Using a sample of 497 Canadian women released into the community from federal prisons, this study examined the extent to which seven dynamic risk factors prospectively assessed at 6-month intervals (four waves) change over time and predict recidivism. Results obtained from a series of within-subject ANOVAs indicate that with the exception of substance abuse, all dynamic risk factors (i.e., employment, marital/family, community functioning, personal/emotional, criminal associates, and criminal attitudes) decreased among those offenders who did not recidivate. In addition, results obtained from a series of Cox regression survival analyses with time-dependent covariates also indicate that proximal assessments of dynamic risk predict recidivism more strongly than more distal assessments of dynamic risk. Employment and associates were the strongest dynamic predictors of recidivism, whereas the remaining factors were weak-to-moderate predictors of recidivism. This study lends support to the utility of repeatedly assessing dynamic risk factors among female offender populations.

Keywords: dynamic risk; predictive validity; female offenders; risk assessment

Women offenders continue to be one of the fastest growing segments of the prison population (Guerino, Harrison, & Sabol, 2011; Public Safety Canada, 2012). Consequently, they are of immense interest to scholars and correctional policy makers alike. One area that has been explored in depth over the last 20 years is the extent to which traditional risk factors for crime are gender invariant (e.g., Andrews et al., 2012; Green & Campbell, 2006; Hubbard & Pratt, 2002; Simourd & Andrews, 1994). However, researchers have seldom investigated whether or not changes in dynamic factors are actually related to criminal recidivism in samples comprised solely of women offenders. This type of research is critical, as it can inform gender-responsive treatment and risk management...
strategies. Consequently, the purpose of the study is to examine whether or not changes in dynamic risk factors that purportedly transcend gender according to mainstream correctional scholars (Andrews & Bonta, 2010) are actually predictive of criminal recidivism in a sample of women offenders. It is important to note that change as a construct can invariably include both positive change, signifying improvement in risk domains, and negative change, signifying increased risk. The specific dynamic risk factors to be examined include employment, personal/emotional factors, substance use, criminal attitudes, criminal associates, marital/family functioning, and community functioning.

MAINSTREAM CORRECTIONS: RISK–NEED–RESPONSIVITY (RNR) AND BEYOND

Regardless of one’s theoretical orientation, assessment and treatment remains the cornerstone of solid correctional practice for male and female offenders alike. Historically, one of the most influential models guiding correctional interventions has been the RNR framework, also known as the “What Works” model of corrections (Andrews & Bonta, 2010). In brief, the risk principle states that an offender’s risk level should determine the intensity (i.e., frequency and duration) of treatment, with high-risk cases receiving the most intense interventions and low risk cases receiving minimal intervention. The need principle stipulates that assessing and targeting dynamic risk factors (also known as criminogenic needs) will yield the greatest reductions in recidivism. Notably, mainstream correctional scholars (e.g., Andrews & Bonta, 2010) would classify the seven needs investigated in this study as criminogenic (criminal attitudes, criminal associates, marital/family functioning, substance abuse, community functioning, personal/emotional, and employment). Lastly, the responsivity principle suggests that treatment is most effective when a cognitive behavioral approach is used and is delivered in a firm-but-fair manner. The responsivity principle also recognizes the need to address individual-level factors that may affect effective delivery such as motivation level, gender, and race/ethnicity. Thus, mainstream correctional scholars, such as RNR proponents, recognize the importance of gender but do not place gender at the forefront of correctional practice.

How correctional decision makers actually assess risk/need factors has advanced considerably over the last 50 years. In sum, this vast body of knowledge has concluded that the structured professional judgment methods as well as actuarial derived risk assessment tools yield better predictive accuracy estimates in comparison with pure unstructured professional judgment (Grove, Zald, Lebow, Snitz, & Nelson, 2000; Hanson & Morton-Bourgon, 2009; Mossman, 1994). Moreover, the field has become saturated with a staggering number of assessment tools that target the general offender population (e.g., Level of Service/Case Management Inventory [LS/CMI]; Andrews, Bonta, & Wormith, 2004), as well as more specialized offender populations including sex offenders (Rapid Risk Assessment for Sex Offense Recidivism; Hanson, 1997), young offenders (Structured Assessment of Violence Risk in Youth; Borum, Bartel, & Forth, 2006), women offenders (Service Planning Instrument for Women; Orbis Partners, 2006), and domestic violence offenders (Ontario Domestic Assault Risk Assessment; Hilton et al., 2004). More recently, assessment tools are actively incorporating hypothesized protective factors and researchers are discovering innovative ways to incorporate treatment change into the calculation of an individual’s risk rating (e.g., Olver, Beggs Christofferson, Grace, & Wong, 2014; Orbis Partners, 2006).
Despite these considerable advancements, there is continued debate as to whether or not dynamic risk factors assessed over time truly add incremental predictive variance over and above static risk factors (Baird, 2009). While some studies have found evidence for the predictive and incremental validity of dynamic risk factors (Beggs & Grace, 2010; Brown, St. Amand, & Zamble, 2009; Howard & Dixon, 2013; Jones, Brown, & Zamble, 2010; Olver, Wong, Nicholaichuk, & Gordon, 2007), others have not (Morgan, Kroner, Mills, Serna, & McDonald, 2013). Furthermore, others have questioned if changes in dynamic risk factors can even be reliably linked to reductions in recidivism (Douglas & Skeem, 2005; Kroner & Mills, 2013; Serin, Lloyd, Helmus, Derkzen, & Luong, 2013). However, a number of experts in the field argue that dynamic reassessment is valid and worthwhile (Andrews & Bonta, 2010; Olver et al., 2007). Indeed, this is a critical debate to resolve as the assessment of dynamic risk among offender populations hinges on the assumption that positive changes in these risk factors will result in reduced rates of recidivism.

THE STUDY OF WOMEN OFFENDERS

Historically, the majority of both primary studies and metaevaluations involving criminal behavior either focused exclusively on male offenders, or failed to disaggregate the data by sex. However, this has now changed. Women offenders are increasingly at the forefront of academic interest. Consequently, a women-centered knowledge base continues to evolve allowing researchers to formulate new research questions and hypotheses, and practitioners to develop and implement gender-responsive assessment and programming (Bloom, Owen, & Covington, 2003; Chesney-Lind & Pasko, 2013; Covington, 2013; Holsinger, 2000; Odgers & Moretti, 2002; Van Voorhis, 2013).

ASSESSING DYNAMIC RISK: SINGLE-POINT STUDIES INVOLVING MALE AND FEMALE OFFENDERS

In response to the criticisms levied against mainstream correctional researchers, several narrative and statistical meta-analytic summaries have explored the extent to which females may have different risk factors, and hence different treatment targets. Earlier narrative reviews concluded that the risk factors are remarkably similar between the genders (e.g., Byrne & Howells, 2002; Sorbello, Eccleston, Ward, & Jones, 2002). Similarly, three earlier meta-analyses examining the correlates and/or predictors of female delinquency found support for the gender-invariance of the following factors: (a) antisocial attitudes, (b) antisocial peers, (c) criminal history, (d) antisocial personality factors (e.g., impulsivity), (e) substance abuse, (f) family factors, (g) employment/school, and (h) leisure/recreation (Green & Campbell, 2006; Hubbard & Pratt, 2002; Simourd & Andrews, 1994). Collectively, these eight factors are known as the Central Eight (Andrews & Bonta, 2010). In addition, one female-specific treatment outcome meta-analysis (Dowden & Andrews, 1999) and a follow-up meta-analysis (Dowden, 2005) also demonstrated that the correlates and/or predictors of crime are largely gender invariant.

Moreover, meta-analyses have also shown that tools premised on the Central Eight risk factors (e.g., LS/CMI; Andrews et al., 2004) are valid for women offenders. Specifically, a meta-analysis examining the relationship between scores on the Level of Service Inventory–Revised (LSI-R) and reoffending among women offenders found an average Pearson’s $r$
effect size of .35 on the basis of 27 effect sizes (Smith, Cullen, & Latessa, 2009). Notably, this meta-analysis was limited to samples of women.

Researchers who study the unique social and economic circumstances underlying female crime have long criticized meta-analyses for excluding small-scale studies and qualitative research—studies that are the norm, rather than the exception within the study of female offending (Hannah-Moffat & Shaw, 2000; Kendall, 2004; Van Voorhis, 2012). Moreover, meta-analyses have rarely compared results between male and female offenders. However, Andrews et al. (2012) recently addressed the latter limitation. Specifically, they examined gender differences in the predictive validity of the LS/CMI and the youth version of this scale (Youth Level of Service/Case Management Inventory [YLS/CMI]; Hoge & Andrews, 2002, 2011) among male and female offenders. Overall, the gender neutrality of each dynamic domain was supported across all validity estimates with area under the curves (AUC) for each risk/need domain ranging from .61 to .71 for males and from .63 to .77 for females. Notably, although each domain was significantly related to recidivism for both genders, substance use was more strongly related to recidivism for females ($M = .46$) than for males ($M = .17$).

Indeed, others have also found that the best dynamic predictors of recidivism, using single-point assessments of dynamic risk, may vary as a function of gender. Manchak, Skeem, Douglas, and Siranosian (2009) examined serious violent offenders (70 female, 1,035 male) and found that while the predictive validity of the LSI-R was relatively equal for males and females, for men the best dynamic predictors of recidivism were the financial and substance use domains; in contrast, only the financial domain was a significant predictor for female offenders. Furthermore, in a large study of male and female offenders from the Netherlands ($N = 16,239$), van der Knaap, Alberda, Oosterveld, and Born (2012) examined the relative predictive validity of several dynamic risk domains and found that problems with accommodation, education and employment, and peer relationships were more significant correlates of recidivism for males than for females. However, relative to males, female offender’s emotional problems were more highly correlated to general recidivism. As a whole, these studies suggest that the predictive validity of certain gender-neutral dynamic risk factors, as assessed at a single time point, may be moderated by gender.

### REASSESSMENT OF DYNAMIC RISK FACTORS: MULTIPoint STUDIES INVOLVING MALE AND FEMALE OFFENDERS

Change in dynamic risk is expected given that dynamic risk factors are considered viable treatment targets. Like their male counterparts, support for the predictive validity of dynamic variables among women offenders has been garnered primarily from single-point research designs (i.e., assessing dynamic risk factors once, for example, at prerelease, and then examining the correlation between the prerelease score and recidivism). Few studies have examined changes in dynamic variables, accomplished either through treatment or simply the passage of time, and subsequently linked that change to reductions in recidivism (Douglas & Skeem, 2005; Serin et al., 2013).

Over the last decade, prediction research has been centered on the reassessment of dynamic risk factors (Andrews & Bonta, 2010; Andrews, Bonta, & Wormith, 2006; Beggs & Grace, 2011; Douglas & Skeem, 2005; Hanson & Harris, 2000; Hanson, Harris, Scott, & Helmus, 2007; Kroner & Yessine, 2013; Motiuk, 1998). Specifically, multiwave (or
Multipoint longitudinal research designs have afforded researchers the opportunity to examine how change in repeated measures of predictor variables is related to criminal recidivism. Detecting changes in intraindividual risk, through the consideration of change in dynamic risk factors, is important as it can serve to direct resources to those on the brink of failure.

Dynamic variables have been examined within the context of a multiwave study using adult (e.g., Andrews & Wormith, 1984; Brown et al., 2009; Jones et al., 2010; Schlager & Pacheco, 2011) and youthful offender populations (e.g., Baglivio & Jackowski, 2013), and have also been carried out with unique subsets of offender populations, including mentally disordered offenders (e.g., Quinsey, Book, & Skilling, 2004; Quinsey, Coleman, Jones, & Altrows, 1997) and sex offenders (e.g., Beggs & Grace, 2010; Hanson & Harris, 1998; Olver & Wong, 2011). Generally, two approaches have been taken for studying change in dynamic risk factors. One approach has been to measure change on a dynamic variable between two (or more) time points and then use a change score to predict a particular outcome (e.g., Beggs & Grace, 2010; Vose, Lowenkamp, Smith, & Cullen, 2009). A second approach has been to assess dynamic variables at multiple time points and subsequently ascertain whether significant change has occurred across time, and then, use the assessment information closest to recidivism to determine if the reassessment of a dynamic variable is more valuable than a single, baseline assessment (e.g., Brown et al., 2009; Dowden, Serin, & Blanchette, 2001; Jones et al., 2010).

Focusing on the former methodology, Serin et al.’s (2013) review of the literature highlighted several gaps in this body of literature. Specifically, upon review of treatment change studies that targeted three main risk factors (substance use, violence, and antisocial cognitions), it was found that only 53 of the 378 studies that measured change explicitly linked that change to an outcome variable. Although Serin et al.’s review did find that positive change in some dynamic variables (e.g., antisocial cognitions) can be linked to reductions in recidivism, it is clear that not enough evidence has amassed to conclude with certainty that change in dynamic risk is in fact related to improved outcomes. This gap in the literature is even more prominent for female offenders. Indeed, only two women offender studies have examined change in dynamic factors over time and then linked that change to an outcome (Dowden et al., 2001; Vose et al., 2009).

Vose et al. (2009) examined scores on the LSI-R for a sample of male (n = 2,448) and female (n = 401) probationers and parolees at two time points. Bivariate correlations revealed that the total score on the LSI-R and recidivism rates were significantly correlated for males and females at both Time 1 and Time 2. Furthermore, correlations between the raw change score in the total LSI-R score (i.e., Time 1 score minus Time 2 score) and recidivism were significant for both males and females. Notably, change was only looked at for the total LSI-R score; consequently, what domains accounted for the change seen was not attested to.

Unlike Vose et al. (2009) who used just two waves of data to examine change in dynamic variables, Dowden et al. (2001) examined change scores across four assessment periods for women (N = 633) who had recently been released into the community from federal custody. Using dynamic risk data obtained using the Community Intervention Scale (CIS, which is the scale being utilized in the present study), results indicated that when scores on the dynamic variables (associates, community functioning, personal/emotional, substance abuse, attitudes, employment, and marital/family) increased in severity while in the
community, women were more likely to recidivate relative to those whose scores stayed the same or decreased. They also found that change scores in each domain were predictive of recidivism. Specifically, those women who had the largest positive change scores were more likely to reoffend than those who showed moderate change or no change (Dowden et al., 2001). It is important to note that although this study included four waves of data, change was accounted for by the largest change score across all assessments, essentially treating the data as a dual-point design.

Indeed, the majority of multiwave studies to examine dynamic risk have used two-wave designs to account for change. It has been suggested that research designs incorporate at least three waves to increase the probability of detecting change (Brown et al., 2009) and to avoid some of the common methodological shortcomings of using change scores within a dual-point design (see McArdle & Nesselroade, 2002). In the last several years, dynamic reassessment studies with more than two time points and larger samples have been carried out (Brown et al., 2009; Howard & Dixon, 2013; Jones et al., 2010; Morgan et al., 2013).

Brown et al. (2009) examined the extent to which dynamic risk factors, measured at three time points, could add incrementally to models comprised of only static factors in the prediction of recidivism. Using a sample of adult male offenders from Canada (N = 136), five static measures and 18 dynamic measures assessed on three separate occasions (prerelease, 1 month postrelease, and 3 months postrelease) were used. Overall, Cox regression with time-dependent covariates and receiver operating characteristic (ROC) analysis found that the reassessment of dynamic risk factors significantly added to models of static risk (AUC = .89 vs. AUC = .81, p < .01). By extending their follow-up to 6.5 years, and adding another wave of data (6 months postrelease), Jones et al. (2010) compared more naturalistic ratings made by parole officers with those made by graduate researchers in their earlier study (see Brown et al., 2009). Again, using Cox regression with time-dependent covariates and ROC analysis, Jones et al. found comparable results to the first study with combined static and dynamic models having the strongest predictive validity for both researcher (AUC = .86) and parole officer assessments (AUC = .83).

More recently, Howard and Dixon (2013) conducted a study using a large multiwave offender data set in the United Kingdom (N = 196,493) to compare the predictive validity of a violence risk assessment instrument when measured repeatedly over time compared with a one-time assessment of risk. This study used data obtained from the Offender Assessment system (OASys; a structured clinical risk-needs assessment tool) and an actuarial assessment tool designed to predict violent offending embedded within this larger assessment (i.e., OASys Violence predictor [OVS]). Using Cox regression with time-dependent covariates, the results showed that both the initial score on the OVS, and changes in dynamic risk factors within the OVS, significantly predicted recidivism better than a model of static risk factors, or a one-time assessment of dynamic risk factors.

Taken together, dynamic reassessment studies have provided preliminary evidence that certain dynamic risk factors are indeed changeable (e.g., Schlager & Pacheco, 2011) and that the addition of time-dependent dynamic variables to static models can improve recidivism prediction (e.g., Brown et al., 2009; Howard & Dixon, 2013; Jones et al., 2010). However, this finding is not uniform across studies; one recent multiwave study found that changes in dynamic risk factors do not add to static models of risk (Morgan et al., 2013). An additional limitation is that research on dynamic change has thus far been limited to studies comprised predominantly or entirely of male offenders. Although multiwave studies with
women offenders do exist (e.g., Holtfreter & Morash, 2003; Holtfreter, Reisig, & Morash, 2004; Reisig, Holtfreter, & Morash, 2006), none have examined change in dynamic risk factors over more than two time points, nor whether the reassessment of dynamic risk improves the predictive validity of actuarial risk tools.

**PRESENT STUDY**

Overall, amid both empirical concerns as well as ideologically based opposition, there is some empirical evidence in support of a variety of dynamic risk measures with female offenders. Notably, this support has generally been garnered with single time point designs. While true tests of dynamic predictive validity are evident within the male-centered research (i.e., multiwave studies, linking change in dynamic risk factors to an outcome variable), this type of research is notably absent with female offender samples. To fill this void, the present study sought to examine (a) the extent to which criminogenic needs change over time among federally sentenced women in the community and (b) the relationship of these risk factors—assessed at both a single time point, and multiple time points—with future criminal recidivism. While no a priori predictions were made as to the amount of change expected within each domain, it was hypothesized that positive change (i.e., improvement) in risk domains would be evident for women who were successful on release into the community.

Three general areas of analysis will be addressed. First, the natural and differential rate of change among the previously discussed dynamic factors will be explored. Second, comparisons of the relative predictive power of these criminogenic needs will be investigated. Lastly, whether or not the reassessment of dynamic risk predictors in the community improves the predictive accuracy over and above an initial assessment at time of release will be examined.

**METHOD**

**PARTICIPANTS**

A sample of 725 federally sentenced adult female offenders was extracted from the Correctional Service of Canada’s automated database, the Offender Management System (OMS)² on May 1, 1999. Included in the study were women who had been (a) released into the community as of the data extraction date, (b) comprehensively assessed for risk and needs on admission to federal custody, (c) had official criminal conviction information (Canadian Police Information Center [CPIC]) records available, and (d) had at least one community-based, dynamic risk assessment conducted during the follow-up period. The sample was further reduced to 658 women as a result of missing data (i.e., having no risk predictor information; \( n = 57 \)) or death (\( n = 10 \)). Notably, there was some irregularity in the time between assessments due to women who had been released in the middle of a new standard for operations being implemented by Correctional Service Canada (e.g., they were released before the policy of using the CIS was established). Therefore, to accommodate this irregularity in assessment dates, four discrete categories were created: Time 1 = 0 to 6 months, Time 2 = 6 to 12 months, Time 3 = 12 to 18 months, and Time 4 = 18 to 24 months. Cases that did not have an assessment completed within each of these time intervals were dropped from the sample, unless they had reoffended before the next assessment was due (\( n = 161 \)). If there were two assessments completed within the same time interval the latter
of the two was retained. After the data cleaning process was complete, the resultant sample size was 497.

The average age of the sample at the time of the study was 36.8 years \( (n = 497, SD = 8.7) \) with a range of 20.6 to 68.9 years. This is comparable with population data that indicate that the average age of women serving a federal sentence in 2006 was 37.7 years (Statistics Canada, as cited in Kong & AuCoin, 2008). More than half of the sample (61%) were either single, separated, or divorced while 33% were living common-law or were married. The sample was predominantly Caucasian (57%) or Aboriginal (19%), with the remaining 24% belonging to other minority groups. At intake, offenders were designated as high \( (n = 126, 25.4\%) \), medium \( (n = 115, 23.1\%) \), or low \( (n = 256, 51.5\%) \) risk as the result of a structured professional judgment assessment process.

Most women in the sample had been previously convicted for property offenses such as theft (60.6%) and fraud (39.8%), followed by drug convictions (46.7%). The most common violent convictions were for weapons-related offenses (30.6%), arson (20.7%), and kidnapping (13.9%). Few women had been convicted for assault (4.8%) or murder (3%).

MEASURES

Dynamic Risk Factors

Dynamic risk was assessed using the CIS, the successor to the Community Risk/Needs Management Scale (CRNMS; Motiuk & Porporino, 1989). Both measures are empirically validated assessment instruments that provide comprehensive, systematic, and ongoing assessments of the changing needs of offenders under community supervision. The original 12 dynamic factors that comprised the CRNMS (including academic/vocational skills, employment pattern, financial management, marital/family relationships, companions/significant others, living arrangements, behavioral/emotional stability, alcohol usage, drug usage, mental ability, health, and attitudes) were subsequently collapsed into seven dynamic factors that now comprise the CIS: employment, marital/family, associates, substance abuse, community functioning, personal/emotional, and attitudes.

Importantly, the CIS is a structured professional judgment tool that is used primarily to assess change in needs over time. An in-depth assessment is carried out at intake to a federal institution to assign an initial needs rating for each domain based on the indicators contained with the Dynamic Factor Identification and Analysis (DFIA; Brown & Motiuk, 2005). For example, to determine a rating for the personal/emotional domain, aggression (sexual and general), interpersonal skills, life planning skills, self-regulation, and interpersonal skills are assessed. The CIS is subsequently administered at release and at regular 6-month intervals once the offender is in the community, to take into consideration any changes that may have taken place in each domain. Each dynamic factor is rated on either a 3- or 4-point continuum ranging from “factor seen as an asset to community adjustment” to “considerable need for improvement.” The two intermediate ratings are “no need for improvement” and “some need for improvement.” The substance abuse and personal/emotional domains are each rated on a 3-point continuum ranging from “no need for improvement” to “considerable need for improvement.” As an illustration, the CIS marital/family domain would be rated as follows:
A. **Factor seen as an asset to community adjustment:** indicates there is a history of positive and supportive relationships with parents, relatives, spouse, or children and there is no evidence of having experienced or perpetrated family violence.

B. **No need for improvement:** there is evidence of a satisfying and caring relationship within a marriage and/or family; therefore, no current difficulties in the community.

C. **Some need for improvement:** evidence of uncaring, hostility, arguments, fighting, or indifference in the marital/family relationships resulting in occasional instability.

D. **Considerable need for improvement:** evidence of a very unstable pattern of marital/family relationships (e.g., uncaring, hostility, arguments, fighting, etc.).


**Recidivism Data**

There has been some debate as to the best way to measure recidivism as base rates for reoffending will differ depending on how it is defined. While some researchers opt to use more lenient criteria such as violations of supervision conditions, others prefer to use more reliable measures of antisocial behavior such as official records of arrest or convictions. Further complicating matters is the length of follow-up used, as this can affect the base rate of reoffending, and consequently can affect one’s results. For example, studies that have examined the utility of the LSI using a long-term follow-up of officially recorded recidivism have found good predictive validity of the tool (e.g., Rettinger, 1998); however, self-reported violations of supervision conditions and rearrest using a short-term follow-up (e.g., 6 months) have produced weaker estimates of predictive validity for the LSI-R (e.g., Holtfreter et al., 2004).

For the purpose of the present study, four measures of criminal recidivism were coded after the first release from custody for the original index offense that encompassed both reincarceration and violations of supervision conditions. Specifically, any failure included conditional release revocations for technical violations, general reconvictions, nonviolent reconvictions, and violent reconvictions. Revocation information was coded from Correctional Service Canada’s OMS database while reconviction data were coded from CPIC records. Nonviolent reconvictions were defined as a conviction for any new general offense (e.g., theft or fraud). Violent reconvictions were defined as any new conviction for an offense involving crimes against persons (e.g., assault, robbery, weapons-related offenses).4

The average follow-up time in the community was 29 months ($SD = 16.6$) and ranged from 5 days to 6 years. The follow-up time was calculated as the time between the individual’s supervision start date until failure or May 1, 1999, when the data were extracted from OMS, whichever date came first. In that time period, 18.9% ($n = 94$) of the total sample were reconvicted for a new criminal offense. Of those reconvicted, 16.1% ($n = 80$) committed a nonviolent crime and 4.0% ($n = 21$) committed a violent crime (seven women were convicted of both violent and nonviolent offenses). Theft (45.3%), failing to appear (29.5%), and fraud (20%) were the most common nonviolent reconvictions. Among the 4% of violent reconvictions, the majority were assault (43%), weapons (21%), and robbery related (21%). Only one woman was reconvicted for manslaughter.
Although women were reconvicted during all four time periods, most were reconvicted during the first 6 months after release. Specifically, 46% (n = 43) of the women were reconvicted before the second assessment (Time 2) and another 30% (n = 28) were reconvicted between the second (Time 2) and third assessment (Time 3). The remaining 16% (n = 15) and 8% (n = 8) were reconvicted between Time 3 and Time 4, and after Time 4, respectively.

**Analytical Approach**

To be genuinely considered a dynamic variable, two criteria must be met: (a) significant within-subject change must be evident between assessment waves and (b) the change in this variable must be able to contribute to the prediction of recidivism (Brown et al., 2009). Specifically, it must be shown that the reassessment of a variable leads to improvement in decision accuracy over and above a one-time assessment of the particular variable.

Consequently, to fully understand how these variables predict recidivism in this population of offenders, a series of steps were taken. Foremost, changes in needs among those women who successfully desisted arrest (n = 64) were examined. To look at within-subject change (i.e., Criterion 1), a doubly multivariate repeated-measures analysis was applied to the data. This analysis was followed by a series of pairwise comparisons to determine where significant change was actually occurring (e.g., Wave 1 vs. Wave 4) and thereby identify when offenders may be at greatest risk.

An examination of the ability of the criminogenic needs assessed to predict recidivism at both a univariate and multivariate level was then carried out. Specifically, the initial assessment of each need was used as a predictor to determine how each variable on its own and in combination (i.e., model of best fit), based on a one-time assessment, predicted the event of interest (i.e., recidivism). To establish how each criminogenic need was independently related to survival time, Cox regression survival analyses were conducted on each of the seven dynamic measures at Time 1. Based on maximum likelihood estimation techniques, this statistical method produces a survival function that generates standardized scores (X'Beta scores) for each individual predictor variable or the best linear combination of the predictor variables. These X'Beta scores are then saved and serve to generate AUC values in ROC analysis. This method was subsequently used to ascertain the relative accuracy of the Time 1 prediction models and each individual dynamic factor. One advantage of using AUC values in contrast to other measures of accuracy (e.g., percentage correct) is that the former are not influenced by recidivism base rates (Swets, Dawes, & Monahan, 2000).

Last, it was necessary to determine whether or not the reassessment of dynamic risk predictors in the community improves the predictive accuracy over and above an initial assessment at time of release. To determine which dynamic factors were most valuable in that they improved in their predictive validity over time, Cox regression survival analysis with time-dependent covariates was used. This procedure has several advantages over the traditional survival analysis that only estimates when, how long, and how often a given event (recidivism) will occur within a given time frame. Cox regression survival analysis with time-dependent covariates can readily incorporate variables that fluctuate over time by using the assessment information closest to recidivism, thereby eliminating the overly common problem of losing participants prior to reassessment. Consequently, women who recidivate before their second assessment will not be dropped from the analysis, as they would be if other statistical methods were used to analyze the data such as the use of change scores as
RESULTS

DATA SCREENING

All variables were examined for data entry errors and the presence of missing data. As approximately only 1% of the cases at each wave had missing data, the relevant variable mode was imputed for missing values. Notably, when missing data are less than 5%, using an alternative method to deal with missingness (e.g., mean substitution, listwise deletion) would not affect the results (P. Allison, personal communication, October 15, 2007). The data were then inspected for univariate outliers, multivariate outliers (via Mahalanobis Distance), indicators of normality (skewness and kurtosis), homoscedasticity, and multicollinearity (correlations in excess of .80) at each wave of data collection. Three variables had univariate outliers, which were truncated at the ±3 standard deviations of the mean of the variable. However, all other assumptions were met. Last, log minus log plots were examined to determine if the ratio of the estimated hazard across time remained constant, a necessary assumption for Cox regression survival analysis. If the lines had crossed on the plot, then a violation would be indicated. No violations were detected for the seven dynamic predictor variables.

DESCRIPTIVE STATISTICS OF DYNAMIC MEASURES

The mean and standard deviations for the seven dynamic factors comprising the CIS are provided in Table 1. Interestingly, all seven variables followed the same trend with reductions in the severity of the need across time. For instance, employment needs were on average at their highest levels \((M = 3.0)\) at Time 1, followed by a slow but steady decline to a mean of 2.3 at Time 4. A similar trend was noted for five of the other needs domains. Most of these variables hovered around a central tendency of 2.0, with the exception of attitudes, which was consistently lower at all four assessment periods.

ASSESSING CHANGE IN DYNAMIC MEASURES

Repeated-Measures Analysis

Although there appeared to be change within the dynamic variables as time passed, it was impossible to determine from this descriptive data whether the change was due to changing proportions of recidivists and nonrecidivists or whether the variables were reflecting genuine change in the CIS measure. Consequently, a within-subject change analysis was conducted, using only those cases that did not fail (i.e., not reconvicted) during their time at risk in the community, to determine whether the change in the variables was authentic. Specifically, a doubly multivariate repeated-measure analysis was conducted on all seven need variables simultaneously. It should be noted that this data set was inherently unbalanced due to the loss of subjects at each wave of assessment as a result of the coding
procedures noted in the Method section of this article. Therefore, attrition at each assessment wave was not just reflecting loss due to recidivism but also subjects being dropped due to variations in storage of assessment information. Consequently, this portion of the analysis was conducted on only those subjects with four completed assessments (\(n = 64\)).

Overall, Wilks’s Lambda criterion indicated that collectively the seven dynamic need factors were significantly changing over time, \(F(7, 64) = 5.31, p < .0001\).

This analysis was then followed with seven single-group univariate repeated-measures analysis to determine which variables were experiencing the most change. As evidenced in Table 2, six of the seven dynamic factors demonstrated significant change in the hypothesized direction. The only exception was substance abuse, which stayed the same throughout each wave.

Pairwise Comparisons

Finally, a series of pairwise comparisons were performed to determine where the significant changes were actually occurring (e.g., Wave 1 vs. Wave 4, Wave 2 vs. Wave 4). Due to the large number of comparisons that were performed, a Bonferroni correction procedure was applied to control for Type 1 errors.

As Table 3 illustrates, substance abuse exhibited no significant difference scores; however, three distinct trends emerged. First, the personal/emotional, attitudes, and marital/family factors exhibited significant change between the first and fourth assessments. Thus, only after being in the community an extended amount of time (18-24 months) was significant change detected from the initial assessment. Second, the employment and attitude factors exhibited change across all four time periods, thereby demonstrating that these variables were in a constant state of flux. Finally, the associates’ factor only showed significant changes between the first and second assessment waves. The change analyses are informative as they demonstrate that one’s need level does improve over time among the successful cases. However, these results must be interpreted cautiously given the small sample size (\(n = 64\)).

RECIDIVISM PREDICTION: UNIVARIATE ANALYSIS

With the dynamic nature of the variables established, a series of Time 1 univariate Cox regression survival analyses was performed to examine the ability of each dynamic factor
These univariate survival analyses were then succeeded with stepwise Cox regressions to identify the strongest Time 1 prediction models. A series of ROC analyses were also conducted to ascertain the relative accuracy of the Time 1 prediction models as well as the individual dynamic factors.

**Table 4** illustrates, five of the seven variables significantly predicted time to reconviction (\( p < .05 \)) at Time 1. The exceptions were the personal/emotional and community functioning variables. On examination of the \(-2\) log likelihood statistic (\(-2\text{LL}\)), the best fit of the survival curve was generated by associates (\( p < .001 \)), followed by attitudes (\( p < .001 \)) and substance abuse (\( p < .001 \)). Although significant, employment and family measures provided relatively weak improvements to the fit between the base survival model and the observed data.

### Cox Regression Survival Analyses (Time 1)

(assessed at Time 1) to predict time to reconviction. These univariate survival analyses were then succeeded with stepwise Cox regressions to identify the strongest Time 1 prediction models. A series of ROC analyses were also conducted to ascertain the relative accuracy of the Time 1 prediction models as well as the individual dynamic factors.
Individually, all of the variables evidenced very modest levels of predictive accuracy as evident through ROC analysis (see Table 4). Initial assessments of attitudes yielded the highest AUC (.61), closely followed by the assessments of associations (.60), family factors (.57), and substance abuse (.56). Community and personal/emotional factors fared no better than chance with AUCs of .51.

The next phase of the analyses assessed which combination of dynamic risk predictors assessed at Time 1 made the strongest predictor model. Cox stepwise regression survival analysis was conducted on the five variables that demonstrated a significant univariate relationship with survival time in the previous analysis. Results showed that only associates and attitudes emerged as significant predictors of time to failure; employment, family, and substance abuse factors did not add significantly to the predictive power of the set.

The X1Beta scores were again used to assess the degree of relationship between the combination of need variables deemed significant (associates and attitudes) and failure on release (Table 5).

The final set of analyses attempted to unearth the best dynamic risk predictors, specifically, those that improve in their predictive ability over time. To do this, seven individual Cox regression survival analyses with time-dependent covariates were conducted on each
separate need variable. All assessments from Time 1 to Time 4 were involved in the analysis. Results were examined to determine which of the seven needs were independently related to survival time in the community. Strong positive relationships were unearthed between all seven variables and the amount of time the offender spent in the community (Table 6).

Table 5: Cox Stepwise Regression and ROC Results: Time 1

<table>
<thead>
<tr>
<th>Dynamic Measure</th>
<th>−2 Log Likelihood (with variable)</th>
<th>λ</th>
<th>Significance</th>
<th>Hazard Ratio</th>
<th>AUC (CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1 Associates</td>
<td>1,177.81</td>
<td>18.2</td>
<td>***</td>
<td>1.64</td>
<td></td>
</tr>
<tr>
<td>Step 2</td>
<td>1,168.39</td>
<td></td>
<td>***</td>
<td>.66 [.52, .71]</td>
<td><img src="https://www.greineret.com/auto.com" alt="" /></td>
</tr>
<tr>
<td>Associates</td>
<td>13.4</td>
<td></td>
<td></td>
<td>1.54</td>
<td></td>
</tr>
<tr>
<td>Attitudes</td>
<td>10.2</td>
<td></td>
<td></td>
<td>1.57</td>
<td></td>
</tr>
</tbody>
</table>

Note. −2 log likelihood (without variable) = 1,196.83; λ = Wilks’s Lambda; A hazard ratio is the ratio of two hazard functions that correspond to unit differences in the value of the associated covariate (Singer & Willett, 2003). Thus, a hazard ratio of 1.0 indicates that the covariate has no influence on survival time; whereas hazard ratios in excess of 1 indicate that as the covariate increases (e.g., as employment problems increase), survival time decreases. ROC = receiver operating characteristic; AUC = area under the curve; CI = 95% confidence intervals. ***p < .001.

Table 6: Univariate Cox Regression With Time-Dependent Covariates and ROC Results

<table>
<thead>
<tr>
<th>Dynamic Measure</th>
<th>−2 Log Likelihood (With Variable)</th>
<th>λ</th>
<th>Significance</th>
<th>Hazard Ratio</th>
<th>AUC (CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment</td>
<td>1,176.12</td>
<td>20.2</td>
<td>***</td>
<td>1.8</td>
<td>.62 [.57, .68]</td>
</tr>
<tr>
<td>Family</td>
<td>1,186.04</td>
<td>10.6</td>
<td>***</td>
<td>1.4</td>
<td>.60 [.54, .66]</td>
</tr>
<tr>
<td>Associates</td>
<td>1,171.60</td>
<td>23.9</td>
<td>***</td>
<td>1.8</td>
<td>.63 [.57, .69]</td>
</tr>
<tr>
<td>Substance abuse</td>
<td>1,178.80</td>
<td>20.3</td>
<td>***</td>
<td>1.7</td>
<td>.59 [.53, .65]</td>
</tr>
<tr>
<td>Community</td>
<td>1,185.39</td>
<td>11.5</td>
<td>***</td>
<td>1.5</td>
<td>.61 [.55, .67]</td>
</tr>
<tr>
<td>Personal/emotional</td>
<td>1,184.74</td>
<td>12.1</td>
<td>***</td>
<td>1.6</td>
<td>.58 [.52, .64]</td>
</tr>
<tr>
<td>Attitudes</td>
<td>1,188.18</td>
<td>9.5</td>
<td>**</td>
<td>1.5</td>
<td>.61 [.55, .67]</td>
</tr>
</tbody>
</table>

Note. −2 log likelihood (without variable) = 1,196.83. λ = Wilks’s Lambda. A hazard ratio is the ratio of two hazard functions that correspond to unit differences in the value of the associated covariate (Singer & Willett, 2003). Thus, a hazard ratio of 1.0 indicates that the covariate has no influence on survival time; whereas hazard ratios in excess of 1 indicate that as the covariate increases (e.g., as employment problems increase), survival time decreases. ROC = receiver operating characteristic; AUC = area under the curve; CI = 95% confidence intervals. **p < .01. ***p < .001.

ROC Analysis: Univariate Time-Dependent Model

The X1Beta scores were again used to assess the degree of relationship between each need variable, measured at multiple waves, and failure on release (Table 6). AUC values ranged from .58 to .63, demonstrating only a modest ability of these need variables to predict time to failure.

RECIDIVISM PREDICTION: MULTIVARIATE ANALYSIS OF TIME-DEPENDENT MODEL

Cox Regression Stepwise Survival Analysis: Multivariate Time-Dependent Model

The last analysis selected the best combination of time-dependent dynamic variables using Cox stepwise regression survival analysis. All seven variables were entered as they all
demonstrated a significant univariate relationship (entry and exit criteria were set at .05) with survival time in the previous analysis for any reconviction. Only associates and employment entered the model, as the other five variables did not add significantly to the predictive power of the set (Table 7).

**ROC Analysis: Multivariate Time-Dependent Model**

X^{1}Beta scores were then used in the ROC analysis to assess the predictive accuracy of this model (associates and employment needs). The AUC for this model endorsed it as the most accurate prediction model presented in this study (AUC = .70). See Table 7 for more information.

**SUMMARY OF STRONGEST PREDICTION MODELS**

The Cox regression survival analysis, based on the initial assessments in the community (Time 1), identified associates and attitudes to be the most relevant and valuable predictors of time to failure in the community (AUC = .66). While substance abuse, family, and employment measures were also found to be predictive of time to failure, they did not significantly add to the prediction model, and thus were not added into the final model.

The Cox regression survival analysis, with time-dependent covariates based on the offenders’ last assessment before failure, again identified associates as one of the strongest predictors of time to failure; however, attitudes were no longer as strong a predictor as the employment measures. Although all seven dynamic risk predictors were considered significantly related to survival time, the stepwise regression generated a two-variable “best fit” model, which included associates and employment needs (AUC = .70). Overall, the time-dependent model was more successful than that derived from the Time 1 evaluations, thereby highlighting the utility of dynamic and repeated need assessment when managing offenders released into the community.

**DISCUSSION**

This study examined the predictive validity of seven dynamic risk factors from the CIS with 497 federally sentenced Canadian women released into the community. Four separate assessments in the community, at 6-month intervals, were analyzed for each of the dynamic
risk factors. There were three main purposes to this study: (a) to examine the natural and differential rate of change among the dynamic factors, (b) to compare the relative predictive power of these criminogenic needs, and (c) to examine whether or not the reassessment of dynamic risk predictors in the community improves the predictive accuracy over and above an initial assessment at time of release. Each of these will be discussed in turn.

**CHANGE IN DYNAMIC RISK FACTORS OVER TIME**

The assessment of dynamic risk among offender populations hinges on the assumption that positive changes in these risk factors will result in reduced rates of recidivism. A necessary first step in testing this assumption, therefore, is to demonstrate that dynamic factors do indeed change over time. Overall, this study showed that with the exception of substance use, all of the dynamic variables (i.e., employment, marital/family, community functioning, personal/emotional, criminal associates, and criminal attitudes) demonstrated significant change in the hypothesized direction across the study period. The employment and community domains demonstrated change between each assessment, with needs in these areas being lower at each subsequent assessment. However, three domains were shown to change more slowly, including personal/emotional, attitudes, and family/marital. This suggests that these variables are more stable in nature, and therefore may take more time to change when targeted in community programs.

Overall, these results suggest that some risk factors may be more stable (i.e., substance abuse, personal/emotional, attitudes, family/marital), while others may be more acute (i.e., employment, community). The utility of distinguishing between acute and stable dynamic risk factors has been articulated by several groups of scholars, most notably among those who carry out research with sexual offenders (e.g., Hanson & Harris, 2000; Hanson et al., 2007; Olver et al., 2007). This body of work describes acute dynamic risk factors as those that change rapidly, often acting as triggers for criminal behavior. Changing acute risk factors may affect one’s risk to reoffend in the short term (e.g., abstaining from alcohol would increase one’s impulse control, thereby decreasing the likelihood of committing an offense), but these efforts would have little impact on long-term risk (Hanson & Harris, 2000). In contrast, stable dynamic risk factors are those that tend to be more enduring and therefore take longer to demonstrate meaningful change (e.g., alcoholism, attitudes, associates). These factors are therefore key targets in correctional treatment if one hopes to ensure lasting change and subsequent success in the community.

Unfortunately, the data used in this study preclude us from being able to speak to the types of programs completed by the women once released into the community. This is important to consider, as it may help to explain at least in part the change seen in these variables. Further complicating matters is evidence to suggest that women have a number of gender-specific concerns (e.g., victimization, mental health) that need to be treated to improve success on reentry (e.g., Holtfreter & Wattanaporn, 2014; Van Voorhis, Wright, Salisbury, & Bauman, 2010; Wright, Van Voorhis, Salisbury, & Bauman, 2012). The Correctional Service of Canada offers programs designed explicitly for women offenders transitioning from custodial facilities to the community, many of which address these gender-specific concerns. Some examples of the types of programming offered within the community include substance abuse programs for women (i.e., Community Relapse Prevention and Maintenance Program), women’s mental health services, programming to address women-specific employment needs, social skills programs, and mother–child programs.
In light of the types of programs offered to women during the reentry process, we are unable to attest to whether addressing these gender-responsive needs (i.e., mental health, parental issues) are in fact the driving force behind the change seen in the variables under study. It could be that simply incorporating gender-responsive elements into the reentry process results in a more successful outcome.

Interestingly, although a common treatment target in the community, substance abuse did not exhibit significant change across time. This variable has been traditionally plagued with a serious quantification issue. Specifically, substance abuse is often directly related to conditions of release and therefore, to reliably measure needs in this domain can be problematic. Furthermore, as the substance abuse subscale on the CIS is scored on a 3-point scale, it is possible that the measure is not sensitive enough to adequately capture change. This is important as there is evidence to suggest that substance use is an acute dynamic risk factor; therefore, capturing changes in this domain could perhaps only be done by utilizing a more sensitive measure.

It should also be noted that although significant change was seen in the associate’s domain across assessment periods, this change was minimal. It could be that the measurement of this variable is beset with the same problems surrounding substance abuse measures. Specifically, avoiding contact with antisocial associates directly relates to conditions of release and therefore the offenders have an invested interest to distort the reality of being in touch with antisocial companions. Therefore, in light of this operational constraint of attaining accurate measurements of this need, the relationships found in the present study could be considered conservative and the results tenuous, considering the logistical problems of attaining a clear evaluation of this construct.

**Relative Predictive Validity of Dynamic Risk/Need Domains**

A second goal of this study was to compare the relative predictive power of each criminogenic need. Overall, an examination of time to failure revealed that five of the seven domains assessed at Time 1, including associates, attitudes, substance use, employment, and marital/family, were found to significantly predict reoffending. However, when using ROC analyses, only the family, associates, and attitudes domains evidenced predictive accuracy greater than chance (AUCs = .57 to .61). Unlike previous studies that have found good predictive validity of all seven of these domains with women offenders (Andrews et al., 2012), these results suggest that assessing these constructs, at least at a single time point, may not produce the most accurate assessment of risk.

When competing for predictive power, only the associates domain and attitudes domain remained strong predictors of recidivism. Overall, these results are not surprising as, according to RNR proponents, these two domains are considered the top two risk factors for criminal behavior (Andrews & Bonta, 2010). In addition, meta-analytic evidence has provided support for the importance of these two domains with female offenders. Specifically, Simourd and Andrews (1994) found the antisocial attitudes and associates domain to be the strongest correlate of criminal behavior for delinquency (average $r = .39$). Furthermore, Hubbard and Pratt’s (2002) meta-analysis found antisocial peers to be the strongest correlate/predictor of criminal behavior among females ($M_{ES} = .53$).

When the reassessment data were utilized within the time-dependent model, all seven domains were (individually) positively related to survival time in the community. However,
only the associates and employment domains emerged when competing in the same model. Interestingly, when the dynamic nature of the variable was taken into account (i.e., time-dependent model), attitudes no longer emerged as a powerful predictor of the set. Notably, the change seen in the attitudes domain was only significant between Time 1 and Time 4.

As the literature on female offenders is void of multiwave dynamic change studies, we can only speculate as to the mutability of dynamic risk factors over time. However, as previously discussed, these results suggest that criminal attitudes may be a stable dynamic risk factor for women and that meaningful change in one’s criminal attitudes needs time to transpire. In contrast, it could be that criminal attitudes are so highly dynamic that change would be more adequately captured with more frequent evaluations. These results also suggest that criminal associates and employment (i.e., losing a job) may in fact be acute dynamic risk factors (i.e., triggers for criminal behavior), thereby emerging as the most salient predictors of failure within a time-dependent model.

Overall, these results suggest that the relative predictive validity of dynamic variables may change depending on whether the dynamic nature of a domain is taken into account. Specifically, although there are a vast number of single time point studies attesting to the validity of the top dynamic risk factors with women (Green & Campbell, 2006; Hubbard & Pratt, 2002; Simourd & Andrews, 1994), the best dynamic predictors may vary as a function of the methodology utilized (i.e., single-point or multiwave design). Further research comparing one-time assessments and multiple assessments of dynamic variables are necessary to delineate the best dynamic risk factors for crime for women.

ONE-TIME ASSESSMENT VERSUS REASSESSMENT OF DYNAMIC RISK

Past research has produced mixed findings as to whether or not the reassessment of dynamic risk predictors in the community improves the predictive accuracy over and above an initial assessment at time of release. While some studies have found evidence for the predictive and incremental validity of dynamic risk factors (e.g., Beggs & Grace, 2010; Brown et al., 2009; Howard & Dixon, 2013; Jones et al., 2010; Olver et al., 2007), others have not (Morgan et al., 2013). Notably, all of these studies were carried out with samples of men. As such, the final goal of this study was to test whether the predictive accuracy is improved when using multiple assessments of dynamic risk factors compared with a single assessment with a sample of women.

Overall, in line with previous research on male offenders (e.g., Brown et al., 2009; Howard & Dixon, 2013; Jones et al., 2010), this study found that the reassessment of dynamic risk factors is worthwhile with women offenders. Specifically, Cox regression survival analysis with time-dependent covariates demonstrated that all seven factors were significantly related to survival time in the community. Furthermore, while AUCs ranged from .51 to .60 for each baseline assessment of dynamic risk, the predictive accuracy of each domain in the time-dependent model was modestly higher, with AUCs ranging from .58 to .62.

When looking at the strongest prediction models, the best time-dependent model (comprised of the employment and antisocial associates domains) also had superior predictive accuracy relative to the one-time assessment of risk (comprised of antisocial associates and criminal peers; AUC = .70 vs. .60, respectively). As mentioned previously, the best models were comprised of different factors suggesting that the importance of these variables in
predicting recidivism varies as a function of the number of times a domain is assessed. Nonetheless, this study has demonstrated that the reassessment of dynamic variables among female offender populations is a profitable pursuit.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Despite this overarching conclusion, this study has limitations. Foremost, there is considerable debate in the correctional literature about what the methodological and statistical gold standard should be in ascertaining whether or not a variable is truly dynamic (e.g., Douglas & Skeem, 2005). Similar to others (e.g., Brown et al., 2009; Jones et al., 2010), the present study took the position that the best way to ascertain dynamic predictive validity is to triangulate three statistical approaches, namely (a) within-subject repeated-measures analyses, (b) Cox regression survival analyses with time-dependent covariates, and (c) ROC analysis. The most significant feature of this three-tiered statistical approach is the elimination of premature sample censoring due to failure prior to the second assessment. This was aptly demonstrated in this study as more than half of the subjects (65%) reoffended before their second assessment. If other commonly used techniques (e.g., change scores, hierarchical regressions) had been used in this study, more than half of this sample would have been lost. In addition, unlike the majority of studies to examine change over time, this study utilized four time points, thereby avoiding some of the methodological shortcomings of a dual-point design (e.g., regression toward the mean). Furthermore, with multiple waves of data, we were able to examine how quickly change occurred on each domain across time by examining change between each wave.

Despite these methodological strengths, we were unable to attest to whether change is due to true offender change or whether it was the result of improved measurement due to repeated assessments (Asparouhov & Muthén, 2009). For example, an observed decrease in an offender’s score on the antisocial attitudes domain could be due to the individual developing more prosocial attitudes, or it could be due to the repeated assessment thereby providing information that is more reliable. Future research may want to examine this issue further.

Relatedly, we were unable to speak to the relative importance of change for various needs. The importance of change on each domain is likely dependent on an offender’s unique characteristics and offense cycle. For example, changing from “no difficulty” to “some difficulty” on the criminal associates domain may be more problematic for a gang offender, whereas this same amount of change on the substance abuse domain may be more salient for an offender with a history of assault while under the influence. Therefore, future research should examine the qualitative differences in change seen in dynamic risk factors over time.

Another important limitation of this study is that the sample was comprised entirely of females; therefore, this study is unable to attest to whether or not the same dynamic risk factors (as assessed at multiple time points) would emerge as the best predictors in a comparable male offender population. Future research should include a male comparison group to determine if the reassessment of dynamic risk is as valuable for males as for females.

Last, it could be argued that the greatest limitation of the study is that it examined the dynamic predictive validity of a gender-neutral assessment tool that was originally developed to work for both males and females, without any a priori consideration for the hypothesized unique needs of women. Although not the focus of our study, a growing body of single-point, predictive research is beginning to examine the extent to which hypothesized gender-specific risk factors (e.g., poverty, abuse, relational dysfunction, depression,
anxiety, negative self-efficacy) predict criminal behavior. Notably, the vast majority of these hypothesized gender-specific risk factors would not be classified as criminogenic within the RNR framework; rather, they would be classified as noncriminogenic or perhaps as responsivity factors. Importantly, however, this growing body of gender-responsive research is starting to support the gender-specificity hypothesis, namely, females may in fact have unique risk factors relevant to their male counterparts (Brown & Motiuk, 2005; Farrington & Painter, 2004; Holtfreter et al., 2004; Odgers et al., 2007; Penney & Lee, 2010; Reisig et al., 2006; Van Voorhis et al., 2010; Vitopoulos, Peterson-Badali, & Skilling, 2012). Nonetheless, debate ensues in regard to the gender-invariance of dynamic risk factors. While the field requires more single-point prediction studies that explicitly include hypothesized female-specific risk factors, it also requires multipoint prediction studies that include gender-neutral, as well as hypothesized female-specific risk factors. In addition, future research that examines the dynamic predictive validity of gender-informed measures built from the ground up for women is needed to ensure that these variables are the most important predictors of reoffending for women. Last, it would be valuable to determine risk predictors for women that yield ROC values that exceed the .80 range.

CONCLUSION

In sum, despite the aforementioned limitations, the results of this study demonstrated that some variables are better predictors of recidivism if their dynamic nature is taken into account. This lends support to those who argue that dynamic risk assessment is valid and worthwhile (e.g., Andrews & Bonta, 2010; Olver et al., 2007). Practically speaking, this study supports the notion that there are dynamic risk predictors for community adjustment that are relevant for both men and women. By continually tracking changes in offender’s criminogenic needs, parole officers are able to intervene in a timely manner. Therefore, using a dynamic case management strategy should provide the greatest likelihood for success on release.

NOTES

1. To assess predictive validity, receiver operating characteristic (ROC) analysis is a statistical technique that produces an area under the curve (AUC) that reflects the predictive accuracy of a domain. AUC values can range from .50 (no better than chance) to 1.0 (100% accuracy).

2. The sample used in this study was also used by Dowden, Serin, and Blanchette (2001). However, due to different participant exclusion criteria (see Law, 2004), the current study used a subsample (n = 497) of Dowden’s original sample (N = 633).

3. A comparative analysis between the dropped and retained cases was conducted. Chi-square and ANOVA analyses revealed that the 228 dropped cases did not differ significantly from the retained cases on the following variables: index offense type and severity, prior convictions (number and type), risk level, and recidivism rates. Only age at the time of data extraction was significantly different, with the dropped cases being significantly older (M = 41.0, SD = 8.7) than the retained cases (M = 36.8, SD = 8.7), p < .001.

4. The base rate for violent offending (n = 21) was too low to draw any meaningful conclusions; as such, the analyses are based entirely on “any reconviction.”

5. The X1Beta can also be defined as the mean-corrected covariates weighted by their regression coefficients (Norušis, 1994).

REFERENCES


Leigh E. Greiner is a PhD candidate in the Department of Psychology, Carleton University, Ottawa, Ontario, Canada. Her current research interests include understanding the etiology of female offending behavior, with a particular focus on gender differences (and similarities) in risk and protective factors for youthful offenders.

Moira A. Law’s current research interests include help-seeking behaviors in marginalized populations and exploring novel applications of risk–need–responsivity (RNR) theory. She loves teaching part-time at the University of New Brunswick (Saint John), Canada.

Shelley L. Brown, PhD, is an associate professor in the Department of Psychology, Carleton University, Ottawa, Ontario, Canada. She uses mixed methods to improve the assessment and treatment of justice-involved girls and women.