LINGUISTIC COMPLEXITY AS A PREDICTOR OF VIOLENT RE-OFFENSE

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ABSTRACT

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by Krista M. Holman

This study examined whether linguistic complexity predicts re-offense among adults prone to engage in violent behavior. Participants consisted of 116 adults who participated in a violence reduction protocol and voluntarily signed a release for their data to be used for research purposes. The participants provided an autobiographical writing sample describing the situation that led them to seek violence reduction training. The linguistic complexity of their written responses was analyzed using computerized language sample analysis software. Post-treatment measures of skills acquired during treatment and publically available reoffense data were used to examine the relationship between linguistic complexity, treatment outcome, and reoffense. Results indicated that several linguistic measures predicted violent re-offense, whereas none were related to skills acquisition in treatment. Additionally, participants who dropped out of treatment were more likely to violently reoffend, although acquisition of skills in treatment did not serve as a protective factor against re-offense, suggesting that preexisting differences or unmeasured benefits of treatment may have helped to prevent treatment completers from reoffending. Application of the results could add to the risk assessment literature by improving the identification of offenders who could benefit from alternative or additional treatment to prevent violent recidivism.

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CHAPTER I

LITERATURE REVIEW

Violent Crime and Recidivism

According to the Federal Bureau of Investigation (FBI), nearly 1.5 million violent crimes were reported to law enforcement in the United States in 2009 (United States Department of Justice, 2010). The FBI defines a violent crime as any criminal offense that uses force or threats of force, including murder (15,241 cases), forcible rape (88,097), robberies (408,217), and aggravated assault (806,843). Due to underreporting of violent offenses (Hart & Rennison, 2003), the actual number of violent crimes committed is likely to be higher than the reported numbers.

A typical sentence for assault consists of supervised probation and mandated treatment to reduce the probability of continued violent behavior. That is, legally mandated consequences of violent crimes often include punishment and rehabilitation aimed at decreasing the potential for future violence (Johnson, 2008). Unfortunately, the available treatments are often not successful at preventing re-offense. Of a sample of 273 men on probation for domestic violence related charges, 41% were arrested for another violent crime within 24 months (Johnson, 2008). Campbell, French, and Gendreau (2009) performed a meta-analysis of 88 studies on risk assessment tools for predicting violent recidivism, which yielded a lower re-offense rate of 21.73%.

The variability in recidivism estimates may be partially due to inconsistent methods of measuring recidivism. Recidivism rates are commonly calculated using reconviction or re-arrest data. Some argue that both measures underestimate recidivism and should be adjusted upward to account for unreported crime, although the amount of adjustment is difficult to determine (Vrieze

& Grove, 2010). Because many violent offenders relapse without the crime being reported, measures of violent recidivism are significantly flawed. Some researchers rely on self-report by offenders in an attempt to correct for this issue, but offenders likely have substantial incentive to underreport their subsequent undetected offenses, also resulting in inaccurate data. Most studies of violent recidivism assess for re-offense within a certain time period after the original crime or after incarceration or treatment is completed, with most follow-up periods ranging from one year (e.g., Hamberger & Hastings, 1990) to five years (e.g., Hanson & Wallace-Capretta, 2004). These studies tend not to assess lifelong rates of recidivism. Regardless of the accuracy and consistency of recidivism measures, concern for the victims of these re-offenses prompts one to consider ways to reduce recidivism of violent crime, such as improving available violence reduction treatments. The majority of people treated do not reoffend, however, so besides focusing on improving current treatments for violent behavior, another strategy for decreasing re-offense might be to identify individuals who are either unlikely to benefit from treatment or are at a high risk for re-offense (Johnson, 2008). These particular violent offenders could then be targeted for alternative incarceration or specifically designed treatments.

The prevalence of violent crime is not a new phenomenon, and the origins of violence and criminal behavior in general have been debated for centuries. Many have argued that criminal behavior is heavily influenced by genetics (Wilson & Herrnstein, 1985), whereas others contend that criminals are merely products of an impoverished environment (Joseph, 2001). This debate over whether criminals are born or made has waxed and waned over time, with general consensus alternating between both sides of the issue. In fact, research suggests that violence is related to both internal and external factors, and that certain genotypes are more vulnerable to environmental influences than others in the development of violent behavior

(Jaffee et al., 2005). In response to these empirical findings, most current instruments for predicting future violent behavior incorporate both internal and external variables. The answer to this research question has implications for how violent offending should be handled in the criminal justice system.

Risk Assessment

Assessment of risk for violence involves predicting the likelihood that an individual will commit a violent act based upon past and present factors, with the goals of protecting the public and designing appropriate treatment (Hart, 1998; Pedersen, Rasmussen, & Elsass, 2010). The accuracy of risk assessment has improved significantly in recent decades. A crucial development was the transition from unstructured clinical judgment to more structured actuarial methods of risk assessment. The study of clinical judgment has identified many heuristics and biases that help us to make sense of the vast amount of information we encounter but also result in significant errors in judgment (Nezu & Nezu, 1989). For example, we use the availability heuristic to estimate the frequency or probability of an event based upon the ease with which an instance of the event is recalled. In risk assessment, our judgment of an individual's risk for violence may be influenced by hearing about violence in the previous evening's news report or by considering a recent client who reoffended, regardless of the individual's actual risk. Another example of a bias in clinical judgment can be found in informational search strategies. When clinicians are gathering information, they tend to focus on information that confirms their hypotheses and ignore or give less weight to disconfirming evidence, resulting in biased judgments (Nezu & Nezu, 1989). During the first generation of risk assessment in the mid-1900s, predictions were mostly based on clinical judgment, resulting in bias (Campbell, French, & Gendreu, 2009).

In contrast, actuarial assessment bases evaluations on the statistical relationship between predictors and outcomes, so that predictions of future violence take into consideration the base rates of violence for an individual's status on certain variables (Hilton, Harris, & Rice, 2010). These predictors of violence are either static or dynamic; static factors are those variables about an individual that generally cannot be changed, whereas dynamic factors can be modified (Campbell, French, & Gendreau, 2009). Research has consistently shown actuarial methods to be superior to clinical judgment at accurately predicting violent recidivism (Grove, Zald, Lebow, Snitz, & Nelson, 2000). To incorporate this knowledge, second generation tools for risk assessment are based upon statistical predictors of recidivism rather than clinical judgment (Campbell, French, & Gendreu, 2009). The Violence Risk Appraisal Guide (VRAG; Quinsey, Harris, Rice, & Cormier, 1998) is an example of a frequently-used second generation risk assessment instrument that consists primarily of static factors, such as age, marital status, past school problems, and history of alcohol problems. The items are grouped into childhood history, adult adjustment, index offense, and assessment results, and the instrument incorporates modifications of pre-existing measures. In fact, second generation risk assessment instruments have been criticized for only incorporating static factors and for being constructed without consideration for theory or rehabilitative value (Bonta, 2002).

Third generation risk assessment tools were developed to account for these limitations by predicting risk as well as assessing dynamic factors to identify targets for reducing risk in treatment (Campbell, French, & Gendreu, 2009). The use of dynamic factors also allows third generation instruments to monitor changes in risk over time. The Historical, Clinical, Risk Management-20 (HCR-20) is a prominent third generation tool that combines actuarial and clinical judgment to estimate risk (Webster, Douglas, Eaves, & Hart, 1997). The HCR-20 contains 10 items measuring historical factors, 5 items pertaining to current clinical status, and 5 items related to future risk management. The historical items primarily measure static factors, whereas the clinical status and risk management items mostly assess dynamic factors, and all items are rated from 0 (definitely does not apply) to 2 (definitely applies). The static and dynamic variables that are assessed are correlates of violent recidivism, but an offender's rating on each variable is decided based on clinical judgment, and a final judgment of low, moderate, or high risk is reached (Pedersen, Rasmussen, & Elsass, 2010). The Psychopathy Checklist—Revised (PCL-R; Hare, 2003) was not specifically developed for predicting recidivism, but it is often used to assess risk for future violence and is incorporated into the HCR-20 and the VRAG (Gonsalves, Scalora, & Huss, 2009). The PCL-R assesses antisocial behavior and affective or interpersonal variables associated with psychopathy, such as glibness, grandiosity, and lack of remorse (Hare, 2003). The short version of the PCL (PCL:SV) is often used, with scores of 18 or higher being recommended as indicative of psychopathy (Pedersen, Rasmussen, & Elsass, 2010).

A recent meta-analytic comparison of the VRAG, the HCR-20, the PCL-R, and several other prominent risk assessment instruments suggested that the measures mostly predict violent recidivism equally well, all demonstrating a moderate ability to predict violence-related outcomes (Campbell, French, & Gendreau, 2009). Third generation instruments, which include dynamic factors, produced slightly better estimates than second generation tools, although the static-based VRAG's performance equaled that of dynamic-based measures. Most subjects included in the meta-analysis were men with a low or moderate risk of re-offense, however, so it is unclear whether the results apply to women or to high risk offenders. The authors suggested that commonly used risk assessment instruments overlap considerably in content, which may account for their equivalence in predictive ability. Perhaps the future of risk assessment lies in identifying new sources of information or new variables for predicting re-offense.

Predictors of Violent Recidivism

Many static and dynamic correlates of violent recidivism have already been identified and are incorporated into current risk assessment measures such as those described above. The relative utility of static and dynamic factors in predicting recidivism has been examined empirically. A meta-analysis found that both types of variables were equally effective at predicting risk (Gendreau, Little, & Goggin, 1996). Because dynamic factors can be altered, actuarial tools that include them are more useful for assessing changes in risk over time than those that include only static factors (Andrews & Bonta, 2006). In addition, dynamic risk factors suggest useful targets for treatment and rehabilitation.

Static Factors

The static correlate of violent recidivism with perhaps the strongest support is age. Research has consistently found that older offenders are less likely to re-offend than younger ones (Morgan, 1993; Johnson, 2008). Gender is another static risk factor, with a higher likelihood of re-offense for men than for women (Morgan, 1993). Education appears to be negatively correlated with violent recidivism, so that individuals with more years of education are less likely to reoffend (Olson & Stalans 2001; Morgan, 1993). Criminal history is another static correlate of violent recidivism, such that individuals with a greater number of prior offenses, both violent and otherwise, are more likely to re-offend (Hanson & Wallace-Capretta, 2004).

There are issues with using correlation data to predict violent behavior. In particular, correlation does not indicate causation. For example, perhaps individuals with more years of education are not less likely to relapse, but are merely more successful at avoiding detection. Similarly, individuals with a criminal history may be more likely to reoffend simply because they continue to be unsuccessful at concealing their crimes. This problem with inferring causation from correlation data operates in conjunction with the fact that measures of recidivism are imperfect measures of actual relapse. Therefore correlates may predict violent recidivism but not necessarily predict relapse of violent behavior and should therefore be interpreted with caution.

Dynamic Factors

Several external and internal dynamic risk factors for violent recidivism have also been identified. An external dynamic factor with quite a bit of empirical support is alcohol or drug abuse. For example, Hamberger and Hastings (1990) found that male spouse abusers who reoffended were more likely to abuse alcohol or drugs than non-recidivists. More recent research has also found alcohol or drug abuse to correlate with violent recidivism (Olson & Stalans, 2001; Hilton & Harris, 2005). Alcohol or drug use likely encourages recidivism by causing poor judgment, increased impulsivity, and instability, although it is also possible that these factors cause both substance abuse and violence. Other indicators of instability in life also predict recidivism, including frequent changes in, or lack of, housing and employment, as well as financial instability (Hanson & Wallace-Capretta, 2004; Johnson, 2008).

Research shows that offenders who drop out of treatment are also more likely than treatment completers to recidivate, and attrition rates for treatment programs for violent offenders are notoriously high, with reports ranging from 22% to 99% (Gondolf, 1997; Daly &

Pelowski, 2000). Perhaps individuals who complete treatment benefit more from it, reducing the likelihood of re-offense. Recidivism and treatment drop-out, however, also share many correlates, such as age, employment status, criminal history, and alcohol or drug use (Jewell & Wormith, 2010), suggesting the possibility that the relationship between treatment attrition and recidivism is spurious, with both being influenced by similar variables. Regardless, the link between recidivism and attrition has been firmly established empirically, although more research is necessary to elucidate the nature of this relationship.

In addition to these external dynamic indicators of risk, several internal dynamic risk factors, such as personality variables and attitudes, have been explored as well. Hamberger and Hastings (1990) determined that re-offenders lacked empathy as measured by several personality dimensions on the Millon Clinical Multiaxial Inventory when compared to non-recidivists. An internal construct related to lack of empathy that is particularly associated with violent crimes is psychopathy. According to Wallace, Schmitt, Vitale, and Neman (2000), individuals with psychopathic qualities engage in twice as much criminal activity and are more than twice as likely to recidivate. The PCL-R, which is the most commonly used measure of psychopathy, has been shown to predict recidivism in many studies (e.g., Walters, 2003). Meta-analytic studies have found, however, that the second factor of the PCL-R, which assesses for antisocial behavior rather than personality or cognitive variables, is a stronger predictor of violent recidivism (Leistico, Salekin, DeCoster, & Rogers, 2008; Walters, 2003).

Gonsalves, Scalora, and Huss (2009) evaluated the incremental validity of the Psychological Inventory of Criminal Thinking Styles (PICTS; Walters, 2002) for predicting violent recidivism over and above the PCL-R and found preliminary support for its use in this manner. The PICTS consists of scales that measure the eight styles of thinking that are theorized to maintain a criminal lifestyle, including Mollification, Cut-Off, Entitlement, Power Orientation, Sentimentality, Superoptimism, Cognitive Indolence, and Discontinuity. Mollification indicates blaming criminal activity on external factors, whereas Cut-Off refers to the elimination of common limits to crime. Entitlement is a conceited sense of privilege, and Power Orientation is a quest for power over others. Sentimentality refers to engaging in apparently benevolent behaviors to justify former criminal behavior. Superoptimism indicates a tendency to believe that one can continue to engage in criminal behavior without experiencing any negative consequences. Cognitive Indolence refers to impulsivity and a deficit in critical thinking, whereas Discontinuity represents inconsistent thinking and behaviors (Walters, 2009). Replication is necessary in order for the PICTS to be used more confidently for predicting recidivism. Still, it seems that internal psychological factors such as personality and cognitive variables may be useful for predicting violent re-offense.

A cognitive variable related to violent recidivism that requires more research is motivation to change. In clinical and legal settings, an offender who does not deny his actions and expresses a desire to change is often viewed more favorably and considered to be at lower risk for re-offending. There has not been much research directly linking motivation to recidivism, however (Hanson & Wallace-Capretta, 2004). Rather, motivation has usually been assessed indirectly, by whether an individual was court- or self-referred and whether they completed treatment. This suggests that research directly examining the predictive power of motivation would be clinically and pragmatically valuable.

Cognitive Complexity

An internal psychological factor that has received little attention in the research literature in relation to violent recidivism is cognitive complexity. Defined broadly, cognitive complexity represents the number of ideas and the degree of idea differentiation and integration within a cognitive system (Burleson & Caplan, 1998). Cognitively complex people have a greater number of constructs and consider a greater number of relationships between these constructs, therefore allowing them to be able to detect nuances of situations and to integrate information to make more accurate conclusions and predictions (Bieri, 1955). Shepherd and Trank (1989) found greater variability in teacher evaluations by cognitively complex students, suggesting that cognitively complex social perceivers are less reliant on global, bipolar evaluations, such as *good/bad*. This implies that cognitively complex people are better able to integrate conflicting information and recognize that individuals or situations are generally composed of both positive and negative qualities. We would expect people who view others as complex individuals with both positive and negative qualities to be more understanding of flaws, and therefore less likely to behave aggressively in conflict situations. Cognitive complexity has been linked to desirable outcomes, such as positive coping with stressful life events (Kalthoff &Neimeyer, 1993). We would expect people who cope better with stress to be less likely to resort to aggressive responses, instead choosing more adaptive ones.

Few studies have directly examined the relationship between cognitive complexity and aggression, however. McKeough, Yates, and Marini (1994) found that behaviorally aggressive boys were developmentally behind in their understanding of human intentionality and wrote stories that were less socially adaptive, both indicators of lower cognitive complexity. It is unsurprising that these boys tended to be more aggressive when they overattributed intentionality, as it has been shown that attribution to unintentionality decreases aggressive responses in adults (Krieglmeyer, Wittstadt, & Strack, 2009). More research is required to determine if a relationship between cognitive complexity and aggression exists in adults as well, although the research on intentionality provides preliminary support for this relationship.

Cognitive complexity is often studied in the context of social perception and interpersonal skills. For instance, cognitive complexity has been linked to the tendency to hypothesize multiple causes and consequences for others' behavior (O'Keefe, Murphy, Meyers, & Babrow, 1989). It is plausible that this cognitive flexibility may have an impact on aggressive responding. That is, an individual without this flexibility may only consider one cause for a person's behavior (e.g., he or she purposely cut the individual off while driving) rather than considering alternatives (e.g., he or she did not see the individual), possibly resulting in a higher likelihood of aggressive behavior.

Cognitive complexity may decrease the likelihood of aggressive behavior by improving problem-solving effectiveness. Karney and Gauer (2010) found that when recently married couples' descriptions of their marital problems were more complex, subsequent problem-solving exercises that they participated in were more positive and effective. The authors surmised that cognitively complex couples have cognitive structures that acknowledge the multiple facets of their partners. Each spouse is viewed as filling multiple roles, so if a wife is being inattentive, for example, her husband can recognize that it may be due to one of her other roles without judging her as being a poor spouse, whereas a less cognitively complex person may not differentiate these roles. Cognitive complexity may also assist couples in understanding and accepting multiple sides of an issue, which might impact how disagreements are resolved by making them less defensive, more flexible, and more willing and able to come to a compromise. We would expect that this ability to be more flexible in viewing situations and to more effectively resolve disagreements may result in fewer acts of aggression.

Linguistic Complexity

A relationship between cognitive and linguistic complexity has been observed (Robinson, 2001), suggesting that measures of verbal complexity might be used to approximate cognitive complexity. A variety of measures of verbal complexity exist, including type token ratio, mean length of utterances, and idea density. Type token ratio indicates the ratio of unique words to total word count in a writing sample, providing a basic measure of lexical diversity. Kemper and Sumner (2001) found that type-token ratio covaried with working memory, indicating that higher type-token ratio is associated with a greater capacity for mentally holding and manipulating information. This suggests that type-token ratio might be a useful measure of verbal complexity to consider for approximating cognitive complexity from written text.

Mean length of utterances in words is adopted from a measure of spoken language indicating the average number of words in a sentence. One study examining mean length of utterances in words found that it differentiated aggressive boys from nonaggressive boys, such that oral narratives constructed by aggressive boys had significantly shorter utterances (Cole, 2001). The author hypothesized that a reduced ability to construct complex sentences might also be related to inferior communication skills, which would have implications in social situations and increase the likelihood of aggressive responses. The results of this study suggest that mean length of utterances in words might be a useful measure to use for approximating cognitive complexity in relation to aggression.

Idea density is calculated by dividing the number of basic propositions in a writing sample by the total number of words. Propositions, which include verbs, adverbs, conjunctions, propositional phrases, and adjectives, are defined as the basic units through which we understand and remember textual information (Brown, Snodgrass, Kemper, Herman, & Covington, 2008).

Put another way, propositions are the most basic parts of a sentence that can be either true or false. Idea density has been linked to cognitive functioning. Snowdon, Kemper, Mortimer, Greiner, Wekstein, and Markesbery (1996) found that low idea density predicted lower cognitive functioning later in life, as well as an increased risk of Alzheimer's disease. Similarly, Kemper and Sumner (2001) found that adults with low idea density had poorer outcomes on measures of processing efficiency. The authors suggested that high idea density is related to an ability to efficiently organize and present information.

Jones and Davidson (2007) found that idea density differentiated the ability to solve unstructured problems, such as those that occur in everyday life. Those with high idea density in their writing samples may have been better able to examine all pieces of information available and effectively use relevant information to solve problems in a more complex manner. The study also measured cognitive complexity separately and found that idea density and cognitive complexity operated similarly in the differentiation of this ability, suggesting that the two are related. A possible link between cognitive complexity and problem solving suggests that problem solving may mediate the relationship between cognitive complexity and various life outcomes, but more research is needed.

CHAPTER II

RESEARCH QUESTIONS

Based upon previous research, we surmised that cognitively complex people communicate better and are more effective at coping with stress and solving problems, providing them with alternatives to aggressive responding. We also theorized that cognitively complex people are more likely to complete treatment and to effectively apply the new skills they learn due to their increased ability to consider alternative viewpoints and ways of behaving. Due to research indicating that linguistic complexity accompanies positive outcomes as well, it was hypothesized that a relationship exists between linguistic complexity, skills acquisition in treatment, and violent recidivism, where linguistically complex individuals are more successful in treatment and commit fewer violent re-offenses. The current study attempted to explore the relationship between linguistic complexity and violence by analyzing autobiographical writing samples written by members of a violence reduction training program about their most recent violent offense. From this new source of information, the study explored the predictive power of variables derived from the manner in which violent offenders tell their stories. The narratives were analyzed for various measures of linguistic complexity, including idea density, mean length of utterances in words, and type-token ratio, and this data was compared to reoffending rates to determine whether a relationship existed between linguistic complexity and violent recidivism. In addition, these measures of linguistic complexity were compared to measures of gains in social problem solving and anger strategies over the course of treatment to determine whether there is a relationship between linguistic complexity and skills acquisition.

Specifically, it was hypothesized that linguistic complexity would correlate with gains in social problem solving and better strategies for managing high conflict situations, with greater linguistic complexity predicting larger improvements in these measures over the course of treatment. It was further predicted that linguistic complexity and improvement in social problem solving and conflict resolution strategies over the course of treatment would predict reoffending during the initial three years following treatment. The results could be helpful in identifying individuals who are at a high risk for violent recidivism, allowing alternative treatments to be chosen.

CHAPTER III

METHODOLOGY

This project was approved by the Institutional Review Board at Central Michigan University.

Participants

Possible participants included 189 adults who participated in a violence reduction training program and voluntarily signed a release for their data to be used for research purposes. Most of these subjects completed the materials necessary for the study (79%; N = 150). The range in narrative length was restricted to reduce variability in linguistic measures due to word count alone. Removing narratives under 25 words or above 225 words from the sample yielded a final sample size of 116. Participants that were included in the study tended to be male (66%), Caucasian (86%; African American = 7%; other = 7%), blue collar workers with a mean age of 26 and mean education of 12 years. Most subjects were court mandated for treatment (88%) and successfully completed the violence reduction protocol (78%).

Materials and Procedure

Pre-Treatment Data

Participants completed a life history questionnaire that included demographic information and an autobiographical writing section. Demographic variables that were assessed included age, gender, race, level of education, occupation, and referral source. The writing sample consisted of a narrative of the events that led them to seek violence reduction training. Specifically, the prompt read: “Please provide a detailed description of the situation surrounding the reasons that led up to you contacting us about this class.” Total word counts of the narratives ranged from one to 522 words. This range was reduced significantly, with narratives with fewer than 25 words or greater than 225 words being excluded from the study to reduce any effects of narrative length on ratings, for a final sample size of 116 (M = 98, SD = 56). Documentation from the remainder of treatment indicates whether or not the participant completed the program. The autobiographical writing samples, demographic information, and program completion information were extracted from archival data for a violence reduction-training program at Central Michigan University.

The writing samples were also analyzed to determine type-token ratio, mean length of utterance in words, and idea density as estimations of linguistic complexity, using several qualitative analysis software programs. The software program SALT was used to analyze type-token ratio and mean length of utterances in words (Miller, 2004). SALT was designed to provide standardized analyses of spoken and written language for measures calculated at the level of words, morphemes, and utterances. SALT is often used to assess developmental status based on comparisons to age-matched peers using several reference databases or to evaluate within-subject change over time. In calculating mean length of utterances in words, SALT defines an utterance as a segment of speech separated by pauses or intonation changes and limits utterances to two independent clauses (Horton-Ikard, Weismer, & Edwards, 2005). SALT calculates mean length of utterances in words by dividing the total word count by the number of utterances, so all scores will be greater than zero, with no upper limit. Type-token ratio, meanwhile, indicates the ratio of unique words (types) to total words (tokens). SALT calculates type-token ratio by dividing the number of different words by the total number of words, yielding a score between zero and one. Larger type-token ratio values indicate that a more diverse sample of vocabulary was given.

The computer software program CPIDR (Computer Analysis of Speech for Psychological Research; Brown, Snodgrass, & Covington, 2007) was utilized to calculate the idea density of the writing samples. As noted previously, idea density is essentially calculated by dividing the number of basic propositions (i.e., verbs, adverbs, conjunctions, propositional phrases, or adjectives) in a writing sample by the total number of words. This measure yields a value between zero and one, with larger values indicating more concise linguistic expression. CPIDR operates by identifying and tagging these aspects of speech for calculating idea density. The program cannot understand full sentences in the way that a human can, so the creators also included additional rules to improve the accuracy of proposition counts. For example, complex verb phrases, such as *may not have been singing*, are attributed fewer propositions, in this case two rather than five. These rules were implemented to allow the program to make a more meaningful count of propositions that corresponds more closely to that of human raters. In a validation study, CPIDR correlated nearly perfectly with the consensus of two trained human raters (r = .97; Brown et al., 2008).

The pre-treatment packet completed by participants also included the short form of the Social Problem Solving Inventory-Revised (SPSI-R; D'Zurilla, Nezu, & Maydeu-Olivares, 2002) as well as a measure of strategies for resolving conflict. The short form of the SPSI-R consists of five scales measuring problem orientation and problem-solving style. The two measures of problem orientation assess general attitude towards problems. High scores on the Positive Problem Orientation (PPO) scale indicate a tendency to view problems as a challenge, whereas high scores on the Negative Problem Orientation (NPO) scale suggest a propensity to consider problems to be threatening. The three measures of problem-solving style, meanwhile, assess the use of specific problem-solving skills for choosing the optimal solution to a problem.

High scores on the Rational Problem Solving (RPS) scale assess rational, systematic, and thoughtful application of problem-solving skills. A high Impulsivity/Carelessness Style (ICS) score, meanwhile, indicates hurried, incomplete application of problem-solving skills with little forethought. A high Avoidance Style (AS) score indicates poor problem-solving skills characterized by procrastination, passivity, or dependency on others (D'Zurilla, Nezu, & Maydeu-Olivares, 2002). Responses on the SPSI-R are keyed so that higher scores indicate more effective social problem solving.

The measure of strategies for resolving conflict consisted of two scores, a positive score for good strategies for resolving conflict, such as thinking through the situation before acting, and a negative score for poor strategies for resolving conflict, such as verbally putting the other person down. Some strategies received scores of higher magnitude than others. For example, the response "I looked for positives" received a score of +1, while "I stuck to the point and solved the problem without aggression" received a score of +3. Similarly, the response "I pretended it didn't bother me when it really did" received a score of -1, while "I beat the other person up" received a score of -3. The ratio of total positive anger strategies to total negative anger strategies was used in these analyses to control for the tendency of some participants to endorse more total items than others. In addition, one point was added to both total positive and total negative anger strategies in case any participants did not endorse any negative anger strategies, which would otherwise be incalculable. Higher ratio scores indicated a greater proportion of positive strategies for resolving conflict.

Post-Treatment Measures

At the end of treatment, participants completed a post-treatment packet that also contained the short form of the SPSI-R and the measure of strategies for resolving conflict. A measure of acquisition of social problem solving skills was derived from pre- and post-treatment SPSI-R scores. Rather than using simple change scores, the pre-treatment score was weighted with the regression coefficient of the post-treatment score on the pre-treatment score, in order to remove the influence of the pre-treatment score. A similar method was used to derive a measure of acquisition of conflict resolution scores. These measures were chosen to indicate treatment success because the particular violence reduction protocol used with these offenders focused primarily on preventing violence by improving problem solving strategies and skills for resolving conflict, allowing the offenders to develop alternative responses to stress and conflict situations.

Follow-Up Data

Finally, violent and nonviolent re-offense data were gathered from a courthouse public access database. The database contained information about all charges occurring within the county in which the violence reduction group was held. Re-offense was measured by the number of charges brought against each participant during the three years following his or her completion of the violence reduction protocol, with separate measures every six months. Consistent with Hanson and Wallace-Capretta (2004) and Hamberger and Hastings (1990), the following and similar offenses would have been classified as violent: domestic violence, assault, battery, sexual assault, statutory rape, child abuse, threats, harassment, armed robbery, manslaughter, and attempted murder. Any offenses that were dissimilar to those listed above were classified as general offenses. Figure 1 lists the offenses committed by the present sample and categorizes them by offense type.

Violent Offenses	Nonviolent Offenses
Malicious destruction of property Criminal sexual conduct Domestic violence Home invasion Resisting/obstructing a police officer Assault and battery	Larceny Embezzlement Possession of controlled substance Delivery of controlled substance Manufacture of controlled substance Breaking and entering Disturbing the peace Preliminary breath test refusal Indecent exposure Operating while visibly impaired Operating while intoxicated False pretenses Attending a nuisance party Fraud Joyriding Interfering with electronic communications Minor in possession Retail fraud Check nonsufficient funds False report of a felony

Figure 1. *List of Offenses Committed by the Present Sample, by Offense Type*

CHAPTER IV

RESULTS

Demographic Variables

Demographic variables included age, gender, ethnicity, referral source, whether or not a participant completed treatment, type of employment, and level of education. Ethnicity was not included in the following analyses because there were too few non-Caucasians in the sample. None of these variables were significantly related to type-token ratio, idea density, or mean length of utterances in words.

Treatment Completion

Treatment completers did not significantly differ from non-completers in regards to employment type, $\chi^2(3, N = 112) = 4.70$, $p = .20$. Chi square analyses revealed that completion status was not significantly related to gender, $\chi^2(1, N = 116) = 2.27$, $p = .13$, or to whether participants were court-ordered, $\chi^2(1, N = 115) = 2.33$, $p = .13$. Those who completed treatment tended to be younger, $t(114) = -1.97$, $p = .05$, and more educated, $t(112) = 2.73$, $p < .01$.

Re-Offense

Although fewer women reoffended than men, this relationship was not significant, $\chi^2(1, N = 116) = 1.73$, $p = .19$, as shown in Table 1. Results were similar at the level of nonviolent re-offenses; the proportions of men and women who reoffended were not significantly different, $\chi^2(1, N = 116) = .81$, $p = .37$. Fewer women committed violent re-offenses than men, however, and this relationship approached significance, $\chi^2(1, N = 116) = 3.09$, $p = .08$.

Among the subset of participants who re-offended, women committed fewer re-offenses than men, which approached significance, $t(26) = 1.94$, $p = .06$. Of those who committed nonviolent re-offenses, the number of offenses did not significantly differ between males and females, $t(17) = 1.46$, $p = .16$. Similarly, among those who violently reoffended, the number of offenses was not significantly different between men and women, $t(12) = 1.01$, $p = .33$. Age, years of education, type of employment, and referral source, meanwhile, did not significantly predict outcome measures.

Table 1. *Descriptive Statistics for Reoffending by Gender*

	% Reoffended	Mean Number of Offenses	χ^2	*p*
General				
Males	28%	1.86	1.73	.19
Females	17.10%	1		
Violent				
Males	16%	1.58	3.09	.08
Females	4.90%	1		
Nonviolent				
Males	18.70%	1.43	.81	.37
Females	12.20%	1		

General = total nonviolent and violent offenses. Mean number of offenses = average number of offenses among the subset of those who reoffended. $N = 116$.

Pre-Treatment Measures

The descriptive statistics for the measures of linguistic complexity, social problem solving, and conflict resolution are presented in Table 2. As seen in Table 3, type-token ratio was not significantly related to mean length of utterances in words, $r = -.12$, $p = .11$, or idea density, $r = -.13$, $p = .09$, although both relationships approached significance. Mean length of utterances in words was significantly correlated with idea density, $r = .26$, $p < .01$, such that longer utterances tended to have greater idea density. Type-token ratio and word count were inversely related, $r = -.79$, $p < .01$. This means that shorter writing samples tended to have higher type-token ratio, perhaps due simply to there being fewer opportunities for commonly used words to be repeated, resulting in inflation of the type-token ratio score. Type-token ratio was clearly sensitive to word count. Given the variability in word count used in the current sample, which ranged from 25 to 225 words, it seems that type-token ratio offers little as a linguistic measure beyond word count.

None of the linguistic measures were significantly related to pre-treatment measures of social problem solving or conflict resolution strategies. Pre-treatment measures of social problem solving and strategies for resolving conflict were related: Those with better social problem solving skills also tended to utilize more positive strategies for resolving conflict, $r = .45$, $p < .01$ (Table 3).

Table 2. *Descriptive Statistics for Pre-Treatment Measures*

	Mean	*SD*	Minimum	Maximum
TTR	.68	.11	.46	.93
MLUw	15.19	5.09	4.33	33
Idea Density	.54	.05	.29	.65
SPSI	68.03	17.46	8	98
Strategies	4.73	4.94	.07	23

TTR = Type token ratio; MLUw = Mean length of utterances in words; SPSI = Social Problem Solving Inventory—Revised; Strategies = Conflict resolution strategies; *SD* = standard deviation; *N* = 116.

Table 3. *Correlations between Pre-Treatment Measures*

	TTR	MLUw	Idea Density	Word Count	SPSI
MLUw	-.12	--			
Idea Density	-.13	.26**	--		
Word Count	-.79**	.12	.11	--	
SPSI	-.04	-.13	-.07	.02	--
Strategies	-.05	-.09	.04	.08	.45**

TTR = Type token ratio; MLUw = Mean length of utterances in words; SPSI = Social Problem Solving Inventory—Revised; Strategies = Conflict resolution strategies; *N* = 116.
**p < .01.

Post-Treatment Measures

Linguistic Complexity and Skills Acquisition

The descriptive statistics for measures of skills acquisition over treatment are presented in Table 4, and the relationships between pre-treatment measures of linguistic complexity and indices of skills acquisition are presented in Table 5. Type-token ratio was inversely related to improvements in social problem solving**,** $r = -.22$, $p < .05$; this relationship was still significant after parsing out the effects of word count, with lower type-token ratio predicting greater treatment gains, $r = -.18$, $p < .05$. Mean length of utterances in words was related to improvements in strategies for resolving conflict, $r = .19$, $p < .05$; after removing the effects of word count, longer utterances still predicted greater treatment gains, $r = .19$, $p < .05$. Other relationships between linguistic measures and indices of skills acquisition were not significant. Among measures of skills acquisition, improvements in problem-solving skills were significantly correlated with improvements in strategies for resolving conflict, $r = .36$, $p < .01$.

Table 4. *Descriptive Statistics for Measures of Skills Acquisition*

	Mean	SD	Minimum	Maximum
SPSI	45.98	10.39	20.44	70.92
Strategies	6.64	5.61	-.82	28.09

SPSI = change in Social Problem Solving Inventory—Revised over treatment; Strategies = change in conflict resolution strategies over treatment; *SD* = standard deviation; *N* = 116.

Table 5. *Correlations between Linguistic Complexity and Skills Acquisition*

	SPSI	Strategies
TTR	-.22*	0
MLUw	-.16	.19*
Idea Density	.02	.07
Word Count	.13	-.07
SPSI	--	.36**

TTR = Type token ratio; MLUw = Mean length of utterances in words; SPSI = change in Social Problem Solving Inventory—Revised over treatment; Strategies = change in conflict resolution strategies over treatment; *N* = 116. *p < .05; **p < .01.

Linguistic Complexity and Treatment Completion

About three quarters of the participants (74%, *N* = 86) completed treatment, with the rest dropping out (26%, *N* = 30). Discriminant function analysis was performed to examine the ability of type-token ratio, idea density, and mean length of utterances in words to discriminate between those who completed treatment and those who dropped out. None of the measures significantly discriminated between these two groups.

Follow-Up Measures

Re-Offense

Within three years following treatment, 24% of the sample received another general conviction, 12% violently reoffended, and 16% acquired another nonviolent conviction. Frequencies by number of convictions are shown in Table 6. Table 7 demonstrates that of those who reoffended, participants lasted an average of 12 months (*SD* = 10) before reoffending in general, 10 (*SD* = 10) months before committing another violent re-offense, and 15 (*SD* = 10) months before being convicted of an additional nonviolent offense.

Table 6. *Frequency of Reoffending by Total Number of Re-Offenses*

Type of Re-Offense	Number of Re-offenses				
	1	2	3	4	5
General	18 (15.5%)	5 (4.3%)	3 (2.6%)	1 (0.9%)	1 (0.9%)
Violent	9 (7.8%)	3 (2.6%)	2 (1.7%)	0 (0%)	0 (0%)
Nonviolent	14 (12.1%)	4 (3.4%)	1 (0.9%)	0 (0%)	0 (0%)

General = total nonviolent and violent offenses. $N = 116$.

Table 7. *Descriptive Statistics for Number of Months until First Re-Offense*

Type of Re-Offense	Mean	*SD*	Minimum	Maximum
General ($N = 28$)	12.04	10.32	0	31
Violent ($N = 14$)	10.43	10.23	0	31
Nonviolent ($N = 19$)	14.95	9.87	0	30

Subset of sample who reoffended. General = total nonviolent and violent offenses. *SD* = standard deviation.

Linguistic Complexity and Reoffending

The relationships between measures of linguistic complexity and reoffending are presented in Table 8. Correlations between the three linguistic measures and measures of nonviolent reoffending did not reach significance. Type-token ratio was related to total number of violent offenses; contrary to our hypotheses, higher type-token ratio actually predicted a greater number of violent offenses, $r = .21$, $p < .05$. Similarly, type-token ratio was inversely related to number of months until first general offense, $r = -.15$, $p < .05$, and first violent offense, $r = -.23$, $p < .01$. That is, a higher type-token ratio predicted sooner reoffending. This relationship can be explained by the observation that type-token ratio and word count were inversely related, $r = -.79$, $p < .01$, suggesting that type-token ratio was confounded by word count. Examining the relationship between total number of words and violence shown in Table 8, word count predicted number of violent re-offenses, $r = -.18$, $p < .05$, such that those who wrote more had fewer re-offenses. Similarly, those who wrote more went longer without reoffending, $r = .19$, $p < .05$. Given the variability in word count used in the current sample, which ranged from 25 to 225 words, it seems that type-token ratio offers little as a linguistic measure for predicting violence beyond word count. Once the variability in type-token ratio accounted for by word count is parsed out, the residual is no longer significantly related to violent offending.

Consistent with our hypothesis, mean length of utterances in words was inversely correlated with number of violent offenses, with longer utterances predicting fewer violent offenses overall, $r = -.19$, $p < .05$. Likewise, mean length of utterances in words was related to number of months until first violent offense, with longer utterances predicting later onset of reoffending, $r = .18$, $p < .05$. Unlike type-token ratio, mean length of utterances in words was not significantly related to word count, although this relationship approached significance, $r = .12$, $p = .09$. After removing the variability of mean length of utterances in words due to word count, the residual was still significantly related to number of violent offenses, $r = -.17$, $p < .05$, and time to first violent re-offense, $r = .16$, $p < .05$. Correlations between idea density and violent re-offense measures did not reach significance.

Discriminant function analysis was performed to test the ability of the linguistic measures to discriminate between those who were charged with another violent crime within three years and those who were not. Only mean length of utterances in words significantly discriminated between violent reoffenders and non-reoffenders, explaining 4% of the variance, $F(1, 114) = 4.78$, $p < .05$. Mean length of utterances in words was also the only linguistic measure to significantly discriminate between those who were convicted of general re-offenses and those who were not, explaining 3.4% of the variance, $F(1, 114) = 3.95$, $p < .05$.

Table 8. *Correlations between Linguistic Complexity and Re-Offense*

	TTR	MLUw	Idea Density	Word Count
General Re-Offenses				
Total Number	.12	-.15*	.02	-.12
Months until First	-.15*	.17*	-.07	.15
Violent Re-Offenses				
Total Number	.21*	-.19*	.05	-.18*
Months until First	-.23**	.18*	-.05	.19*
Nonviolent Re-offenses				
Total Number	-.02	-.05	-.02	.01
Months until First	-.01	.07	0	.04

TTR = Type token ratio; MLUw = Mean length of utterances in words; General = total nonviolent and violent offenses; *N* = 116.
*p < .05; **p < .01.

Skills Acquisition and Reoffending

Measures of skills acquisition were not significantly related to violence-related outcome variables. Table 9 reveals that change in conflict resolution strategies over the course of treatment was, however, related to total number of violent and non-violent offenses, $r = .18$, $p < .05$. Contrary to our hypothesis, this indicated that greater improvements in strategies for resolving conflict predicted more frequent reoffending. Interestingly, the relationship was no longer maintained when offenses were divided into violent and nonviolent offenses. From a conceptual standpoint, it is difficult to explain this finding. Statistically, a closer look at the data revealed that a single outlier accounted for this relationship. When this outlier was removed from the analysis, the correlation between conflict resolution strategies and general reoffending reversed and was no longer significant, $r = -.11$, $p = .17$. This participant had committed three violent crimes and two nonviolent crimes, which helps to explain why his total count of five crimes strongly influenced the relationship between general reoffending and skills acquisition but not the relationships between violent or nonviolent reoffending and skills acquisition.

Table 9. *Correlations between measures of Skills Acquisition and Re-Offense*

	SPSI	Strategies
General Re-Offenses		
Total Number	.06	.18*
Months until First	.01	-.02
Violent Re-Offenses		
Total Number	.07	.17
Months until First	.03	-.04

SPSI = change in Social Problem Solving Inventory—Revised over treatment; Strategies = change in conflict resolution strategies over treatment; General = total nonviolent and violent offenses. $N = 116$.
*$p < .05$.

Treatment Completion and Reoffending

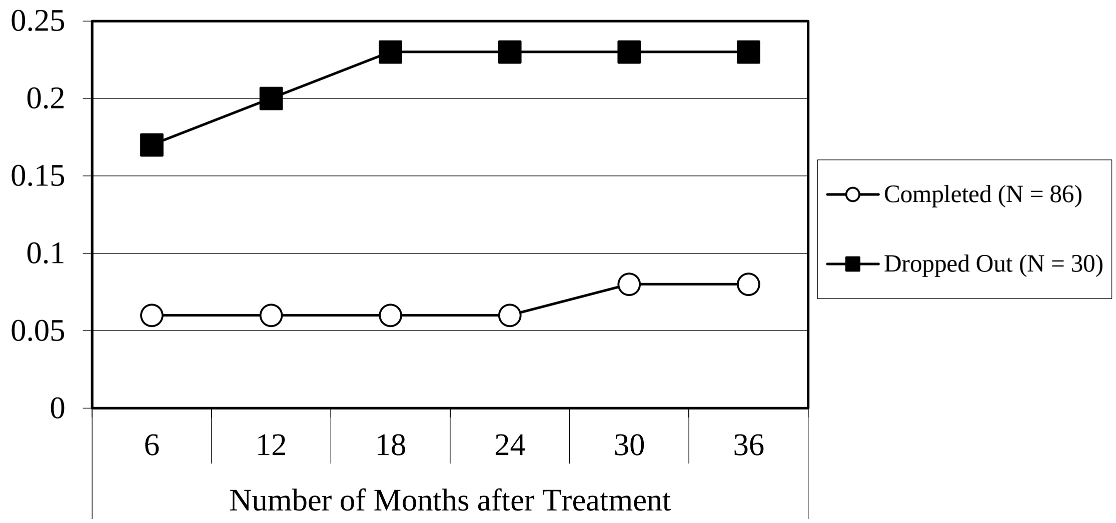
A chi-square test of independence was conducted to explore the relationship between treatment completion and violent re-offense, which was significant, χ^2 (1, N = 116) = 4.84, $p <$ .05; treatment completers were less likely to violently reoffend than those who dropped out of treatment. Table 10 compares the number of participants in each completion group who committed violent re-offenses to the number who did not reoffend. As shown, 23% of those who did not complete treatment reoffended, compared to only 8% of those who completed the protocol. Conversely, 92% of treatment completers were not convicted of another violent crime over the next three years, whereas only 77% of treatment drop-outs avoided reconviction.

Figure 2 illustrates the results of a survival analysis conducted on outcome measures as a function of treatment completion group. Survival analysis revealed that three years following treatment, 20% of treatment completers had been convicted of another general offense, versus 37% of participants who did not complete treatment. Those who completed treatment lasted an average of 32 months before reoffending, whereas those who left treatment early reoffended after 26 months on average. Specifically in regards to violence, 8% of those who completed treatment had been convicted of another violent offense compared to 23% of those who dropped out of treatment. On average, treatment completers were first convicted of an additional violent offense after 34 months, whereas those who dropped out were first convicted of another violent offense after 29 months.

Table 10. *Frequency of Violent Reoffending by Completion Group*

	Treatment Completion		
Violent Re-Offense	Yes	No	Total
Yes	7	7	14
No	79	23	102
Total	86	30	116

N = 116.



N = 116

Figure 2. *Cumulative Percentage of Violent Re-Offense by Completion Status over Time*.

CHAPTER V

DISCUSSION

Linguistic Complexity

The present study explored the relationship between linguistic complexity and violent reoffending. In addition, it examined other variables relevant to re-offense, including acquisition of skills in treatment and treatment completion. Several measures of linguistic complexity were derived from autobiographical narratives completed by members of a violence reduction group. The results provide some support for a relationship between linguistic complexity and re-offense. Contrary to our hypotheses, idea density and type-token ratio as measures of linguistic complexity did not predict reoffending. Upon closer examination, type-token ratio was highly sensitive to word count, which may have confounded the measure. Perhaps an alternative sample with a shorter range in word count may have yielded different results regarding type-token ratio. As it is, type-token ratio was unrelated to violent reoffending after the effects of word count were removed. Participants who wrote more overall, however, were less likely to reoffend. Similarly, participants who had longer mean length of utterances in words were less likely to reoffend. Interestingly, the relationship between overall word count and mean length of utterances in words was not significant.

One could hypothesize why those who wrote more would be less likely to reoffend. Perhaps those who were more motivated in treatment and willing to change their behavior devoted more time to completing the intake paperwork and were also less likely to reoffend. In a court-ordered population, motivation in treatment is often a significant issue that can influence treatment drop-out and other variables (Evans, Li, & Hser, 2009). In regards to mean length of utterances, a previous researcher proposed that a reduced ability to construct complex sentences might be related to communication deficits in aggressive boys (Cole, 2001). He suggested that this might increase the likelihood of aggressive responding in social situations. This explanation may also apply to the adult sample in the present study.

Alternatively, linguistic measures such as word count and mean length of utterances in words may be related to intelligence. In addition, those with greater cognitive ability may be less likely to re-offend, either because they learn from their mistakes better or are cleverer at eluding detection when they commit crimes. In this framework, a person who is more intelligent might write more as well as avoid reoffending. The present study did not directly measure intelligence. Education is sometimes used as a proxy of intelligence, however, and in the present sample, none of the linguistic measures were significantly correlated with education, providing some evidence against this theory.

Skills Acquisition and Treatment Completion

Contrary to what was expected, those who made greater improvements in social problem solving and conflict resolution strategies were not less likely to reoffend. This suggests that acquiring these particular skills in treatment did not prevent participants from committing other crimes following treatment. Yet, those who dropped out of treatment were more likely to reoffend than those who completed treatment, which is consistent with previous research (Gondolf, 1997; Daly & Pelowski, 2000). This suggests either that other treatment variables serve as protective factors against reoffending or that there are differences between treatment completers and those who drop out.

Regarding the former interpretation, other treatment variables that may be beneficial include social support from other group members, the therapeutic relationship, or the acquisition of other skills that were not measured in this study. Because the majority of the participants were court-ordered for treatment, those who dropped out may have been incarcerated as a result, where increased stress or modeling by other inmates may have contributed to future reoffending.

In support of the latter interpretation, treatment completers in the present study differed from those who dropped out of treatment on several demographic variables, including employment, age, and education. Perhaps these or other differences between the completion groups accounted for why treatment non-completers were more likely to re-offend. That is, pre-existing differences between completion groups rather than aspects of the treatment itself may account for why those who dropped out were more likely to reoffend.

Methodological Issues

Several methodological issues likely influenced the results of the present study. First, the word count range was large enough to interfere with type-token ratio. Perhaps a writing sample with more detailed instructions and a more restricted range in word count would provide a clearer measure of type-token ratio. Second, the sample was predominantly Caucasian, so the generalizability of the results to other populations may be limited. Third, the narratives were not randomly selected. Many attendees of the treatment group did not complete the narrative and were obviously excluded. In addition, many who completed the narrative did not consent for their responses to be used for research studies. As a result, all narratives with a signed consent form were used. There may have been differences between those who completed the narrative and those who did not, as well as between those who did or did not sign the consent form. For instance, those who were more motivated to complete treatment may have also been more motivated to thoroughly complete the paperwork. These potential group differences may also limit the generalizability of the results.

Fourth, the re-offense measures used for the current study are inherently flawed. Additional charges in the county that the treatment group is located in were used as a measure of reoffending. As a result, any offenses that did not result in legal involvement were not measured. In addition, any charges that were accrued outside of the county were not detected either. Thus, the measure used represents a mere approximation. An alternative would have been to contact participants and rely on self-report to estimate re-offense rate, although this method would introduce its own complications, such as dishonest reporting or difficulty contacting any participants who have moved away. These are the issues that face all researchers who are measuring recidivism, and there is no consensus as to which strategy introduces the least amount of error (Vrieze & Grove, 2010).

Future Research

Before measures of linguistic complexity can justifiably be used in an applied setting, the link between linguistic measures and re-offending must be explored in more detail. Future studies might examine some of the reasons for this link that were proposed above. For instance, providing an external motivation for completing the narrative would help to rule out motivation as a factor in the relationship between word count and reoffending. If future research provides additional support for the use of linguistic measures to predict reoffending, linguistic measures might be added to existing risk assessment tools to increase their accuracy.

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