<tr>
<td>Robbery</td>
<td>9.0 (7)</td>
</tr>
<tr>
<td>Other Violent</td>
<td>2.6 (2)</td>
</tr>
<tr>
<td>Other Non-Violent</td>
<td>1.3 (1)</td>
</tr>
<tr>
<td>Third-Strike</td>
<td>5 (4)</td>
</tr>
<tr>
<td>Age at Evaluation M (SD)</td>
<td>50.55 (13.07)</td>
</tr>
<tr>
<td>Time Served Prior to Hearing M (SD)</td>
<td>21.55 (9.44)</td>
</tr>
</tbody>
</table>

Note. M = mean. SD = standard deviation. Since most cases had multiple index offenses, the most serious offense was chosen for each case. Offence type values may not sum to 100%, as some applicants belonged to both a specific offence type and the third-strike offence category.

Despite attempts to randomize the proportion of low, moderate, and high risk cases, there were no high-risk cases in the selection of cases from June 2021. Rather, the sample consisted of 35 low-risk cases (45%) and 43 moderate-risk cases (55%). The lack of high risk cases was not deliberate and was most likely due to a low proportion of high risk individuals with scheduled hearings in June 2021. Nonetheless, the present sample is still somewhat reflective of a typical caseload of CBPH members, as moderate risk cases outweighed low risk cases, and both outweighed the number of high risk cases.
**Interrater Reliability**

Interrater reliability (IRR) is the degree of agreement on ratings between independent observers of a specific phenomenon. In the case of the present study, IRR was calculated to assess the agreement on parole decisions (grant versus deny) between two raters: myself and a senior Ph.D. student who was also trained in using the SDMF and involved in the development of an e-learning curriculum in California. The two raters coded 10 CRA files (13% of the sample) using the SDMF and agreement was reached on 80% of cases. Inter-rater reliability was determined to be in the moderate range (intraclass correlation coefficient [ICC] = 0.62).4

**New SDMF Decisions**

*Proportion of SDMF Ratings Across Domains.*

As displayed in Table 4, the majority of cases were rated as neutral for the domains of Criminal and Parole History, Self-Control, and Institutional Behaviour. Interestingly, a large proportion of cases were given a rating of mitigating for Programming (73%) and Offender Change (63%). In terms of Release Plan, most cases were rated as either neutral (44%) or mitigating (50%). Furthermore, the majority of cases were rated mitigating for Case Specific Factors, indicating that the majority of the sample had either youth offender considerations, elderly parole considerations, or both (77%). The Criminal and Parole History domain had the largest proportion of aggravating ratings (32%).

---

4 ICC values ranging from .60 to .74 are considered good for inter-rater reliability (Cicchetti, 1994).
Table 4

Proportion of Aggravating, Neutral, and Mitigating Ratings Across SDMF Domains

<table>
<thead>
<tr>
<th>SDMF Domain</th>
<th>Aggravating (-) % (n)</th>
<th>Neutral % (n)</th>
<th>Mitigating (+) % (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criminal and Parole History</td>
<td>32 (25)</td>
<td>53 (41)</td>
<td>15 (12)</td>
</tr>
<tr>
<td>Offender Self-Control</td>
<td>10 (8)</td>
<td>65 (51)</td>
<td>24 (19)</td>
</tr>
<tr>
<td>Programming</td>
<td>4 (3)</td>
<td>23 (18)</td>
<td>73 (57)</td>
</tr>
<tr>
<td>Institutional Behaviour</td>
<td>6 (5)</td>
<td>81 (63)</td>
<td>13 (10)</td>
</tr>
<tr>
<td>Offender Change</td>
<td>2 (2)</td>
<td>35 (27)</td>
<td>63 (49)</td>
</tr>
<tr>
<td>Release Plan</td>
<td>6 (5)</td>
<td>44 (34)</td>
<td>50 (39)</td>
</tr>
<tr>
<td>Case Specific Factors</td>
<td>–</td>
<td>23 (18)</td>
<td>77 (60)</td>
</tr>
</tbody>
</table>

Note. The Case Specific Factors domain was rated as either present (mitigating) or absent (neutral).
Proportion of Domain Ratings by Risk Level.

Table 5 presents the proportion of aggravating, neutral, and mitigating ratings for each SDMF domain by applicant risk level. For Criminal and Parole History, the most common rating across risk levels was neutral, with 60% of low risk cases and 47% of moderate risk cases given a neutral rating. Furthermore, more moderate risk cases were given a rating of aggravating (42% compared to 20%) for this domain and more low risk cases were given a rating of mitigating (20% compared to 12%). However, the differences in aggravating, neutral, and mitigating ratings between low and moderate risk cases were not statistically significant, $\chi^2 (1) = 4.42, p = .109$.

The majority of the sample was also rated neutral for the Offender Self-Control domain, with 18 low risk cases and 33 moderate risk cases given a neutral rating. Due to the low number of cases in certain cells, Fisher’s Exact test was conducted in place of a chi-square test. According to Fisher’s Exact test, the proportion of ratings within the offender change domain were significantly different between low and moderate cases ($p < .01$). Moderate risk cases were more often rated neutral (77%) or aggravating (14%), while low risk cases more often received a rating of mitigating in this domain (43% compared to 9%). Few cases were rated aggravating in offender change ($n = 8$).

Similar to the previous domain, the Programming domain had two cells with less than five cases, so Fisher’s Exact test was conducted to compare the proportion of ratings between low and moderate cases. While most cases were rated as mitigating for this domain, low risk cases (77%) were more likely than moderate risk cases (67%) to earn this rating. Furthermore, a larger proportion of moderate risk cases (30% compared to 14%) were rated

---

5 Chi-Square analyses assumes (1) that individual observations are independent of one another and (2) the expected cell frequencies should not be less than 5 cases (McHugh, 2013). The first assumption was met for all Chi-Square analyses in this study. Regarding the second assumption, Fisher’s Exact Test was used in place of Chi-Square for cases where expected cell frequencies were less than 5.
### Table 5

**SDMF Domain Ratings by Applicant Risk Level**

<table>
<thead>
<tr>
<th>SDMF Domains</th>
<th>Low Risk</th>
<th>Moderate Risk</th>
<th>$\chi^2$</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$n = 35$</td>
<td>$n = 43$</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Criminal and Parole History</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>7 (20%)</td>
<td>18 (42%)</td>
<td>4.42</td>
<td>.109</td>
</tr>
<tr>
<td>Neutral</td>
<td>21 (60%)</td>
<td>20 (47%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>7 (20%)</td>
<td>5 (12%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Offender Self-Control</strong></td>
<td></td>
<td></td>
<td>11.92†</td>
<td>.002**</td>
</tr>
<tr>
<td>Aggravating</td>
<td>2 (6%)</td>
<td>6 (14%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td>18 (51%)</td>
<td>33 (77%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>15 (43%)</td>
<td>4 (9%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Programming</strong></td>
<td></td>
<td></td>
<td>3.72†</td>
<td>.174</td>
</tr>
<tr>
<td>Aggravating</td>
<td>3 (9%)</td>
<td>1 (2%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td>5 (14%)</td>
<td>13 (30%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>27 (77%)</td>
<td>29 (67%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Institutional Behaviour</strong></td>
<td></td>
<td></td>
<td>5.63†</td>
<td>.069</td>
</tr>
<tr>
<td>Aggravating</td>
<td>2 (6%)</td>
<td>3 (7%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td>25 (71%)</td>
<td>38 (88%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>8 (23%)</td>
<td>2 (5%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Offender Change</strong></td>
<td></td>
<td></td>
<td>6.25†</td>
<td>.024*</td>
</tr>
<tr>
<td>Aggravating</td>
<td>1 (3%)</td>
<td>1 (2%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td>7 (20%)</td>
<td>20 (47%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>27 (77%)</td>
<td>22 (51%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Release Plan</strong></td>
<td></td>
<td></td>
<td>8.32†</td>
<td>.013*</td>
</tr>
<tr>
<td>Aggravating</td>
<td>3 (9%)</td>
<td>2 (5%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td>9 (26%)</td>
<td>25 (58%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>23 (66%)</td>
<td>16 (37%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Case Specific Factors</strong></td>
<td></td>
<td></td>
<td>0.34</td>
<td>.561</td>
</tr>
<tr>
<td>Neutral</td>
<td>7 (20%)</td>
<td>11 (26%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>28 (80%)</td>
<td>32 (74%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* Some risk percentages may not sum to 100% due to rounding. Percentages represent the proportion of individuals given each rating by risk level. † Indicates Fisher’s Exact test was conducted in place of $\chi^2$ to account for cells with less than 5 cases. * $p<.05$, ** $p<.01$, *** $p<.001$. 
neutral for their participation in programming. Fisher’s Exact test demonstrated that these differences in ratings were not statistically significant ($p = .174$).

The Institutional Behaviour domain was most often rated as neutral for both low (71%) and moderate (88%) risk cases. Low risk cases had more ratings of mitigating (23%) in the institutional behaviour domain compared to moderate risk cases (5%). Since some cells contained less than 5 cases, Fisher’s Exact test was used once again. It was determined that the distribution of ratings by risk level was not significant in terms of the institutional behaviour of parole applicants ($p = .069$).

The proportion of aggravating, neutral, and mitigating ratings for the Offender Change domain was significantly different between low and moderate risk cases ($p < .05$). While ratings of aggravating were similarly low for both low (3%) and moderate (2%) risk cases, these cases differed most in terms of the proportion of neutral and mitigating ratings. Moderate risk cases were more often rated as neutral for offender change (47%), while low risk cases were more often deemed mitigating (77%) in this domain.

Fisher’s Exact test was additionally used to compare the proportion of ratings of the Release Plan domain, finding the proportion of aggravating, neutral, and mitigating ratings to be significantly different between low and moderate risk cases ($p < .05$). Low risk cases (66%) typically had release plans that earned them a rating of mitigating more so than moderate risk cases (37%) and moderate risk cases had more neutral ratings (58%) compared to low risk cases (26%). Low risk cases also had a slightly higher (4%) proportion of aggravating ratings compared to moderate cases.

Lastly, a 2 x 2 chi-square test of independence demonstrated that there were no significant differences in the proportion of neutral and mitigating ratings between low and
moderate risk cases in terms of Case Specific Factors, $\chi^2 (1) = 0.34, p = .561$. The majority of low risk (80%) and moderate risk (74%) cases involved either youth offender considerations, elderly parole considerations, or both. The remaining cases that were rated neutral—20% of low risk cases and 26% of moderate risk cases—had no youth or elderly considerations related to their release.

**CBPH Decisions versus SDMF-Based Decisions**

Regarding the second hypothesis, chi-square analyses revealed that parole decisions between the CBPH and the new SDMF decision were not significantly different, $\chi^2 (1) = 1.77, p = .184)$. Of the 78 cases, I granted parole to 51 (66%) individuals and denied parole to 27 (34%). The CBPH granted parole to 34 individuals (44%) and denied parole to 44 individuals (56%). As presented in Table 6, the CBPH decision makers and me both granted parole to 25 cases and both denied parole to 18 cases. However, in 26 cases where I granted parole to a particular individual, the CBPH denied parole to that same individual. Alternatively, there were 9 cases in which the CBPH granted parole, while I denied parole. While overall decisions were comparable, at the individual case level, there were marked differences.

**Table 6**

*Cross-Tabulation Chi-Square Analysis of Overall Parole Decisions*

<table>
<thead>
<tr>
<th></th>
<th>CBPH Grant</th>
<th>CBPH Deny</th>
<th>$\chi^2$</th>
<th>Cramer's V</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SDMF Grant</td>
<td>25</td>
<td>26</td>
<td>1.77</td>
<td>.15</td>
<td>.184</td>
</tr>
<tr>
<td>SDMF Deny</td>
<td>9</td>
<td>18</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Comparison by Risk Levels**

As previously stated, 45% of cases in the present sample were rated by CBPH psychologists as representing a low risk of reoffending, while the remaining 55% represented a moderate risk to reoffend. Table 7 presents the cross-tabulation of grant and denial rates between
Table 7

Cross Tabulation of New SDMF Decisions Compared to CBPH Decisions by CRA Rating (Risk Level)

<table>
<thead>
<tr>
<th>CRA Rating</th>
<th>CBPH Grant</th>
<th>CBPH Deny</th>
<th>( \chi^2 )</th>
<th>Cramer’s V</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>SDMF Grant</td>
<td>19</td>
<td>11</td>
<td>6.93(^{†})</td>
<td>.44</td>
</tr>
<tr>
<td></td>
<td>SDMF Deny</td>
<td>0</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>SDMF Grant</td>
<td>6</td>
<td>15</td>
<td>0.72</td>
<td>.13</td>
</tr>
<tr>
<td></td>
<td>SDMF Deny</td>
<td>9</td>
<td>13</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. \(^{†}\) Indicates Fisher’s Exact test was conducted to account for cells with less than 5 cases. * \( p < .05 \), ** \( p < .01 \), *** \( p < .001 \).

the CBPH and the New SDMF Decision according to risk level. For low risk cases, the New SDMF Decision and CBPH Decision were both grants in 19 cases. Alternatively, both decision methods resulted in denials in 5 low risk cases. For 11 cases in which I granted parole using the decision rules, the CBPH denied parole. Furthermore, there were no cases in which I denied parole while the CBPH granted parole. These differences in decisions between the New SDMF Decision and CBPH Decision for low risk cases were significantly different, \( \chi^2(1) = 6.93, p < .05 \).\(^6\)

Cross-tabulation between New SDMF Decisions and CBPH Decisions for moderate risk cases revealed that the CBPH and I agreed to grant parole for 6 cases and agreed on parole denial for 13 cases. However, there were 15 cases in which I granted parole while the CBPH denied parole. Furthermore, in 9 cases, the CBPH granted parole while I denied parole. These differences in grant and denial rates between the New SDMF Decisions and the CBPH Decisions were not statistically significant, \( \chi^2(1) = 0.72, p = .396 \). These results indicate that while there were differences between the CBPH Decisions and the New SDMF Decisions, these differences are only statistically significant for low risk cases.

\(^6\) This \( p \) value corresponds to Fisher’s Exact Test.
Factors Influencing Parole Decisions: Binary Logistic Regression

Developing a ‘Total Score’

The Decision Rules associated with the SDMF provide a suggested parole decision given an applicant’s CRA risk rating, the proportion of mitigating domains relative to aggravating domains, and the ratings for the domains of Institutional Behavior, Offender Change, Release Plan, and Case-Specific Factors. To convert these components into a numeric total score, I represented each component as its own variable: a variable representing CRA Risk as a numeric score (0, 1), a variable representing the proportion of mitigating and aggravating domains (0, 1, 2), and a variable representing the relevant domains (1, 2, 3). This process is exhibited in Table 8.

The first component of each Decision Rule is CRA Risk. The first two decision rules are specific to high risk cases, so they were not relevant to the current study. The remaining decision rules incorporate “if/then” statements dependent on risk ratings. Decision Rule #3 pertains to moderate risk cases while Rules #4 through #6 pertain to low risk cases. Rules #7, #8, and #9 are relevant to both low and moderate risk cases. The CRA Risk variable was created using SPSS compute statements that assigned a value of 1 if the case was rated as low risk and a value of 0 if it was rated as moderate risk.

Next, I created a variable to represent the proportion of mitigating domains relative to aggravating domains for each case. This variable, named Proportion of Ratings, was relevant to Decision Rule #3, which states that if the individual is moderate risk, mitigating domains must outweigh aggravating domains. The Proportion of Ratings variable is also relevant to Decision Rules #4 through #6, which indicate that if the individual is low risk, mitigating domains must outweigh (greater or equal to) aggravating cases in order for parole to be granted. Cases in which
Table 8  
Scoring System for the Development of a Decision Rule-Based Total Score

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Moderate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk Level Score</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Proportion of Ratings Score</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating &gt; Aggravating</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Mitigating = Aggravating</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Mitigating &lt; Aggravating</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Domain Score</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Institutional Behavior</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>3</td>
<td>n/a</td>
</tr>
<tr>
<td>Neutral</td>
<td>3</td>
<td>n/a</td>
</tr>
<tr>
<td>Aggravating</td>
<td>0</td>
<td>n/a</td>
</tr>
<tr>
<td>Offender Change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mitigating</td>
<td>3</td>
<td>3**</td>
</tr>
<tr>
<td>Neutral</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Aggravating</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Release Plan</td>
<td></td>
<td>n/a</td>
</tr>
<tr>
<td>Mitigating</td>
<td>3</td>
<td>n/a</td>
</tr>
<tr>
<td>Neutral</td>
<td>3</td>
<td>n/a</td>
</tr>
<tr>
<td>Aggravating</td>
<td>0</td>
<td>n/a</td>
</tr>
<tr>
<td>Total Score</td>
<td>Risk Level +</td>
<td>Risk Level +</td>
</tr>
<tr>
<td></td>
<td>Proportion of Ratings Score +</td>
<td>Proportion of Ratings Score +</td>
</tr>
<tr>
<td></td>
<td>Domain Score (avg)</td>
<td>Domain Score (Offender Change)</td>
</tr>
</tbody>
</table>

*Bolded values indicate scores that meet the Decision Rules for each risk-level; for low risk cases, mitigating domains must be greater than or equal to aggravating domains (score of 1 or 2) and relevant domains must be rated as either mitigating or neutral (score of 3); for moderate risk cases, mitigating domains must outweigh aggravating domains (score of 2) and Offender Change must be mitigating (score of 3). *Domain Score for low risk cases was calculated by summing the rating scores for each of Institutional Behavior, Offender Change, and Release Plan, as per Decision Rules, and dividing this score by 3 to be consistent with Domain Score for moderate risk cases. **Domain Score for moderate risk cases is equal to domain rating for Offender Change, as per Decision Rules.
the number of mitigating domains outweighed the number of aggravating domains were assigned a value of 2 using “if/then” compute statements. Similarly, cases in which mitigating and aggravating domains were equal in number were assigned a value of 1. If aggravating domains outweighed the number of mitigating domains, however, that case was assigned a value of 0. Thus, depending on the risk level of each case, an individual’s score for this variable ranged from 0 to 2.

The Proportion of Ratings variable also ensured that Decision Rules #7 and #8 were addressed. These two Rules specify that youth offender and elderly parole considerations, if mitigating, should apply for both low and moderate risk cases. Since the Case-Specific Factors domain was included in the count of mitigating domains relative to aggravating domains, the presence of youth considerations or elderly parole considerations would be reflected in the count of mitigating ratings. Thus, youth or elderly parole considerations, where relevant, had the potential to increase scores in this domain if mitigating and aggravating domains were otherwise equal in number.

The next variable, Domain Scores, was a combination of ratings for Institutional Behavior, Offender Change, and Release Plan. The Decision Rules indicate that in order to grant parole to moderate risk cases, the number of mitigating domains must outweigh that of aggravating domains and offender change must be rated as mitigating. Since these are the only specifications for moderate risk cases, if/then compute statements were used to ensure that the Domain Scores for moderate risk cases only included their score on Offender Change. Thus, if a case was moderate risk and Offender Change was mitigating, a value of 3 was assigned. However, if a moderate risk case was rated as neutral or aggravating on Offender Change, they received a score of 0. Assigning values of 0 and 3 ensured that moderate risk individuals’ scores in this domain
would be consistent with the combined scores of Institutional Behavior, Release Plan, and Offender Change for low risk individuals.

For low risk cases, there were slightly more conditions. A low risk case may be granted parole if mitigating domains are either equal to or greater than the number of aggravating domains and if the domains of Institutional Behavior, Offender Change, and Release Plan are all rated as either neutral or mitigating. A new version of each of these three variables was created to assign new values. For each of the three specified domains, if a low risk individual scored either neutral or mitigating, they received a score of 3. On the other hand, if a low risk case was rated as aggravating in any of these three domains, they received a score of 0. Since there are three domains, each case could receive a maximum score of 9. The Domain Scores variable was then created by calculating the average score across these three domains (summed scores divided by 3). This ensured that low risk cases and moderate risk cases were standardized in terms of scoring.

Thus, for low risk cases, if an applicant scored aggravating for any of the three specified domains, their score for the Domain Scores variable would be less than 3 (0, 1, 2). Low risk cases that scored aggravating on two of the three domains would receive a score of 3, making their overall domain score 1 (3/3=1). Those who scored aggravating on only one of the three domains would receive a score of 6, making their overall domain score 2 (6/3=2). Finally, low risk applicants that had no aggravating ratings across the three domains would receive a score of 9, making their overall domain score 3 (9/3=3). Thus, meeting the standards of the Decision Rules for low risk cases—Institutional Behavior, Offender Change, and Release Plan must be rated as either neutral or mitigating—would be reflected by an overall domain score of 3. Similarly, meeting the Decision Rules for moderate risk cases—Offender Change must be
mitigating—would be reflected by an overall domain score of 3. The score of 3 was chosen since there were three domains for the Domains Scores variable for low risk cases, which allowed for the average to be comparable to moderate risk cases. This coding process ensured that there was consistency across risk levels and that cut-off scores could differentiate between cases that should be granted parole and those that should not. Furthermore, it ensured that cases with different combinations of risk ratings that did not meet the Decision Rules could not be summed in a way that would be higher than those who met the decision rules.

The Total Score variable was then computed by summing the three new variables: CRA Risk, Proportion of Ratings, and Domain Scores. Total Score values could range from 0 to 6, with scores of 5 and above indicating that parole should be granted and scores less than 5 indicating that parole should be denied. Total Score values for each case were then compared to the New SDMF Decision both to ensure that the scoring and cut-offs resulted in the correct decision and to ensure that the New SDMF Decisions were correct based on the decision rules. SPSS “if/then” computations were used to create a new decision variable based off the Total Score values, where scores greater of equal to 5 received a grant and scores less than 5 received a denial. The Total Score Decision was then compared to the New SDMF Decision and confirmed 100% agreement between decisions.

Descriptive statistics were calculated for the Total Score variable across the sample. The average Total Score was 4.27 ($SD = 1.97$). The majority of the sample received a Total Score of either 5 or 6 (28.2% and 37.2%, respectively), which is supported by the fact that parole was granted to 64% of the sample. Of the cases that did not meet the cut-off for being granted parole, most received a Total Score of 2 (19.2%). Very few cases received scores of 0 (6.4%) or

7 Parole was granted to 64% of the sample as rated by me.
1 (3.8%). The Total Score was then included as a predictor variable in the following binary logistic regression to determine whether a holistic score of the SDMF could predict decisions made by the CBPH.

**Data Preparation**

**Dummy Coding.** Due to the categorical nature of the data, dummy coding was incorporated to allow the data to be properly represented. The outcome variable, CBPH Decisions, was coded so that grants were represented by a value of 1 and denials were represented by a value of 0. Furthermore, each categorical predictor (Criminal and Parole History, Self-Control, Institutional Behavior, Programming, Offender Change, Release Plan, and Case-Specific Factors) was dummy coded so that ratings of aggravating were represented numerically as 1-0 and ratings of neutral were represented as 0-1. Mitigating ratings were represented as 0-0, since mitigating was chosen as the reference category. Case-Specific Factors were rated as either neutral or mitigating, thus neutral was represented as 1 and mitigating was represented as 0. In terms of risk-level, low risk cases were represented as 0 and moderate risk cases were represented as 1.

**Assumptions Testing.** Binary logistic regression assumes certain things about the characteristics of the data in question. First, binary logistic regression assumes that the outcome variable is binary in nature (Harris, 2021). Since the outcome in the present analysis is CBPH Decisions, with only grant or deny as a response option, this assumption was met. Second, it is important for binary logistic regression that observations are independent (Harris, 2021). Since each observation in the present study represented a different applicant to the CBPH, this assumption was also met. Third, binary logistic regression assumes the presence of one or more
independent variables (Harris, 2021). Since the present study involved multiple independent variables, this assumption was not violated.

Fourth, binary logistic regression assumes no multicollinearity between predictor variables (Harris, 2021). Multicollinearity was assessed by calculating bivariate correlations between all predictor variables of interest (Criminal and Parole History, Self-Control, Institutional Behavior, Programming, Offender Change, Release Plan, Case-Specific Factors, and Total Score). Any correlations higher than +/- 0.70 indicates potential multicollinearity (Harris, 2021). The only instance of potential multicollinearity between the predictor variables occurred between the Offender Change and Total Score variables ($r = 0.81$). However, this strong relationship is to be expected, given that scores on Offender Change are influential in the Decision Rules and, therefore, are also influential in the Decision-Rule-based Total Score. Thus, despite the potential multicollinearity assumption being violated, I made the decision to keep Offender Change and Total Score in the regression analysis.

Binary logistic regression also assumes a linear relationship between any continuous predictors and the log odds (Harris, 2021). This assumption was tested in SPSS by creating a natural log variable of the continuous predictor (Total Score) and inputting the interaction between the Total Score and the natural log of the Total Score as a predictor in a binary logistic regression. If the interaction is a not significant predictor of the outcome, this implies that the independent variable is linearly related to the logit of the outcome variable and the assumption is not violated. Statistical significance of the interaction term would indicate non-linearity between the variable and the logit, violating this assumption (Know-how, 2021). In the present study, the interaction term between the Total Score and the log odds was not statistically significant ($p = .998$), indicating this assumption was not violated.
The sixth and final assumption of binary logistic regression relevant to the present study is the absence of outliers (Stoltzfus, 2011). The majority of the predictor variables in the present analyses were categorical, however, the continuous predictor, Total Score, was still assessed for outliers in SPSS using standardized residuals. Since no cases had z-scores above the critical value of 3.3 as suggested by Tabachnick and Fidell (2013), no cases were considered extreme outliers and this assumption was not violated.

**Binary Logistic Regression**

Binary logistic regression was employed to assess whether the SDMF domains and the Framework as a whole predict CBPH Decisions. As previously mentioned, the binary outcome variable in this analysis was CBPH Decisions, with grants represented as 1 and denials represented as 0. A total of two models were tested using binary logistic regression to address the final two hypotheses. The first model included CRA Risk Rating and the seven SDMF domains (Criminal and Parole History, Self-Control, Institutional Behavior, Programming, Offender Change, Release Plan, and Case-Specific Factors) as predictors. The fourth hypothesis posited that the SDMF would moderately predict CBPH Decisions. Since the process of the SDMF includes considering the CRA ratings and the ratings of each of the seven domains, the first model represents the contribution of the entire Framework as a whole to the final parole decisions. The second model included the same predictors as the first model, with the addition of the newly created Total Score as a predictor. Since the Total Score is a numeric representation of the Decision Rules, this model also assessed the contribution of the Framework as a whole. The second model, however, represents a more numeric analysis of the impact of the SDMF on release decisions, given that the Decision Rules are now part of the SDMF process.
The first model, comprised of CRA rating and the seven SDMF domains, significantly predicted CBPH Decisions, $\chi^2(14) = 40.53, p < .001$, and accounted for approximately 40.5% of the variance in CBPH release decisions. As displayed in Table 9, Model 1 revealed that Programming, Release Plan, and CRA Rating were predictive of CBPH parole decisions. Ratings of neutral in the Programming domain was associated with a 0.92 decrease in the odds of being granted parole compared to those who were rated mitigating ($\text{Exp}(B) = 0.082, p < .05, 95\% \text{ CI } [.010, .666]$). Similarly, Release Plan overall was significantly predictive of release decision ($p < .05$). Surprisingly, ratings of neutral for the Release Plan domain were associated with a 13.195 increase in the odds of being granted parole compared to ratings of mitigating ($\text{Exp}(B) = 13.195, p < .01, 95\% \text{ CI } [2.080, 83.705]$). Lastly, CRA Rating was predictive of parole grants, with moderate risk cases being associated with a 0.903 decrease in the odds of being granted parole compared to low risk cases ($\text{Exp}(B) = 0.097, p < .01, 95\% \text{ CI } [.018, .520]$).

The second model (Table 10) was also significant, $\chi^2(15) = 42.15, p < .001$, accounting for approximately 41.7% of the variance in CBPH release decisions. However, in this model, which included the Total Score representing the Decision Rules, only Release Plan was individually predictive of CBPH release decisions ($p < .05$). Similar to the first model, ratings of neutral for the Release Plan domain were associated with a 12.881 increase in the odds of being granted parole compared to ratings of mitigating ($\text{Exp}(B) = 12.881, p < .01, 95\% \text{ CI } [2.003, 82.811]$). The Total Score was not significantly predictive of CBPH grants, indicating that the inclusion of Decision Rules was not individually influential of parole decisions.

Lastly, Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) statistics were calculated for both the regression models and the individual domains to determine the
### Table 9

*Binary Logistic Regression Examining the Prediction of Parole Grants Using the SDMF*

<table>
<thead>
<tr>
<th>Domain</th>
<th>B</th>
<th>Exp(B) [95% CI]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Criminal and Parole History</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>1.846</td>
<td>6.336 [.830, 48.54]</td>
</tr>
<tr>
<td>Neutral</td>
<td>1.164</td>
<td>3.202 [.530, 19.30]</td>
</tr>
<tr>
<td><strong>Self-Control</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>-19.765</td>
<td>.000 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>-1.237</td>
<td>.290 [.052, 1.630]</td>
</tr>
<tr>
<td><strong>Programming</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>-59.263</td>
<td>.000 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>-2.496*</td>
<td>.082 [.010, .666]</td>
</tr>
<tr>
<td><strong>Institutional Behavior</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>-41.459</td>
<td>.000 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>.966</td>
<td>2.626 [.328, 21.035]</td>
</tr>
<tr>
<td><strong>Offender Change</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>-20.144</td>
<td>.000 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>.969</td>
<td>2.634 [.461, 15.038]</td>
</tr>
<tr>
<td><strong>Release Plan</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>40.393</td>
<td>3.487E+17 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>2.580**</td>
<td>13.195 [2.080, 83.705]</td>
</tr>
<tr>
<td><strong>Case-Specific Factors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td>.811</td>
<td>2.250 [.530, 9.550]</td>
</tr>
<tr>
<td>CRA Rating</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>-2.329**</td>
<td>0.097 [.018, .520]</td>
</tr>
</tbody>
</table>

*Note. * p<.05, ** p<.01, ***p<.001. Ratings of “Mitigating” were input as the reference category for each SDMF domain included as a predictor. The rating of “Low” was input as the reference category for CRA Rating.*
Table 10

*Binary Logistic Regression Examining the Prediction of Parole Grants Using the SDMF and SDMF Decision Rules (Total Score)*

<table>
<thead>
<tr>
<th>Domain</th>
<th>B</th>
<th>Exp(B) [95% CI]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criminal and Parole History</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>1.933</td>
<td>6.909 [.861, 55.457]</td>
</tr>
<tr>
<td>Neutral</td>
<td>1.017</td>
<td>2.766 [.452, 16.940]</td>
</tr>
<tr>
<td>Self-Control</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>-18.739</td>
<td>.000 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>-1.134</td>
<td>.322 [.056, 1.843]</td>
</tr>
<tr>
<td>Programming</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>-60.526</td>
<td>.000 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>-2.102</td>
<td>.122 [.012, 1.206]</td>
</tr>
<tr>
<td>Institutional Behavior</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>-41.704</td>
<td>.000 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>.913</td>
<td>2.491 [.299, 20.734]</td>
</tr>
<tr>
<td>Offender Change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>-18.211</td>
<td>.000 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>3.794</td>
<td>44.446 [.078, 25193.001]</td>
</tr>
<tr>
<td>Release Plan*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggravating</td>
<td>40.950</td>
<td>6.085E+17 [.000, –]</td>
</tr>
<tr>
<td>Neutral</td>
<td>2.556**</td>
<td>12.881 [2.003, 82.811]</td>
</tr>
<tr>
<td>Case-Specific Factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td>.950</td>
<td>2.585 [.589, 11.344]</td>
</tr>
<tr>
<td>CRA Rating</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>-1.093</td>
<td>.335 [.021, 5.278]</td>
</tr>
<tr>
<td>Total Score</td>
<td>1.004</td>
<td>2.729 [.359, 20.762]</td>
</tr>
</tbody>
</table>

*Note.* *p* < .05, **p** < .01, ***p*** < .001. Ratings of “Mitigating” were input as the reference category for each SDMF domain included as a predictor. The rating of “Low” was input as the reference category for CRA Rating.
extent of their ability to predict parole grants.\(^8\) The AUCs for the regression models were calculated by creating a new variable based on the predicted probabilities from each regression analysis. This new variable was then input as the test variable for the AUC calculation in SPSS. The first model, which did not include Total Score, was significantly predictive of CBPH Decisions, with an AUC value of .877, indicating a large effect.\(^9\) The second model, which did include Total Score, was also significant (AUC = .880), once again indicating that the SDMF (including the Decision Rules) as a whole had a large effect on CBPH decisions. Furthermore, AUCs were calculated to assess the predictive ability of each individual domain and Total Score, presented in Table 11. ROC Analysis indicated that Self-Control (AUC = .636), Programming (AUC = .634) had small effects on CBPH Decision. In particular, Self-Control was significantly predictive of parole grants. The AUC values for the remaining domains, including Criminal and Parole History (AUC = .432), Release Plan (AUC = .491), and Case-Specific Factors (AUC = .496), demonstrated predictive abilities no better than chance.

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\(^8\) Note, AUC values were used here to predict parole grants, rather than release outcome.

\(^9\) According to Rice and Harris (2005), AUC values about .539 suggest a small effect, values above .639 suggest a moderate effect, and values above .714 suggest a large effect.
Table 11
Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) Values for the SDMF in Predicting Parole Grants by the CBPH

<table>
<thead>
<tr>
<th>SDMF Component</th>
<th>AUC [95% CI]</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1 (SDMF)</td>
<td>.877 [.803, .952]</td>
<td>.001***</td>
</tr>
<tr>
<td>Model 2 (SDMF + Total Score)</td>
<td>.880 [.806, .954]</td>
<td>.001***</td>
</tr>
<tr>
<td>Criminal and Parole History</td>
<td>.432 [.303, .560]</td>
<td>.304</td>
</tr>
<tr>
<td>Self-Control</td>
<td>.636 [.513, .760]</td>
<td>.040*</td>
</tr>
<tr>
<td>Programming</td>
<td>.626 [.503, .749]</td>
<td>.057</td>
</tr>
<tr>
<td>Institutional Behavior</td>
<td>.565 [.438, .692]</td>
<td>.326</td>
</tr>
<tr>
<td>Offender Change</td>
<td>.525 [.396, .654]</td>
<td>.709</td>
</tr>
<tr>
<td>Release Plan</td>
<td>.491 [.362, .620]</td>
<td>.892</td>
</tr>
<tr>
<td>Case-Specific Factors</td>
<td>.496 [.366, .626]</td>
<td>.952</td>
</tr>
<tr>
<td>CRA Rating</td>
<td>.598 [.470, .725]</td>
<td>.141</td>
</tr>
<tr>
<td>Total Score</td>
<td>.634 [.507, .761]</td>
<td>.043*</td>
</tr>
</tbody>
</table>

Note. * p<.05, ** p<.01, ***p<.001.

Discussion

The present study offered insight into the parole decisions being made in California since the implementation of the SDMF. California has observed changes in decision making since the SDMF was implemented in 2018. Furthermore, the fidelity of CBPH members to the SDMF was not found to be concerning, as differences between CBPH members’ decisions and decisions made by faithfully following the SDMF did not significantly differ. Holistically, the SDMF can predict the release decisions of the CBPH, indicating that the Framework may have been influential in Commissioners’ decisions. However, the domains that were individually predictive of the CBPH decisions were not necessarily the most important factors to consider in the final parole decisions, according to the Decision Rules. Thus, the present study suggests that there may still be a gap between how CBPH decision makers are using the SDMF to make parole decisions and how they should actually be using the SDMF. Regardless, the results of this study indicate that the SDMF, at least to some extent, has led to changes in decision making in California.
Overview of Study 1: SDMF Implementation in California

It was expected that grant and denial rates following the implementation of the SDMF in California would differ from those prior to implementation. However, this hypothesis was not fully supported. While the proportion of overall grant and denial rates assigned by the CBPH did not significantly differ between pre- and post-SDMF implementation, denial rates individually showed a significant change between 2018 and 2020 with respect to the risk-level of applicants. Denial rates for low risk offenders decreased by 4% between 2018 and 2020, indicating a positive shift toward the release of individuals who appear most likely to succeed upon release to the community. For high risk applicants on the other hand, there was a 4% increase in denial rates, indicating more strict considerations for those posing a higher risk to the public. These statistically significant changes in parole denials indicate slight improvements in decision making in California.

Given the recommendations of the SDMF and empirical evidence related to low risk individuals, low risk cases should typically be granted parole unless there is sufficient evidence to suggest that they would fail in the community, as per CBPH policy of presumptive release (Shaffer, 2021). The results of the comparison between pre- and post-SDMF implementation demonstrate—at least to some degree—that this recommendation has been put into practice in California, given the decrease in low risk denials. Alternatively, the SDMF recommends that high risk cases should not be granted parole unless compelling reasons have been presented (e.g., evidence of increased motivation, good parole plan, strong performance in programming and change, etc.; Serin, 2019; Wardrop et al., 2019). Thus, an increase in denials for high risk cases is not unexpected given the recent implementation of the SDMF.
The lack of significant change in denial rates for moderate risk applicants since the implementation of the SDMF was also unsurprising, as Commissioners are typically more risk averse given the consequences of a false positive (Serin et al., 2020). Rather than focusing solely on risk ratings, moderate risk cases require decision makers to more carefully consider the risk factors and circumstances of each individual to determine whether they possess the critical skills and support needed to succeed in the community. Furthermore, decision makers must determine whether these skills and support outweigh the individual’s perceived risk of reoffending. However, it would have made sense to observe an increase in grant rates for moderate risk cases, given that the SDMF would have discouraged Commissioners from placing undue weight on applicants’ risk level when making parole decisions. This lack of change in decision rates for moderate risk cases suggests that there is still room for improvement for decision makers in California, as does the apparent slippage in decisions at the individual case level.

Overview of Study 2: CBPH Decisions and the SDMF

Contrary to the second hypothesis, the CBPH Decisions did not significantly differ from New SDMF Decisions. While these findings do not necessarily prove that the CBPH is accurately using the SDMF in their decision-making processes, the results do at least confirm that they are not making decisions that are concerningly different from decisions made using the SDMF. Significant differences between the two decision making parties would have indicated that the CBPH Commissioners were potentially making incorrect decisions that were not informed by empirical evidence (e.g., domain-relevant information, which domains are more related to risk than others, etc.). The decisions I made while strictly following the SDMF differed from the CBPH decisions in 37 cases: 26 cases where I granted parole and the CBPH denied parole and 9 cases in which I denied parole and the CBPH granted parole. Thus, while the
differences between decision rates in the present study were not significant, there are still
concerning discrepancies between the decisions being made in California and what the decision
should have been if following the SDMF. These discrepancies, however, may improve with the
continued implementation and use of the Framework over time. These findings suggest a review
of these cases may prove informative for CBPH.

Similarly, the results of this study were also contrary to the third hypothesis, which
predicted that the differences between the New SDMF Decisions and the CBPH Decisions would
be most notable for moderate risk cases. Unexpectedly, these differences were only significant
for low risk cases. For low risk cases, the CBPH denied parole to 11 cases that would have been
granted using the SDMF. As previously mentioned, the SDMF and policy recommends that low
risk case should presumptively be granted parole unless there is sufficient evidence to suggest
that the individual will be unsuccessful in the community. That is, there is a nexus between a
domain and current dangerousness. In terms of the SDMF, this “evidence” is reflected in the
Decision Rules. According to the Decision Rules, low risk cases should be denied parole if the
number of aggravating domains outweighs the number of mitigating domains and if Offender
Change, Institutional Behavior, and Release Plan are aggravating. However, since the Decision
Rules have been recently created and are not explicitly provided to the CBPH, it makes sense
that Commissioners may be denying low risk cases based upon other factors—whether they are
factors relevant to the Framework or not.\footnote{As previously mentioned, the policy and legal statutes that the Decision Rules are derived from are not new, but the Rules themselves have not been dispersed among CBPH members.} Thus, with continued use of and training with the
SDMF in California, these differences across risk levels may become less common.

The lack of significant differences between SDMF-based and CBPH decisions for
moderate risk cases, on the other hand, was surprising. Specifically, it was surprising that
disagreement on 24 out of 43 moderate risk cases did not reach statistical significance. The lack of significance despite the differences in decisions between myself and the CBPH may have been the result of the small sample size or the fact that there was still agreement for 19 cases. Regardless of significance, these differences in decisions highlight a concerning lack of consistency in decision making for individuals of this risk level. Given that moderate risk cases have more strict requirements in order to be granted parole using the SDMF (e.g., mitigating domains must outweigh aggravating domains and Offender Change must be mitigating), it is difficult to determine whether Commissioners were correctly identifying which domains are influential for moderate risk cases or whether they are focusing on other aggravating factors within SDMF (e.g., Criminal History, Institutional Behaviour, etc.) or even extralegal factors (e.g., victim comments) to decide to deny parole. Regardless, these findings provide evidence for a lack of consistency in the area of parole decision making, that will hopefully continue to be reduced with continued incorporation of the SDMF.

Predicting Parole Decisions

The SDMF as a whole, both with and without the inclusion of the Decision Rules (Total Score) was predictive of CBPH parole decisions, as expected. The SDMF demonstrated large effects on CBPH Decisions, as opposed to the moderate effect that was predicted. These findings suggest that the CBPH was at least somewhat incorporating the Framework when making decisions. Unexpectedly, however, Offender Change did not significantly predict CBPH Decisions, suggesting that Commissioners did not place much importance upon this risk factor when deciding whether to release individuals in this sample. Rather, Release Plan (both models), Programming (Model 1), and Moderate risk (Model 1) were individually predictive of CBPH Decisions. Moderate risk ratings being predictive of Commissioner decisions and decreasing the
odds of being granted parole is unsurprising, given that it was expected that Commissioners would be risk averse. Furthermore, while participation in programming was not a major component of the Decision Rules, correctional programming can still be influential in the likelihood that an individual will reoffend (Andrews & Bonta, 2010). This, however, may reflect the state of programming in CDCR in terms options and dosage, such that Commissioners’ expectations are low regarding efficacy and their impact of offender change. Thus, the finding that being rated neutral for the Programming domain was associated with a decrease in the likelihood of being granted parole compared to being rated mitigating. Those who actively participated in risk-and need-relevant programming would have a greater likelihood of succeeding in the community (Andrews & Bonta, 2010). This finding, however, was only true for a model in which Total Score was not involved. Once the Decision Rules were represented in the regression model (by the Total Score), Programming was no longer indicative of CBPH decisions. Thus, in the case of the present study, Commissioners seemed to place more weight on SDMF domains different from the Decision Rules, which is also demonstrated by the findings related to Release Plan.

The Release Plan domain was predictive of CBPH grants in both models. However, the impact of Release Plan ratings on the likelihood of parole grants was unexpected. In the present sample, being rated neutral on Release Plan increased the odds of being granted parole compared to being rated mitigating. Logically, one would expect that ratings of mitigating, which indicate decreased risk of recidivism, would be associated with greater odds of being granted parole. However, since the outcome variable was the decisions made by CBPH Commissioners, there may have been many cases in which they granted parole to more cases that I had rated neutral for Release Plan or even denied parole to cases that I had rated mitigating. It should be noted that
CDCR provides stable accommodation (e.g., halfway house) for all Lifers to facilitate community re-entry given their period of long incarceration. It is possible that since CBPH members were less critical of parole applicants’ plans for release, given that they knew these individuals would be provided with stable housing regardless of the rest of their plans.

Release Plan is an important factor in determining whether an individual is likely to succeed in the community (Dickson & Polaschek, 2014; Ullrich & Coid, 2011). Those with strong plans for release that involve positive social support, employment, housing, and intentions for community programming and practicing risk management skills are less likely to reoffend compared to those with limited release plans (Maruna, 2010). It is possible that the CBPH did focus on Release Plans in their decisions but may have been rating the plans of applicants less critically than I did. If that was the case, it would be expected that individual CBPH ratings in this domain would be rated mitigating. Or, as mentioned previously, Commissioners may have considered the cases which I rated mitigating to have parole plans that were more problematic than they were. Either way, these findings provide evidence that while the SDMF was predictive of CBPH members’ decisions, board members had different ideas of what constitutes aggravating, neutral, and mitigating ratings in each domain and of which domains should be the focal points in the determination of a final parole decision. Optimistically, these differences should become less common as the SDMF continues to be used across California. As Commissioners and board members continue to incorporate the SDMF in their decision making, it can be expected that future studies of the fidelity and impact of the SDMF will find improved decisional accuracy and decisional consistency with the Framework.
The Influence of the SDMF in California

With the SDMF now implemented in California, it would be expected that the state will continue to see improved accuracy in decision making and the outcomes of these release decisions. As previously mentioned, states in which the SDMF has already been implemented have observed improved decision making and better identification of those who are likely to reoffend versus those who are not (Gobeil & Serin, 2009; Wardrop et al., 2019). California should observe similar benefits with the continued use of the SDMF. In fact, the benefits of the implementation of the SDMF in California have already been observed. The CBPH has reported improvements in the conciseness of reports, the length of parole hearings, and decisions themselves (Kusaj, 2020). Furthermore, with California’s recent increase in the number of individuals on parole, the improvements that the SDMF will provide in decision making accuracy should be reflected in a decrease in recidivism for individuals on parole. For example, in 2019 in the state of Connecticut—which has used the SDMF since 2012—only 8.2% of those exiting parole committed a new offense (3.7%) or revocation (4.5%), while 42% successfully completed parole (Oudekerk & Kaeble, 2021). Furthermore, 59% of individuals exiting parole in Kansas, another state in which the SDMF has been implemented, successfully completed parole without a new offense or revocation (Oudekerk & Kaeble, 2021). Continued use of the SDMF and subsequent improvements in parole decision making in California has the potential to lead to similar results.\(^\text{11}\)

Better parole decision making in California would also lead to improvements in the state’s large incarceration rate relative to the rest of the country. The SDMF has already increased the number of low risk individuals that are re-entering the community, reducing the

\(^{11}\) Parole outcome data was not reported for the state of California.
financial strain of housing individuals in correctional institutions and reducing the structural strain caused by intense overpopulation in these institutions across North America (Serin, et al., 2020; Heard, 2020). Should the SDMF continued to be used and suitable individual continue to be released, these strains should continually decrease. Given that individuals are typically less likely to reoffend if released on community supervision compared to those continuing their sentence in correctional institutions (Jolliffe & Hedderman, 2015; Petrich et al., 2021), recidivism rates should also continually decrease with more individuals on parole in California. In addition, the use of a more structured decision-making process should solve many of the aforementioned issues in parole decision making and provide paroling authorities with a best-practice model by which to explain their decisions.

**Implications for Decision Making, Parole, and Corrections**

Paroling authorities have typically been criticized for inaccurate decisions, decisions that lack empirical support, and a lack of both transparency and structure in their decision-making processes. The SDMF has been shown to improve decisional accuracy (Wardrop et al., 2019). In the present study, California parole board members made parole decisions that were not significantly different from those made by explicitly following the SDMF, indicating improvements in decisional accuracy. Correct parole decisions have the potential to increase public safety and improve the public’s trust in decision makers. Making accurate decisions and releasing individuals who are prepared and well-suited for crime-free lives in the community ensures that less members of the public are victimized by individuals who would have otherwise been incapacitated. Thus, accurate release decisions have the potential to protect the public and reduce the criminal justice costs related to additional prosecutions and victim compensation.
Furthermore, given the attention that serious parole failures receive in the media and by the public, improved decisional accuracy should see fewer of these cases, thus improving public faith regarding the decision-making abilities of releasing authorities. If decision makers are consistently releasing individuals who do not reoffend, the public will trust that decision makers are competent completing a very challenging task. It should be noted that quality of parole supervision also has an impact on client outcome (Bonta et al., 2008; Chadwick et al., 2015). But this study did not examine client outcome. Nonetheless, any catastrophic parole failures that do come to light should be easily defended by following the SDMF. Any decisions to release an individual could be defended by each domain rating and the relevant empirical evidence behind each domain.

As mentioned, paroling authorities have historically relied upon criminal histories and individual characteristics that are not actually influential on recidivism when choosing whether to release or deny release to applicants (Serin et al., in press; Serin et al., 2020). Factors such as mental health (Bonta et al., 2014) and empathy (Gottschall et al., 2014) have been used as reason to deny parole, despite the lack of empirical evidence to suggest these factors influence recidivism. Furthermore, the use of decisional shortcuts by decision makers to come to parole decisions faster has also been a criticism, as this practice invites room for irrelevant factors and implicit bias to influence final parole decisions (Gobeil & Serin, 2009). The implementation of the SDMF, which is entirely based upon factors that have been empirically proven to influence an individual’s likelihood of reoffending, has the potential to solve this issue in relevant jurisdictions. While the results of this study suggest that decision makers in California may still place undue weight on certain SDMF domains over others in their determination of a parole decision, these domains are at least relevant to recidivism and outcomes in the community.
Continued use of the Framework may see these issues become less prevalent. Reliance on these empirically supported domains and the policy and legal statutes relevant to the newly implemented Decision Rules, in turn, addresses the issue of lack of transparency.

Both the public and individuals applying for parole have criticized paroling authorities for their lack of transparency regarding how and why certain parole decisions were made (Serin et al., 2020). As previously mentioned, parole failures create questions from the public as to why these individuals were released (Serin et al., 2020). On the other hand, decisions to deny parole may bring to light questions from the applicants to whom parole was denied, who may have expected to be released based upon their efforts to improve their risk ratings (Schwartzapfel, 2015). Both of these circumstances require paroling authorities to defend their decisions. If decision makers are relying on irrelevant factors, or ignoring relevant factors, and have no decision model to follow, their decisions cannot be easily defended in the event of an unexpected negative community incident.

Since the SDMF is grounded in empirical evidence and can easily demonstrate the process through which a decision is made, decision making becomes transparent and easily defensible. For example, while the present study had only moderate inter-rater reliability, both raters could review, case-by-case, exactly why each domain rating was given and use the Decision Rules (relevant policy and legal statutes) to defend each parole decision made. There may be slight differences between decision makers as to what the “correct” decision should be, but the SDMF ensures that regardless of the decision to grant or deny parole, your decision can be explained and defended by empirical evidence to the public, parole applicants, and legislators. Furthermore, the structure provided by the SDMF limits variability in decisions.
A decision-making guide that lacks structure would create opportunity for irrelevant information to be included in the decision-making process and for decision makers to ignore information that may be critical in determining an individual’s true likelihood of success in the community (Serin et al., 2020). While the SDMF incorporates some elements of structured professional judgement to ensure that each parole applicant and their case-specific information are treated as unique individuals, these elements of SPJ do not outweigh the overall structure of the guide. That is, decision makers must still consider the information relevant to each domain, rate each domain, and then make an informed decision. The new Decision Rules provide additional structure to the determination of the final decision by indicating specific conditions which must be met in order for parole to be granted. While CBPH decision makers do not have access to the explicit rules, they do have access to the relevant policy, legal, and empirical information that inform decision makers of which factors are the most important to consider in release decisions. If the decision maker chooses to over-ride the Rules (i.e., policies, legislature, etc.), then a compelling rationale should be provided. Research in risk assessment indicates that over- and under-rides degrade accuracy (Cohen et al., 2016). Thus, individual differences between decision makers, the influence of irrelevant information, and the influence of overly focusing on certain domains are limited through the use of the SDMF. Overall, the SDMF can address the aforementioned issues related to parole decision making. Therefore, fidelity to the Framework is important if trying to improve decision making.

The present study investigated whether the implementation of the SDMF in California has led to changes in decision making and whether the decisions being made by CBPH members were consistent with what the SDMF-recommended decisions. While there was evidence of changes in decision making between pre- and post-implementation and a lack of significant
differences between the CBPH decisions and SDMF-based decisions, there is room for improvement to ensure that at-risk individuals are not being released and that the suitable individuals are not being continually incarcerated. Overall, the results of this study indicate that decision making in California is changing and future studies can improve upon the present study to explore the extent of these changes more in-depth.

**Strengths, Limitations, and Future Considerations**

The current research provided valuable information regarding the state of parole decision making in California. The study benefited from extensive detail in its materials and design. The CRA files provided by the CBPH were incredibly detailed and allowed for more accurate ratings of each SDMF domain. These reports by CBPH psychologists were an average of 15 pages long and included discussions of the most relevant factors that contributed to each individual’s risk, making it easy to identify whether any problematic factors were present. Furthermore, both raters benefited from completed in-depth training in the use of the SDMF and Decision Rules, ensuring that our SDMF decisions were as accurate as possible. This detailed training and the case study practice incorporated into the training process instill confidence in the New SDMF Decisions being representative of the most consistent decision one should come to if correctly following the SDMF. While these are strengths of the present study, there were also certain limitations that could be improved upon in future research related to the SDMF and parole decision making.

The present study was partly limited by its sample. While 78 cases allowed for adequate power (.76), a larger sample may have allowed for a more in-depth examination of differences in parole decisions from a more representative proportion of parole applicants. As previously mentioned, there were no high risk cases in the present sample. While high risk cases must meet very strict standards for release compared to low and moderate risk cases (e.g., all domains must
be rated mitigating, etc.), it would be both interesting and beneficial to investigate which
domains are often rated aggravating for this specific subpopulation. Such research could further
enlighten what we know about individuals classified as high risk and long-term incarceration.

Relatedly, to date the SDMF has only been implemented in California for use with Long-Term
Offenders (Lifers). While this population is unique in their risk factors and characteristics
relevant to recidivism, the narrow focus on a single population may limit the generalizability of
this study to individuals who are eligible for parole after a shorter period of time. Further
research would benefit from expanding the application of the SDMF to retrospective cases
serving lesser sentences to investigate whether there are any differences in decision making.

Furthermore, there were very few ratings of aggravating throughout the sample and
across domains. This pattern could be specific to this particular set of parole applicants. If so, a
larger sample may have provided more individuals with problematic behaviors, attitudes, and
motivations, although they may not apply for parole. However, given that the sample consisted
solely of indeterminately sentenced Lifers—most of whom had already spent more than two
decades incarcerated—it is unsurprising that ratings of aggravating were rare. In preparation for
parole hearings throughout their time in prison, most applicants became involved in
programming to address their risks and needs, became less involved in institutional misconducts,
and demonstrated reduced impulsivity and substance use issues. Thus, while these domains may
have been considered aggravating in their first few years of their sentence, time and intervention
would have decreased their risk on certain domains to neutral or even mitigating. A larger
sample with a wide range of criminal histories and personal characteristics associated with
change may see different patterns in terms of domain ratings.
Relatedly, the sample size limited the extent of statistical analyses that could have been conducted. The previously mentioned low number of aggravating ratings across domains did not allow for a concise understanding of the influence that aggravating ratings may have had on parole decisions, especially for the domains that were incorporated in the Decision Rules. It was surprising that none of the domains rated aggravating were associated with a decrease in the odds of being granted parole. One would expect, given that most Decision Rules indicate that ratings of aggravating in Offender Change, Institutional Behavior (specific to low-risk cases), and Release Plan (specific to low-risk cases) warrant parole denial, that aggravating ratings in these domains would decrease the likelihood of being granted parole. Indeed, Wardrop et al. (2019) found Offender Change to be the most robust predictor of both the parole decision and post-release outcome. This lack of statistical significance may have been due to the low number of aggravating ratings, which could change in future studies. However, these results could also be accounted for given that Commissioners were not following the Decision Rules and that they may have had different individual domain ratings.

Another limitation of the present sample was related to timing. Firstly, the sample was a random collection of cases eligible for a parole hearing in the month of June 2021, specifically. The limited time period from which this sample was collected is a strength in that it controlled for any policy changes or timely events that may have influenced decision making. However, it only represents a very small number of cases considered annually by that the CBPH. Despite the fact that the SDMF makes decision making quicker and more structured, busy periods of time could still tempt decision makers to use decisional short cuts to save time. A sample spanning a larger period of time would ensure that such time-related extraneous factors are less influential.
Secondly, the short timespan from which the present sample was drawn did not allow for the examination of outcome data. It would be beneficial to investigate not only whether the CBPH is making correct decisions according to the SDMF, but whether those decisions correctly released individuals who would not reoffend and correctly denied release to those who would reoffend. Regarding success rates, Kusaj (2020) reported very low base rates for any failure (i.e., 3.2 %) for the Lifer population who are released. Previous studies of the SDMF in other states found preliminary evidence of the SDMF’s ability to differentiate between recidivists and non-recidivists in non-Life cases (Wardrop et al., 2019). Extending research into the efficacy of the SDMF in other jurisdictions is a goal of a recently convened Community of Practice (R. C. Serin, personal communication, August 12, 2022). Future research involving the SDMF in California and other jurisdictions should determine if these findings are applicable elsewhere.

Furthermore, it is possible that some degree of subjectivity may have influenced the findings of the present study. While the SDMF is a structured guide, it still leaves room for professional discretion, specifically in the ratings of each domain and a final decision. For each domain, the relevant case information was considered and the individual received a rating of either mitigating, neutral, or aggravating. Extensive examples of cases that embody each of these rating options and individual characteristics or behaviors that warrant each rating provide helpful insight regarding the most appropriate rating to give each case. However, individual differences between raters can impact whether a specific domain is rated as aggravating, neutral, or mitigating.

For example, substance abuse is a factor to consider within the domain of Self-Control. Substance use or abuse has the potential to increase the likelihood of recidivism (Håkansson, & Berglund, 2012). For some decision makers, a history of intense substance abuse and substance-
related incidents of institutional misconduct would warrant a rating of aggravating in this domain. However, based on the Framework and relevant training, if the individual has remained substance free for the last 5 years of their incarceration, discussed their motivation to remain substance-free, and participated in programming addressing this risk factor, substance abuse is no longer a currently relevant risk factor on the CRA and should not be rated as aggravating. It is possible that Commissioners would consider any substance abuse-related institutional misconduct or histories as warranting an aggravating rating (this could be relevant to both the Institutional Behavior and Self-Control domains). Thus, differences between decision makers and raters—as observed in the analysis of inter-rater reliability and in the small, yet significant effect of Self-Control found in the present study—may be attributed to different individual opinions on what warrants a particular domain rating. As previously discussed, the extent of training and resources for the use of the SDMF as well as the detailed CRA files supplied by the CDCR are strengths of the present study. Such strengths can be used to mitigate such differences between decision makers.

Similarly, since the CDCR and CBPH do not explicitly follow the SDMF, nor do they organize reports according to the relevant domains, it is unknown how this may have impacted the archival research. If the reports followed the SDMF, then a comparison between CRA ratings and the CBPH Commissioner ratings could better examine fidelity considerations at the Commissioner level and at the aggregate level for the CBPH. Future research into the SDMF, whether in California or in additional jurisdictions, would benefit from larger more representative samples, extensive training for both researchers and decision makers, and more in-depth information regarding how paroling authorities are making their decisions using the SDMF, perhaps via online surveys or focus groups.
Lastly, it is important to note that a major limitation of the present study and of any research involving retrospective decision making is the lack of pressure actually faced by parole decision makers in the field. Myself as a researcher must acknowledge that I did not face the same high-stakes decisions that must be made by individuals making parole decisions for actual individuals. Parole decisions have implications on both applicants and the public. As previously mentioned, denying an individual who has the potential to be successful in the community can negatively impact their future reintegration and outcomes in life. Alternatively, releasing an individual who is not well suited for a crime-free life in the community puts the public at undue risk. Paroling authorities are continually faced with these high-pressure and high-stakes decisions, which have the potential to influence who they are willing to “risk” releasing. Such an influence cannot be fully replicated in research. Thus, it is important to be aware that differences in decisions between the CBPH and myself—or other paroling authorities and other researchers—are to be expected.

**Conclusion**

Despite the limitations of the present study, the SDMF has been proven to be a beneficial guide for releasing authorities in a variety of jurisdictions in the U.S. and federally in Canada (Wardrop et al., 2019; Serin et al., 2016). The Framework offers a structured, evidence-based guide through the most influential factors to consider when making release decisions (Serin et al., in press), while allowing for structured professional judgement to account for case-specific discrepancies and considerations that actuarial tools do not (Serin et al., 2016). Since the implementation of the SDMF, California has observed a decrease in the length of parole hearings, increase in grant rates, and improvements in decisional accuracy (Kusaj, 2020). The present study confirmed that the parole decisions of Commissioners in California are not
significantly different from decisions made by explicitly following the SDMF. Furthermore, the SDMF was able to predict CBPH members’ decisions. Regardless of whether these Commissioners based their decisions on the most relevant domains according to the Decision Rules, it appears that the guide was influential to final parole decisions. Overall, the SDMF has the potential to continue to improve release decisions in California and improve the outcomes of individuals on parole in jurisdictions in which the SDMF has been implemented.
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