Validation Of A Bayesian Method
For Assessing Sexual Recidivism Risk

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Abstract

The most robust finding in criminology is that recidivism decreases with age. Hanson (2006) recently compiled an updated actuarial experience table for Static-99 that broke down the recidivism rates for a large sample (N=3,425) of sex offenders into four risk groups and five age groups. Not finding a significant interaction between age and risk, he concluded that age-related declines in sexual recidivism “should be expected for low, moderate, and high risk offenders.” Both Doren (2006) and Hanson (2006) expressed concern, however, that this age-invariance effect had not been replicated and implied that factoring the effects of age into Static-99 was largely beyond the reach of evaluators. The research reported in this paper found an age-sensitive version of Bayes’s Theorem replicated Hanson’s (2006) updated Static-99 table (r=.97). Comparing estimates from the age-sensitive formula with estimates from an age-restricted one, the predictive validity for the first formula was greater than the second. One implication of these results is that an actuarial table may be replicated using probabilistic data if the data are independent of the table. Replication of updated Static-99 with an age-sensitive version of Bayes’s Theorem holds some additional implications. For one, it provides a confirmation of the age invariance effect. For another, the predictive superiority of the age-sensitive equation means that age-restricted actuarials for the prediction of sexual recidivism are obsolete. Overall, Bayes’s Theorem and Bayesian co-ordinates provide a precise method that takes age and actuarial measures into account in order to predict sexual recidivism. Factoring the effects of age into an actuarial test therefore falls well within the reach of evaluators as long as they understand the principles of probabilistic reasoning, identify sources from which Bayesian co-ordinates might be compiled, and are ready to collect supplementary data when necessary.

Key words: sexual recidivism, actuarial risk assessment, Bayes’s Theorem, age invariance
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For many years it has been recognized that the most robust cross-sectional finding in the field of criminology is that the prevalence and incidence of criminal behavior by adults goes steadily down with age (Moffitt, 1993). In what is now a classic paper, Hirschi and Gottfredson (1983), reviewed many studies pointing up the “invariance” of this relationship. In particular, they documented a pattern showing that crime rates decreased with age for offender groups who a) lived in different centuries, b) came from different countries, c) differed with respect to age and gender, d) were at large in the community or incarcerated; and e) committed different types of crimes. Figure 1 presents an illustration of the dramatic impact this effect has on violent crime, including rape, from cross-sectional data compiled by the Federal Bureau of Investigation in 1980, 1994, and 2001 (OJJDP, August 2004).

Insert Figure 1 about here

Until recently, only longitudinal research findings were needed to definitively confirm the age-invariance theory. These are now available. In 2004, Sampson & Laub published a 70-year longitudinal study of 475 “serious, persistent delinquents” that controlled for both the effects of death and incapacitation. Not only did they find that violent crimes were infrequently committed by offenders as they got older, but that the violent crime rate for offenders with high actuarial scores converged with the violent crime rate for low scoring offenders over time. Since violent offenses include sexually violent offenses (Harris, Rice, Quinsey, Lalumiere, Boer, & Lang, 2003; Quinsey, Harris, Rice, & Cormier 1998; Rice and Harris, 1997), this study provides strong evidence that sexual recidivism declines with age.
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Research on sex offenders in general buttresses this conclusion (Barbaree & Blanchard, in press; Barbaree, Blanchard, & Langton, 2003; Fazel, Sjostedt, Langstrom, & Grann, 2006; Hanson, 2002; Hanson, May 2004; Hanson, 2005; Hanson, 2006; Harris & Hanson, 2004; Milloy, December 2003; Nicholaichuk and Yates, 2002; Wollert, 2006). Hanson (2002), for example, found that sexual recidivism risk declined almost 4% per year as a function of age at release from custody for 4,763 sex offenders who were stratified into four types of offenders (rapists, molesters, incest offenders, and unclassified offenders) and nine age categories (18-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-59, 60-69, 70+). Collapsing across Hanson’s offender types, Wollert (2006), found that a linear model estimated the obtained data most accurately ($R^2 = .98$). He also found that the ratio of age-wise recidivism (symbolized as $P_y$) to the overall recidivism rate (symbolized as $P$ and equaling about 18%) over an 8-year period was greatest for those in the 18-24 age group ($P_{18}/P = 1.538$) and decreased over the lifespan ($P_{27}/P = 1.302$; $P_{32}/P = 1.114$; $P_{37}/P = .803$; $P_{42}/P = .797$; $P_{47}/P = .714$; $P_{52}/P = .493$; $P_{62}/P = .195$; $P_{70}/P = 0$). Figure 2 plots the decline in this ratio, referred to by the author as the “age-wise specifier,” over the lifespan.

![Insert Figure 2 about here](image)

Other research shows that the age invariance effect pertains to offenders who are thought to represent a high risk for sexually re-offending as well as those in lower risk categories. In a 2006 article, for example, Hanson reported that age accounted for additional variance in the prediction of sexual recidivism rates after the effects of an actuarial test known as Static-99 (Hanson & Thornton, 2000) were controlled. He also compiled a new Static-99 experience table that broke down the recidivism rates for a very large sample ($N=3,425$) of sex offenders into four
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risk groups and five age groups and tested whether a significant interaction was present between age and risk level. Finding none, he concluded that “the age-related decline (in sexual recidivism) should be expected for low, moderate and high risk offenders as defined by Static-99” (p. 351). He also recommended that “evaluators using Static-99 should consider advanced age as one factor in their overall estimate of risk” (p. 353).

In a recent manuscript, Wollert and Waggoner (2007) re-specified Hanson’s (2006) expectancy table to correct for recidivism findings that were artifacts of “double-counting” age as a risk factor for the youngest group of offenders. This re-specification, presented as Table 1, indicates that recidivism “rates” or “frequencies” were compiled for 20 specific age and test score combinations (symbolized as $Q_{y,j}$) by dividing the number of recidivists in each cell by the total number of offenders in the cell. The right-most column indicates that recidivism rates were also compiled for four different test scores (symbolized as $Q_j$): high (symbolized as “H” in Table 1), moderately high (MH), moderately low (ML), and low (L). Comparing the value of $Q_j$ in any row with the variations in $Q_{y,j}$ from the same row, it seems intuitively clear that risk estimates that take both age and score levels into account are more precise than risk estimates that are based only on the level of a test score. One score size, in otherwords, doesn’t fit all age sizes.

By providing a method of weighing age when using an actuarial to estimate recidivism risk, Hanson’s new research promises to enhance procedures that are used to evaluate sex offenders. In a 2006 paper, however, Doren concluded that evidence for the operation of the age invariance effect among sex offenders had not been replicated adequately and warned practitioners that “we have a lot of work to do before we can say we understand how to consider
offender age in sexual recidivism risk assessments” (p. 157). Even Hanson, in his article reporting the updated Static-99 table, qualified the significance of this development by observing that

How best to consider age remains unresolved by the current study ... although it is possible to compute numeric estimates of the combined effect of Static-99 and advanced age using the numbers in Tables 2 and 3, the stability of these estimates will be unknown until they have been replicated in independent samples … consequently, evaluators using Static-99 with older offenders are left with the familiar problem of knowing that a factor external to an actuarial scheme contributes information to risk assessment, but lacking sufficient scientific evidence to formally include the factor in the actuarial measure” (p. 353).

Doren’s and Hanson’s assumption – that factoring the effects of age into an actuarial test lies beyond the methodological reach of evaluators except for the oldest of offender groups – is erroneous under certain conditions, however. By extrapolating from one or more Static-99 samples, for example, it is feasible to estimate the accuracy (symbolized as $L_{j+}$) with which a given score (e.g., 5 points on Static-99) discriminates between recidivists and non-recidivists in the criminal population from which a sex offender is selected for evaluation. It is also feasible to estimate the recidivism risk for the offender’s age group by taking the age-wise specifier (symbolized as $P_{y}/P$) for his group from Figure 2 and multiplying it by the population base rate (symbolized as $Q$). Relying on these estimates, an evaluator may easily calculate the probability ($P$) of recidivism ($R+$) for those in the criminal population who are the same age ($A_{y}$) and have the same Static-99 score ($S_{j}$) as the subject offender (symbolized, in total, as $P \left( R+ | A_{y} \& S_{j} \right)$ by
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solving an “age-sensitive” version of a probability formula known as Bayes’s Theorem (Wollert, 2006). This version, for which the notation is

\[
P(R+ | A_y & S_j) = \frac{\left( \frac{P_y}{P} x Q \right) x L_j^+}{1 + \left( \frac{P_y}{P} x Q \right) x L_j^+}
\]

may be contrasted with the following version that is more restrictive because it considers only the two levels of age that are currently specified among the Static-99 items:

\[
P(R+ | S_j) = \frac{Q x L_j^+}{1 - Q x L_j^+}
\]

Since equation (1) will predict the recidivism rate for any age and score combination when estimates of \( P_y/P, L_j^+, \) and \( Q \) are available, it can be used under these conditions to predict all of the entries in a “criterion” actuarial table such as the updated version of Static-99. As long as the values for \( P_y/P \) and \( LR+ \) are estimated from sources external to this criterion, a high correlation between the probability results obtained with equation 1 (i.e., \( P(R+ | A_y & S_j) \)) and the frequency values (i.e., \( Q_{y,j} \)) in Table 1 would constitute a conceptual replication and cross-validation of updated Static-99. Furthermore, the age invariance effect would be confirmed again if the table estimated from equation (1) matched the criterion table better than the table estimated from equation 2. Such a finding would also mean that methods of sexual recidivism prediction that specify the effects of age, such as equation (1), possess greater predictive validity than age-restricted methods.
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The next section of the paper at hand reports (a) the procedures that the author used to estimate the specifiers for different age groups (i.e., \(P_y/P\)) and the accuracy (\(L_j+\)) with which different Static-99 scores differentiated recidivists from non-recidivists, (b) the replication of Static-99 that was achieved when the values obtained by solving equation 1 were correlated with the corresponding frequency values (\(Q_{y,j}\)) from Table 1, and (c) the superior validity that was found for equation (1) when its performance for predicting the criterion table was compared to that of equation (2). The implications of these findings and the value of Bayesian methods for rendering recidivism predictions are discussed in the concluding section.

Method

Description of Static-99

Static-99 (Hanson & Thornton, 2000) is composed of 10 items, one of which is a restrictive item about age (younger than 25 versus older than 24 at release), and no more than 12 points may be obtained on the test. As noted earlier, subjects were placed in one of 4 risk groups in the updated Static-99 experience table. The “L” risk group included offenders with actuarial scores of 0 or 1. Those in the “ML” group had scores of 2 or 3. Those in the “MH” risk group had scores of 4 or 5. Those in the “H” risk group had scores of 6 or more. Validity studies indicate that Static-99 is of moderate predictive accuracy in that risk scores are correlated about .33 with sexual recidivism (Hanson & Thornton, 2000; Hanson & Morton-Bourgon, 2004) and the average ROC (relative operating characteristic) curve (Mossman, 1994; Rice & Harris, 1995) is approximately .70. The five-year recidivism rate for subjects in Hanson’s (2006) table was 12%, 6 percentage points lower than the rate recorded for subjects in the developmental sample compiled by Hanson and Thornton in 2000.
Several considerations point to the conclusion that Static-99 is the instrument of choice for the prediction of sexual recidivism. One of these is that Static-99 was originally compiled on a reasonably large (\(N = 1,086\)) and diverse developmental sample (Hanson and Thornton, 2000) that was characterized by a five-year recidivism rate of 18%. Another is that it has been studied in many other populations since its dissemination (Harris, Phenix, Hanson, & Thornton, 2003). Still another is that, being the most widely used test for the prediction of sexual recidivism (McGrath, Cumming & Burchard, 2003), follow-up research on Static-99 is potentially available from a number of databases on sex offenders compiled in different countries (Doren, 2004). Finally, the most recent experience table for the Static-99 has been specified for four more age categories than the MnSOST-R (Epperson, Kaul, Huot, Goldman, & Alexander, December 2003) or the RRASOR (Hanson, 1997), the only other actuarials that table sexual recidivism rates.

**Estimation of Age-Wise Specifiers**

As the first step in estimating the age-wise specifiers (i.e., \(P_y/P\)), the author compiled the six-year sexual recidivism rates for four age groups (21-30, 31-40, 41-50, and older than 51) included in a sample of 468 sex offenders that were provided to him by Howard Barbaree and Calvin Langton and referenced by Barbaree and Langton in other articles and treatises (Barbaree, Blanchard, & Langton, 2003; Barbaree & Blanchard, in press; Langton, 2003) Then he divided each of the group-wise rates by the sample rate of 11.3%. After this he completed a regression analysis in which \(P_y/P\) was regressed on the midpoints of the age groups. Estimating the midpoints of the age groups studied by Hanson (2006) from data reported previously (Wollert, 2006, Table 1), he used the equation from the regression analysis (predicted \(P_y/P = 2.27 - .0321(A_y)\)) to calculate \(P_y/P\) for the midpoints of each of Hanson’s groups.
Column C of Table 2 presents the age-wise specifiers that were obtained from these procedures. These estimates were independent of the corresponding weights compiled from data relied upon by Hanson, cited at the end of the third paragraph in the introduction, but were almost identical to these weights and, as before, reflected a strong linear component ($R^2 = .99$; $F(2) < .01$).

Insert Table 2 about here

**Estimation of the Accuracy of Test Scores for Differentiating Recidivists from Nonrecidivists**

The formula for calculating the accuracy of a given test score $j$ for differentiating recidivists from nonrecidivists, as reported by Donaldson & Wollert (2007) and Mossman (2006), is

$$L_j^+ = \frac{P(S_j | R^+)}{P(S_j | R^-)}$$

where

$L_j^+ = \text{the accuracy, or “positive likelihood ratio,” for score } j$,

$P(S_j | R^+) = \text{the percentage of all recidivists with scores of } j \text{ in a sample’s distribution of recidivists}$,

$P(S_j | R^-) = \text{the percentage of all nonrecidivists with scores of } j \text{ in a sample’s distribution of nonrecidivists}$.

As equation (3) indicates, one must know the number of recidivists and nonrecidivists in each Static-99 score group in a sample to estimate test accuracy. Doren (2004) reported the recidivism rates for each Static-99 score group over a 5-year period for 7 samples (Beech, Friendship, Erikson, & Hanson, 2002; Dempster, 1998; deVogel, deRuiter, van Beek, & Mend, 2002; Harris et al., 2003; McGrath et al., 2003; Nicholaichuk, 2001; Sjostedt & Langstrom,
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2001) that were not included among the samples from which Hanson updated Static-99. The author and his colleagues Diane Lytton and Jacqueline Waggoner, in order to verify the sources of variance in the recidivism rates reported by Doren, obtained these samples from the researchers who had provided them to him. In a recent technical report, Waggoner and Wollert (2007) broke down the distributions for recidivists and nonrecidivists by score groups for the combined set of the samples. Drawing on information in this report, the author compiled \( P(S_j | R^+) \) and \( P(S_j | R^-) \) for each Static-99 score group by relying on data from all the samples except one that clearly did not use representative sampling procedures (Dempster, 1998). The score-wise likelihood ratios that were obtained from the six combined samples (N=2,638) are presented in column D of Table 2. Although these ratios are from data sets other than Hanson’s, their pattern and elevation is similar to corresponding ratios reported by Mossman (2006) for the original Static-99.

Application of Equations (1) and (2) to Estimate Cell-Wise Recidivism Rates

All other things being equal, recidivism estimates (e.g., \( P(R+| A_y \& S_j) \) and \( P(R+| S_j) \)) will vary as a function of the sample-wise base rate (Donaldson & Wollert, 2007; Mossman, 2006). The recidivism rate for Hanson’s 2006 Static-99 sample (12%) was inserted as the value for Q in equations (1) and (2) to control for this effect. Other relevant values from Table 2 were then inserted into equation (1) and equation (2). To estimate the probability of recidivism on the condition of being 45 years old and having a high Static-99 score, for example, a \( P_y/P \) of .83 was first multiplied by a Q of .12 and a \( L_j^+ \) of 3.28 (the first and last values are from columns C and D in row 3 of Table 2). The product of this operation (i.e., .83 x .12 x 3.28 = .327) was then divided by 1 minus \( P_y/P \) times Q (1 – .83 x .12 = 1 – .10 = .90). Lastly, the quotient from the second operation (.327/.90 = .363) was divided by one plus the quotient (1.363) to arrive at a
recidivism estimate of 26.7% (see the intersection of column E and row 3 in Table 2). To estimate the probability of recidivism only on the condition of having a high Static-99 score, thereby ignoring the effect of being 45 years old, a Q of .12 was multiplied by a L\textsubscript{j} of 3.28. The product of this operation (.12 x 3.28 = .394) was divided by 1 minus Q, or .88. Lastly, the quotient from the second operation (.394/.88 = .447) was divided by one plus the quotient (1.447) to arrive at an alternative recidivism estimate of .309 (the intersection of column F and row 3).

These examples indicate that only a few simple operations need to be undertaken to solve Bayesian equations (1) and (2). A comparison of the absolute differences between each estimate and the criterion value Q\textsubscript{y,j} (see the intersections of columns G, H, and I with row 3) also points to the conclusion that equation (1) gives a better approximation to the criterion than equation (2) for an offender who is 45 years old and has a high Static-99 score because the absolute difference from the criterion is one percentage point for the estimate based on equation (1) while it is over five percentage points for the estimate based on equation (2).

**Results**

The set of estimates from equations (1) and (2) are presented in columns E and F, respectively, of Table 2. Each set was correlated with the Hanson’s 2006 results to test whether it was possible to replicate his findings. A predictor-criterion correlation of .97 (p<.001) was found for equation (1) while a correlation of .77 (p<.001) was found for equation (2). Regarding evidence for the presence of the age invariance effect and the comparative validity of age-specified over age-restricted methods of sexual recidivism prediction, the former correlation was found to be significantly larger than the latter (t (17) = 5.35, p<.001). In addition, as shown in columns H and I, the estimates from equation (1) most closely approximated Hanson’s estimates.
in 85% of 20 possible matches (N=17), which was significantly different from chance ($X^2 = 3.18, p < .01$). Figure 3 provides a graphic illustration of the high degree of overlap between the recidivism models of Hanson and Wollert.

To determine the relative superiority of age-specified methods over age-restrictive ones, the percentage of subjects who fell in each cell of Hanson’s table was determined by dividing the number of offenders per cell presented in Table 1 ($n_{y,j}$, where n = number, y = age, and j = Static-99 test score) by 3,425 (N, the total number of offenders in Hanson’s sample). Each cell entry in columns H and I was then multiplied by the value of $n_{y,j}/N$ with which it corresponded, and the 20 products were summed. These calculations indicated that age-specified estimates, on the average, fell .019 percentage points away from Hanson’s estimates. The difference for the age-restrictive estimates was .041. Age-specified actuarials and probabilistic formulas are therefore more than twice as accurate as age-restrictive methods for the prediction of sexual recidivism.

Discussion

The research reported in this paper found an age-sensitive version of Bayes’s Theorem replicated Hanson’s (2006) updated Static-99 table in which the risk estimates were originally calculated from frequency data. Comparing the estimates from the age-sensitive formula with estimates from an age-restricted one, the hypothesis was confirmed that the predictive validity for the first formula was greater than that for second.

One implication of these results is that an actuarial prediction table may be replicated using probabilistic data if these data are independent of the table. From teaching graduate students and conversing with colleagues, however, the author’s impression is that many
psychologists think only in terms of the collection and compilation of frequency data when they consider the issue of actuarial replication. Since this assumption is probably due in large part to the stress that is placed on frequentist methods of data analysis in research design and statistics courses, these courses should be modified to include a greater emphasis on Bayes’s Theorem and probabilistic reasoning.

Replication of the updated version of Static-99 with an age-sensitive version of Bayes’s Theorem also holds a number of implications. For one, it provides another in a long string of confirmations of the age invariance effect. For another, the predictive superiority of equation (1) over equation (2) means that age restrictive actuarials for the prediction of sexual recidivism – including the MnSOST-R (Epperson et al., December 2003), the RRASOR (Hanson, 1997), and the original Static-99 (Hanson & Thornton, 2000) – are obsolete. Finally, by verifying the stability of Hanson’s risk estimates at a general level, the present set of findings should erase any lingering doubts that evaluators may have had about using age-specified Static-99 in place of original Static-99 for the purpose of estimating sexual recidivism risk when the base rate in the local population including a sex offender under evaluation is about 12%.

If the base rate for the local population from which an offender is drawn diverges from 12%, however, Table 1 should not be used as it will provide inaccurate recidivism estimates. Under such circumstances it would be more accurate to use equation (1) and the procedures described above to either construct an actuarial table that applies to all possible age and score combinations in the local population or to generate a risk probability that pertains to a specific offender.

Fortunately, Bayes’s Theorem and Bayesian co-ordinates (Dawid, 2002; Donaldson & Wollert, 2007; Mossman, 2006; Waggoner & Wollert, 2007; Wollert, 2006; Wollert, 2007;
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Wollert & Waggoner, 2007) enable the accomplishment of these tasks by providing a clear and precise scientific method for simultaneously taking age and actuarial measures into account for the prediction of sexual recidivism. Factoring the effects of age into an actuarial test therefore falls well within the reach of evaluators as long as they understand the principles of probabilistic reasoning, identify sources from which base rates and evidence weights might be compiled, and are ready to collect some supplementary data when necessary.
References


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Author’s Note

Portions of this paper were presented at the 2005 and 2007 meetings of the Western Psychological Association. The author is indebted to Drs. Jaqueline Waggoner, Howard Barbaree, Calvin Langton, and Terry Nicholaichuk for consulting with him on previous versions of this paper. Requests for reprints of this paper and correspondence should be sent to the author at 1220 S.W. Morrison St. #930, Portland, OR 97205. The author may also be contacted at 360-737-7712 or rwwollert@aol.com. The address of his website is richardwollert.com.
Table 1  Five-year sexual recidivism rates broken down by age and Static-99 risk categories (from Wollert & Waggoner, 2007)

<table>
<thead>
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<th>Age at Release</th>
<th>18-24.9</th>
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<th>40-49.9</th>
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<th>60 and older</th>
<th>All ages</th>
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<td>recidivism</td>
<td>n</td>
<td>recidivism</td>
</tr>
<tr>
<td>L</td>
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<td>7.5</td>
<td>486</td>
<td>6.7</td>
<td>321</td>
<td>5.5</td>
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<tr>
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<td>12.8</td>
<td>590</td>
<td>11.7</td>
<td>260</td>
<td>6.7</td>
</tr>
<tr>
<td>MH</td>
<td>117</td>
<td>26.2</td>
<td>321</td>
<td>24.3</td>
<td>124</td>
<td>13.8</td>
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<tr>
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<td>37.5</td>
<td>71</td>
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<tr>
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<td>1513</td>
<td>14.4</td>
<td>776</td>
<td>8.8</td>
</tr>
</tbody>
</table>
Table 2. Cross-Validation Of Bayesian Risk Estimates For Released Sex Offenders

| A. Static-99 Risk Groups | B. Age In Mean Years | C. Age Weights: \( \frac{P_j}{P} \) | D. Score Weights: \( L_j \) | E. Estimated Risk\(^a\) Per Score/Age: \( \frac{P(R^+|A_j, & S_j)}{P(R^+|A_j, & S_j)} \) | F. Estimated Risk\(^b\) Per Score Only: \( P(R^+|S_j) \) | G. Obtained Recidivism Per Table 1: \( Q_{y,j} \) | H. \( |G-E| \) | I. \( |G-F| \) |
|-------------------------|---------------------|-----------------|-----------------|---------------------------------|---------------------------------|-----------------|---------|---------|
| 1. H                    | 21.5                | 1.58            | 3.28            | .435                            | .309                            | .404            | .031    | .095    |
| 2. H                    | 33                  | 1.22            | 3.28            | .359                            | .309                            | .375            | .016    | .066    |
| 3. H                    | 45                  | .83             | 3.28            | .267                            | .309                            | .257            | .010    | .052    |
| 4. MH                   | 21.5                | 1.58            | 1.43            | .251                            | .163                            | .262            | .011    | .099    |
| 5. MH                   | 33                  | 1.22            | 1.43            | .197                            | .163                            | .243            | .046    | .080    |
| 6. H                    | 55                  | .51             | 3.28            | .173                            | .309                            | .243            | .07     | .066    |
| 7. MH                   | 45                  | .83             | 1.43            | .137                            | .163                            | .138            | .001    | .025    |
| 8. ML                   | 21.5                | 1.58            | .66             | .134                            | .083                            | .128            | .006    | .045    |
| 9. MH                   | 55                  | .51             | 1.43            | .111                            | .163                            | .194            | .083    | .031    |
| 10. ML                  | 33                  | 1.22            | .66             | .101                            | .083                            | .117            | .016    | .034    |
| 11. ML                  | 45                  | .83             | .66             | .068                            | .083                            | .067            | .015    | .016    |
| 12. L                   | 21.5                | 1.58            | .28             | .065                            | .037                            | .075            | .010    | .038    |
| 13. ML                  | 55                  | .51             | .66             | .054                            | .083                            | .043            | .011    | .040    |
| 14. L                   | 33                  | 1.22            | .28             | .046                            | .037                            | .067            | .021    | .030    |
| 15. H                   | 68                  | .09             | 3.28            | .035                            | .309                            | .091            | .056    | .218    |
| 16. L                   | 45                  | .83             | .28             | .030                            | .037                            | .055            | .025    | .018    |
| 17. L                   | 55                  | .51             | .28             | .025                            | .037                            | .025            | .000    | .012    |
| 18. MH                  | 68                  | .09             | 1.43            | .010                            | .163                            | .048            | .038    | .115    |
| 19. ML                  | 68                  | .09             | .66             | .010                            | .083                            | .030            | .020    | .053    |
| 20. L                   | 68                  | .09             | .28             | .000                            | .037                            | .000            | .000    | .037    |

\(^a\) Each entry in column E was estimated by applying equation (1) to entries in each row. For row 1, for example, the value in column C was multiplied by the sample-wise recidivism rate of 12% to estimate the age-wise recidivism rate of 19%. This rate was then subtracted from 1 to obtain the age-wise nonrecidivism rate of 81%. The first rate was then multiplied by \( L_j+ \) from Column
D and the product divided by the second rate. The quotient of this operation (i.e., .19 x 3.28/.81 = .77) was then divided by one plus the quotient to obtain the estimate reported in Column E (.77/1.77=.435).

b Each entry in column F was estimated by applying equation (2) to entries in each row. For row 1, for example, the age-wise recidivism rate was assumed to equal the sample-wise recidivism rate of 12%. This rate was then subtracted from 1 to obtain the age-wise nonrecidivism rate of 88%. The first rate was then multiplied by L_j+ from Column D and the product divided by the second rate. The quotient of this operation (i.e., .12 x 3.28/.88 = .45) was then divided by one plus the quotient to obtain the estimate reported in Column F (.45/1.45=.309). As this example illustrates, the only difference between the calculation reported in E and that reported in F is that a step is added to the former so that the effects of age on recidivism may be specified over five different levels.
Wollert: Bayesian Method

![Graph of arrests per 100,000 population by age and year (1994, 2000, 1980)]
Figure Caption

Figure 1. The relationship between age and violent crime arrests in the United States.
Wollert: Bayesian Method

Figure Caption

**Figure 2.** The relationship between sexual recidivism and age at release from custody for sex offenders (data points from Wollert, 2006).
Wollert: Bayesian Method

Presented at the 115th Annual Convention of the American Psychological Association at San Francisco, California, August 2007
Wollert: Bayesian Method

Figure Caption

Figure 3. Estimates for each risk group in Hanson’s and Wollert’s recidivism models.