SHINING LIGHT ON THE DARK FIGURE OF SEXUAL RECIDIVISM

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SVP Commitment Criteria

1. Qualifying sexual crime(s)
2. Mental condition that results in serious difficulty controlling sexual behavior ("SVP mental disorder")
3. **SVP mental disorders makes the individual likely to engage in dangerous sexual behavior**

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Disconnect between law and science

Actual ≠ Detected

- Statutory definition of sexual dangerousness not dependent upon whether sexual recidivism is detected officially
- Sexual recidivism actuarial measures account for legally detected sexual reoffense

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Attempts to Address Legal Conundrum

- Self-report of undetected sexual crimes by persons previously detected of sexual crimes ("PDP")
- Lifetime sexual reoffense rates
- Statistical modeling

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Self-Report Study

- Abel et al. (1987)
  - 561 PDP referred for evaluation and treatment is USA under Federal waiver from reporting child abuse
  - Mean number arrests to self-report of sexual crimes
    - violent sex crimes = 1:30
    - noncontact sexual crimes 1:150
- Limitations of data
  - Mean values skewed by outliers with high self-report rates
  - Included homosexuality

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Self-Report Study

- Langevin and Curnoe (2012)
  - 2,190 PDP treated or evaluated in Canada between 1996 & 2009
  - Rate of undetected sexual crimes reported by PDP for each decade between 1960 and 2000 :
    - Mean = 27.7% (range 7.8% - 78.3%)
  - Effect of undetected sexual reoffense on detected sexual recidivism base rate:
    - 78.3% undetected rate increased base rate by 26.3%
    - 7.8% undetected rate increased base rate by 1.5%

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Limitations of Self-Report Studies

- Captures unreported sexual offenses leading up to the point of detection
- Does not separate individuals who repeatedly committed undetected sexual crimes before being caught the first time from those PDP who reported committing undetected sexual recidivism

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Lifetime Sexual Recidivism Rates

- Constant multiplier (Doren, 2010; Elwood, 2018)
  - 1.5 X 20% = 30% over 20 years
- Limitations
  - Relies on detected sexual reoffense
  - Does not account of undetected sexual recidivism
  - Research indicates constant increase in sexual reoffense over 20 years is not supported (Hanson et al., 2014)
  - Procedure is inaccurate and unreliable in computing long term sexual recidivism with actuarial measures (Wollert & Cramer, 2012)

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Lifetime Sexual Recidivism Rates

- Thornton et al. (2019) Survival Analysis Tables
  - Modeled 20-year sexual recidivism rates for 7,740 PDP using Cox Regression Analysis
  - Devised Excel spreadsheet to compute the effect of remaining free from sexual or other criminal reoffense on long term sexual recidivism rate
    - On average a 50% reduction in long-term sexual reoffense with each 5-year period of no sexual or other criminal offending
- Fails to account for undetected sexual recidivism

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Statistical Modeling

- Hanson & Price (2003) "Real Recidivism Rate," as reported by Thornton (2018)
- Devised statistical formula with the following inputs:
  1. Number of victims per recidivist
  2. Rate of undetected sexual offenses
  3. Observed sexual recidivism rate
  4. Detection rate per individual

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Limitations of Real Recidivism Rate (Thornton, 2018)

1. Lack of precision in estimating number of victims per recidivist and rate of undetected sexual offenses
2. Does not control for factors that may decrease unreported sexual recidivism by PDP:
   1. Less opportunity to reoffend because in increased societal vigilance
   2. Authorities easily suspect them of reoffending
   3. Allegations against them more easily believed
3. Imprecise inputs produce erroneous estimation

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A New Model: Scurich and John (2019)

- Monte Carlo simulation method using the following parameters
  - Frequency of sexual offenses per offender per year (fixed rate each year)
    - 9 values ranging between 1/16 to 16 offenses per offender per year
  - Probability that sexual offenses are reported to authorities or P_r
    - 3 values of P_r = 0.15, 0.35, & 1.0
  - Rate at which reported crimes result in convictions or P_c
    - 3 values of P_c = 0.25, 0.50, & 0.75
- Applied to hypothetical individuals convicted of sexual offenses ("ICSO") presumed to represent diverse characteristics (each distribution tested with N = 100 & 1,000 trials)

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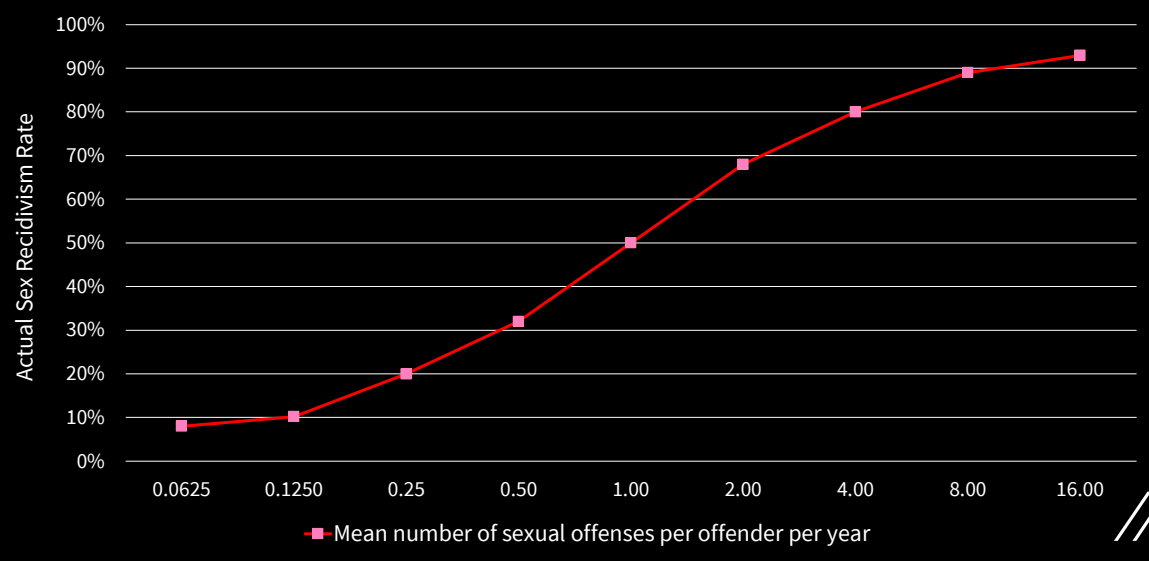
Modeling Results: Actual Sex Recidivism Rate



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Testing Model Assumption #1

- Per offender per year offense frequency assumption not based on known data from real PDP
- Assumes that PDP persistently commit sexual offenses over their adulthood. Is this supposition supported?
  - Miethe et al. (2006) 9,806 individuals convicted of sexual offenses from 14 states and examined up to 99 arrest cycles divided into thirds
    - 73% of individuals who commit rape desisted
    - 63% of individuals who molested children desisted

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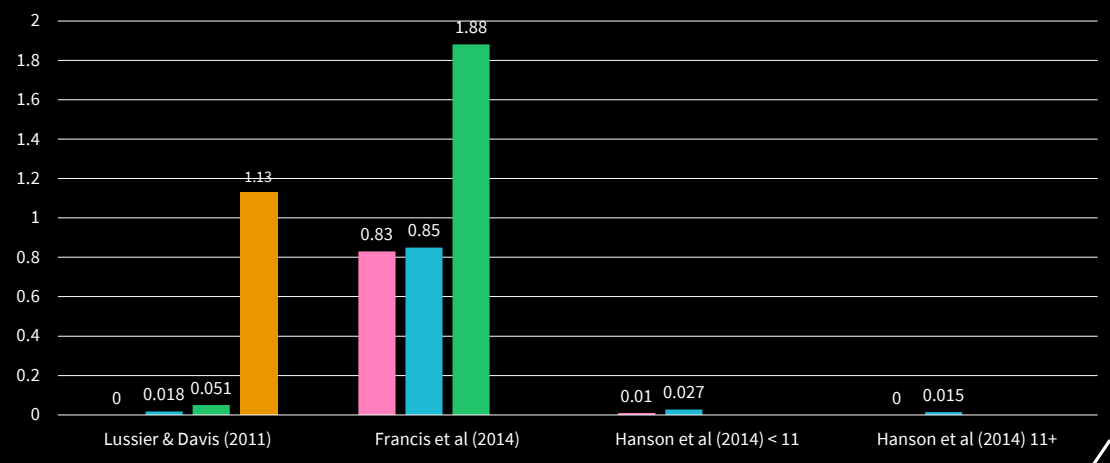
Mean Sex Offenses Per Offender Per Year



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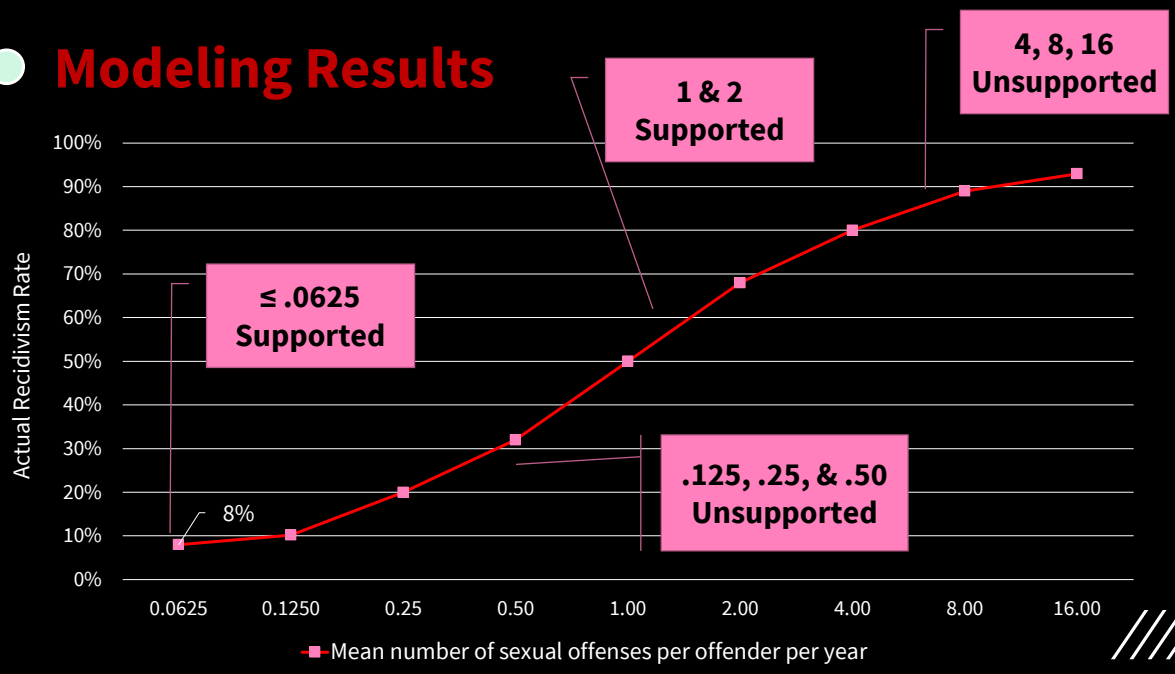
Modeling Results



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Testing Model Assumption #2

- Rates of reported sexual crimes from victim survey studies
  - Daly & Bauhours (2010)
    - NCVS average between 1992-2000 = 32%
    - Other USA surveys: 15% & 19%
  - Planty & Langton (2013)- NCVS
    - 36% average rate between 2003-2010
    - High of 59% (2003) and low of 32% (2010)
- Limitations of survey data
  - Did not include victims under age 12
  - Survey data does not identify if perpetrators were PDP

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Finkelhor et al. (2008; 2011)

- Rates of reported sexual crimes that included children < age 12
  - Ranged between 65% and 75% when children sexually abused by adults
  - Type of sexual crime, not controlling for relationship with perpetrator, influenced rate of reports
    - Completed or attempted rape- 10% reported
    - Witnessed indecent exposure- 7% reported
    - Statutory rape- 2% reported

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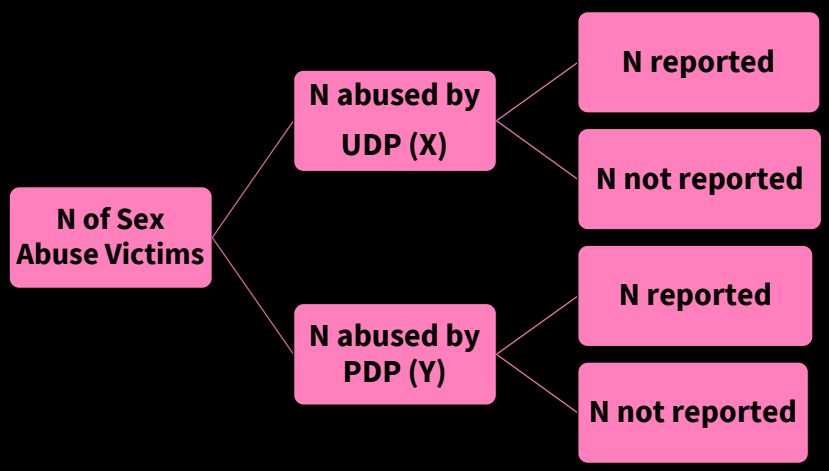
Separating Offenders from Offenses



UDP = Persons who have gone undetected for their sex crimes
PDP = Persons who have been detected for sex crimes by report or arrest

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Identifying Undetected Sex Recidivism

Incorrect Assumption

$$\frac{\text{Unreported sex crimes by UDP + PDP}}{\text{All sex offenses by UDP + PDP}}$$

Correct Specification

$$\frac{\text{PDP unreported sex recidivism}}{\text{All sex recidivism by PDP}}$$

UDP = Persons who have gone undetected for their sex crimes
PDP = Persons who have been detected for sex crimes by report or arrest

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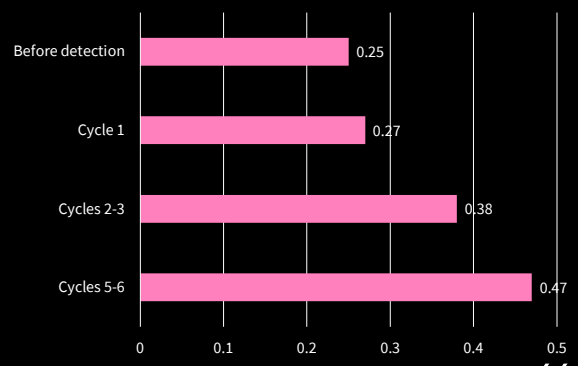
A Study of Actual Sexual Offenders

Kelly (2018)

- 100 SVPs from midwestern civil commitment program
- From official records and self-report calculated ratio of unreported to reported sexual crimes prior to first detection and 6 arrest cycles thereafter

Proportion of Sex Crimes Reported



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Other Factors Affecting Report Rate

Deducting false reports of sexual crimes would increase report rate

Range of false report: 0.011 – 0.41

Source: Campbell et al. (2008); Morabito et al. (2019); Spohn & Tellis (2012)

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Probability of Convictions

- Assumption about rates of convictions at .25, .50, & .75 appear overly optimistic
  - Available research reveals conviction rates between 6.5% and 14% , which fall below the lowest assumed value.
    - Campbell et al. (2008); Morabito et al. (2019); Spohn & Tellis (2012)
  - But….
    - Conviction data combines individuals who had first detection and those PDP who reoffend sexually.
    - Studies indicate most sexual crimes committed by first time offenders (Miethe et al., 2006; Sandler et al., 2008)
    - Removing wrongful successful prosecutions would increase conviction rate

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Exonerations

- Walsh et al. (2012)- Examined DNA results of individuals convicted of sex offenses in Virginia
  - 11.6% wrongful conviction rate
- National Registry of Exonerations (2014)
  - 31% of all exonerations involved rape or child sexual assault between 1989 and 2013
    - Increasing rate of exonerations related to trial penalty

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Calibration of Observed Rates

- Scurich and John (2019) selected 4 studies purportedly reporting observed sexual recidivism and calibrated the rates using the study assumptions to recompute a range of actual sexual recidivism rates.
  - Mean number of sexual offense per year per individual
  - 1 – report rate (3 report rates: 1.0, .35, & .25)
  - 1 – conviction rate (3 conviction rates: .75, .50, & .25)

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Calibration Results: Actual Sex Recidivism Rate ("ASRR")

	Hanson et al. (1993)	Prentky et al. (1997)	Hanson & Bussiere (1998)	Hanson et al. (2014)
Observed base rate	40%	25%	15%	5%
Follow-up period (years)	31	25	5	5
Criterion	Violent Conviction	Sexual Conviction	Sexual Varied	Sexual Arrests
Range of ASRR	47% - 95%	32%-90%	19% - 82%	7% - 58%

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Conclusions

- Monte Carlo simulation model provides promising method to calculate ASRR but requirement for constant rate of sex offending over time is not supported by actual studies
- Difficult to identify precise parameters from real ICSO necessary to compute ASRR
- Based on research on mean per year rates of offending with known ICSO , the Scurich and John modeling indicates:
  - Most likely that ASRR is less than 10%
  - With some ICSO, ASRR may reach between 50% and 68%

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Conclusions

- Relying on survey data of unreported sexual crimes likely contributes to inflating ASRR due to:
  - Including individuals not previously detected for sexual offending
  - Not considering moderator variables
  - Data does not include children under age 12 years
  - Does not adjust for false reports
- Conviction rate assumption unreliable
  - Fails to consider conditional probabilities for sexual crimes committed by ICSO only and convictions of ICSO only for sexual crimes
  - Does not account for wrongful successful prosecutions

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Research and Practice Implications

- Need for linear and non-linear statistical models to account for variations in parameters and to control for moderating variables
  - For example: Path analysis or machine learning
- In forensic practice must limit opinion regarding ASRR
  - While it is reasonable to conclude that the actual sexual recidivism rate exceeds the detected rate, the magnitude of that difference remains elusive (i.e., speculative opinion).

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Questions

Comments

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SPECIAL ISSUE ARTICLE

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Illuminating the dark figure of sexual recidivism

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Abstract

Detected or reported ("observed") rates of sexual reoffending have long been recognized as underestimating the occurrence of actual sexual recidivism. Past attempts to bridge the gap between the two rates have been unsuccessful. Scurich and John try to reverse this course by presenting a simulation model to estimate the predicted actual sexual recidivism rates among individuals convicted of sexual offenses based on three parameters; they also apply these data to calibrate the sexual recidivism rates from four sexual recidivism studies. The accuracy of the predicted actual sexual recidivism rates is wholly dependent upon the reliability of the inputs to the model. This analysis relies upon scientific studies and literature to delve into the precision of the parameters of Scurich and John in relation to the accuracy of their predicted actual sexual recidivism rates and the validity of the calibration process. The results reveal that some of the assumptions by Scurich and John about the parameters are supported empirically, while others are not. Overall, the simulation model parameters suffer from significant deficiencies that likely produce inaccurate predicted actual sexual recidivism rates. Moreover, the methodologies of the comparison studies used in the calibration process do not actually meet the requirements of the analytic strategy of Scurich and John, which effectively invalidates their findings. Until computational strategies are employed that account for linear and nonlinear effects of model parameters, closing the gap between observed and actual sexual recidivism rates will remain elusive.

1 | INTRODUCTION

Rates of observed sexual recidivism (i.e., observed (detected) by official sources such as reports, arrests, charges, or convictions) among individuals detected for sexual offenses (i.e., those who are reported, arrested, prosecuted, or convicted for sexual crimes) underestimate the actual sexual recidivism rate. The actual sexual recidivism rate is the composite of the total detected and unreported illegal sexual acts committed by individuals who have reoffended after being detected previously for committing sexual offenses. The magnitude of the difference between observed and actual sexual recidivism rates has yet to be reliably established. For this reason, typically only observed sexual recidivism rates are considered by personnel in the criminal justice and civil confinement systems who address legal matters related to risk for sexual reoffense and by policy makers who enact measures that protect the community from individuals convicted of sexual offenses (ICSOs).

ICSOs are subject to various legal proscriptions that seriously infringe upon their liberty interests to protect the larger community, including registration, residency restrictions, imprisonment, intensive community supervision, community notification, and involuntary civil confinement if deemed to be sexually violent predators or persons (SVPs). Such laws seek to reduce the risk for sexual recidivism posed by ICSOs (Bonnar-Kidd, 2010). Nonetheless, controversy abounds as to whether the relatively low rates of observed sexual recidivism among ICSOs justify laws that impose blanket exclusionary methods of social control for them (Montaldi, 2015; Sandler, Freeman, & Socia, 2008; Vess, Day, Powell, & Graffam, 2014; Zgoba, Veysey, & Dalessandro, 2010). In response to these challenges, it is argued that observed sexual recidivism rates only capture a fraction of any illegal sexual behavior, both reported and unreported, that such laws seek to prevent (Scurich & John, 2019). A difference between the actual sexual recidivism rate and the observed phenomena has long been recognized, as evidenced by three lines of research that have sought to bridge this gap, including offender self-report, rates of life-time sexual reoffending, and statistical modeling.

Self-report research employs surveys administered to individuals who have been officially detected for committing sexual offenses ("previously detected persons" or PDPs") that led to their referral for treatment or evaluation. Abel et al., (1987) obtained self-reported frequencies of paraphilic sexual acts from 561 PDP. Some of the paraphilic acts were considered sexual crimes. The self-reported information was kept confidential under a federal waiver from mandated reporting of child abuse. Abel et al. (1987) found that the ratio of mean number of arrests for sexual crimes to the mean number of self-reported sexual offenses was 1:30 for violent sexual crimes and 1:150 for noncontact sexual offenses. The mean frequencies of self-reported paraphilic acts for each category were right skewed for two reasons. One, each paraphilic category contained a small number of outliers who reported enormous frequencies of sexual acts. Two, homosexuality was considered as a paraphilia at the time of the study per the American Psychiatric Association's (1980) *Diagnostic and Statistical Manual—Third Edition*, as well as a crime in many jurisdictions, and this category produced the highest mean number of sexual acts. In this situation, the median for the group provides a more accurate description regarding average rates for committing sexual acts. For instance, among individuals who sexually abused male prepubescent children unrelated to them, the mean number of sexual acts was 281.7 while the median was 10.1.

In another offender self-report study, Langevin and Curnoe (2012) examined the reoffending patterns among 2190 PDPs from Canada who were treated or evaluated in an outpatient clinic between 1996 and 2009. The mean percentage of undetected sexual crimes reported by the PDPs, within each decade between 1960 and 2000, was 27.7% (range = 7.8%–78.3%). There was a substantial downward trend in the rate of self-reported sexual crimes over time, which dramatically reduced the actual recidivism rate. The rate of self-reported sexual crimes charges in the 1960s increased the observed sexual recidivism base rate by 26.3%, whereas the effect diminished to 1.5% in the 2000s. Langevin and Curnoe (2012) suspect that the decline in self-reported sexual crimes over time happened because of the advent of child abuse reporting laws that inhibited self-disclosure by offenders. Other studies that employ polygraph testing about individuals' sexual histories reveal that PDPs report numbers of undetected victims

double their known numbers of victims (Ahlmeyer, Heil, McKee, & English, 2000) or more than 10 times the detected number of victims (Bourke et al., 2015).[1]

Self-report studies document the extent of unreported sexual offenses leading up to the point where PDPs are detected for the commission of sexual crimes and referred for evaluation or treatment. The self-report data do not distinguish PDPs who commit undetected sexual reoffenses from individuals who repeatedly engage in undetected sexual crimes before being apprehended for the first time. Including persons from the latter groups would act to spuriously inflate the effect of undetected sexual recidivism for PDPs. Therefore, this line of research is not informative in quantifying the extent of undetected sexual recidivism perpetrated by PDPs.

A second line of empirical inquiry, known as the constant multiplier, purports to produce lifetime sexual recidivism rates (Doren, 2010; Elwood, 2018). This is accomplished by dividing long-term observed base rates of sexual recidivism (e.g., 20-year values) by short-term base rates (e.g., 5-year values). The theory of this method assumes that PDPs reoffend sexually over their lifetimes at constant rates and the constant multiplier can be applied to any short-term observed sexual recidivism base rate to compute a lifetime sexual recidivism base rate. Since this procedure only addresses observed sexual reoffense rates it is not informative in computing actual sexual recidivism rates. The constant multiplier has also been criticized as inaccurate and lacking sufficient research to establish its reliability (Wollert & Cramer, 2012). Moreover, data from a large sample of PDPs did not support a constant rate of sexual reoffending over time (Hanson, Harris, Helmus, & Thornton, 2014). These outcomes likely explain why the constant multiplier approach has not gained much traction in assessing sexual recidivism risk among PDPs.

An alternate, related procedure for computing lifetime rates of sexual recidivism has been recently suggested (Thornton, Hanson, Kelley, & Mundt, 2019). This work builds upon a study about the sexual reoffense experiences of 7740 PDPs that was modeled over 25 years (Hanson, Lunetta, Phenix, Neeley, & Epperson, 2014). The study reveals that the risk for detected sexual reoffenses decreases by about one-half for every five years that offenders remain free in the community without committing a sexual crime. Thornton et al. (2019) have devised a Microsoft Excel calculator for clinical and forensic applications that uses survival analysis parameters to compute lifetime risk (i.e., 20 years) based on the amount of time free in the community without a subsequent sexual crime less any time spent in custody for nonsexual crimes or community supervision violations. Since this procedure relies on the detected sexual reoffense rate, it fails to account for the effect of undetected sexual reoffending committed by PDPs that is necessary to estimate actual sexual recidivism rates.

The final line of empirical study involves the use of statistical models to compute actual recidivism rates. Thornton (2018) chronicles the efforts of himself and two colleagues (Hanson and Price) to develop and implement a statistical formula, first released in 2003, to compute real sexual recidivism rate ("RRR formula"), which is analogous to the term actual sexual recidivism rate as presented herein. The RRR formula adjusts the observed sexual recidivism rate by the number of victims per recidivist and by the rate at which sexual crimes go undetected. Thornton (2018) described two serious limitations of the RRR formula. One, the key parameters, including the number of victims per recidivist and rate of undetected sexual reoffense, lack precision. As a result, even small differences in the parameters cause significant variation in the predicted actual sexual recidivism rates. Second, Thornton (2018) hypothesizes that the number of victims per recidivist and the rate of sexual reoffending among individuals whose sexual offenses go undetected may not be reliable when applied to PDPs for three reasons: they are subject to increased societal vigilance that results in them having less opportunity to reoffend sexually, they are easily suspected of reoffending, and allegations against them are more easily believed. Because of these seemingly insurmountable hurdles, Thornton (2018) abandoned RRR formula in favor of the lifetime sexual recidivism rate (Thornton et al., 2019).

Nearly 16 years later, Scurich and John (2019) devised and employed a probabilistic simulation model that is conceptually similar to the RRR formula to predict actual sexual recidivism rates among ICSO. Scurich and John (2019) process three model parameters, of which two are similar to the RRR formula, including the frequency of sexual offenses per offender per year and the probability of a sexual offense being reported to police. The

similarities between the two models end there, as Scurich and John (2019) utilize more sophisticated analytic methods to produce their actual sexual recidivism rates and they also use these data to calibrate observed sexual recidivism rates from four comparison studies. It is the difference between the actual and observed (detected) sexual recidivism rates that Scurich and John (2019) coin "the dark figure of sexual recidivism," a term commonly used in criminal justice recidivism research (Maxfield, Weiler, & Widom, 2000), but one that could be viewed as pejorative.

As with any simulation model, the accuracy of the predicted outcome depends upon the precision of the assumptions fed into the model (Henley, Golden, & Kashner, 2020). In other words, the values of the model parameters should represent, as accurately as possible, actual field conditions as observed among ICSOs who commit detected and undetected sexual reoffenses. While Scurich and John (2019) claim they considered reasonable values for the model inputs based on empirical studies (p. 172), closer inspection of the precision of the parameter values is warranted based on the cautions that Thornton (2018) raised.

2 | PROBABILISTIC SIMULATION MODEL BY SCURICH AND JOHN

Scurich and John (2019, Section 6) present a comprehensive description of the probabilistic simulation model to which the interested reader is referred. A brief overview of the simulation model will be presented below followed by detailed examination of three model assumptions and the calibration process.

Scurich and John (2019) employ the Monte Carlo method to process certain values for each of three assumptions: (i) propensity for committing sexual offenses (i.e., frequency of sexual offenses per offender over a specific time period); (ii) probability of sexual offenses being reported to authorities (P_r); and (iii) the rate at which reported sexual offenses result in criminal convictions or what they term as successful prosecutions (P_c). The Monte Carlo method is a computational algorithm that builds models of possible results by substituting a range of values that are inherently uncertain such as the three previously specified assumptions. It then calculates the result over and over, each time using a different set of random values from the assumptions that produces distributions of possible outcome values.

Scurich and John (2019) use a three-way factorial model with 81 possible combinations of values (i.e., input distributions) where each combination comprises a single simulation. All input distributions were assumed to be uncorrelated. Each simulation contained a hypothetical population size of 100 ICSOs and it was run for 1000 independent trials. Based on the average number of offenses committed over the period, the number of sexual recidivists in each trial was obtained by computing the ratio of hypothetical ICSOs who committed one or more sexual offenses during the time period divided by the total number of hypothetical ICSOs (N_s/N). This value represents the predicted actual sexual recidivism rate. In performing the calibration process, Scurich and John (2019) matched an exponential population mean with a corresponding base rate from each of the four comparison studies. The results were then adjusted by the probabilities for unreported sexual crimes (i.e., $1 - P_r$) and unsuccessful prosecutions (i.e., $1 - P_c$).

2.1 | Frequency of sexual offending per offender

The model of Scurich and John (2019) for individual offending assumes a diverse population of hypothetical ICSOs who reflect different individual propensities for sexual reoffending that is represented by the individual's Poisson distribution (λ_i). λ_i represents the count of sexual reoffenses committed, as opposed to the likelihood for sexual recidivism. λ_i is characterized by a constant rate of sexual reoffending over a fixed one-year period (see Scurich & John, 2019, fig. 3) and was derived by running 1000 random trials. λ_i is assumed to follow an exponential distribution of the gamma type with shape parameter = 1. As evidenced by figs 3 and 4 from Scurich and John (2019), both the

individualized Poisson and exponential distributions are right skewed, which indicates that the majority of the sexual reoffense frequencies for the hypothetical ICSOs fall in the lower levels of the distribution and that a decreasing number of sexual reoffense frequencies are spread out along the higher levels of the distribution. The simulation model tests nine different exponential distributions of hypothetical ICSO populations for which the mean sexual reoffense rates range between 1/16 and 16 per year. It is further assumed that characteristics of the populations such as age and types of sexual offense committed (among other factors) are putatively diverse over different time periods of reoffending (Scurich & John, 2019). Scurich and John (2019) do not cite authorities supporting the validity for the range of fixed mean values of sexual reoffending over time nor do the theoretical ICSO populations account for factors that may increase or decrease the occurrence of sexual reoffending over time. The resulting computations (Scurich & John, 2019, fig. 6) yield a linear increase in their actual sexual recidivism rates per 100 offenders over the nine offense frequencies, similar to the S-shaped logistic function, with values ranging between about 6% (at 1/16 offense per offender per year) and about 94% (at 16 offenses per offender per year). Scurich and John (2019) conclude that the assumptions of λ_i that produce the wide range of actual sexual recidivism rates may be violated after several years or decades (at p. 171). As discussed next, research using group-based modeling with PDPs reveals results that mostly contradict the constant per year mean rates used by Scurich and John (2019).

Miethe, Olson, and Mitchell (2006) examined the arrest cycles (up to a maximum of 99) for 9806 ICSOs released from prison for rape and child molestation in 14 of the United States in 1994. The arrest cycles for each individual were divided into three intervals. For example, if an individual had 15 arrest cycles, then each interval would consist of five arrest cycles. The three intervals do not represent lifetime rates of sexual offending. About one-fourth (27%) of individuals who committed rape and 37% of those who molested children were arrested for sexual crimes in each of the three intervals. Rapists were twice as likely to desist from sexual reoffending as child molesters over the three intervals. These data suggest that the majority of ICSOs who commit child molestation and rape do not demonstrate a constant rate of sexual reoffending over their criminal offending history.

Lussier and Davies (2011) examined the sexual offending trajectories among 246 PDPs using Cox proportional hazards regression analysis. The results generated six sexual offense trajectories, each over 6 years, based on age (three age groups) and two sexual offending patterns over time (very low rate and high-rate increasers). Four of the trajectories produced per year mean sexual offense rates between 0.0 and 0.018 and the remaining two categories generated 0.051 and 1.13 mean sexual offenses per year.

Francis, Harris, Wallace, Knight, and Soothill (2014) studied the life course offending trajectories of 780 ICSOs that resulted in their referral to the Massachusetts Treatment Center (MTC) for consideration of civil confinement in lieu of prison commitment between 1959 and 1984. Their analysis discovered a four-trajectory model, where three groups displayed consistent mean sexual offense charges per year (0.83, 0.85, and 0.85) and the fourth group demonstrated a mean rate of 1.88 sexual crime charges per year. The mean rates of charges per year were calculated over periods ranging between 9 and 13 years.

The variations in the mean frequencies of sexual offenses per year from Lussier and Davies (2011) and Francis et al. (2014) were influenced by specific circumstances endemic to the model development. Lussier and Davies (2011) discovered that the ages at which the individuals in each of the two offender categories committed sexual offenses influenced the mean number of sexual offenses. The members of the very low-rate group demonstrated a constant but very low rate of sexual offending over the three time periods (ages 18-23; ages 24-29, and ages 30-35), whereas the high-rate increasers did not commit sexual offenses during the first age period but demonstrated a threefold increase in sexual offending from the second to the third time frames. Francis et al. (2014) found that a variety of factors affected the sexual offense trajectories, including age of onset of sexual offending, age of at time of referral for civil confinement, duration of sexual offending history, age window at peak offending, sexual offender type, and whether the ICSOs were civilly committed or returned to court for criminal sentencing.

Using 25 years of sexual reoffense data from 7740 PDPs, Hanson, Harris, Letourneau, Helmus, and Thornton (2018) report one-year hazard rates generated from survival analysis that represent the mean proportions of individuals who reoffended sexually each year based on the fact they had not sexually reoffended in any previous

year. During the initial 10 years free in the community, the annual mean rates of sexual reoffense for the individuals ranged between 0.01 and 0.027 and these rates declined in linear fashion over time. After the 10-year inflection point, the trend continued toward decreasing annual mean rates of sexual reoffense over time that ranged between 0.00 and 0.015. No individual recidivated sexually between years 22 and 25. Hanson et al. (2018) further discovered that the commission of nonsexual crimes caused the rate of sexual reoffense to increase over a period of about 3 years, after which time the 12% annual decrease in the odds for sexual recidivism continued for individuals who remained free of further nonsexual criminal offenses.

The studies presented above reveal findings that would meaningfully affect the validity of the predicted actual sexual recidivism rates. While it is important to recognize that a few of the per year mean number of sexual reoffenses entered in the Scurich and John (2019) simulation model (e.g., 0.0625, one or two mean sexual offenses per year) appear accurate as applied to ICSOs, many mean per year sexual offenses do not. This creates imprecision in the model inputs in two ways. One, the higher per year mean rates of 4, 8, and 16 sexual reoffenses do not appear to be supported by the available research. This, in turn, calls into serious question the validity of the corresponding predicted actual sexual recidivism rates as applied to ICSOs. Two, it is more typical for PDPs as a group to exhibit mean per year sexual reoffense rates that are between 57% and 84% less than the lowest limit of 0.0625 (i.e., 1/16 per year) postulated by Scurich and John (2019). This will produce predicted actual sexual recidivism rates that fall below the lowest actual sexual recidivism rate of 6% over five years that Scurich and John (2019) considered. This finding further suggests that the simulation model output of Scurich and John (2019) tends to overestimate the actual sexual recidivism rates for ICSOs.

Two other conditions call into question the reliability of the per year mean rates of sexual offending, which in turn casts doubt on the validity of the resulting predicted actual sexual recidivism rate. The assumption about the constant rate of sexual offending over time fails to consider the effect of individuals who desist from committing sexual crimes over time. The fact that the Scurich and John (2019) simulation model cannot control for the variability in persistency of sexual offending over time introduces a potential major source of error that compromises the validity of the predicted actual sexual recidivism rates. Finally, the personalized Poisson and exponential distributions are both right skewed. In such situations, the mean value for the number of sexual offenses per year is likely inflated because of the effect of the small proportions of individuals who engage in high-frequency sexual offending. In such outlier situations, Abel et al (1987) found that the median value more fairly represents the average rate of sexual offending for the group. Since Scurich and John (2019) do not report the median number of sexual offenses per year, it unknown whether the results of their actual sexual recidivism rates, based on mean rates, are inflated spuriously.

2.2 | Rate of reported sexual offenses

A second input into the probabilistic model is the assumption that the occurrence of a sexual offense is reported to police (P_r) at some constant probability across individual offenders in the population and across multiple offenses for the same offender (Scurich & John, 2019, Section 6.2.3). 1 – P_r is one of two probabilities used in the calibration process to calculate the actual sexual recidivism rate for the four comparison studies. Three proportions of P_r are proposed, including 0.15 ("low P_r"), 0.35 ("moderate P_r"), and 1.0 ("high P_r"). The high P_r is considered an "optimistic limiting condition" (Scurich & John, 2019) that will not be addressed herein.

The low P_r and moderate P_r assumptions were derived from survey data that examine the report rates of sexual assaults to police among individuals in the community who declare they had been victims of criminal sexual acts (Daly & Bouhours, 2010; Planty, Langton, Krebs, Berzofsky, & Smiley-McDonald, 2013). These studies did not investigate the report rates of children under the age of 12 years, which raises questions regarding the precision of low P_r and moderate P_r as they relate to younger children. Initial examination of two data sets consisting of children under age 12 years (Finkelhor, Hammer, & Sedlak, 2008; Finkelhor, Ormrod, Turner, & Hamby, 2011) indicated that

the low P_r and moderate P_r assumptions appear accurate for children under age 12 years. However, closer inspection of the data from Finkelhor et al. (2011) revealed wide variation in police report rates depending upon the circumstances of the sexual offenses committed. The report rates for children sexually abused by adults known to them (65%) and nonspecific adults (75%) fall between the moderate P_r and high P_r, so these report rates would be accounted for in the simulation model of Scurich and John. Other types of sexual offense situation, however, were reported to police at rates much less than the low P_r, including completed or attempted rape (10.0%), witnessing indecent exposure (7.1%), and statutory rape (1.7%). In these situations, low P_r would contribute to the underestimation of the predicted actual sexual recidivism rate.

Since the premise of Scurich and John (2019) is to address predicted actual sexual recidivism rates of ICSOs, it is reasonable to expect that the calculation of P_r should at least consider the sexual recidivism status among the class of PDPs, if not, arguably, ICSOs only. As will be seen shortly, this is a moot point, since data for neither group are obtained in victim survey studies. The survey data that Scurich and John (2019) rely upon to compute P_r and its inverse ($1 - P_r$) presumes that all reported and unreported sexual crimes derived from sexual abuse victim surveys were perpetrated by ICSOs and that these sexual crimes were recidivistic in nature, when neither assumption is true.

Obtaining precise values of P_r and its opposite requires first identifying and removing those victim reports that meet either of the following two conditions: (i) reports about individuals who commit sexual offenses, whether once or multiple times, without being detected by authorities; or (ii) reports about persons who engage in one or more unreported sexual offenses that occurred before the individuals were apprehended by legal officials for the first time. The two groups comprise a class of individuals whose sexual offenses go undetected by legal authorities and will be referred to as persons undetected for committing sexual offenses ("undetected persons" or UDPs). The second class consists of individuals who have been previously apprehended (e.g., reported, arrested, prosecuted, or convicted) for committing sexual offenses; these individuals were previously designated in this article as PDPs (i.e., previously detected persons). The ICSOs, who are a focus of Scurich and John (2019), are a subset of the PDP class. The values of P_r would only be accurate if they represented the product of the number of victims who report recidivistic sexual crimes committed by PDPs divided by the total number of victim reports involving PDPs who engaged in sexual reoffending. Victim survey studies do not collect the necessary data to properly compute P_r, nor would it be reasonable to expect sexual assault victims to know such information.

Figure 1 helps to visualize the proper specification of the value of P_r. Among the total number of persons reporting sexual victimization, a certain number are abused by UDPs (X), some of whom report the offenses to police (X_{r+}), and some of whom do not (X_{r-}). Among the proportion of all victims who are sexually assaulted by PDPs (Y), some report the reoffenses to police (Y_{r+}) and others do not (Y_{r-}). The probability of sexual reoffenses committed by PDPs being reported to police (PY_{r+}) is a function of the box labeled "Y_{r+}" in Figure 1 divided by the box titled "Y." The probability that sexual recidivism among PDPs goes unreported is computed as $1 - PY_{r+}$. It is important to note that the group of interest as it relates to the Scurich and John (2019) P_r values consists of ICSOs, and that the proportions of the total numbers of PDPs making up Y, Y_{r+}, and Y_r consisting of ICSOs is uncertain. Thus, the values of P_r considered by Scurich and John (2019) are imprecise by an unknown magnitude. The fact that their computation erroneously includes sexual offenses committed by UDPs also infects the accuracy of $1 - P_r$.

Frequency data for values corresponding to the notations represented in Figure 1 necessary to compute P_r for PDPs were not ascertained by the victim surveys, and such data are also lacking in other sources. The probabilities of PDPs and UDPs committing sexual offenses that are reported to police may be equivalent or disparate. If the probabilities are roughly equivalent, then the model assumptions for P_r, as postulated by Scurich and John (2019) would be accurate as applied to PDPs. Disparities in the report rates for PDPs and UDPs and the corresponding inverse probabilities could markedly affect the accuracy of the predicted actual sexual recidivism rates. While accurate data about values of P_r for UDPs are unknown, one study involving ICSOs sheds some light on the possible values of X and Y as specified in Figure 1.

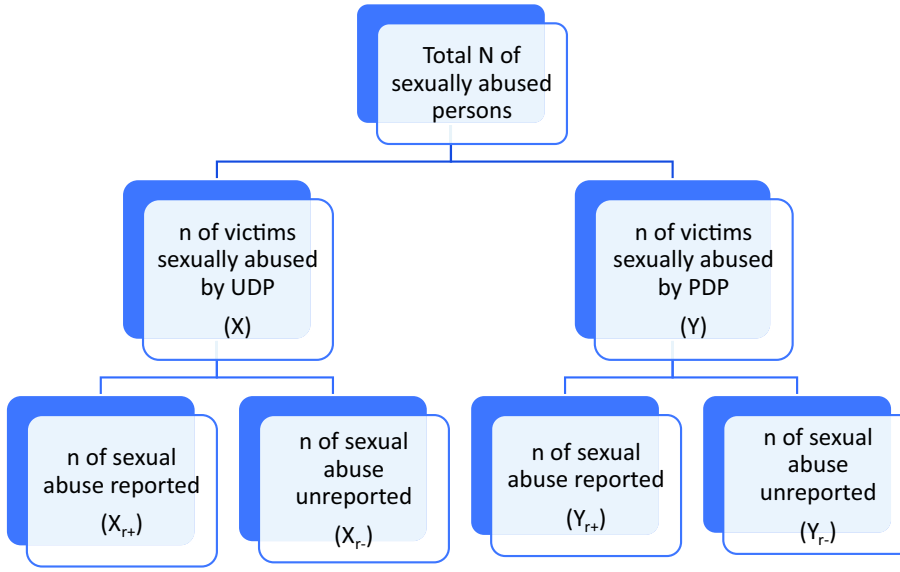

FIGURE 1 Disentangling the rates of sexual crimes reported to police (P_r) committed by individuals previously detected for sexual offending (PDPs) and those who have gone undetected for having committed sexual offenses (UDPs). The relevant data for determining the probability for reporting sexual reoffenses committed by PDPs is Y_{r+}/Y. The probability that victims do not report the sexual offenses committed by PDPs is represented by Y_{r-}/Y. It is unknown what proportion of the PDPs in each condition consist of individuals convicted for sexual offenses [Colour figure can be viewed at wileyonlinelibrary.com]

Kelley (2018) studied 100 ICSOs who were involuntarily committed as sexually violent predators in a Midwestern state. The research team is in the process of entering data for another 100 subjects, so the results from the larger sample were not available at the time of this writing (S. Kelley, personal communication, 3 July 2020). Participants in the study completed sexual history questionnaires preceding the administration of polygraph examinations. Responding to items on the questionnaire, the participants reported both detected and undetected victims they sexually assaulted prior to their first sexual offense arrest and leading up to subsequent sexual offense apprehensions up to a maximum of seven arrest cycles. The results from arrest cycle one would address the ratio of reported and unreported sexual crimes among UDPs (i.e., the *X* values in Figure 1), while the data from arrest cycles two to seven inform about the rates of reported and unreported sexual reoffending among PDPs (i.e., the *Y* values in Figure 1). Kelley (2018) defines reported sexual offenses as instances where the individuals described making hands-on sexual contact with the victims that resulted in their arrests. This differs from the victim survey studies, relied upon by Scurich and John (2019), that count any sexual offense reported to police. It is reasonable to infer that Kelley's (2018) narrow criterion to define reported sexual offenses, as compared to Scurich and John (2019), would likely increase the report rate to police.

With the aforementioned methodology in mind, the author used the frequency data from Kelley (2018) to compute ratios comparing unreported to reported sexual reoffending and the corresponding values of P_r for UDPs and PDPs. As it relates to UDPs, the ratio of undetected to detected sexual crime arrests prior to the first arrest was 3:1; this corresponds to a P_r of 25%, which falls between the low P_r and moderate P_r of Scurich and John (2019). However, the analyses pertaining to PDPs, in particular the subset of ICSOs, produces a different result. For this group, the ratio of unreported to reported sexual reoffending was near 3:1 for the second arrest cycle and it became less disparate, at about 3:2, during arrest cycles three and four. The ratio was nearly 1:1 by the last arrest cycle, which combined arrest cycles five and six. Data from arrest cycle seven was not reported because it contained a single person. The value of P_r increased for arrest cycles two to four (range = 27%–38%) and reached

47% by the last arrest cycle. Comparing these rates with the model assumptions yields no support for low P_r for ICSOs; instead, the results were most consistent with the moderate P_r assumption.

The model assumption about P_r further presumes that all reported sexual offenses are true. Research examining rates of false reports of sexual offenses by Campbell, Bybee, Ford, and Patterson (2008), Spohn and Tellis (2012), Kanin, 1994, and Morabito, Williams, and Pattavina (2019) contradict this notion. Each study found that investigating police officers determined that some sexual assault reports were baseless or false, with the proportions ranging between 0.011 and 0.41 of all reported sexual crimes. Removing false reports of sexual crimes would increase P_r and contribute to a decrease in the predicted actual sexual recidivism rate.

2.3 | Rate of successful prosecutions

Scurich and John (2019, section 6.2.4) describe the next uncertainty as the rate by which a hypothetical ICSO is eventually convicted of a sexual crime (P_c). P_c attempts to control for the funnel effect as reported sexual assault cases progress through the criminal justice system, where a progressively decreasing number of suspects reach various stages of the criminal justice process (e.g., identification as the suspect, arrest, police officer presenting case to prosecutor, charging document being issued, and criminal trial or negotiated plea resulting in conviction). The value of $1 - P_c$ is used in the calibration of the observed sexual recidivism rates from the four comparison studies. Scurich and John (2019) state that they considered a broad range of conviction rates, including 0.25, 0.50, and 0.75, because data about P_c is lacking in the literature. Despite this assertion, several studies (Campbell et al., 2008; Daly & Bouhours, 2010; Morabito et al., 2019; Spohn & Tellis, 2012) reveal that between 6.5% and 14% of individuals arrested for sexual crimes are later convicted for sexual offenses. This range of values is less than even the lowest limit of 25% considered in the simulation model. Taken at face value, this suggests that the rates of P_c posited by Scurich and John (2019) would contribute to underestimating their actual sexual recidivism rates.

However, the value of P_c presumes that all reports of and convictions for sexual crimes involve only ICSOs—an erroneous presumption. The reports of sexual crimes are comprised of individuals who are detected by police for committing sexual offenses for the first time and those who have been previously reported, arrested, charged, or convicted for sexual crimes. It is reasonable to infer that when police investigate reports of sexual crimes they are more likely to arrest suspects who are identified as ICSOs than individuals who have not been previously detected for sexual crimes. Prosecutors would be more apt to file charges against ICSOs and to obtain convictions from ICSOs by plea or verdict. Moreover, it would be expected that the ICSO group would comprise the smallest proportion of individuals reported for sexual crimes (Miethe et al., 2006; Sandler et al., 2008). Therefore, the values of P_c must be adjusted by the probability with which all reported sexual crimes are committed by ICSOs and the probability that members of the group convicted for sexual offenses are comprised of ICSOs. Without considering these conditional probabilities, the value of P_c is inaccurate in unmeasurable ways.

Finally, the calculation of P_c fails to account for the effect of wrongful successful prosecutions. Omitting this source of error would effectively increase the value of P_c and contribute to a decrease in the predicted actual sexual recidivism rates. Walsh, Hussemann, Flynn, Yahner, and Golian (2012) used the results of DNA testing that were exculpatory and supportive of exoneration to estimate an 11.6% wrongful conviction rate for individuals convicted of sexual offenses in Virginia. The researchers conducted a secondary analysis and concluded that the 11.6% rate of wrongful convictions for sexual offenses appeared representative across 43 other states that were studied. The results from Walsh et al. (2012) are consistent with anecdotal findings about exonerations of ICSOs wrongfully convicted across the United States. According to The National Registry of Exonerations (2014), nearly one-third of all exonerations (31%) between 1989 and 2013 involved rape or child sexual assault. A limitation of the data about exonerations is that they do not reflect the ratio of wrongful convictions to the total convictions of ICSOs, which would be necessary to evaluate the precision of P_c. The National Registry of Exonerations (2014) discovered an increasing rate of exonerations resulting from what is known as the trial penalty (Jones & Conrelssen, 2019; National Association

of Criminal Defense Lawyers, 2018) whereby defendants plead guilty to false charges to avoid more serious criminal sanctions if convicted by a jury. While this phenomenon merits mention as a possible explanation leading to wrong successful prosecutions, the data were not specified by offense type.

2.4 | Calibration with rates of observed sexual recidivism

Scurich and John (2019, section 6.4) calibrate the sexual recidivism rates from four comparison studies (Hanson & Bussiere, 1998; Hanson et al., 2014b; Hanson, Steffy, & Gauthier, 1993; Prentky, Lee, Knight, & Cerce, 1997). Table 1 lists recidivism information for each study relevant to the ensuing analysis. Before pursuing that analysis, the following briefly summarizes the calibration process, and the interested reader is referred to Scurich and John (2019) for a detailed explanation. The sexual recidivism rate reported for each comparison study was matched to a corresponding value from the simulation model representing the number of putative recidivistic ICSOs divided by the total number of hypothetical ICSOs (i.e., N_c/N). [Correction made on 9 December 2020, after first online publication: In the preceding sentence, 'putative ICSOs' was corrected to 'putative recidivistic ICSOs' and 'hypothetical-sexual offenders' was corrected to 'hypothetical ICSOs' in this version] The identified exponential distribution associated with the value of N_c/N represents the actual sexual recidivism rate. It is the nonreport rate (i.e., $1 - P_r$) and unsuccessful prosecution rate ($1 - N_c$) that make-up the difference between the observed and actual sexual recidivism rates. As discussed below, however, it appears that none of the four comparison studies meet the assumptions of Scurich and John (2019) for the calibration analysis.

The calibration process of Scurich and John (2019) assumes that the outcome of all four studies was reconviction for a sexual offense. As can be seen in Table 1, however, only one of the four studies in the calibration analysis used reconviction for sexual offenses as the outcome (Prentky et al., 1997). While Hanson et al. (1993) did report reconviction as the recidivism criterion, they did so for both sexual and nonsexual violent crimes. The inclusion of nonsexual violent crimes inflates the sexual recidivism rate by an unknown magnitude. This means that three of the four studies Scurich and John included in their calibration analysis do not actually meet the assumptions their analysis requires. This leaves Prentky et al. (1997) as possibly the only comparison study that fits the analytic strategy of Scurich and John (2019).

Fungibility between the individuals studied by Prentky et al. (1997) and the hypothetical exponential population of ICSOs appears unlikely because of the unique composition of the comparison sample. The study sample consists only of rapists and child molesters. The diversity of the sample from Prentky et al. (1997) is narrowed further because the study participants were culled from a larger group of ICSOs who were considered for involuntary civil commitment as sexually violent predators in lieu of serving prison sentences. If it is assumed that diversity of offender types comprising the exponential population would include all ICSOs from a variety of settings (not the civil confinement evaluation setting only) and those who committed noncontact sexual offenses (e.g., indecent exposure, peeping, child pornography viewing, etc.), then this study unlikely fits the conditions necessary to conduct their calibration analysis.

3 | DISCUSSION AND CONCLUSIONS

The mathematics of the Scurich and John (2019) simulation model appear sound and the assumptions fed into it appear logical on their face as possible explanations for the difference between observed and actual sexual recidivism rates. As with any simulation model, however, the validity of the outcomes, in this case their actual sexual recidivism rates, is wholly dependent upon the reliability of the inputs. The foregoing analysis found support for some of the parameters Scurich and John (2019) considered in the simulation model and even an instance where the model parameter (for successful prosecutions) appeared generous. Consistent with the observations of

TABLE 1 Recidivism information from four comparison studies

	Hanson et al. (1993)	Prentky et al. (1997)	Hanson and Bussiere (1998)[a]	Hanson et al. (2014a)
Follow-up time (years)	31	25	5	5
Recidivism rate over time	42%	25%[b]	15%[c]	5%
Recidivism type	Sexual & violent nonsexual	Sexual	Sexual	Sexual
Recidivism criterion	Conviction	Conviction	Arrest, conviction, self-report, or parole violation	Charge
Offender types	Child molesters only	Rapists	Rapist child molesters	Rapist child molesters
		Child molesters	Noncontact offenders	Noncontact offenders
Method to calculate recidivism rate	Survival analysis	Probability	Probability	Probability

[a]Based on results of meta-analysis of 61 studies consisting of 23 393 individuals.
[b]For child molesters only.
[c]Actual reported rate was 13.4%.

Thornton (2018), however, this investigation discovered meaningful imprecision in many of the model assumptions by Scurich and John (2019) that raises substantial concerns about the validity of the actual sexual recidivism rates as applied to ICSOs and when used in the calibration process.

The assumption about the nine rates of sexual offending per year that make up the individualized Poisson distributions presumes a constant rate of sexual offending over time that is not fully supported by the available data examining the trajectory of sexual offending over time. The need for precision of this assumption cannot be overstated because the increase in per year mean number of sexual offenses produces rapid acceleration in the actual sexual recidivism rates that exceeds 90% at 16 sexual offenses per year. While Scurich and John (2019) question the validity of the personalized Poisson distributions over long periods of time, this analysis raises reasonable doubts about whether the range of values are supported even in the short term.

The available literature reviewed (Francis et al., 2014; Hanson et al., 2018; Lussier & Davies, 2011; Miethe et al., 2006) indicates that the assumptions of 4, 8, or 16 sexual reoffenses per year diverge sharply from what we know about the rates at which PDPs engage in sexual reoffending. For this reason, the resulting predicted actual sexual recidivism rates between about 80% and about 93% are not valid forecasts as applied to actual PDPs. Results from some of the studies are consistent with PDPs committing one or two mean sexual reoffenses per year, which corresponds to predicted actual sexual recidivism estimates of about 50% and about 68%, respectively. Most of the findings from group modeling studies, especially the investigation of more than 7500 PDPs over 25 years by Hanson et al., (2014b), shows that real PDPs engage in per year mean rates of sexual reoffending consistent with actual sexual recidivism rates at 6% or less. This revelation is vital because the predicted actual sexual recidivism rates would be virtually no different from the observed (detected) sexual recidivism base rates (over 4 to 5 years) reported by contemporary sexual recidivism studies (DeClue & Rice, 2016; Duwe & Rocque, 2018; Helmus, Hanson, Thornton, Babchishin, & Harris, 2012; Hanson et al., 2014b; Kuzyk, 2012).

The assumption about the constant rate of sexual offending does not consider that most individuals desist from committing sexual offenses longitudinally (Francis et al., 2014; Hanson et al., 2018; Lussier & Davies, 2011; Miethe et al., 2006). The deceleration in rates of sexual reoffending over time mirrors literature about desistance of

general criminal behavior associated with age related positive personal and social changes over the life course (Sampson & Laub, 2003). Research has discovered that individuals desist from committing sexual reoffenses because of age-related declines in sexual drive, lack of victim accessibility, benefits from treatment for sexual offending, fear of returning to custody, resilience to progress beyond their offending past, and time free in the community without committing nonsexual crimes (Barbaree & Blanchard, 2008; Hanson, 2005; Francis et al., 2014; Hulley, 2016; Harris, 2016; Thornton et al., 2019). Moreover, various nonsexual and sexual criminal history variables appear to influence the rate of sexual reoffending over time (Francis et al., 2014; Hanson & Bussiere, 1998). Because the individualized Poisson distributions cannot account for the effect of the above mentioned linear or nonlinear changes on the persistency of sex reoffending or its cessation over time, this casts further doubts on the validity of predicted actual sexual recidivism rates.

The individualized Poisson and exponential distributions of mean number of sexual reoffenses per year may also be overestimates due to the effect of outliers involving high frequencies of sex reoffending. If true, the median number of sexual reoffenses per year would likely provide a fairer representation of rate of sexual reoffending over time. The uncertainty as to the precision of the mean per year number of sexual reoffenses raises additional suspicions about the accuracy of the predicted actual sexual recidivism rates.

The basis for the assumptions of Scurich and John (2019) about low P_r and moderate P_r were generated using data that lack proper fit to ICSOs and to children under age 12 in certain circumstances. Finkelhor et al. (2011) found substantial variation in P_r (2%–10%) from the low P_r of Scurich and John (15%) when the children's sexual victimization involved certain types of sexual crime. This would cause the low P_r value to underestimates the rate at which certain types of sexual crime committed against young children are reported to authorities, which, in turn, would contribute to inaccuracy in the calculation of the predicted actual sexual recidivism rate. More generally, however, the low P_r and moderate P_r are biased by including data from victim survey studies involving sexual crimes committed by UDPs. Because respondents in victim survey studies would not be expected to know the legal status of the individuals who sexually assaulted them (i.e., UDP versus PDP), it is impossible to identify the correct class of individuals from which to compute the value of P_r for recidivistic sexual crimes committed by PDPs or ICSOs. Because of this incorrect specification, substantive uncertainty exists as to whether the values of P_r proposed by Scurich and John (2019) are accurate (i.e., over- or underestimate P_r) when applied to PDPs or ICSOs. This in turn calls into question not only the accuracy of the predicated actual sexual recidivism rate, but also creates uncertainty about the validity of the $1 - P_r$ that was used, in part, to calibrate the observed sexual recidivism rate from the four comparison studies. Despite the doubts about the precision of the P_r values, the results from Kelley (2018), which examines rates of reported and unreported sexual recidivism among a unique group of ICSOs, appears to support only the moderate P_r of Scurich and John (2019).

This analysis also revealed that rates of reporting sexual crimes appear to be influenced by other variables not accounted for by P_r. The value of P_r is likely to increase as a function of individuals incurring increasing number of sexual offense arrest cycles, which appears consistent with Thornton's (2018) observation that sexual reoffenses committed by PDPs are more likely to be reported because of greater societal vigilance, and the probability for detection increases as the rate of reoffenses rise over time (Hanson, Morton, & Harris, 2003). Such variations are not considered by P_r nor is it understood how these factors might influence the overall value of P_r. Finally, P_r assumes that all reports made by victims are true, yet this is unlikely correct. Review of the limited literature on this topic, as presented earlier, indicates that police officers investigating reported sexual crimes find that between 1% and 41% of reports are considered false. The simulation model assumptions do not consider how this countervailing force would increase P_r, and, in turn, contribute to the decrease in the predicted actual sexual recidivism rate.

The studies that addressed the assumptions of Scurich and John (2019) about the rate of convictions for reported sexual crimes or P_c revealed that the values of P_c were too generous. Convictions rates for reported sexual crimes were roughly one-half to two-thirds lower than the smallest value of P_c (Campbell et al., 2008; Daly & Bouhours, 2010; Morabito et al., 2019; Spohn & Tellis, 2012). This suggests that the values of P_c used in the

simulation model would likely contribute to underestimating the predicted actual sexual recidivism rates. Nonetheless, the values of P_c are based on the untenable presumption that all reported sexual crimes and the resulting number of convictions were generated by ICSOs. This is untrue, because the computation of P_c includes individuals who were apprehended for the first time for committing sexual offenses (i.e., not previously convicted of sexual offending). An accurate estimation of P_c should be computed on the number of all sexual crimes committed by ICSOs and the corresponding number convicted from this group. Another confounding factor related to an accurate estimation of P_c involves the probability for false reports of sexual offenses and wrongful convictions. The research in these areas is limited so the reliable quantification of this effect remains ambiguous.

The calibration procedure of Scurich and John (2019) for the four comparison studies presumes that each study reported the proportions of reconvictions for sexual offenses. Three studies did not meet this condition, so these calibration analyses should be considered invalid. Of the one study that met this condition (Prentky et al., 1997), it is doubtful that the unique characteristics of the sample fit the presumption of the simulation model that the hypothetical ICSOs represent a diverse population. If true, this means that the calibration analysis performed by Scurich and John (2019) for this study is invalid also.

In conclusion, Scurich and John (2019) provide what appears to be a promising framework and methodology to ascertain valid estimations of actual sexual recidivism rates. However, closer examination of studies relating to the parameters fed into the simulation model reveals complex, multi-faceted variations in results that confound the accurate computation of actual sexual recidivism rates. With the exception of the victim surveys about the report rates of sexual crimes to the police, the other two assumptions (i.e., constant rate of sex offending over time and successful prosecution) were based on hypothetical parameters. It is evident from the analysis herein that the precision of the three parameters is substantively uncertain and that this affects the accuracy of the predicted actual sexual recidivism rate in unknown ways. The results of this analysis speak to the need for simulation modeling that provides algorithms that account for linear and nonlinear effects of the inputs (e.g., path analysis or machine learning), which in turn may lead to more precise estimation of predicted actual sexual recidivism rates. In the meantime, while courts and policy makers should not assume that the detected sexual recidivism rates reflect actual sexual recidivism rates, they should also recognize that precise estimation of the extent to which actual sexual recidivism rates exceed detected sexual reoffense rates still remains elusive.

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ENDNOTE

[1] The validity of the results from Bourke and Hernandez (2009) have been hotly contested in the literature because of certain demand characteristics of the prison treatment environment that may have led study subjects to falsely report hands-on contact with victims (cf., Wollert & Skelton, 2017).

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SPECIAL ISSUE ARTICLE

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The dark figure of sexual recidivism

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Empirical studies of sexual offender recidivism have proliferated in recent decades. Virtually all of the studies define recidivism as a new legal charge or conviction for a sexual crime, and these studies tend to find recidivism rates of the order of 5–15% after 5 years and 10–25% after 10+ years. It is uncontroversial that such a definition of recidivism underestimates the true rate of sexual recidivism because most sexual crime is not reported to legal authorities, a principle known as the "dark figure of crime." To estimate the magnitude of the dark figure of sexual recidivism, this paper uses a probabilistic simulation approach in conjunction with the following: (i) victim self-report survey data about the rate of reporting sexual crime to legal authorities; (ii) offender self-report data about the number of victims per offender; and (iii) different assumptions about the chances of being convicted of a new sexual offense given that it is reported. Under any configuration of assumptions, the dark figure is substantial, and as a consequence the disparity between recidivism defined as a new legal charge or conviction for a sex crime and recidivism defined as actually committing a new sexual crime is large. These findings call into question the utility of recidivism studies that rely exclusively on official crime statistics to define sexual recidivism, and highlight the need for additional, long-term studies that use a variety of different measures to assess whether or not sexual recidivism has occurred.

1 | INTRODUCTION

The rate at which sexual offenders recidivate has been a source of persistent controversy. The public appears to believe that a significant proportion of sexual offenders will commit additional sexual offenses. For example, Levenson, Brannon, Fortney, and Baker (2007) reported that a sample of Florida residents believe (on average) that 76% of child molesters and 74% of rapists will commit an additional sexual offense. Similarly, Scurich, Gongola, and Krauss (2016) asked a sample of California jurors to estimate the likelihood a sexual offender would commit a sexual offense within a year if released into the community unsupervised; the mean response was 66% (see also Scurich & Krauss, 2014).

The United States Supreme Court has even endorsed the notion that a substantial proportion of sexual offenders will reoffend. In *McKune v. Lile* (2002), the Court quoted material produced by the US Department of Justice, which stated

> *[T]he rate of recidivism of treated sex offenders is fairly consistently estimated to be around 15%, whereas the rate of recidivism of untreated offenders has been estimated to be as high as 80% (at 33).*

One year later, in *Smith v. Doe* (2003), a case upholding an Alaska law permitting the identification of sexual offenders on a public registry, the Court adverted to the 80% recidivism figure and held

> *Alaska could conclude that a conviction for a sex offense provides evidence of substantial risk of recidivism. The legislature's findings are consistent with grave concerns over the high rate of recidivism among convicted sex offenders and their dangerousness as a class. The risk of recidivism posed by sex offenders is "frightening and high" (at 34).*

Numerous academics have decried the Court's estimate of recidivism (e.g., Cucolo & Perlin, 2018; Montgomery, 2017). The most vociferous critics are Ellman and Ellman (2015), who thoroughly investigated the source of the 80% recidivism figure. Apparently, this figure was cited in a practitioner's guide for treating sexual offenders published by the US Department of Justice. However, within the guide, the source cited to support the 80% recidivism figure is a 1986 article published by two clinicians in *Psychology Today*, a popular press outlet. Following an expose by *The New York Times* (Feige, 2017), the lead author of the article disavowed the 80% figure, stating he did not intend to imply that the 80% figure applies to all sex offenders and that it should not be considered seriously because "[*Psychology Today*] is not a scientific journal." The author of the Department of Justice report similarly disavowed the 80% figure, stating that a dearth of research at the time required her to "make[] a bunch of guesses" about the recidivism rate.

The recidivism rate of sexual offenders has been the subject of numerous empirical studies. One of the most widely cited studies is a meta-analysis conducted by Hanson and Bussiere (1998), which synthesized 61 individual recidivism studies and found a mean sexual recidivism rate of 13.4% within four to five years. A nearly identical rate (13.7%) was reported in a follow-up analysis by Hanson and Morton-Bourgon (2005), although the rates of individual studies vary, with some finding considerably lower rates of recidivism. For example, a study published by the US Department of Justice found that just 3.5% of sexual offenders released in 1994 were convicted of a new sexual offense within 3 years (Langan, Schmitt, & Durose, 2003; for a similar figure see Cohen, 2018). As one group of academics summarized the empirical studies, "…the best empirical research on the base rates of sexual reoffending suggests that, in fact, only a minority of sex offenders recidivate" (Calkins, Jeglic, Beattey, Zeidman, & Perillo, 2014, p. 449).

There is, obviously, a substantial gulf between the sexual recidivism rates observed in the empirical studies and the rates supposed by the laity and endorsed by the Supreme Court. Based on the assumption that the empirical studies are correct in their conclusion that sexual recidivism rates are "low," academic commentary has universally castigated the enactment of laws and statutes that are ostensibly predicated on a "high" recidivism rate (e.g., Huffman, 2016; Wright, 2014; but see Bierie, 2016). Consider Ellman and Ellman (2015): "The *simple fact* is that the risk level, for nearly everyone on the registry, is nowhere near the 'frightening and high' rate assumed by *Smith* and *McKune* and all the later decisions that rely on them" (p. 507, emphasis added). Indeed, "the problem… [of]

alarmingly high rates of recidivism does not exist" (Montgomery, 2017, p. 541). And as a consequence, some researchers have concluded that "[the] laws are driven by emotional responses to sexual violence rather than by empirical data" (Levenson et al., 2007, p. 4).

We take no position on the propriety of sexual offender legislation. However, we do question challenges to that legislation to the extent that they are based on current empirical assertions that sexual offender recidivism is "low." In doing so, we first probe deeply the very concept of *sexual recidivism*. As will be shown, the concept depends crucially on three components, which are rarely defined with any precision when discussing sexual offender recidivism or legislation. We next show that the definition of sexual recidivism commonly used in academic research (i.e., a legal conviction for a new sexual offense) is likely to be an extreme underestimate of actual sexual reoffending because *most* sexual crime is not reported to authorities (Planty, Langton, Krebs, Berzofsky, & Smiley-McDonald, 2013). Finally, this paper utilizes a probabilistic simulation approach that incorporates victim and offender self-report data to estimate the true rate of sexual recidivism among convicted sexual offenders.

2 | DEFINING "SEXUAL RECIDIVISM"

Three definitional factors affect the observed rate of sexual recidivism (Koehler, 2002; Scurich & John, 2012): the (i) reference class; (ii) time period; and (iii) operational definition of outcome event. Changing any of these components will affect the rate of recidivism. Each factor will be discussed in turn.

The *reference class* refers to the population of interest. For example, this class could be all offenders convicted of a sexual offense, or only offenders who are incarcerated for a sexual offense, setting aside those who receive an alternative sanction. Another possible classification of sexual offenders, one that is commonly used, is based on the type of victim in the predicate offense (e.g., "child molester" or "rapist") or the nature of the predicate offense (e.g., "contact offender" or "non-contact offender"). The reconviction rate for a new sexual offense could be different for each of these populations, though this important difference is lost when one speaks broadly about "sexual offenders."

The *time period* refers to the period during which an individual is free to offend or not. Many sexual offender recidivism studies use follow-up periods that are relatively short, on average about 5 years (see Hanson & Bussiere, 1998). Very few have used follow-up periods of 25 years or longer, which is understandable given the enormous costs associated with tracking individuals for extended periods of time. It is uncontroversial that longer follow-up periods will result in more sexual offenses and thus a higher rate of sexual recidivism (see, e.g., Harris & Hanson, 2004, page 4, Table 1). This principle is illustrated by Prentky, Lee, Knight, and Cerce (1997), who tracked a sample of rapists and child molesters for 25 years, and noted that "If we were to adopt the common risk period of 5 years, we would miss slightly under two thirds (63%) of new sexual charges for child molesters and half (51%) of new sexual charges for rapists" (p. 652). A similar finding is reported by Hanson, Steffy, and Gauthier (1993), who tracked a sample of 197 child molesters for up to 31 years: "Forty-two percent of this sample were eventually reconvicted, with 23% of the recidivists being reconvicted more than 10 years after they were released" (p. 650).

The third factor—*the operational definition of the outcome event*—has the potential to exert the largest impact on recidivism rates. The vast majority of the academic studies operationally define "sexual recidivism" as either a charge or conviction for a new sexual offense. For example, 84% of the studies contained in the meta-analysis by Hanson and Bussiere (1998) defined recidivism as a new conviction (p. 350). Again, it is uncontroversial that such a definition of sexual recidivism underestimates the actual rate of recidivism, because it includes only those sex offenses that: (i) are reported to the police in the first place; (ii) are investigated by the police; (iii) result in arrest; (iv) result in a formal charge; and (v) lead to a conviction for a sexual offense, rather than a dismissal on technical grounds or a conviction for a non-sexual offense (see Rice, Harris, Lang, & Cormier, 2006). The effect of this process is depicted in Figure 1, which contains illustrative values from an empirical study of sexual offender recidivism (Prentky et al., 1997).

While only a relatively small percentage (26%) of all sexual offenders received a new legal charge for a sexual offense, this figure may substantially underestimate the number of offenders who recidivated, given the requisite

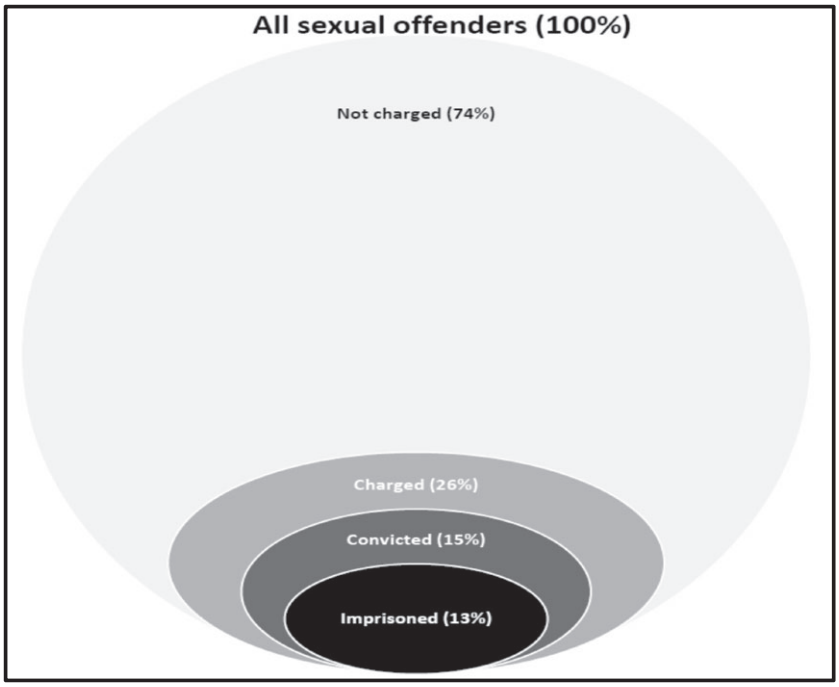


FIGURE 1 Venn diagram of released sexual offenders who were subsequently charged, convicted, and imprisoned for a new sexual offense. The values depicted in the figure originate from Prentky et al. (1997), page 643, Table 2a

preconditions necessary to be charged with a criminal sexual offense. This general pattern has also been reported by other researchers (e.g., Rice et al., 2006), including most strikingly by Marshall and Barbaree (1988), who found that combining information from child protection agencies and police reports led to a "recidivism" rate 250% larger than if they had relied on official crime statistics alone. Note also that the difference between the percentage of those charged (26%) and those convicted for a new sexual offense (15%) is relatively large—the first rate is nearly double the second. Thus, while the difference between defining recidivism as a "new charge" versus a "new conviction" or "incarceration" for a sexual offense may seem trivial, it has the potential to influence the estimated "recidivism" rate substantially.

Figure 1 masks a lurking complexity in that it deals only in officially recorded crime statistics. Because not all crime is reported to the authorities, one should not assume that the 74% of offenders who were not *charged* with a new sexual offense did not *commit* a new sexual offense. The difference between official crime statistics (or crime statistics based on official records) and actual crime rates is known as the "dark figure" of crime, one of the most well-known principles in criminology (Biderman & Reiss, 1967). This principle applies to sexual offending (Hanson, 2000). Two sources of data that speak to the magnitude of the dark figure are victim self-report surveys and offender self-report surveys.

3 | VICTIM SELF-REPORT DATA

The Bureau of Justice Statistics' National Crime Victimization Survey queried a nationally representative sample of individuals age 12 or older who live in US households (Planty et al., 2013). Based on their reports, the survey found that, over the course of 15 years (1994–2010), approximately 35% of rape and sexual assault victimizations against females were reported to the police (p. 7, Table 10). An even more extreme figure is reported by Kilpatrick, Saunders, Veronen, Best, and Von (1987), who interviewed a sample of 391 women in South Carolina and found that while

41.4% of all crimes were reported to the police, only 7% of completed rapes were reported. Daly and Bouhours (2010) aggregated 13 large, national scale studies from five different countries (Australia, Canada, England and Wales, Scotland, and the United States) and found that overall 14% of sexual assault victims reported the crime to the police (see p. 575, Table 1).

The figures are similar if one looks specifically at child sexual assault. Hanson et al (1999) conducted a nationally representative survey and found that only 12% of child sexual assaults were reported to authorities. Mullen, Martin, Anderson, Romans, and Herbison (1993) found that only 8% of child sexual assaults were reported to authorities, and male victims are slightly less likely to disclose child sexual assault than female victims (Finklehor et al., 1990).

The actual degree of victim underreporting varies by a variety of different factors (e.g., crime type, see Kilpatrick et al., 1987) and for a variety of different reasons (see, e.g., Sable, Danis, Mauzy, & Gallagher, 2006), and there are, of course, methodological issues associated with using victim self-report surveys that may distort the reported percentages (Heydon & Powell, 2018; Koss & Gidycz, 1985). Nonetheless, the existing literature suggests that the underreporting problem with regard to sexual offenses is substantial. Indeed, *at a minimum*, a majority of sexual offenses do not get reported by victims to the police.

4 | OFFENDER SELF-REPORT

Another way to mitigate the underreporting problem is to use offender self-reports of misbehavior rather than rely exclusively on official crime statistics (Monahan et al., 2001). Using this approach, Langevin et al. (2004) followed a sample of 320 Canadian sexual offenders for 25 years. The recidivism rate was 61.1% using official conviction as the definition, yet it was 88.3% when official crime statistics were combined with self-report data.[1] Similarly, Abel et al. (1987) conducted interviews with 561 sexually disordered psychiatric patients about their offending history, communicated under the condition of confidentiality; they note

> *Initially, we thought that the validity of subjects' self-report could be substantiated by comparing it to his arrest record. Examining available arrest records, however, proved to be of minimal assistance because the frequency of self-reported crimes was vastly greater than the number of crimes for which subjects had been arrested. For example, the ratio of arrest to commission of the more violent crimes such as rape and child molestation was approximately 1:30 (pp. 10–11).*

If anything, offender self-reports will probably be an underestimate of recidivism because some offenders will naturally minimize the extent of their offending behavior. To counter this problem, some researchers have used polygraphy to examine and substantiate the veracity of such claims (for a review see Elliott & Vollm, 2018). The results are often striking. Bourke et al. (2015) examined a sample of 127 sexual offenders with no official history of contact offenses. Initially, 4.7% of the sample admitted to sexually abusing a child. However, after being polygraphed about their previous sexual behavior, an additional 52.8% disclosed that they had in fact committed a contact sexual offense that was never detected (see also Bourke & Hernandez, 2009). Ahlmeyer, Heil, McKee, and English (2000) similarly examined 60 sexual offenders incarcerated in Colorado; the sample initially admitted to having 50 victims (total), but that number increased 99 victims following the first polygraph examination and 110 following a second polygraph examination (p. 129, Table 1). Similar effects have been reported in The Netherlands (Buschman et al., 2010).

5 | CURRENT STUDY

It seems plausible that at least some of the disparity between what the public believes about sexual recidivism and what academics generally believe about sexual recidivism is attributable to whether one defines “recidivism” as a legal conviction for a new sexual offense (herein “observed recidivism”) or whether “recidivism” is defined as a new illegal

sexual act, regardless of whether it is reported to the police and prosecuted (herein "actual recidivism"). The differences could also be attributable to whether one assumes the time window is relatively short (e.g., 5 years) or long (a lifetime) (but see Scurich et al., 2016). Of course, these are empirical questions that could be answered by conducting a simple survey.

In our opinion, the more pressing and pragmatic question concerns understanding the actual sexual recidivism rate, since legal statutes define sexual recidivism risk in these terms (see Knighton, Murrie, Boccaccini, & Turner, 2014). For example, to be committed as a sexually violent predator in California, among other criteria, it must be established that the respondent is "likely that he or she will engage in sexually violent criminal behavior" (Sexually Violent Predator Act, Cal. Welf. & Inst. Code § 6600(a)(1) (2006). The code does not refer to whether the person is likely to be *convicted* for a sexually violent criminal behavior; rather, it focuses on whether he or she will *engage* in such behavior. The latter is aptly captured by the actual recidivism rate.

Nearly two decades ago Hanson (2000) noted "The observed recidivism rates are underestimates of the actual rates because many sexual offenses are never detected. The extent of the underestimation is the topic of active debate—a debate that is likely to remain active because definitive evidence is, by definition, unavailable" (p. 106). While the actual recidivism rate may be unavailable in many studies, it can be estimated based on different assumptions about the factors responsible for the discrepancy between actual and observed sexual recidivism rates. One well-known judge—Richard Posner, formerly of the Seventh Circuit Court of Appeal—has attempted to do just this.

In *Belleau v. Wall* (2016), an appellate case considering the constitutionality of requiring released sexually violent predators to wear a GPS ankle monitor, Judge Posner was presented with research finding a sexual recidivism rate of 3% in three years. He went on to note

> *Although non-sex offenders had a higher re-arrest rate (68 percent) than sex offenders and only 3 percent of child molesters were re-arrested for a child-molestation offense, these numbers don't take account of the very high rate of underreporting of sex offenses. If only 20 percent of child molestations result in an arrest, the 3 percent recidivism figure implies that as many as 15 percent of child molesters released from prison molest again (at 934, citations omitted).*

Posner is right to note that the 3% sexual recidivism rate is an underestimate because of underreporting, but his arithmetic is problematic in two noteworthy respects. First, his analysis implies that every sexual offense that is reported will also result in an arrest. This assumption is conceptually and empirically untenable. Indeed, empirical evidence suggests the majority of reported sexual offenses will not result in arrest. For example, Planty et al. (2013) found that approximately 39% of sexual assaults reported to the police resulted in an arrest.

Second, Posner's analysis mixes units of observation, as the 20% refers to *offenses* and the 3% refers to *offenders*. Using these different units of observation is appropriate if, and only if, one assumes that each offender commits exactly either one or zero offenses. That assumption is also conceptually and empirically untenable. As the offender self-report studies show, the number of unreported sexual offenses is a highly skewed distribution with relatively few offenders having many victims. For example, Abel et al. (1987) report that 22% of their sample had committed rape (i.e., 22% were rapists), and the mean number of rapes committed per rapist was 7.2 (median = 0.9). Similarly, non-incest pedophiles with male victims comprised 23.5% of the sample, and had an average of 281.7 (median 10.1) pedophilic acts. Lisak and Miller (2002) found that 6.4% of a sample of college students disclosed committing rape or attempted rape and 63% of this group admitted to committing more than one rape, on average 4 rapes per individual.

In short, Posner's skepticism about relying exclusively on a re-arrest rate as an estimate of sexual recidivism is proper, but his analysis comes up short. A more appropriate analysis would follow these steps: (i) separate out the number of sexual *offenses* from the number of sexual *offenders*; (ii) take into account the likelihood that each sexual offense will be reported; and (iii) take into account the likelihood that each reported offense will result in a conviction (setting aside for brevity the intermediary steps of arrest, charge, etc.). We propose a model that does just this.

6 | MODEL AND ANALYSIS

6.1 | Overview

We developed a probabilistic simulation model to estimate the rate of actual sexual recidivism in a group of non-incarcerated sexual offenders (i.e., men convicted of a sexual offense who have served their time and been released). The model allows us to estimate mean rates of actual recidivism, conditional on a distribution of reoffending over the population and on fixed probabilities for reporting and successful prosecution for each offense. We conduct sensitivity analysis on model parameters for the distribution of reoffending over individuals and on the fixed probabilities for reporting each offense and for convicting each offense that is reported.

Figure 2 is a schematic representation of the complete simulation model. Uncertainty is represented by ovals, including the distribution of offending propensity in the population of offenders (μ_o), the individual distributions of sexual offenses for each individual offender (λ_i), the likelihood that a sexual offense will be reported (P_r), and the likelihood that a reported offense will result in a conviction (P_c). The rounded rectangles in the third row represent, for each individual (i) in the population, the count over a given time period of sexual offenses committed (S_i), sexual offenses reported (R_i), and sexual offenses successfully prosecuted to a conviction (C_i). The rounded rectangles in the bottom row represent the number of individuals over the time period who commit one or more sexual offenses (N_s), who are reported to have committed one or more sexual offenses (N_r), and who are successfully prosecuted to a conviction for sexual offenses (N_c). Details of the model assumptions are provided below.

6.2 | Model assumptions

6.2.1 | Individual offending

The number of sexual offenses for a given individual in a population of offenders is assumed to follow a Poisson distribution. Approximating criminal offending as a Poisson process is a common method of computing probabilistic

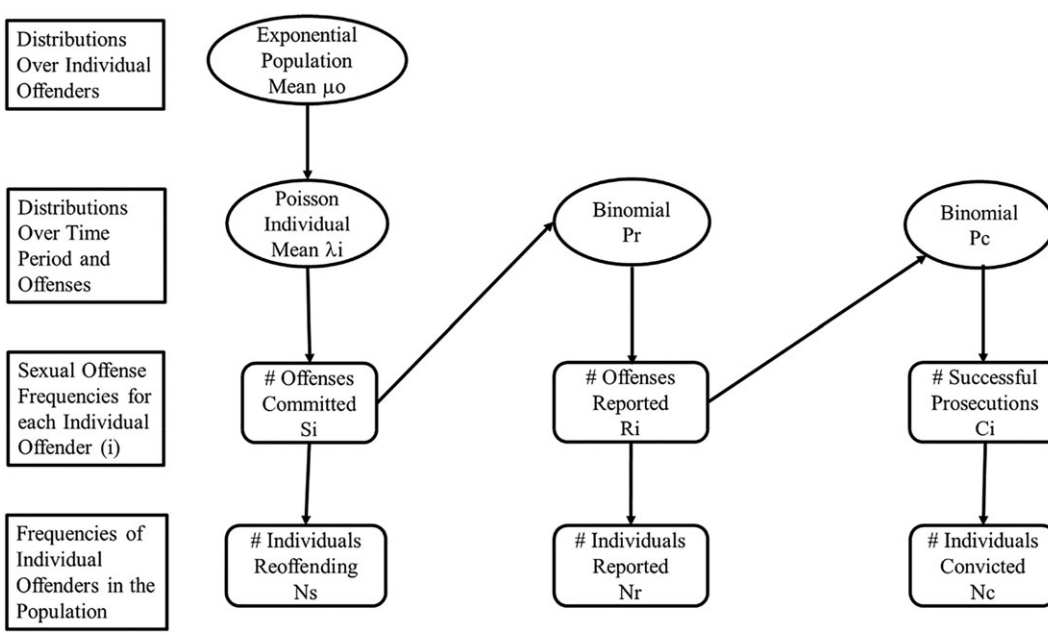


FIGURE 2 Schematic diagram of the probabilistic simulation model

models of recidivism (Maltz, 1996). This Poisson distribution is defined for offense frequencies (e.g., 0, 1, 2, 3, …) for a particular time interval, *T*. The Poisson distribution of offenses for each individual offender has a single parameter, the mean, λ_t (which is also equal to the variance.) The Poisson distribution of offenses can be generalized to any time period, since the ratio of the expected number of offenses for any two periods is the same as the ratio of the length of the time periods. For example, if the mean number of offenses for 5 years is 4, then the mean number of offenses for 1 year is 0.8, and the mean number of offenses for 25 years is 20.

Approximation of offending as a Poisson process was proposed in the mid-1970s (Maltz, 1996), and is motivated by a simple assumption that for any given (short) time period, e.g., a day, the likelihood that an individual commits a single offense follows a Bernoulli process. The Bernoulli process describes any random process with two possible outcomes (e.g., offense = 1, no offense = 0) in which we have the following: (i) trials are independent (i.e., offending in any particular short time period is independent of offending in any other short time period); and (ii) outcome probabilities are constant across repeated trials (i.e., the probability of offending in a fixed time period, e.g., a day, is constant). The assumption of a Bernoulli process with a constant probability (p) of an offense (e.g., $p = 0.01$) implies that the number of offenses over N time periods (e.g., $N = 100$ days) will follow a binomial distribution with parameters p and N, with mean = Np (=1 for our example). The Poisson distribution exactly describes this situation for the case in which the mean (Np) remains constant. For example, if the time period considered is hourly, we would need 24 additional time intervals to represent the same time period, and the probability of offending in each hour would be 1/24 of that for days. For our example of 100 days and $p = 0.01$ per day, $N = 2400$ h, $p = 0.01/24$, and Np remains a constant 1.0.

Figure 3 provides a histogram representation (based on 1000 random trials) of a Poisson distribution for offender *i* with mean (λ_i) = 4. The distribution is right skewed, with an interquartile range (IQR) = (3, 5).

The distribution of offenses for each individual is conditional on the individual not being incarcerated over the time period. If the individual commits one or more offenses that are reported and result in a conviction, then other potential offenses are moot since the individual is considered to have reoffended during the time period. That is to say, once a reoffense is observed, whether the offender would have reoffended again over the period has no bearing on the actual reoffending rate, since the (re)offender is counted as a reoffender with the first reoffense. The model is not designed to capture an unfolding sequence of sexual offenses, reports of offenses, or convictions over time. Rather, the model focuses on variability across individuals in an offender population and on variation in the actual number of sexual offenses committed in any given time period by each individual in the offender population. The

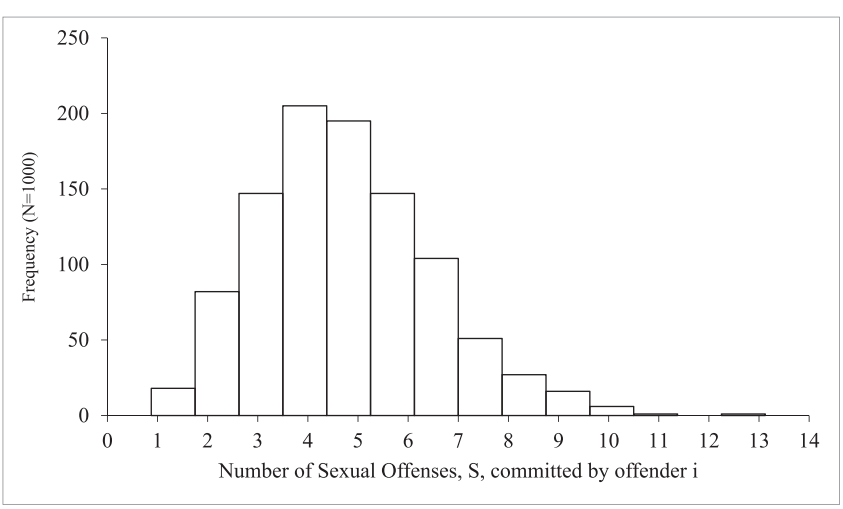


FIGURE 3 Example Poisson distribution histogram of sexual offenses committed by offender *i* during time period of interest, $\lambda_i = 4.0$

model is entirely generalizable to any length period of time by modifying the distribution of individual sexual offense means, λ_i.

6.2.2 | Offending population

As described above, the frequency of sexual offenses for each individual is assumed to follow a Poisson distribution that is constant over time. Each individual's offending propensity is defined by the mean, λ_i, of the individual offender's Poisson distribution. Unlike early models of offending and recidivism that assumed a constant λ for all offenders (Maltz, 1996), we assume a diverse population of offenders with different propensities of offending, λ_i. We assume that the distribution of λ_i is right skewed over individual offenders and can be represented by a gamma distribution, consistent with later models of offending and recidivism (Maltz, 1996). In particular, we assume that λ_i follows an exponential distribution, which is a special case of a gamma distribution with shape parameter = 1. Figure 4 displays a histogram representation for an exponential distribution with mean λ_i (μ) = 4. The exponential distribution is continuous and right skewed, meaning that most offenders have relatively low means of sexual offenses over the time period but there are some individuals in the offender population with a much greater number of mean sexual offenses over the time period.

For the current simulation, we consider nine different exponential distributions of offender populations, with means of 1/16, 1/8, 1/4, 1/2, 1, 2, 4, 8, and 16 sexual offenses per year. Note that each individual offender in the population is characterized by his own propensity to commit sexual offenses, and the entire population of offenders is characterized by an exponential distribution over offenders for that population. By modeling nine different populations, we are able to characterize a broad range of different levels of propensity for sexual offenses. These distributions span a broad range of mean frequency of sexual offending, corresponding to different population characteristics (e.g., age, type of sexual offense, etc.), as well as different periods of time (e.g., 1 year, 5 years, 25 years, etc.). Note that the model is entirely generalizable in the sense that the exponential distribution could be replaced with any distribution thought to describe sexual offending propensity for a particular population of offenders over a given period of time.

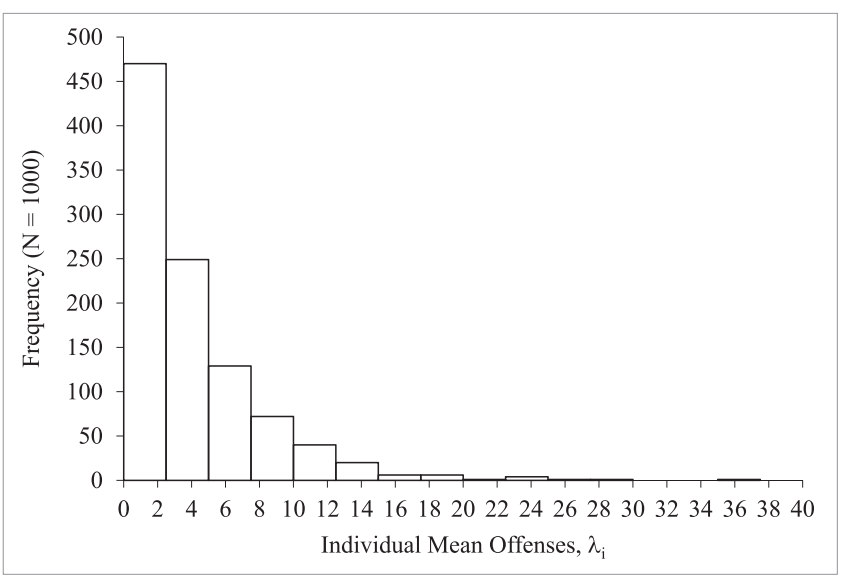


FIGURE 4 Example exponential distribution histogram over individual mean number of sexual offenses, λ_i, in the time period, μ_o = 4.0

6.2.3 | Reported sexual offenses

Each sexual offense committed is assumed to be reported with some probability, P_r, that is constant across individual offenders in the population and across multiple offenses for the same offender. That is, for the current model, we assume the same constant probability that any sexual offense committed will be reported. We include three different assumptions for P_r in the present analysis, including a low estimate based on reports from a large survey of sexual offense victims (P_r = 0.15) (Daly & Bouhours, 2010), an intermediate estimate based on the National Crime Victimization Survey (P_r = 0.35) (Planty et al., 2013), and an optimistic limiting condition (P_r = 1.0) in which every single sexual offense is reported.

6.2.4 | Successful prosecution of reported sexual offenses

Each sexual offense that is reported is assumed to result in a conviction or plea with a constant probability, P_c. The probability of successful prosecution includes uncertainty about identifying the offender, capturing the offender, bringing the offender to trial, securing a conviction, etc. (Note that each of these steps could be modeled separately, but for the current model, we have combined these into a single uncertainty.) As for the reporting probability described above, this present model assumes that P_c is constant across individual offenders and across different charged offenses for the same offender. In the absence of any reported data on the likelihood of a successful prosecution of reported sexual offense, we assumed three possible values of P_c spanning a broad range, including P_c = 0.25, 0.50, and 0.75.

6.3 | Monte Carlo simulation results

We conducted Monte Carlo simulations for populations of size N = 100 offenders using a three-way factorial design for values of μ_o (1/16, 1/8, 1/4, 1/2, 1, 2, 4, 8 and 16) × P_r (0.15, 0.35, and 1.00) × P_c (0.25, 0.50, and 0.75). In all, we ran the Monte Carlo simulation for 81 separate combinations (based on the nine variations of μ_o, the three variations of P_r, and the three variations of P_c described above). Each of the 81 simulations was run for 1000 independent trials and all input distributions are assumed to be independent (uncorrelated). The simulations were implemented in Microsoft Excel 2016, using the add-in tool RiskSim. The number of reoffenders for each trial was obtained by counting which offenders committed one or more sexual offenses during the time period; the actual reoffending rate is then calculated as the ratio, N_s/N.

Figure 5 presents a histogram representation of the distribution of the number of offenders, N_s, who commit one or more sexual offenses in a fixed time period, for the case in which the mean number of offenses over individuals is set to μ_o = 4.0. That is, each of the 100 individuals in the population commits a number of sexual offenses during a fixed time period, determined from a Poisson distribution with a mean λ_i drawn from an exponential with mean μ_o = 4. The mean of this distribution is 79.91 (SD = 4.31), with an IQR = (77, 83), indicating that, on average, nearly 80% of the offending population commits one or more sexual offenses over the fixed time period.

The means of each of the output distributions are plotted in Figure 6 as a function of nine different assumptions regarding the mean rate of offending during a given time period. The figure shows that the actual recidivism rate is entirely dependent on the Poisson parameter for the mean rate of offending over a fixed time period. For example, if the mean number of sexual offenses over the period per offender were 4 (which is the seventh category on the *x*-axis) then the actual recidivism rate would be 80%. For a five-year time period, this 80% actual recidivism rate would result from an average of 0.8 sexual offenses per offender per year; similarly, for a 25-year time period, the 80% actual recidivism rate would result from an average of 0.16 sexual offenses per offender per year. Thus, one would expect the same actual recidivism rate (80 in 100) for relatively low rate offenders (mean = 0.16/year) followed for 25 years as for much higher rate offenders (mean = 0.80/year) followed for only 5 years. The actual rate of

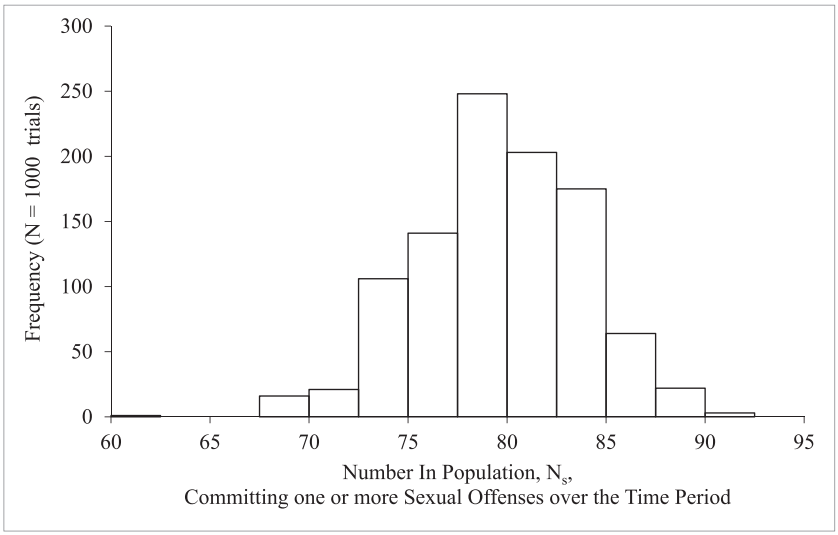
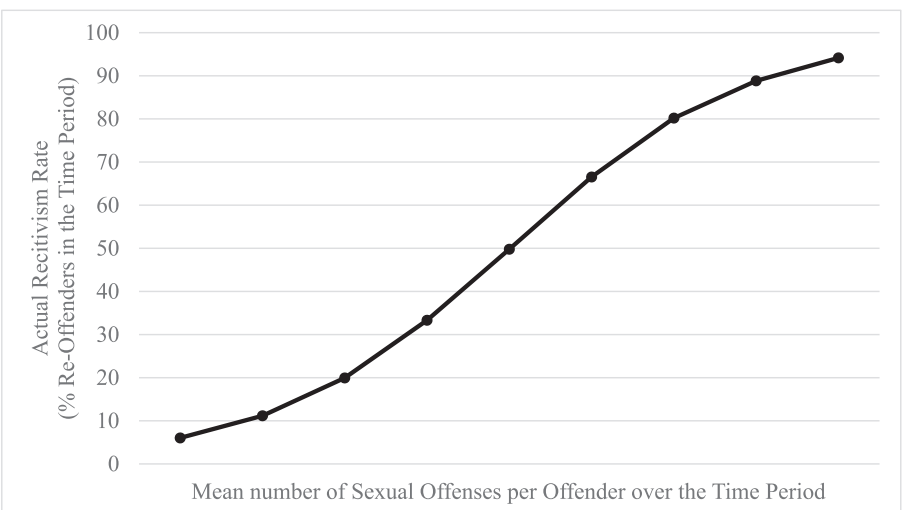


FIGURE 5 Histogram distribution of the number of reoffenders, N_s, over the time period from a population of size N = 100 for whom the average number of offenses over the period is 4.0



Period Means	0.0625	0.1250	0.2500	0.5000	1.0000	2.0000	4.0000	8.0000	16.0000
5 year annual	0.0125	0.0250	0.0500	0.1000	0.2000	0.4000	0.8000	1.6000	3.2000
25 year annual	0.0025	0.0050	0.0100	0.0200	0.0400	0.0800	0.1600	0.3200	0.6400
31 year annual	0.0020	0.0040	0.0081	0.0161	0.0323	0.0645	0.1290	0.2581	0.5161

FIGURE 6 Mean number of actual reoffenders (N_s) from a population of N = 100 over a fixed time period by mean number of sexual offenses per offender over the time period (from 1/16 (=0.0625) to 16). Annualized offense rates are also provided for three different fixed time periods: 5 years, 25 years, and 31 years

reoffending over the time period spans nearly the entire possible range, from 6 (in 100), assuming an average of 1/16 offenses in the period per offender, to 94 (in 100), assuming a mean of 16 offenses in the period per offender. Note that even a mean rate of 1.0 sexual offenses over the time period per individual results in an actual recidivism rate of 50% over the time period.

While Figure 6 demonstrates the flexibility of the rather simple Poisson model to reflect a broad range of actual recidivism rates, we need to calibrate the sexual offense propensity parameter, μ_o, with observed recidivism rates that lower the actual recidivism rate due to non-reporting of sexual offenses (P_r < 1.0) and failure to secure a conviction for reported sexual offenses (P_c < 1.0). In the next section we present results for actual recidivism, calibrated to four different observed recidivism rates reported in the literature using quite different populations of offenders and varying time periods.

6.4 | Calibration with reported recidivism rates

An overview of the calibration process is represented schematically in Figure 7. The empirical estimates of observed recidivism rates from the literature (top node) are used to impute values of the propensity parameter for fixed rates of reporting and successful prosecution. We utilized four separate studies that report observed recidivism rates ranging from 5% to 40% over a time period ranging from 5 years to 31 years. Our analysis includes observed recidivism rates from the following studies: Hanson et al (1993), 40% over 31 years; Prentky et al. (1997), 25% over 25 years; Hanson and Bussiere (1998), 15% over 5 years; Hanson, Lunetta, Phenix, Neeley, and Epperson (2014), 5% over 5 years.

For each of these four reported observed rates of reoffending, and each of the nine possible combinations of reporting probabilities and successful prosecution probabilities, we determine a value of the propensity parameter, μ_o, such that the observed recidivism rate from the simulation, N_c/N, matches the observed recidivism rate reported in the literature. The identified value of μ_o is then used to estimate a value of the actual recidivism rate (output node on the right in Figure 7). For example, for a reporting rate of 35% and a successful prosecution rate of 50%, the model requires an (exponential) distribution of with mean 1.0 to define the individual (Poisson) offense distributions in order to match the recidivism rate of 15% over 5 years observed by Hanson and Bussiere (1998) . For this combination of assumptions (35% reporting rate, 50% successful prosecution rate, and a mean of 1.0 offense over the 5 year time period), the model indicates an actual recidivism rate of 50% (Figure 6). The difference between the observed (15%) rate and the actual (50%) rate is due to non-reporting and unsuccessful prosecutions.

Table 1 displays the estimated actual recidivism rates corresponding to each of the four observed recidivism rates reported in the literature for nine combinations of reporting rate and successful prosecution rate. The estimated

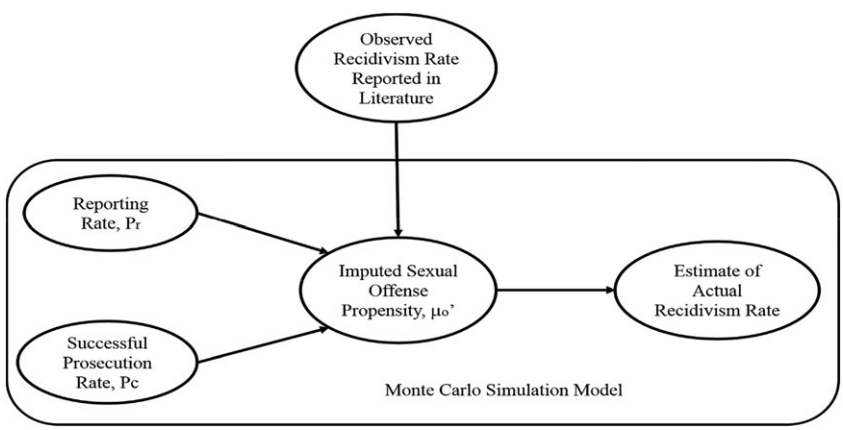


FIGURE 7 Schematic diagram for estimation of actual recidivism rates for sexual offenses corresponding to observed recidivism rates reported in the literature, conditional on reporting rate, P_r, and successful prosecution rate, P_c

TABLE 1 Actual reoffending rate and mean offense rate by observed reoffending rate, reporting rate, and successful prosecution rate

		Hanson et al. (1993)		**Prentky et al. (1997)**		**Hanson and Bussiere (1998)**		**Hanson et al. (2014)**	
Time period		31 years		25 years		5 years		5 years	
Observed reoffending % over period		40%		25%		15%		5%	
Reporting rate per offense	Successful prosecution rate per offense	Poisson mean over period μ_o	Actual reoffending rate over period N_c/N	Poisson Mean over Period μ_o	Actual reoffending rate over period N_c/N	Poisson mean over period μ_o	Actual reoffending rate over period N_c/N	Poisson mean over period μ_o	Actual reoffending rate over period N_c/N
100%	75%	0.90	**47%**	0.48	**32%**	0.24	**19%**	0.07	**7%**
	50%	1.30	**55%**	0.70	**40%**	0.37	**26%**	0.11	**10%**
	25%	3.00	**73%**	1.40	**56%**	0.75	**42%**	0.24	**19%**
35%	75%	2.50	**70%**	1.30	**55%**	0.70	**40%**	0.22	**18%**
	50%	4.00	**80%**	2.00	**66%**	1.00	**50%**	0.31	**23%**
	25%	8.00	**89%**	4.00	**80%**	2.00	**66%**	0.55	**35%**
15%	75%	6.00	**84%**	3.00	**73%**	1.60	**60%**	0.50	**33%**
	50%	10.00	**90%**	6.00	**84%**	2.40	**69%**	0.75	**42%**
	25%	18.00	**95%**	10.00	**90%**	4.80	**82%**	1.50	**58%**

actual recidivism rates for sexual offenses for each of the 36 cases are in bold, to the right of the corresponding sexual offense propensity parameter, μ_o. It is important to realize that these parameters are for the time period specified in the reported study (31 or 25 or 5 years), and annualized offense rates can be determined by dividing by the number of years for each particular study.

The gaps between observed recidivism rates and actual recidivism rates depend on the reporting rate and successful prosecution rate in each of the four studies examined. As one would expect, the actual recidivism rates are higher for longer time periods. Also, the actual recidivism rate increases as the reporting rate decreases and the rate of successful prosecution decreases. This simply means that the observed rates of recidivism reported in the literature should be interpreted conditional on both reporting and successful prosecution rates. For the middle categories of 35% reporting and 50% successful prosecution, actual recidivism rates are estimated to be 80% over 31 years (compared with the observed rate of 40%), 66% over 25 years (compared with the observed rate of 25%), and either 50% or 23% over 5 years (compared with the observed rates of 15 and 5%, respectively). Note that, in the most pessimistic case of 15% reporting rate and 25% successful prosecution rate, actual recidivism estimates are elevated to 95% over 31 years, 90% over 25 years, and either 82% or 58% over 5 years.

6.5 | Model implications and limitations

The probabilistic simulation model just described allows us to estimate actual recidivism rates for sexual offenders given observed rates of reoffending. In all realistic cases considered, the actual recidivism rate was substantially greater than the observed recidivism rate.

The primary limitation of this probabilistic model is the absence of attention to dependency, sequence, and feedback. Dependencies between uncertainties about the number of offenses committed and the likelihood of each being reported and/or successfully prosecuted are not accounted for in the model; all uncertainties are modeled as independent (hence uncorrelated). Although this assumption is reasonable as a first approximation, accounting for dependencies and estimating their impact can be accomplished within the Monte Carlo simulation by assessing correlations among uncertainties.

As indicated previously, there is no attention to the sequence of sexual offenses unfolding over time. That is, there is no consideration of learning or escalation by offenders; they are assumed to commit offenses consistent with a personalized Poisson distribution that remains the same over a fixed time period. For short periods of time (a few years), this may be a reasonable assumption. However, for longer time periods of several years or decades, this assumption may well be violated. Capturing dynamic changes in offending over time would require a more general model with multiple states of offending, or that allows for feedback over time, or both.

The Monte Carlo simulation model presented here is entirely generalizable through modification of the input distributions. For example, population propensities to commit sexual offenses can be represented with alternative distributions for λ_i. For example, some sub-group of the population could be identified to have $\lambda_i = 0$, and a new distribution capturing this sub-group substituted for the exponential distribution for the Poisson means.

Further extensions of the model could allow for uncertain values of P_r and P_c, characterized by standard beta distributions (defined between 0 and 1). These beta distributions would characterize variation and uncertainty in the application of public policy related to encouraging victim reporting, investigation and charging of the offense, and resources devoted to obtaining a conviction. Like the exponential distribution describing population propensity to commit sexual offenses, these beta distributions over rates of reporting, charging, and conviction would allow analysis of the impact of public policy initiatives aimed at decreasing sexual offenses that are not reported, charged, or successfully prosecuted. In addition, modeling uncertainty in the rates of reporting, charging, and convicting would allow us to explore the impact of dependencies among the uncertainties on the true recidivism rate of sexual offenders.

7 | DISCUSSION

We do not endorse any specific sexual recidivism rate as the "correct" one. As we attempted to make plain, any rate will depend on decisions about definitional parameters (e.g., 5 year versus 25 year follow-up) and assumptions about the degree of underreporting, the average number of victims per offender, and the chances of being convicted given that the offense is reported, among other things. We used a range of reasonable values based on empirical studies to derive our estimates, precisely to drive home the point that there is no single, universal recidivism rate that describes all varieties of sexual offenders. By parity of reason, sweeping proclamations that "…only a minority of sex offenders recidivate" (Calkins et al., 2014, p. 449) are inapposite.

The primary objective of this paper is to stimulate thought and critical reflection about the near-universal practice of limiting the definition of sexual recidivism to a new legal charge or conviction for a sexual offense. Such definitions are convenient for the purposes of research, but they are also of limited relevance to legal policy and decision makers, who are concerned with *actual* rather than *observed* recidivism. The analyses reported in this paper make clear that these two quantities, even under favorable assumptions, are very different and should not be conflated. Several implications follow from these observations.

First, we believe it is untenable for researchers to rely exclusively on sexual recidivism that is based on official crime statistics; the majority of sexual recidivism is not detected by such a definition. Moreover, legal and policy decision makers are understandably concerned with actual recidivism, not observed recidivism. Researchers often make short shrift of the underreporting issue by furnishing a cursory acknowledgement of the problem and then move on to discuss studies of observed recidivism, often in highly confident and dispositive terms. The reality, as demonstrated in this paper, is that such studies may be capturing only a tiny sliver of actual sexual recidivism and that not much is known empirically about actual sexual recidivism—which may constitute the bulk of sexual recidivism.

Second, given that observed recidivism may be such a small sliver of actual recidivism, serious questions arise about the appropriateness of using actuarial risk assessment instruments trained to predict *observed* recidivism to address legal issues that are concerned with *actual* recidivism (a similar issue was raised by Rice & Harris, 2006). No existing actuarial risk assessment instruments predict *actual* sexual recidivism or account for the difference between observed and actual recidivism rates. Whether it is appropriate for the current state of affairs to continue is an issue that should be considered seriously by the field, and certainly those who use actuarial risk assessment instruments to assess sexual recidivism for legal purposes have an obligation to explain this distinction to the legal factfinder and be candid that risk estimates of observed sexual recidivism are underestimates of actual sexual recidivism.

Finally, we note that no policy decision is impelled by any particular sexual recidivism rate (for a general explanation of this point, see Windschitl & Wells, 1996). Policy decisions to restrict liberty are grounded in moral and legal judgments (Morse, 2008; Schopp & Quattrocchi, 1995). It is, of course, important that policy makers be accurately apprised of actual sexual recidivism rates; however, reasonable people can and will disagree agree about what constitutes a sufficiently "high risk of recidivism" to justify a given liberty intrusion (Scurich, 2018). There is nothing "irrational" or "emotional" about reaching a different policy decision. Indeed, it may be perfectly rational for different stakeholders to reach different policy conclusions based on the same sexual recidivism rate estimate, given the different underlying values and objectives of the stakeholder groups (Scurich, 2016; Scurich & John, 2010).

7.1 | Final thoughts

One sexual recidivism researcher recently propounded

> *The world's leading researchers on sex offender risk have been studying recidivism for over 2 decades and have amassed a compelling body of evidence about the longitudinal patterns of post-conviction offending. Across studies, sexual recidivism rates average between 5 and 15%, depending on the sample and the follow-up period (Levenson, 2018, p. 21, citations omitted).*

Claims such as this are the orthodoxy in academic circles, which refer to single digit/low teen sexual recidivism rates as "simple facts" (Ellman & Ellman, 2015). But these claims are also specious and seriously betray the reality of sexual recidivism. As demonstrated in this paper, under any realistic assumptions, the rate of *actual* sexual recidivism is substantially larger than the rate of *observed* sexual recidivism. In our judgment, it is time for the field to reflect and take stock; while we have come a long way, we still have a long way to go in understanding sexual recidivism. One thing is clear: the field would benefit enormously from additional longitudinal studies of sexual offenders that use a variety of measures to assess whether additional sexual offending has or has not actually occurred.

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ENDNOTES

[1]The Langevin et al. (2004) study was criticized for, among other things, having a "biased sample" since it involved individuals who were referred to a psychiatric clinic for treatment and thus potentially unrepresentative of the "average" sexual offender (Webster, Gartner, & Doob, 2006). However, this criticism was countered cogently by Rice and Harris (2006), who noted that Langevin et al. (2004) made no claims about specific rates of recidivism but instead offered an illustration of the "uncontroversial" point that "a large portion of violent and sexual offenses go undetected by the criminal justice system" (p. 97; see also Langevin, Curnoe, & Fedoroff, 2006). We cite the Langevin study for this purpose.

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