Next generation assessment technology: The potential and pitfalls of integrating individual and community risk assessment

Article *in* Probation Journal · August 2017

DOI: 10.1177/0264550517720851

2 authors:

James Byrne
University of Massachusetts Lowell

April Pattavina
University of Massachusetts Lowell

Probation Journal
The Journal of Community and Criminal Justice

Article

Probation Journal
1–14

DOI: 10.1177/0264550517720851
journals.sagepub.com/home/prb
SAGE

Next generation assessment technology: The potential and pitfalls of integrating individual and community risk assessment

James Byrne and April Pattavina
University of Massachusetts Lowell, USA

Abstract
The recent inclusion of *community-level* risk variables in (some) fourth generation risk assessment instruments, ostensibly to make more accurate *individual-level* predictions of the likelihood of reoffending among the populations of probationers and parolees under community supervision, is examined in the following review. This development raises a thorny issue: what if the price of improved predictive accuracy is increased gender, race, or class-based disparity? Our review underscores the problems (conceptualization and measurement related) inherent in combining individual risk variables with community-level risk variables in order to assess an offender's risk for re-offending during a specified follow-up period. In recognition of the likely disparity that will result from the conflation of neighborhood risk into individual risk assessments, we suggest an alternative: conduct a separate neighborhood risk assessment that can be used to simultaneously develop (1) a community-based treatment plan for individual offenders and (2) a resource development plan identifying and addressing service shortfalls and other risk factors in the neighborhoods where offenders reside.

Corresponding Author:
James Byrne, Professor, School of Criminology and Justice Studies, University of Massachusetts, Lowell, 113 Wilder Street, HSSB, 4th Floor, Lowell, MA 01854, USA.
Email: james_byrne@uml.edu

Keywords
community safety, corrections, evidence-based practice, probation, recidivism, risk assessment

Introduction

Every recent review of risk assessment technology begins with a brief history lesson, describing how risk assessment instruments have 'evolved' over the past several decades from rather crude and subjective first generation risk assessment instruments to the current fourth generation of comprehensive risk/need assessment tools (see, e.g., Taxman, 2017; Burrell, 2017; Taxman et al., 2013; Desmarais and Singh, 2013; Andrews et al., 2006). However, it is an open question whether the current generation of risk assessment instruments represents a significant improvement over earlier and simpler tools, not only in terms of ease of administration and overall accuracy of the risk prediction, but also in terms of the potential disparity (gender, race, class) inherent in the design of these new models (Baird, 2009; Gandy, 2007).

In the following review, we describe how risk assessment instruments have changed in recent years and then highlight the potential for increased institutionalized disparity associated with the inclusion of *community-level* risk variables in (some) fourth generation risk assessment instruments, ostensibly to make more accurate *individual-level* predictions. This raises a thorny issue: what if the price of improved predictive accuracy is increased gender, race, or class-based disparity? In recognition of the likely disparity that will result from the conflating of neighborhood risk into individual risk assessments, we suggest an alternative: conduct a separate neighborhood risk assessment that can be used to simultaneously develop (1) a treatment plan for individual offenders and (2) a resource development plan identifying and addressing service shortfalls and other risk factors in the neighborhoods where offenders reside.

Risk assessment tools: Changes across four generations

First generation assessment tools relied on clinical assessment, based largely on a combination of an offender's criminal history and the reviewer's assessment of the personal characteristics of the offender that – in the professional judgement of the reviewer – related to offender risk of reoffending. As Desmarais and Singh (2013: 4) have observed:

> This method of assessment was widely accepted for decades prior to the development of structured risk assessment tools in the 1970's. Today, it is less frequently used, but nonetheless remains a prominent risk assessment strategy, despite evidence that accuracy of unstructured assessments are less accurate than chance.

While professional judgement is still valued, criminal justice decision-makers recognize the value of being able to point to the results from objective risk classification tools that support their decisions (e.g. pretrial release, probation supervision level, parole release and community supervision).

Second generation risk assessment tools relied on actuarial risk assessment, rather than the subjective judgement of community corrections professionals. They focused primarily on static or historical indicators of an individual offender's risk. The second generation assessment instruments were simple to score using a small number of variables that researchers had demonstrated, based on reviews covering over 90 years of research, to be linked to offender recidivism. These variables included prior arrests, prior incarcerations, gender, age at first offence, employment status, substance abuse, and a few other quantifiable measures. Support for second generation risk classification was found in research that directly compared the predictive accuracy of these first and second generation systems, and found the actuarial models to be – on average – about 10 percent more accurate than models based solely on professional judgement (Gottfredson, and Moriarty, 2006).

The assumption underlying the use of second generation risk assessment tools was described at the time by criminologists Vince O'Leary and Todd Clear as limited risk control: community corrections should focus their attention, and limited resources, only on those factors with a known link to an offender's risk of recidivism (O'Leary and Clear, 1984). The problem inherent in this strategy is that most of the risk variables that were included in these models were static variables (e.g. age, priors) not amenable to change. While community corrections officers would also complete a separate needs assessment that included several dynamic factors (e.g. education, skills, housing, family ties, mental health) that *were* amenable to change, rehabilitation advocates feared that the focus on risk control would limit the prospects for individual offender change. To address this problem, new risk assessment instruments were designed that included a combination of static and dynamic risk variables. The focus at this stage in the development of risk assessment technology was not on improving predictive accuracy; improving case management was the goal.

Unlike the second generation risk assessment tools – which focused on classifying the risk level of offenders placed under community supervision using a small number of static risk variables – third generation tools were designed to integrate risk and need assessment in a single risk assessment instrument.[1] Table 1 provides an overview of the types of variables included in third generation risk assessment tools. The most common third generation risk classification instrument used today in community corrections systems is the LSI-R (Level of Service Inventory, Revised). According to a 2009 study by Smith, Cullen, and Latessa, the LSI-R was being used in over 900 corrections agencies across North America alone at the time of their review, with more recent estimates suggesting even higher rates of utilization across other global regions.[2]

Table 1. Dynamic risk factors in four popular risk instruments.

Item	LSI-R[1]	ORAS[2]	COMPAS[3]	Wisconsin[4]
Education/Employment	✓	✓	✓	✓
Financial	✓	✓		✓
Family/Marital	✓	✓	✓	✓
Accommodation	✓		✓	
Leisure/Recreation	✓		✓	
Companions/Associates	✓	✓	✓	✓
Substance Use	✓	✓	✓	✓
Emotional/Personal	✓			✓
Attitudes/Orientation	✓	✓	✓	
Neighborhood		✓	✓	
Mental Health				✓
Health/Wellness				✓
Sexual Behavior				✓

Source: Taxman and Pattavina, 2013: 84 (Table 4.2)
[1]Level of Service Inventory-Revised
[2]Ohio Risk Assessment System (Community Supervision Tool)
[3]Correctional Offender Management Profiling for Alternative Sanctions
[4]Wisconsin Risk-Needs Assessment

The LSI-R instrument requires the classification of each offender in 10 unique areas, using a total of 54 items, including the following:

1. Criminal history (10 items)
2. Education and employment (10 items)
3. Financial (2 items)
4. Family and marital (4 items)
5. Accommodations (3 items)
6. Leisure and recreation (2 items)
7. Companions (5 items)
8. Alcohol and drugs (9 items)
9. Emotional and personal (5 items)
10. Attitude and orientation (4 items)

The LSI-R is just one example of the type of 'new generation' risk instruments available to the field. Other popular third generation risk instruments are ORAS, COMPAS, and the Wisconsin risk/need assessment instruments.[3] What distinguishes these third generation classification instruments from earlier risk instruments is the incorporation of dynamic risk factors – those items amenable to change – in the risk model. In the past, risk levels were largely determined by static risk factors – such as criminal history – that by definition are not amenable to change; a separate needs assessment instrument was used to identify the treatment needs of these offenders. These third generation risk assessment tools attempted to combine both assessments in a single assessment instrument. The integration of dynamic and static risk variables in a single instrument has raised concerns about potential inter-rater reliability problems that have been largely ignored by community corrections researchers. For example, Desmarais and Singh (2013) have reported that only two of the 53 validation studies they reviewed included data on the level of inter-rater reliability. Given the subjective assessments required to code the dynamic variables included in these models (e.g. attitudes, criminal thinking, and peer associates), it is not surprising that third generation risk assessment tools have been described as presenting significant implementation challenges (Latessa and Lovins, 2010).

Third generation risk assessment instruments have also been criticized on conceptual and methodological grounds. Austin (2006) found that only a small number of the 54 risk items (mainly the 10 criminal history variables) on the LSI-R were needed to accurately classify offenders; in fact, overall predictive validity actually was higher in the more parsimonious risk model. Austin's research findings are supported by several other reviews of the available research on the predictive accuracy of second vs. third (and fourth) generation risk assessment tools. Hess and Turner (2017: 94) reviewed this body of research and noted that: 'Some find that the predictive value of second generation assessment tools is at least equivalent to third and further generation tools (Andrews et al., 2006; Baird, 2009; Barnoski and Aos, 2003; Coid et al., 2011; Pattavina and Taxman, 2007).'

This raises an obvious question: if the primary purpose of risk classification is to determine risk level, why would you include variables in the model that do not improve overall model accuracy? The short answer appears to be that instrument developers want to ensure that line community corrections staff will develop supervision strategies that focus on addressing the *needs* of this offender population. By identifying these needs during assessment, staff are being told by managers that these are the areas they need to address during case management. Latessa and Lovins (2010: 210) have argued that despite the increased cost and training associated with combined risk/need instruments: '. . . the advantage of these types of tools is that they facilitate the development of case and treatment plans, since they take into account the full range of factors associated with risk'. Their rationale for third generation risk models is a variation on an oft repeated mantra: 'what gets measured gets done' (Burrell and Gelb, 2007).

Finally, questions have been raised about the need for independent validations of third generation risk instruments, because with only a few exceptions, it is the instrument developers who are conducting the validation studies available for review. In those small number of validation studies conducted independently, the accuracy of the risk instrument was noticeably lower (Desmarais and Singh, 2013). Overall, independent reviews of the available body of risk assessment instruments reveal variations in overall predictive accuracy by the performance indicators used, and the types of subgroup analyses conducted.[4]

Fourth generation risk assessment tools have expanded the emphasis on dynamic risk/need factors by providing community corrections agencies with case management tools that match each offender's unique risk/need profile to an identifiable, evidence-based treatment plan (Taxman and Pattavina, 2013). One recent development in this area is the recognition that an individual's risk of recidivism is the product of a combination of individual-level and community-level factors, which has led some commentators to suggest that we need to develop risk instruments that incorporate *community context* indicators into the next generation of risk classification models. The recognition of person-environment interactions in the prediction of recidivism has been a basic tenet of social ecologists for several decades (see, e.g., Gottfredson and Taylor, 1986; Sampson, 1993, 2008). More recently, research on the impact of community-level factors on an individual's risk of recidivism has received considerable attention, resulting in efforts to incorporate community risk into next generation risk models (see Berk and Hyatt, 2015; Byrne, 2008, 2009; Hess and Turner, 2017; Hipp et al., 2010; Jacobson, 2006; Latessa et al., 2009; Kubrin and Stewart, 2006; Kubrin et al., 2007; Pennsylvania Commission on Sentencing, 2013; Stahler et al., 2013).

There is wide variation in the types of community context indicators included in these studies. For some researchers (Hess and Turner, 2017; Pennsylvania Commission on Sentencing, 2013), community context is simply measured by including residential location in the risk models, along with the usual array of individual-level predictors. A second group of researchers, using machine learning techniques, include residential location, available community-level variables, such as housing value, crime rates, and a full range of individual-level predictors, such as gender, age, and race (Berk and Hyatt, 2015). A third group of researchers have developed rather elaborate measures of neighborhood disadvantage, using census tract data on such factors as employment, family income, and poverty (Kubrin and Stewart, 2006; Kubrin et al., 2007), the percentage of the population receiving public assistance, percentage of vacant housing units, percentage of renters, and the percentage of population with a high school diploma (Stahler et al., 2013). A final group of researchers have examined the impact of neighborhood-level resource availability on an individual's risk of reoffending (Jacobson, 2006). Despite differences across studies – in the operational definition of community context, in the research design employed, and the analytic strategy – these researchers all offer support for the view that community-level factors have an impact on the likelihood of an individual reoffending while under community supervision. The question becomes: how can the identification of community-level risk factors be used to improve the effectiveness of the community corrections system?

As can be seen by reviewing Table 1, neighborhood and/or community-level variables are already included in two of the four most popular risk assessment tools in use today: ORAS and COMPAS. Table 2 identifies the neighborhood measures included in the current risk assessment scoring systems for both of these risk instruments. In these models, an individual's risk level is partially a function of his/her residential location and social environment. In the ORAS risk model, community risk level is measured by classifying an individual offender's neighborhood in terms of its crime rate and the availability of drugs. In the COMPAS model, the PO is asked to classify an offender's neighborhood using a social environment scale that includes measures of gang activity, crime, drug use, safety, employment of residents, and the criminality of residents in the neighborhood. Research supporting the use of these neighborhood-level variables in

Table 2. Community context variables included in COMPAS and ORAS.

COMPAS: SOCIAL ENVIRONMENT SCALE
F. SOCIAL ENVIRONMENT: Do any of the following characterize the area immediately surrounding the offender's residence? (check)
Drug availability
Gangs
Weapons
Violent crime
Most people are employed in regular jobs
It's safe at night
People look out for each other
People are law abiding
Social environment score:
ORAS: NEIGHBORHOOD PROBLEMS SCALE
1 High Crime Area
0=No
1=Yes
2 Drugs Readily Available in Neighborhood
0=No, Generally Not Available
1=Yes, Somewhat Available
2=Yes, Easily Available
Total Score in Neighborhood Problems:

Source: for the COMPAS instrument, see Lansing 2012, Appendix A; for ORAS, see Latessa et al., 2009.

each model is found in the validation studies completed to date.[5] For example, Latessa and colleagues (2009) examined the neighborhood scale included in the ORAS model, and found that 17 percent of offenders with low scores on the neighborhood problems scale were re-arrested (one-year follow-up), as compared to 35 percent with a moderate score (1), and 45 percent with high scores (1, 2) on this scale.[6]

Serious questions can, and should, be raised about using *neighborhood*-level variables to assess *individual*-level risk and determine supervision level. It is certainly possible that consideration of these neighborhood-level variables will result in the closer community supervision and control of minority residents who are more likely to live in these high-crime, poverty-pocket communities. In addition, the strategies used to assess neighborhood context utilize subjective assessments by staff and offenders about the neighborhood that may or may not be accurate. No study has been conducted to date that examines the accuracy of the neighborhood assessment data included in these risk models. Perhaps more disturbing is the fact that no research has been conducted to date on whether the inclusion of neighborhood context variables will result in poor, minority residents living in high crime neighborhoods being subjected to higher levels of community supervision than their community corrections counterparts who are lucky enough to reside in lower risk environments.

The recent body of high quality research reporting that community-level factors have an independent effect on an individual offender's risk of recidivism[7] should not come as a surprise to criminologists, since this is a basic tenet of social ecologists (Byrne, 2008; Byrne and Sampson, 1986). What is surprising is how quickly we have moved to improve the overall predictive accuracy of our risk models – by including measures of neighborhood context – without a full discussion of the potential for racial/class based disparity that may result from incorporating these variables into current risk assessment tools. The identification of community-level influences on individual-level outcomes – both positive and negative – represents an important line of inquiry, but the challenge for community corrections managers will be to decide exactly what to do with this information (Byrne, 2009).

The decision to include or exclude neighborhood risk variables in next generation risk assessment instruments may represent a critical tipping point in the development of next generation risk assessment tools. If our primary objective is overall predictive accuracy, then it certainly makes sense to include in a prediction model any and all variables, both at the individual level and community level, that result in increased predictive power. With the aid of machine learning techniques, some researchers are offering the promise of increased accuracy in risk prediction without the need to say exactly what will, and will not, be in the predictive model. As Hess and Turner (2017: 95) observe:

> While classical statistics attempt to fit models to the data, machine learning procedures do not depend on the a priori selection of a model. Instead, they search through the data for associations with the outcome, a process also known as data mining. Machine learning depends on the selection of a search algorithm rather than a data model (Brieman, 2001).

While there is some evidence that the use of random forest models and other similar techniques will improve overall accuracy (Brennan, 2017; Berk and Bleich, 2013), the improvement is only incremental, and it comes at a price: *we do not know precisely which variables are included in these models.*

Which variables are included in, and excluded from, risk assessment models matters if you care about two equally desirable outcomes: predictive accuracy and procedural justice. For example, Richard Berk has developed and tested predictive analytic tools on a population of probationers in Philadelphia, Pennsylvania. His models take into account *all available data* on a given individual when making a risk prediction, including individual-level data (age, race, gender, education, arrests, income, home value, etc.) and community-level data (housing value of community, crime rate, employment statistics, school rankings, etc.), based on a goal of maximizing predictive accuracy (Berk and Hyatt, 2015). He argues that these new statistical models will make pre-trial release decisions more accurate than traditional (regression-based) risk models, and more precisely distinguish recidivists from non-recidivists in our probation and parole populations.

However, these machine learning/statistical tools (e.g. random forest models) have been criticized because of what is included in the models (e.g. variables that assess social class at individual and at neighborhood level), and because the weights given to individual variables change from individual to individual.[8] Even assuming that Berk is correct in his assessment that the machine learning models he has developed improve predictive accuracy, there is a price to pay for this improvement: institutionalized bias against individuals who happen to reside in poor, socially disorganized, high crime neighborhoods (Gandy, 2007).

Next generation risk assessment: Evolution or devolution?

Risk assessment instruments continue to change, but it would be a mistake to assume that every new enhancement to existing risk assessment technology represents a step forward. What gains we achieved in improved case management and service delivery by incorporating static and dynamic risk factors in third generation risk instruments may have been offset by reductions in the overall predictive accuracy of these risk assessment tools. The inclusion of community-level variables into the risk assessment processes – ostensibly to improve predictive accuracy – poses a different set of potential problems related to race and class biases associated with the assessment of community risk. Even if the predictive accuracy of the models is *reduced* when community context variables are removed, the end – more accurate predictions – does not justify the means. The potential for disparity – race-based, class-based, and gender-based – is simply too great (Gandy, 2007).

However, the fact that the validation studies for both the ORAS and COMPAS risk instruments documented the significant, independent effects of two very different sets of neighborhood context indicators (again, see Table 2) underscores the importance of recognizing a simple truth: you cannot change offenders without changing the communities in which they reside. It has been documented that in many areas:

> . . . the treatment resources available to offenders will vary by the risk level of the neighborhood, with higher-risk neighborhoods offering fewer (and lower quality) treatment options to offenders living in these areas. (Byrne and Pattavina, 2006: 66)

We need to consider the potential influence of community context on the implementation of risk reduction strategies, but this assessment should not be used to determine an individual's level of supervision. The next generation of risk assessment instruments needs to distinguish individual risk assessment from community risk assessment. The influence of community context on risk reduction strategies can and should be measured in a number of different ways, including indicators such as neighborhood-level crime rates, treatment resource availability, employment, and housing/health care (see, e.g., Hipp et al., 2010; Kubrin and Stewart, 2006). Indeed, mapping community context (e.g. offender concentrations, treatment facility locations) appears to be an increasingly popular approach to highlighting the need for improved treatment options in high-risk communities with large concentrations of offenders. In addition, community corrections departments in a few communities are now developing web-based apps designed to link offenders with services, mentors, and treatment providers in their neighborhoods (Pattavina et al., 2010).[9] This strategy could represent a viable alternative to incorporating neighborhood-level variables in next generation risk models. However, the problem of how to *address* the root causes of crime in these high-risk neighborhoods remains:

> Because residents of these communities do not have the social capital to address adequately the long-standing problems found in high-risk, high-poverty pocket areas, the prospects for community change are bleak, with some arguing that *relocation* may be the only viable strategy at this time; even here, the research on the impact of large-scale relocation experiments offers – at best – a mixed bag of positive and negative consequences (Sampson et al., 2008). The fact that these poverty pocket, high-crime areas are areas with very large concentrations of minority – mostly black – residents suggests that racial disparity continues to play a central role in the creation – and control – of this country's crime problem. (Byrne, 2008: 266)

We suspect that the USA is not alone in this regard, and there is much to be gained by critically examining recent efforts to measure the multiple dimensions of community context,[10] link offenders to available resources in their communities, and to develop strategies to address the gaps in services in these areas. As Rose and Clear (2003: 318) note:

> . . . individualistic public policies that focus solely on offenders overlook the importance of neighborhoods. Local areas must be considered when we think about the impact of incarceration and reentry because they provide the environments that contextualize the lives of offenders and non-offenders alike. Local areas afford opportunities and constraints for both normative and non-normative behavior.

We know community context matters; and the accurate measurement of community risk represents an important next step in the development of risk assessment technology. We now need to decide how to incorporate knowledge about the key dimensions of community context (e.g. community resource availability, community attitudes and support, community structure) into next generation community corrections strategies. These next generation strategies will likely incorporate a variety of persuasive technology innovations designed to support the dual goal of individual desistance and positive community change.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Notes

1. According to a review by Taxman and colleagues (2013: 84): 'In some risk-need instruments, risk and needs are added together to calculate a total score; in others they are

considered separate scores with a matrix guiding the user as to the proper placement for the offender being assessed.'

2. International estimates on the current utilization of the LSI-R can be found on the company's website (https://ecom.mhs.com/(S(dioh5u55i2gstt55poy4ipf2))/saf_om.aspx?id=ConferenceList). While there is some controversy about the use of the LSI-R to assess the risk level of female offenders (Reisig et al., 2006), there is a body of research that suggests that, overall, the LSI-R is about as accurate as other risk instruments being used today (Smith et al., 2009; Andrews and Bonta, 2010).
3. For an overview of the key features of these risk assessment tools, see Taxman and Pattavina (2013); for a summary of available research on the predictive accuracy of each of these tools, see Desmarais and Singh (2013).
4. According to a recent review by Desmarais and Singh (2013: 21): 'Overall, and consistent with prior research reviews, no one instrument stands out as producing more accurate [assessments] than the others, with validity varying with the indicator reported.' This review included performance rankings (p. 21) for each of the four risk instruments described earlier: LSI-R, COMPAS, ORAS, and WRN.
5. For the ORAS model, see Latessa et al. (2009); for the COMPAS model, see Lansing (2012). A number of reviewers have pointed out that the overall predictive accuracy of risk instruments – second to fourth generation – is always lower when the validation study is conducted independently. Far too often, it is the developers of the model that conduct their own internal validation study. Questions can also be raised about scale construction and inter-rater reliability problems that are likely to occur in the more complex, and subjective, scoring systems.
6. Latessa and colleagues (2009) do not provide details on the independent effect of the neighborhood problems scale, controlling for individual-level variables, but they do provide estimates of the overall predictive accuracy of their model. It should be noted that the ORAS model was used in conjunction with a four variable initial screening tool that included the following: (1) number of adult prior convictions, (2) currently employed full time, (3) drugs readily available in neighborhood, and (4) criminal friends.
7. For an overview of research identifying the independent effect of a range of community context indicators on individual offender risk of recidivism, see Stahler et al. (2013) or Byrne (2008). According to an earlier review by Sampson et al. (2002): 'the weight of evidence . . . suggests that there are geographic "hot spots" for crime and problem related behaviors and that such hot spots are characterized by the concentration of multiple forms of disadvantage' (p. 446).
8. For a detailed examination of the issues involved in both traditional (multiple regression) risk assessment instrument design and the new (machine learning) models being developed by Berk and colleagues, see Brennan (2017). For research testing/comparing the accuracy of machine learning vs. regression-based models, see Tollenaar and Van der Heijden (2013). They found no improvement in overall performance for machine learning models.
9. More detail and some very preliminary evaluation results of the NYC NeON initiative can be found in McGarry, Yaroni and Addie (2014). According to the NeOn on the NYC probation department webpage: 'The New York City Department of Probation is one agency that is leading the way, giving clients a digital tool to hold themselves accountable: a goal-tracking web app. The app, MyNeON, is rooted in seven community-based brick-and-mortar locations called Neighborhood Opportunity Networks (NeONs). Each NeON is a group of community organizations, government agencies, local businesses, and community residents focused on connecting probation

clients who live in target neighborhoods to opportunities, resources and services' (http://www.nyc.gov/html/prob/html/neon/neon.shtml).
10. Even a cursory examination of the scales used to assess neighborhood problems (ORAS) and social environment (COMPAS) in the two risk instruments highlighted in this review underscores the measurement problems inherent in collecting these data, either from probationers or from probation officers.

References

Andrews DA and Bonta J (2010) *The Psychology of Criminal Conduct*. Cambridge, MA: Elsevier Science.

Andrews DA, Bonta J and Wormith J (2006) The recent past and near future of risk and/or need assessment. *Crime and Delinquency* 52(1): 7–27.

Aos S, Miller M and Drake E (2006) *Evidence-based Public Policy Options to Reduce Future Prison Construction, Criminal Justice Costs, and Crime Rates*. Olympia, WA: Washington State Institute for Public Policy.

Austin J (2006) How much risk can we take? The misuse of risk assessment in corrections. *Federal Probation* 70(2): 58–63.

Baird C (2009) *A Question of Evidence: A Critique of Risk Assessment Models Used in the Justice System*. Madison, WI: National Council on Crime and Delinquency.

Berk R and Bleich J (2013) Statistical procedures for forecasting criminal behavior. *Criminology & Public Policy* 12(3): 513–544.

Berk R and Hyatt J (2015) Machine learning forecasts of risks in criminal justice settings. *Federal Sentencing Reporter* 27(4): 222–228.

Brennan T (2017) An alternative scientific paradigm for criminological risk assessment: Closed or open systems, or both? In: Taxman F (ed.) *Handbook on Risk and Need Assessment: Theory and Practice*. New York: Routledge Taylor & Francis, 164–190.

Brieman L (2001) Statistical modeling: The two cultures. *Statistical Science* 16(3): 199–231.

Burrell W (2017) Risk and needs assessment in probation and parole: The persistent gap between promise and practice. In: Taxman F (ed.) *Handbook on Risk and Need Assessment: Theory and Practice*. New York: Routledge Taylor & Francis, 23–48.

Burrell W and Gelb A (2007) *You Get What You Measure: Compstat for Community Corrections*. Washington, DC: Public Safety Performance Project, Pew Charitable Trusts.

Byrne J (2008) Editorial introduction: The social ecology of community corrections: Understanding the link between individual and community change. *Criminology and Public Policy* 1(2): 1201–1213.

Byrne J (2009) *Maximum Impact: Targeting Supervision on Higher-Risk People, Places and Times*. Public Safety Performance Project, the PEW Center on the States, July.

Byrne J and Pattavina A (2006) Clinical and actuarial risk assessment in an evidence-based community corrections system: Issues to consider. *Federal Probation* 70(3): 64–67.

Byrne J and Sampson R (1986) *The Social Ecology of Crime*. New York: Springer Verlag.

Byrne J and Taxman F (2006) Crime control strategies and community change: Reframing the surveillance vs. treatment debate. *Federal Probation* 70(1): 3–12.

Clear T (2007) *Imprisoning Communities: How Mass Incarceration Makes Disadvantaged Neighborhoods Worse*. New York: Oxford University Press.

Desmarais S and Singh J (2013) *Risk assessment instruments validated and implemented in correctional settings in the United States*. New York: Council on State Governments Justice Center.

Gandy O (2007) *Race and Cumulative Disadvantage: Engaging the Actuarial Assumption*. The B. Aubrey Fisher Memorial Lecture, Department of Communication, University of Utah, 18 October.

Gottfredson S and Moriarty L (2006) Clinical versus actuarial judgements in criminal justice decisions: Should one replace the other? *Federal Probation* 70(2): 15–18.

Gottfredson S and Taylor R (1986) Person-environment interactions in the prediction of recidivism. In: Byrne J and Sampson R (eds) *The Social Ecology of Crime*. New York: Springer Verlag, 133–156.

Hess J and Turner S (2017) Accuracy of risk assessment in corrections population management: what's the value added? In: Taxman F (ed.) *Handbook on Risk and Need Assessment: Theory and Practice*. New York: Routledge, 93–113.

Hipp JR, Petersilia J and Turner S (2010) Parolee recidivism in California: The effect of neighborhood context and social service agency characteristics. *Criminology* 48(4): 947–979.

Jacobson J (2006) Do drug treatment facilities increase clients' exposure to potential neighborhood-level triggers for relapse? A small-area assessment of a large, public treatment system. *Journal of Urban Health* 83(2): 150–161.

Kubrin C and Stewert E (2006) Predicting who reoffends: The neglected role of neighborhood context in recidivism studies. *Criminology* 44(1): 165–197.

Kubrin C, Squires G and Stewart E (2007) Neighborhoods, race, and recidivism: The community-re-offending nexus and its implications for African Americans. *Race Relations Abstracts* 32(1): 7–37.

Lansing S (2012) *New York State COMPAS-Probation Risk and Need Assessment Study: Examining the Recidivism Scale's Effectiveness and Predictive Accuracy*. New York: New York State Division of Criminal Justice Services, Office of Justice Research and Performance.

Latessa E and Lovins B (2010) The role of offender risk assessment: A policy maker guide. *Victims and Offenders* 5: 203–219.

Latessa E, Smith P, Lemke R, Makarios M and Lowenkamp C (2009) *Creation and Validation of the Ohio Risk Assessment System: Final Report*. Cincinnati, OH: Authors. Available at: http://www.uc.edu/ccjr/Reports/ProjectReports/ORAS_Final_Report.pdf (accessed 17 January 2017).

McGarry P, Yaroni A and Addie S (2014) *Innovations in NYC Health and Human Services Policy Adult Probation and Neighborhood Opportunity Network Initiative*. New York: VERA.

Mears D and Bhati A (2006) No community is an island: The effects of resource deprivation on urban violence in spatially and socially proximate communities. *Criminology* 44(3): 509–547.

Nilsson A and Estrada F (2007) Risky neighborhood or individuals at risk? The significance of neighborhood conditions for violent victimization in residential areas. *Journal of Scandinavian Studies in Criminology and Crime Prevention* 8: 2–21.

O'Leary V and Clear T (1984) *Community Corrections in the1990's*. Washington, DC: National Institute of Corrections.

Pattavina A and Taxman F (2007) Community corrections and soft technology. In: Byrne J and Rebovich D (eds) *The New Technology of Crime, Law, and Social Control*. Monsey, NY: Criminal Justice Press, 327–346.

Pattavina A, Miofsky-Tusinski K and Byrne J (2010) Innovation in community corrections: From monitoring technology to persuasive technology. *Journal of Offender Monitoring* 23(1): 1–5.

Pennsylvania Commission on Sentencing (2013) *Risk/Needs Assessment Project, Interim Report 7, Validation of Risk Scale*. Available at: http://pasentencing.us (accessed 15 January 2017).

Reisig M, Holtfreter K and Morash M (2006) Assessing recidivism risk across female pathways to crime. *Justice Quarterly* 23: 384–405.

Rose, Dina R., and Todd R. Clear (2003) Incarceration, reentry, and social capital: Social networks in the balance. In: Jeremy Travis and Michelle Waul (eds.), *Prisoners Once Removed*. Washington, DC: Urban Institute Press.

Sampson R (1993) The community context of violent crime. In: Wilson WJ (ed.) *Sociology and the Public Agenda*. Newbury Park, CA: Sage, 259–286.

Sampson R (2008) Moving to inequality: Neighborhood effects and experiments meet social structure. *American Journal of Sociology* 114(1): 189–231.

Sampson RJ, Morenoff JD and Gannon-Rowley T (2002) Assessing 'neighborhood effects': Social processes and new directions in research. *Annual Review of Sociology* 28: 443–478.

Smith P, Cullen FT and Latessa EJ (2009) Can 14,737 women be wrong? A meta-analysis of the LSI-R and recidivism for female offenders. *Criminology & Public Policy* 8(1): 183–208.

Stahler G, Mennis J, Belenko S, Welsh W, Hiller M and Zajac G (2013) Predicting recidivism for released state prison offenders: Examining the influence of individual and neighborhood characteristics and spatial contagion on the likelihood of reincarceration. *Criminal Justice & Behavior* 40(6): 690–711.

Taxman F (ed.) (2017) *Handbook on Risk and Need Assessment: Theory and Practice*. New York: Routledge Taylor & Francis

Taxman F and Pattavina A (2013) *Simulation Strategies to Reduce Recidivism: Risk Need Responsivity (RNR) Modeling for the Criminal Justice System*. New York: Springer.

Taxman F, Pattavina A, Caudy M, Byrne J and Durso J (2013) The empirical basis for the RNR model with an updated conceptual framework. In: Taxman F and Pattavina A (eds) *Simulation Strategies to Reduce Recidivism: Risk Need Responsivity (RNR) Modeling for the Criminal Justice System*. New York: Springer, 73–114.

Tollenaar N and Van der Heijden P (2013) Which method predicts recidivism best?: A comparison of statistical, machine learning and data mining predictive models. *Journal of the Royal Statistical Society Series A* 176(2): 565–584.