The Creation and Validation of the Ohio Risk Assessment System (ORAS)*

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THE OHIO RISK ASSESSMENT SYSTEM (ORAS) was developed as a statewide system to assess the risk and needs of Ohio offenders in order to improve consistency and facilitate communication across criminal justice agencies. The goal was to develop assessment tools that were predictive of recidivism at multiple points in the criminal justice system. Specifically, assessment instruments were to be developed at the following stages: 1) pretrial,[1] 2) community supervision, 4) institutional intake, and 4) community reentry.

A major goal of the ORAS was to conform to the principles of effective classification. In doing so, the Ohio Department of Rehabilitation and Correction (ODRC) hoped to efficiently allocate supervision resources and structure decision-making in a manner that reduces the likelihood of recidivism. As a result, ORAS was developed to classify the risk level of offenders in the system while also identifying both criminogenic needs and barriers to programming.

The Principles of Effective Classification

The principles of effective classification have been developed to guide criminal justice agencies in the use of risk assessment systems. In short, the principles of effective classification suggest that agencies should use actuarial assessment tools to identify dynamic risk factors, especially in high risk offenders, while also identifying potential barriers to treatment. The risk principle suggests that correctional interventions and programs are most effective when their intensity is matched to the risk level of the clientele (Andrews, Bonta, & Hoge, 1990; Van Voorhis, 2007; Lowenkamp, Latessa, & Holsinger 2006). That is, the most intensive programming should be allocated to moderate- and high-risk cases, while low-risk cases should be allocated little if any programming.

Another consistent finding in correctional programming is that the most effective programs target dynamic risk factors (Andrews et al., 1990; Lowenkamp, Latessa, & Smith, 2005; Lowenkamp & Latessa, 2004). Dynamic risk factors (also called criminogenic needs) are factors that, when changed, have been shown to result in a reduction in recidivism. The needs principle suggests that effective classification systems should identify dynamic risk factors directly related to recidivism so that they can be used to target programmatic needs.

The responsivity principle[2] focuses on identifying barriers to treatment (Van Voorhis, 2007). Although dynamic risk factors are directly related to recidivism, there are other issues that are likely to keep individuals from engaging in treatment, such as intelligence, reading ability, and language barriers. If left unaddressed, it is likely that these influences can interfere with the completion of treatment and, as a result, indirectly prevent a reduction in recidivism.

Finally, the principle of professional discretion recognizes that case managers and counselors are responsible for processing the risk, need, and responsivity information and making decisions based on the information provided (Andrews, Bonta, & Hoge, 1990). Further, actuarial tools are designed to treat offenders in the aggregate and cannot be structured to anticipate every possible case or scenario. As a result, it is important to allow

[1] For more details on the Pretrial instrument see: Lowenkamp, CT., Lemke, R. and Latessa E. (2008). *Federal Probation* 72(3)2-9.

[2] The responsivity principle touches on two related aspects of responsivity–specific and general. This article, and assessment in general, usually focuses on assessing specific responsivity.

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criminal justice personnel the ability to override the assessment instruments in specific circumstances.

The Advantages of Constructing a Statewide Risk Assessment System

Although many criminal justice agencies have been implementing standardized risk classification instruments to efficiently manage their target populations, they often use empirically derived tools developed on samples from a different population (Jones, 1996). This is because resource constraints often limit the development of risk assessment instruments for specific jurisdictions and populations (Jones, 1996). Although using preexisting risk assessments is less costly, it assumes that the instrument is a valid predictor of recidivism for each agency's specific population (Wright, Clear, & Dickerson, 1984; Jones, 1996; Gottfredson & Moriarty, 2006). Since it is unlikely for a single instrument to have universal applicability across various offending populations, validating risk assessment instruments on specific target populations is important (Wright, Clear, & Dickerson, 1984). Further, different populations of offenders are likely within jurisdictions. For example, the population of defendants on pretrial supervision is likely different from the population of individuals who are released from prison. As a result the Ohio Risk Assessment System was designed to predict recidivism at different points in the Ohio criminal justice system.

The use of a standardized assessment tool in Ohio allows consistency in the assessment of risk across jurisdictions. Prior to the creation of the ORAS, counties in Ohio used different methods of assessment, creating a great deal of variation in the practices for assessing the risk and needs of offenders. Therefore, one of the purposes of ORAS was to promote consistent and objective assessment of the risk of recidivism for offenders in Ohio.

Another advantage of using a risk assessment system that follows offenders through the criminal justice system is that it improves communication and avoids duplication of information. In fact, many of the items in the individual assessments carry over into assessments at later dates. The total number of risk items collected from all assessment instruments is 63. Of these, 24 items are used on at least two if not more assessment instruments. Further, since ORAS will be automated, items that are assessed at earlier stages have the potential to auto-populate into assessments at future dates.

The Current Study

The current study outlines the construction and validation of four assessment tools[3]: the Pretrial Assessment Tool (PAT), the Community Supervision Tool (CST)[4], the Prison Intake Tool (PIT), and the Reentry Tool (RT). A prospective design was utilized in the creation and validation of ORAS. To accomplish this, offenders across the Ohio criminal justice system were extensively interviewed for potential risk factors and were subsequently followed for one year to gather official measures of recidivism. Data collection instruments gathered information using a self-report questionnaire and semi-structured interviews that together provided over 200 potential risk factors that were used to construct each instrument.[5] The structured interview and self-report process took approximately 45-90 minutes to complete per offender. Four independent samples of offenders were gathered at different stages in the criminal justice system: at pretrial, on community supervision, at prison intake, and just prior to community reentry. Table 1 presents the number of cases in each sample. There were a total of 1,839 cases in all four samples: 452 in the pretrial sample, 681 in the community supervision sample, 427 in the prison intake sample, and 279 in the community reentry sample.

The pilot sites for the project were selected with the considerations of geographic representation across the state, recommendations from DRC staff, and whether the site was available and willing to participate during the data collection process. Potential sites were asked to both facilitate access to the cases and provide a physical location to conduct the interviews. Although some logistical and scheduling issues arose at several sites, no site declined to participate in the project. Seven Ohio counties provided data for the PAT, fourteen counties participated in data collection for the CST, and eight correctional facilities participated in data collection for the PIT and the RT.

Table 1.
Number of Cases in Each Sample

Sample	N
Pretrial	452
Community Supervision	678
Prison Intake	423
Community Reentry	277
Total	1,830

Participants

In order to be included in the pretrial sample, each individual had to be an adult charged with a criminal offense and referred to pretrial services during the period of data collection. To be included in the community supervision sample, each individual had to be an adult charged with a criminal offense that was recently referred to probation services during the period of data collection. Individuals were selected for the prison intake sample if they: a) were admitted to an intake correctional facility within the last six months and b)were within six months of release. The limited sentence length was necessary in order to provide an adequate follow-up time for recidivism in the community. The community reentry sample consisted of individuals who: a) were within six months of their release/discharge date and b) had not been admitted to prison within the past six months.

Recidivism

Collection of the follow-up data for all samples was completed approximately one year following the conclusion of the structured interviews. The primary measure of recidivism for this study was arrest for a new crime. Although data were gathered on a variety of other potential outcome measures (e.g., conviction, probation violation, institutional rule infraction), arrest was used for two major rea-

[3] Space constraints limit a full presentation of the methodology involved in the validation and construction of ORAS; for a full review see Latessa et al. (2009).

[4] Due to the high volume of offenders on community supervision, an abbreviated version of the CST was developed as a screening tool to identify moderate and high risk cases for the full assessment. Latessa et al. (2009) provides a detailed description of the Community Supervision Screening Tool.

[5] Due to differences in access, interview availability, due process issues, and ethical considerations, pretrial defendants were assessed during different interview protocols and data collection tools. See Latessa et al. 2009 for a further explanation of the differences in data collection between the pretrial instrument and other assessment instruments.

sons. First, measures that gather information later in the criminal justice process, such as convictions, require a longer follow-up period than the 12 months used in this study. Second, using arrests in the community as an outcome allows the assessment tools to identify criminogenic needs that are likely to result in danger to the community. Although factors that are predictive of rule violations (e.g., probation violations or institutional violations) are of concern to criminal justice personnel, of most concern are factors that are related to criminal behavior.[6]

Data on recidivism came from a variety of sources. For the pretrial sample, information was gathered by the counties from public records searches and searches of the cases file. For the community supervision sample, county agencies gathered the arrest data on offenders under their supervision through public records searches and file reviews. This information was verified through the Ohio Law Enforcement Gateway (OHLEG). OHLEG is especially useful because the information it provides is not specific to the county of supervision. Because not all inmates who were released from correctional facilities were placed on community supervision, OHLEG was the only source of information for regarding new arrests for these samples.

Assessment Construction

For each assessment, items gathered from the structured interviews and self-report surveys that were associated with recidivism were used to create each tool. Cases were excluded if they had missing information on four or more items.[7] After the items associated with recidivism were identified, these items were scored to create scales that indicated increases in the likelihood of recidivism. A modified Burgess method was used to assign point values to each item. The Burgess method assigns a point (a score of 1) to the presence of the risk factor, and assigns a score of zero when it is false or not present. Some items have multiple increasing risk scores, and as a result were scored with increasing values (i.e., 0, 1, 2). The items were then combined to create risk scales for each assessment tool. Once the risk scales were calculated, cutoffs were created to divide cases into different risk categories.

Priorities in Case Management

Another goal in developing ORAS was to assist Ohio criminal justice agencies with case management by providing the agencies with tools to identify and prioritize specific treatment domains. Each assessment instrument is broken down by domain (e.g., criminal associates, criminal attitudes, substance abuse, etc.) and specific categories divide offenders into groups based on their likelihood to reoffend. Stated differently, the assessment process not only provides an overall risk level, but also provides risk levels by case management domains. Presenting risk levels by domain gives practitioners specific information regarding the likelihood of recidivism based on individual criminogenic domains in order to encourage a more efficient allocation of treatment resources.[8]

Responsivity Assessments

In keeping with principles of effective classification, a goal in developing the ORAS was to gather information about potential barriers to treatment. As a result, additional case planning items are incorporated into the final assessment. Table 2 provides a list of areas that are gathered for responsivity. As indicated in the table, responsivity items range from factors such as intelligence and literacy to child care and transportation. These items are not directly related to recidivism, but instead have the potential to restrict the efficacy of treatment. Responsivity items are not used in the final calculation of risk, but instead are used as case planning factors that should be addressed to improve likelihood that programming will reduce recidivism.

Table 2.

Areas Assessed for Responsivity Treatment Barriers

Treatment Barriers	
Low intelligence	Physical handicap
Reading and writing limitations	Mental health issues
History of abuse/ neglect	Treatment motivation
Transportation	Child care
Language	Ethnicity and cultural barriers

The Pretrial Assessment Tool (PAT) Validation Results

The original pretrial data collection instruments provided over 100 potential predictors of recidivism. Of these, seven items from four domains were found to be related to recidivism: three items measuring criminal history, one item measuring employment, one item measuring residential stability, and two items measuring substance abuse.[9] Overall, the PAT scores ranged from 0 to 9 and had a correlation of .23 ($p<.00$) with recidivism.

Table 3.

Descriptive Statistics for the Pretrial Assessment Sample (n=452)

Variable	N	Percent
Sex		
Male	345	79
Female	107	23
Risk Level		
Low (0-2)	207	46
Moderate (3-5)	225	50
High (6+)	20	4
Arrest or FTA		
Yes	379	84
No	73	16

Table 3 presents descriptive statistics for offenders in the pretrial sample. Eighty percent of the sample is male, 46 percent is African American, and 16 percent were either arrested or committed a new offense. Table 3 also presents the distribution of cases by risk score. Scores of zero to two were categorized as low risk, three to five moderate risk, and six to nine as high risk. Of the total sample,

[6] Unlike the other assessment tools, the outcome used in the construction of the Pretrial Assessment Tool was *either* a new arrest or failure to appear. Failure-to-appear was included as an outcome because one of the major goals of the pretrial tool was to assist court actors in the decision to release or hold the defendant prior to trial. A major concern of court actors in making this decision involves both the potential for new criminal activity and the likelihood that the defendant will appear at court date.

[7] The number of cases excluded for each tool because they have more than four items missing were: pretrial sample = 0, community supervision sample = 3, prison intake sample = 10, reentry sample = 2.

[8] Latessa et al. (2009) provides a thorough description of the priorities in cases management, included analyses for each instrument that provide the likelihood of recidivism for each domain.

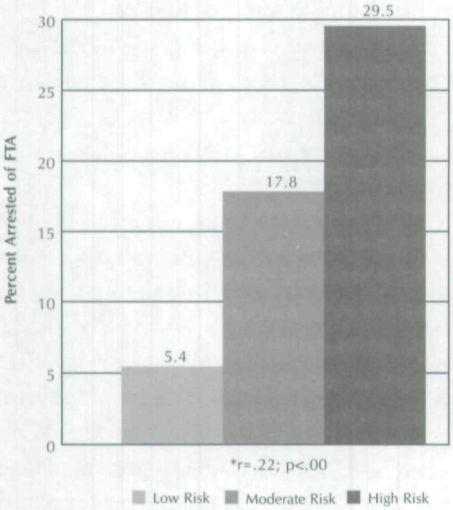
[9] Latessa et al. (2009) provides the scoring sheets that list all items for each assessment instrument.

29 percent of cases were categorized as low risk, 54 were categorized as moderate risk, and 17 percent as high risk.

Figure 1 presents information regarding the predictive validity of the PAT. The chart illustrates that each risk level is associated with progressively higher rates of recidivism. Specifically, 5 percent of low risk cases were arrested, 18 percent of moderate risk cases were arrested, and 30 percent of high risk cases were arrested. The r value of .22 provides further indication that the assigned levels of risk can significantly distinguish between groups that have progressively higher rates of recidivism.[10]

Figure 1.

*Predictive Validity of the Pretrial Assessment Tool (n = 452)**



The Community Supervision Tool (CST) Validation Results

Initial data for the community supervision sample was gathered through site visits to local county probation offices and community-based corrections facilities and provided information from 678 individuals. The self-report survey and structured interview guide provided a total of 200 potential predictors of recidivism. In all, the CST consisted of a total of 35 items within 7 domains: criminal history; education, employment, and finances; family and social support, neighborhood problems, substance abuse, antisocial associates; and antisocial attitudes and behavioral problems. Risk scores on the CST ranged from 0 to 43 and had a correlation of .37 (p<.00) with recidivism.

Table 4 presents descriptive statistics for the community supervision sample. Of particular interest are the final risk levels, cutoffs, and number of cases falling at each level. To provide optimal risk levels and cutoff scores, preliminary analyses revealed that males and females should be given different cutoff scores to categorize risk groups. This is primarily because females tended to have lower scores on the assessment instruments. For males, cutoffs for risk levels are as follows: low risk = zero - 14; moderate risk, 15 - 23; high risk = 24 - 33; and very high risk = 34 and higher. For females the cutoffs are as follows: low risk = zero - 14; moderate risk = 15 - 21; high risk 22 - 28; and very high risk = 29 and higher.

Figure 2 presents the failure rates for each risk level of the CST for male and female offenders in the community supervision sample. The table clearly illustrates incremental increases in the rates of recidivism for each group. For males, failure rates are nine percent for low risk, 34 percent for moderate risk, 59 percent for high risk, and 70 percent for very high risk offenders. The r value of .37 reveals that the relationship between risk level and recidivism is moderate and performs slightly higher than r-values generated in other research on dynamic risk assessment instruments (Gendreau, et al., 1996). Similarly, Figure 2 indicates that for females, risk levels are 9 percent for low risk, 22 percent for moderate risk, 40 percent for high risk, and 50 percent for very high risk. The r value of .30 reveals a moderate relationship with recidivism.

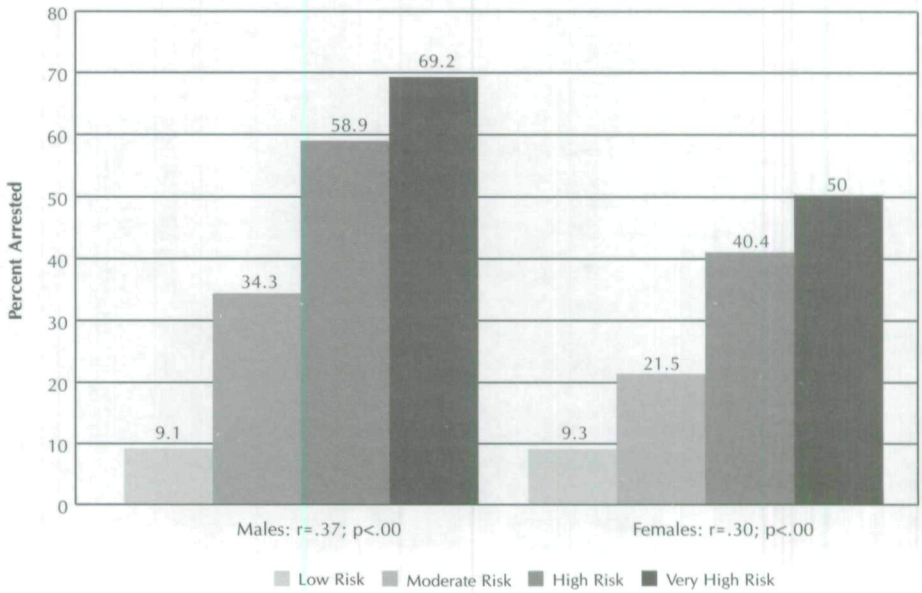
Table 4.

Descriptive Statistics for the Community Supervision Sample (n=678)

Variable	N	Percent
Sex		
Male	513	76
Female	165	24
Any New Arrest		
Yes	259	38
No	419	62
Males		
Low (0-14)	77	15
Moderate (15-23)	207	40
High (24-33)	190	37
Very High (34-49)	39	8
Females		
Low (0-14)	43	25
Moderate (15-21)	65	40
High (22-28)	47	29
Very High (29-49)	10	6

Figure 2.

Predictive Validity of the Community Supervision Tool



[10] r values are reported to indicate the predictive validity of each assessment instrument because they are widely understood and easy to interpret. Receiver Operating Characteristics (ROC) analyses were also performed to gauge the predictive validity. The Area Under the Curve (AUC) values that resulted from these analysis are as follows:
Pretrial Assessment Tool AUC=.65, p<.00; Community Supervision Tool male AUC=.71, p<.00; Community Supervision Tool female AUC=.69, p<.00; Prison Intake Tool male AUC=.67, p<.00; Prison Intake Tool female AUC=.69, p<.00; Reentry Tool male AUC=.65, p<.00, Reentry Tool female AUC=.77, p<.00.

The Prison Intake Tool (PIT) Validation Results

The PIT is designed to provide case managers with an assessment instrument that can be used to prioritize prison treatment based on the likelihood of recidivism. A total of 30 items from 5 domains were found to be significantly related to new arrests following their release from prison. The five domains of the PIT are: criminal history, education employment and finances, family and social support, substance abuse, and criminal lifestyle. Scores on the PIT range from 0 to 40 and have an r value of .36 when predicting new arrests after release.

Table 5 presents descriptive statistics for the prison intake sample. Preliminary analyses indicated that the PIT produced four distinct risk levels for male offenders while only three risk levels were appropriate for females. For males, nine percent of the cases are low risk, 41 percent are moderate risk, 43 percent are high risk, and 6 percent are very high risk. For females, low risk cases account for 42 percent of the sample, moderate risk cases account for 39 percent of the sample, and high risk cases account for 19 percent of the sample.

Figure 3 presents the percentage of cases that were arrested for each risk level on the PIT by gender. The chart illustrates that for both males and females, increases in recidivism are associated with increases in risk level. Further, there are acceptable r values for both genders (r = .32 for males and r = .35 for females). For males, 17 percent of low-risk cases recidivated, 32 percent of moderate-risk cases recidivated, 58 percent of high-risk cases recidivated, and 71 percent of very high-risk cases recidivated. Although only having three risk levels, risk levels for females were also associated with increases in recidivism: low-risk cases had a recidivism rate of 17 percent, 33 percent of moderate-risk cases recidivated, and 63 percent of high-risk cases recidivated.

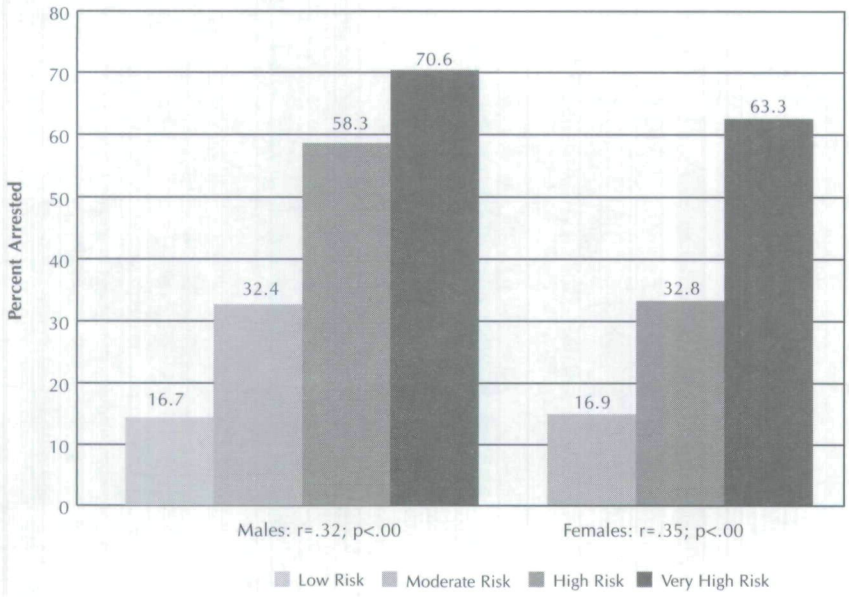
Table 5.

Descriptive Statistics for the Prison Intake Sample (n=423)

Variable	N	Percent
Sex		
Male	267	63
Female	156	37
Males		
Low (0-8)	24	9
Moderate (9-16)	111	41
High (17-24)	115	43
Very High (25+)	17	6
Females		
Low (0-12)	65	42
Moderate (13-18)	61	39
High (19+)	30	19
Any New Arrest		
Yes	169	40
No	254	60

Figure 3.

Predictive Validity of the Prison Intake Tool (n=423)



The Reentry Tool (RT) Validation Results

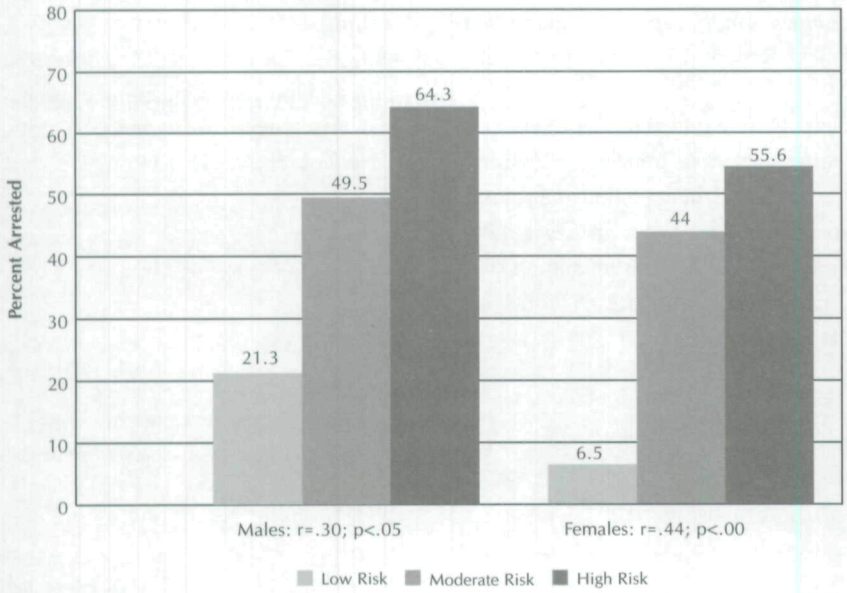
The RT was designed to be administered within 6 months of release from prison. The average length of incarceration for the prison release sample ranged from 2 to 452 months, with an average of 35 months. In all, the RT consisted of a total of 20 items from 4 domains and had potential scores that ranged from 0 to 28. Domains for the RT are: age, criminal history, social bonds, and criminal attitudes. The correlation between risk score and recidivism is .36. Table 6 presents descriptive statistics for the reentry sample. Preliminary analyses revealed that separate cut-off scores should be made for males and females. For males, the majority of cases are moderate risk, with similar percentages of cases falling at low- and high-risk levels. On the other hand, low risk is the modal value for females. These findings are similar to the PIT and indicate that females tend to score at lower risk levels than males on the assessment instruments.

Figure 4 presents the percentages of offenders that recidivated for each risk level of the RT by gender. The results indicate that both male and female groups experienced increasing rates of recidivism for each risk level. For males, 21 percent of low-risk cases were rearrested, 50 percent of moderate-risk cases were rearrested, and 64 percent of high-risk cases were rearrested. The r value of .29 indicates that the RT does a good job of distinguishing between low-, moderate-, and high-risk cases. For females, only six percent of low-risk females were arrested, while 44 percent of moderate-risk cases were arrested, and 56 percent of high-risk cases were arrested. The large r value for females (r = .44) is likely a result of the substantial difference between low- and moderate-risk females. Still, the findings for females should be taken with caution because of the small number of female offenders in the reentry sample (n = 65).

Table 6.
Reentry Sample (n=277)

Variable	N	Percent
Sex		
Male	212	76.5
Female	65	23.5
Males		
Low (0-9)	47	22.2
Moderate (10-15)	109	51.4
High (16+)	56	26.4
Females		
Low (0-10)	31	47.7
Moderate (11-14)	25	38.5
High (15+)	9	13.8
Any New Arrest		
Yes	118	42.6
No	159	57.4

Figure 4.
Predictive Validity of the Reentry Tool



Conclusion

The ORAS consists of a series of assessment tools that measure the likelihood of recidivism at different points in the criminal justice system. The validation results are promising and reveal that all assessment instruments are able to significantly distinguish between risk levels. Further, r values are relatively large, and depending upon the assessment instrument, range from .22 to .44.

Although the findings presented here are encouraging, two major limitations of this study should be taken into account. The first limitation revolves around the generalizability of the sample to all offenders in the Ohio criminal justice system. Although the data collection period gathered information on over 1,800 offenders in Ohio, it would be imprudent to assume that the findings are representative of all offenders in Ohio. First, resource constraints limited the inclusion of cases from all counties and correctional institutions. Second, although the samples were gathered from specific populations, certain types of cases may be underrepresented in the population (e.g., sex offenders, Hispanic offenders, female offenders). The underrepresentation in the population leads to small numbers of these types of offenders in the sample. For example, the findings from the RT were based on a sample size of 65 females. Although the results provide evidence that females have a distribution on the risk levels that is different from men, the findings should be considered preliminary until data can be collected on a larger sample of women who are released from prison.

Measurement error creates a second limitation for this study. The major source of data collection for this study was the structured interview, which was undertaken by trained research staff, not criminal justice personnel that will administer the assessment once it is implemented. Further, the informed consent process identified a sample of offenders who agreed to participate in the interview process. In short, the structured interview process used to gather the data will likely be somewhat different from the process used by criminal justice officials to interview cases and assign risk once the ORAS is implemented.

The limitations of this study suggest that ODRC follow several important recommendations. The first major recommendation is that ODRC conduct revalidation studies of ORAS. Revalidation studies will provide further evidence that the instruments in ORAS can predict recidivism across multiple samples from the same population. Further, the automation and storage of ORAS data will allow researchers to gather stratified probability samples in order to 1) provide a sample that is representative of all counties in Ohio and 2) oversample underrepresented groups (such as women and sex offenders). Also, revalidation studies should seek to extend the follow-up time. Although an average follow-up of 12 months is adequate, research suggests that 18 to 24 month follow-up times are optimal (Jones, 1996).

Revalidation studies can also address the threat that measurement error poses to this study. That is, revalidations studies will involve gathering data from assessments that are given by personnel within the criminal justice system, examining the predictive validity of ORAS in a "real world" setting. Another important step to help ensure the validity of ORAS is proper training. To ensure this, a specific training protocol has been developed for training personnel on the assessment instruments. Proper training cannot be stressed enough, because the efficacy of every assessment is heavily dependent upon the person who conducts the interview and scores the risk instrument. This is especially important because, although the interview questions are structured to maximize reliability, scoring for some of the items relies upon the professional judgment of the interviewer. Training will also help to minimize the potential measurement error from differences between having criminal justice personnel conducting the interviews instead of university research staff. Not only is initial training important, but it is recommended that a system be developed that specifies the training process, provides reliability checks for interviewers, and speci-

fies guidelines for retraining.

Although the study's limitations should be kept in mind, ORAS provides some distinct advantages. For example, not only does ORAS classify offenders into risk categories, it also provides case managers with the tools to prioritize treatment needs. That is, each assessment instrument can be broken down into domains and the likelihood of recidivism within each domain can be used to flag problematic domains. As a result, the treatment domains provide a means to efficiently allocate treatment resources in a manner that reduces recidivism. ORAS also provides assessments that are constructed based on samples of Ohio offenders and are specific to different stages in the criminal justice system. Another advantage is that ORAS increases the consistency in assessment across counties and agencies. Using ORAS is likely to encourage agencies to conform to the principles of effective classification. This is because ORAS provides assessments that 1) separate Ohio offenders into risk groups based on their likelihood to recidivate, 2) identify dynamic risk factors that can be used to prioritize programmatic needs, 3) identify potential barriers to treatment, and provide an override option.

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