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Psychological pathways of violent and non-violent criminals: an exploration combining network analysis and Bayesian modeling

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Criminal behavior poses a significant threat to social security and public health, with notable psychological differences between violent and non-violent offenders. However, current research lacks a systematic investigation into multidimensional psychological variables and their interactions. This study explored differences in key psychological variables and their interactions between violent and non-violent offenders using network analysis and Bayesian network modeling. Psychological assessments were conducted on 749 male incarcerated individuals (335 violent, 414 non-violent offenders), covering impulsivity, personality traits, mindfulness, reinforcement sensitivity, childhood trauma, moral disengagement, criminal cognition, and risk attitudes. Results indicated mindfulness significantly influenced neuroticism and openness in non-violent offenders but not in violent offenders. Reinforcement sensitivity had a stronger impact on neuroticism among violent offenders. Criminal cognition significantly affected risk-taking via moral disengagement, with different pathways between groups. In non-violent offenders, criminal cognition was negatively moderated by agreeableness and positively related to reinforcement sensitivity; these effects were absent in violent offenders. This study highlights distinct psychological pathways between offender types, suggesting mindfulness-based interventions for non-violent offenders and emotional regulation training for violent offenders, providing practical implications for correctional interventions.

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Introduction

Criminal behavior poses a long-term and serious challenge to social security and public health, with its complex psychological mechanisms attracting widespread academic attention. In criminological research, violent and non-violent crimes are thought to exhibit significant differences in behavioral patterns and psychological characteristics, involving factors such as personality traits, emotion regulation, moral disengagement, and cognitive mechanisms (de Almeida Brites, 2024; Walters et al., 2024). General theories of crime provide important frameworks for understanding criminal behavior, suggesting that impulsivity and lack of self-control are core driving factors (Gottfredson & Hirschi, 1990). Individuals with insufficient self-control are more prone to impulsive actions and are inclined to seek immediate rewards and engage in high-risk decision-making. Additionally, environmental factors, such as childhood trauma, may further impair self-control and increase the likelihood of criminal behavior.

Within this theoretical framework, recent studies have increasingly focused on the influence of emotional traits, self-regulation abilities, and cognitive mechanisms on criminal behavior. Personality traits, as foundational characteristics that shape emotional and behavioral tendencies, offer a crucial lens for understanding the psychological mechanisms of offenders. Research has shown that violent offenders often exhibit high neuroticism, low agreeableness, and low conscientiousness, traits closely associated with aggression, impulsivity, and difficulties in emotion regulation (Gwarzo & Danja, 2024; Xie et al., 2023). Neuroticism is significantly linked to emotional dysregulation and high-risk decision-making, while low agreeableness reflects a tendency toward antagonistic social behavior (Grogans et al., 2024; Walters, 2023). In contrast, non-violent offenders typically demonstrate higher levels of agreeableness and emotional stability, which allow them to better control impulsivity and avoid high-risk behaviors.

Mindfulness, as a psychological mechanism that enhances emotional regulation and cognitive control, has been shown to mitigate impulsivity-related risks, particularly in forensic populations. Studies indicate that low mindfulness skills correlate with higher impulsivity and stress levels among incarcerated individuals, while mindfulness interventions can reduce stress, depressive symptoms, and impulsive behavior, ultimately improving psychological well-being (Horváthné Pató et al., 2023). Additionally, controlled studies in prison settings show that mindfulness enhances cognitive flexibility and emotional resilience, supporting better self-regulation and reducing impulsivity (Gallego et al., 2023). By improving self-control, mindfulness aligns with general theories of crime and offers practical implications for correctional strategies.

General theories of crime also posit that impulsivity and self-control directly influence behavioral choices, with reinforcement sensitivity playing a key role as a psychological mechanism governing responses to reward and punishment stimuli. This mechanism is closely associated with impulsivity and risk preference (Gottfredson & Hirschi, 1990). High reward sensitivity drives individuals to seek immediate gratification, manifesting as stronger impulsivity and a preference for high-risk behaviors, while high punishment sensitivity is linked to emotional instability and risk-avoidant tendencies (Drnas, 2020; Katz et al., 2020). Research has shown that violent offenders tend to exhibit higher reward sensitivity and lower punishment sensitivity, making them more inclined toward high-risk decisions and impulsive actions, whereas non-violent offenders, with their higher punishment sensitivity, are more likely to avoid risks (Hahn et al., 2020; Reyna et al., 2018). Recent network analysis of forensic psychiatric patients further confirms that impulsivity is a central factor influencing both risk behaviors and treatment outcomes (Bant & Bogaerts, 2025). Reinforcement sensitivity thus serves as a critical psychological foundation for criminal behavior by regulating emotional and behavioral choices.

Reinforcement sensitivity not only directly influences decision-making but also promotes criminal behavior through distortions in criminal cognition. Criminal cognition refers to the psychological mechanism by which individuals rationalize criminal behavior through cognitive restructuring, with moral disengagement being a central manifestation. This process diminishes feelings of guilt and moral responsibility among offenders (Brugués & Caparrós, 2022). Violent offenders are more likely to rationalize their actions through dehumanization and advantageous comparisons, whereas non-violent offenders more commonly rely on mechanisms such as displacement of responsibility and neglect of consequences (Gómez & Durán, 2024). This cognitive pattern not only weakens behavioral constraints but also reinforces tendencies toward high impulsivity and risk-taking.

Furthermore, general theories of crime emphasize that environmental factors significantly impact the development of impulsivity and self-control. Childhood trauma, by impairing emotional regulation and cognitive control, substantially increases the likelihood of high-risk behaviors (Likitha & Mishra, 2021). Studies have found that violent offenders report significantly more childhood trauma than non-violent offenders, leading to greater emotional dysregulation and the imitation of violent behaviors (Yao, 2023). Moreover, incomplete parental marriages and education play gender-specific roles in shaping violent criminal behavior, emphasizing the influence of familial and social structures (Yan et al., 2024). The profound impact of such trauma on personality traits and self-control provides essential context for understanding the psychology of criminal behavior.

Despite previous research on the psychological variables underlying criminal behavior, several gaps remain in the literature: (1) a lack of systematic investigation into the interactions among multidimensional psychological characteristics; (2) insufficient attention to the differences in psychological mechanisms between violent and non-violent offenders; and (3) limited exploration of the complex network relationships among psychological variables. These gaps may stem from the reliance on hypothesis-driven approaches in traditional research, while the specific relationships among psychological variables in criminal behavior remain unclear.

To address these gaps, this study employs network analysis and Bayesian network modeling to explore the complex associations among crime-related psychological variables. While existing theories, such as the self-control theory, and research on personality traits, mindfulness, reinforcement sensitivity, and moral disengagement provide a theoretical framework, our approach remains fundamentally data-driven. Rather than imposing predefined directional hypotheses, we aim to uncover unexpected relationships among variables and generate more refined hypotheses to explain the psychological pathways underlying violent and non-violent crime.

1. Based on this research framework, we focus on the following key questions: What are the distinguishing characteristics of key psychological variables (e.g., personality traits, mindfulness, reinforcement sensitivity, criminal cognition) between violent and non-violent offenders?
2. How do the structural relationships among different psychological variables vary by crime type?
3. How do psychological variables interact to shape the distinct behavioral patterns of violent and non-violent offenders?

Although both network analysis and Bayesian network modeling are used to examine relationships among variables, they have distinct focuses in research. Network analysis provides an undirected graphical representation that reveals the complex pattern of conditional associations among psychological variables, allowing us to identify key variables with high centrality that may function as potential intervention targets (Borsboom et al., 2021). In contrast, Bayesian network modeling extends this investigation by inferring directed relationships that suggest potential causal pathways among these variables (Denis & Scutari, 2014). This directed approach is particularly valuable for understanding how psychological mechanisms might unfold sequentially in criminal behavior. By integrating these complementary methodologies, we can not only identify important psychological variables (through network analysis) but also explore how these variables might influence each other in potential causal chains (through Bayesian networks), thereby providing a more nuanced understanding of the psychological mechanisms underlying different types of criminal behavior. This multi-method approach enhances the robustness of our findings and provides richer insights for developing targeted intervention strategies.

Methods

Participants. The data for this study were collected from a prison in Shandong Province, China, using stratified sampling to conduct a survey across different sections of the prison. A total of 1306 inmates were invited to participate in the study, and 1226 completed the questionnaire, resulting in an effective response rate of 93.9%. During the data screening process, certain samples were excluded based on the following criteria: (1) individuals whose crimes did not match the study's focus, including drug-related crimes, sexual offenses, and other categories ($n = 358$); (2) individuals with incomplete questionnaire responses or those who demonstrated careless answering ($n = 119$). After processing and screening, 749 valid questionnaires were retained for analysis. All participants were male (mean age = 41.21 years, SD = 11.16 years).

Participants were divided into two groups based on their crime type: the violent offender group and the non-violent offender group. The violent offender group consisted of 335 individuals who had committed violent crimes (mean age = 41.35 years, SD = 10.63 years). The non-violent offender group comprised 414 individuals who had committed property crimes, cult-related crimes, computer crimes, or negligent offenses (mean age = 41.10 years, SD = 11.58 years).

The study received ethical approval from the Ethics Committee of Nanjing Normal University (Approval No. NNU202310027).

Measurements

Barratt Impulsivity Scale (BIS). The Chinese version of the Barratt Impulsivity Scale was used to measure impulsivity among participants. This scale is an adaptation of the original English version and includes three dimensions: cognitive impulsivity, motor impulsivity, and non-planning impulsivity. While the original scale used a 4-point scoring system, this study adopted a 5-point Likert scale (1 = "never," 2 = "rarely," 3 = "sometimes," 4 = "often," 5 = "always") due to comprehension difficulties observed during the pilot study. To localize the scale, some items were adjusted during the translation and validation process; only six items retained their original wording, while others were revised or replaced based on pilot testing. Higher scores indicate higher levels of impulsivity. The Cronbach's alpha for the scale in this study was 0.94.

Reinforcement Sensitivity Scale (RSC). The Chinese version of the Reinforcement Sensitivity Scale(Yang & Guo, 2016) was used to assess participants' reinforcement sensitivity. This scale is based on Gray's reinforcement sensitivity theory and evaluates individuals' responsiveness to reward and punishment stimuli. It consists of two dimensions: reward sensitivity and punishment sensitivity, each comprising 10 items. The scale uses a 5-point Likert scoring system (1 = "strongly disagree," 5 = "strongly agree"), with higher scores indicating greater sensitivity in the respective dimension. The total score reflects overall reinforcement sensitivity, with higher scores indicating stronger responses to reinforcement. The Cronbach's alpha for this scale was 0.85.

Five Facet Mindfulness Questionnaire (FFMQ). The Five-Facet Mindfulness Questionnaire (Baer et al., 2008) was used to measure participants' mindfulness levels. Mindfulness refers to an open and non-judgmental awareness and acceptance of one's internal and external experiences in the present moment. The FFMQ assesses mindfulness across five dimensions: observing, describing, acting with awareness, non-judging, and non-reactivity. Participants rated their agreement with each item on a 5-point Likert scale (1 = "does not describe me at all," 5 = "describes me very well"). Each dimension score was calculated as the sum of its item scores, with higher scores indicating stronger mindfulness in that dimension. The total score, obtained by summing all dimension scores, reflects overall mindfulness. The Cronbach's alpha for the scale in this study was 0.88.

Childhood Trauma Questionnaire-Short Form (CTQ-SF). The Childhood Trauma Questionnaire-Short Form (Bernstein et al., 2003) was used to assess participants' childhood abuse and neglect experiences. Developed by clinical psychologist Bernstein, the CTQ-SF is an internationally recognized self-report scale for evaluating childhood trauma in adults. It includes five subscales: emotional abuse (CEA), sexual abuse (CSA), physical abuse (CPA), emotional neglect (CEN), and physical neglect (CPN), with each subscale comprising five items. Participants rated the frequency of experiences on a 5-point Likert scale (1 = "never," 5 = "very often"). Higher scores indicate more severe childhood trauma. The Cronbach's alpha for this scale in this study was 0.90.

Moral Disengagement Scale (MDS). The Moral Disengagement Scale, developed by Bandura et al. and adapted into Chinese by Wang Xingchao and Yang Jiping (Wang & Yang, 2010), was used in this study. Moral disengagement refers to the process by which individuals rationalize their unethical behaviors through cognitive restructuring, thereby reducing feelings of self-condemnation. The questionnaire includes eight dimensions: moral justification, euphemistic labeling, advantageous comparison, displacement of responsibility, diffusion of responsibility, distortion of consequences, dehumanization, and attribution of blame. The scale adopts a 5-point Likert scoring system, with higher scores indicating higher levels of moral disengagement. The Cronbach's alpha for the scale in this study was 0.92.

Criminogenic Cognitions Scale (CCS). The Criminogenic Cognitions Scale(Tangney et al., 2002; Vaske et al., 2017)was used to measure participants' levels of criminal thinking. Criminal cognition refers to distorted thinking patterns that rationalize criminal behavior, reducing feelings of guilt and responsibility. The scale comprises five dimensions: externalization of responsibility, entitlement, negative attitudes toward authority, short-term orientation, and insensitivity to the impact of crime. Items are rated on a 4-point Likert scale (1 = "strongly agree," 4 = "strongly disagree"). Higher scores indicate lower levels of criminal thinking. The Cronbach's alpha for this scale in this study was 0.84.

Domain-Specific Risk-Taking Scale (DOSPERT). The Domain-Specific Risk-Taking Scale (Blais & Weber, 2006) was used to assess participants' risk-taking attitudes. This scale includes 40 items across five domains: financial, health, recreational, ethical, and social. Participants rated their likelihood of engaging in risk-related behaviors on a 5-point Likert scale (1 = "very unlikely," 5 = "very likely"). Higher scores indicate a greater propensity for risk-taking. The Cronbach's alpha for this scale in this study was 0.91.

NEO-Five Factor Inventory (NEO-FFI). The NEO-Five Factor Inventory (Costa & McCrae, 1992) was used to measure participants' personality traits. This shortened version of the NEO-PI consists of 60 items, with 12 items per dimension, covering neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. Participants rated items on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." Each dimension score reflects an individual's level of the corresponding personality trait. The overall Cronbach's alpha for the scale was 0.85, with subscale alphas of 0.81 (neuroticism), 0.72 (extraversion), 0.58 (openness), 0.62 (agreeableness), and 0.78 (conscientiousness).

Data analysis. Data analysis for this study was conducted using the R 4.2 environment and comprised three main steps: independent samples *t*-test, network analysis, and Bayesian network modeling.

Firstly, independent samples *t*-tests were employed to examine the differences in scores between the two groups across various scales. Prior to conducting the *t*-tests, the assumptions of normality and homoscedasticity were assessed using the Shapiro-Wilk test and Levene's test, respectively. The Levene's test was performed using the car package in R. In cases where the assumption of homoscedasticity was violated, Welch's correction was automatically applied to the *t*-test. Additionally, an a priori power analysis for the independent samples *t*-test was conducted using the pwr package. With an expected effect size (Cohen's *d*) of 0.5, a significance level of 0.05, and a desired power of 0.90, the analysis indicated that approximately 85 participants per group are required. The actual sample sizes of 335 and 414 far exceed this minimum requirement. The analysis was performed using the psych and dplyr packages, with the significance level set at $p < 0.05$ to determine whether the differences in psychological characteristics between the two groups were statistically significant.

Secondly, network analysis was conducted separately for the non-violent and violent crime groups using the bootnet and qgraph packages. The networks were estimated using the graphical lasso (glasso) method and regularized based on the Extended Bayesian Information Criterion (EBIC) to ensure the stability and sparsity of the network structures. For estimating cross-sectional network models, sample sizes ranging from 250 to 350 are generally sufficient for sparse networks with 20 nodes or fewer (Constantin, 2018). When plotting the network graphs, a threshold of 0.1 was applied solely for visualization purposes to improve clarity by filtering out weaker edge weights. This threshold was chosen after examining the distribution of edge weights, which revealed natural breaks around 0.1. Importantly, all edges were included in the quantitative analyses of network properties, and the full adjacency matrices are provided in the supplementary materials (Figs. S1 and S2) to ensure complete transparency. In the network diagrams, nodes represent psychological variables, and edge weights indicate the conditional dependencies between variables, controlling for the influence of other variables. The size of the nodes and the thickness of the edges reflect the importance of each variable. After constructing the networks, centrality measures were calculated for each node, including strength (the sum of absolute edge weights connected to the node), closeness centrality (the average shortest path distance from the node to all other nodes in the network), betweenness centrality (the number of times a node appears on the shortest paths between other nodes), and expected influence (the total sum of edge weights connected to the node). To assess the stability of the network structure, we applied three bootstrap procedures using the bootnet package in R: nonparametric bootstrap for edge weight confidence intervals, bootstrap difference tests for centrality measures, and a case-dropping bootstrap to assess stability. (Epskamp et al., 2018). In addition, to formally compare the non-violent-crime and violent-crime networks, we performed a permutation-based Network Comparison Test (NCT) with 1000 permutations using the NetworkComparisonTest package. The NCT yields a global-strength statistic (*S*), indexing differences in overall connectivity, and an *M* statistic, indexing the largest edge-specific difference; statistical significance was determined by comparing observed values with the corresponding permutation distributions.

Finally, Bayesian network modeling was performed for both the non-violent and violent crime groups using the bnlearn package. A Bayesian network consists of a directed acyclic graph (DAG) and a set of probability distributions. The network structure was determined using the Hill-Climbing algorithm, where nodes represent psychological variables and the direction of edges reflects the directed dependencies between variables. The Hill-Climbing algorithm was selected due to its robust performance and suitability for datasets with multiple psychological variables and complex interrelations, as demonstrated by prior research in psychological network analysis (D'Urso & Vitale, 2020; Yan et al., 2024). For Bayesian network modeling, research suggests that even with a small sample size, robust Bayesian inference can still be achieved (De Santis, 2006). To validate the stability of the network, bootstrap methods were employed with 1,000 iterative samples. Edges that exhibited significant strength and consistent directionality were retained, with a threshold set at 85% (i.e., edge strength greater than 0.85 and direction consistency exceeding 50%). The thresholds for edge strength (0.85) and directional consistency (50%) in the Bayesian network analysis were selected based on established practices in the literature. The 0.85 threshold for edge strength represents a conservative approach that prioritizes the retention of robust and reliable connections, consistent with recommendations (Scutari & Denis, 2021). The 50% threshold for directional consistency follows the principle that edges appearing in more than half of the bootstrap samples indicate reliable directional relationships (Nagarajan et al., 2013). These thresholds balance sensitivity and specificity in detecting meaningful relationships while minimizing spurious connections. The Extended Bayesian Information Criterion (EBIC) was applied with a hyperparameter value of $\gamma = 0.5$, as recommended for balancing model parsimony and fit in psychological networks. This value provides a moderate level of regularization that helps prevent overfitting while still allowing meaningful connections to emerge (J. Chen & Chen, 2008; Foygel & Drton, 2010). Based on the bootstrap results, an average network was constructed, and the final network diagrams were visualized using the Rgraphviz package.

Results

Descriptive statistics. Descriptive statistics revealed significant differences between the different crime type groups in certain psychological characteristics and behavioral variables (see Table 1). Among the Big Five personality dimensions, the non-violent crime group scored significantly higher in Agreeableness compared to the

Table 1 Descriptive statistics for the measurements.

Variable	Non-violent crime group		Violent crime group		*t*	*p*	*Cohen's d*
	M	SD	*M*	SD			
neuroticism	34.92	6.94	36.10	6.84	−2.33	<0.05	−0.17
extraversion	37.87	5.88	37.78	5.46	0.23	0.82	0.02
openness	38.25	4.90	37.04	4.58	3.48	<0.001	0.25
agreeableness	39.65	5.24	38.14	5.24	3.93	<0.001	0.29
conscientiousness	41.44	6.18	40.82	5.62	1.42	0.16	0.10
BIS	37.20	16.26	42.46	15.80	−4.47	<0.001	−0.33
RSC	67.27	16.23	64.89	13.96	2.16	<0.05	0.16
FFMQ	108.80	11.49	107.90	15.44	0.89	0.38	0.07
CTQ-SF	33.25	12.20	35.07	19.95	−1.47	0.14	−0.11
MDS	72.18	21.40	77.76	19.48	−3.73	<0.001	−0.27
CCS	55.62	11.37	57.98	9.90	−3.04	<0.01	−0.22
DOSPERT	110.17	24.55	112.03	21.52	−1.10	0.27	−0.08

violent crime group ($t = 3.93$, $p < 0.001$, *Cohen's* $d = 0.29$). In terms of Openness, the non-violent crime group also scored significantly higher than the violent crime group ($t = 3.48$, $p < 0.001$, *Cohen's* $d = 0.25$). Conversely, Neuroticism scores were significantly higher in the violent crime group compared to the non-violent crime group ($t = -2.33$, $p < 0.05$, *Cohen's* $d = -0.17$).

BIS scores were significantly higher in the violent crime group than in the non-violent crime group ($t = -4.47$, $p < 0.001$, *Cohen's* $d = -0.33$). RSC scores were significantly higher in the non-violent crime group compared to the violent crime group ($t = 2.16$, $p < 0.05$, *Cohen's* $d = 0.16$). MDS scores were significantly higher in the violent crime group than in the non-violent crime group ($t = -3.73$, $p < 0.001$, *Cohen's* $d = -0.27$). CCS scores were significantly lower in the non-violent crime group compared to the violent crime group ($t = -3.04$, $p < 0.01$, *Cohen's* $d = -0.22$).

Network analysis. To explore the relationships among various psychological characteristics within different crime type groups, this study employed network analysis based on the graphical lasso method and utilized Extended Bayesian Information Criterion regularization to ensure network sparsity. In the non-violent crime group, 21.2% of the edges were regularized to zero, whereas in the violent crime group, this proportion was 34.8%. The study found significant differences in the relationships between certain factors depending on the crime type (see Fig. 1):

1. Neuroticism (NEU) and Reinforcement Sensitivity (RSC) exhibited a stronger positive association in the violent crime group (weight = 0.34) compared to a weaker association in the non-violent crime group (weight = 0.15).
2. Mindfulness (FFM) showed substantial differences in its relationships with Neuroticism (NEU), Extraversion (EXT), and Openness (OPE) across groups. In the non-violent crime group, mindfulness was negatively associated with Neuroticism (weight = −0.2), positively associated with Extraversion (weight = 0.13), and positively associated with Openness (weight = 0.2). In contrast, in the violent crime group, mindfulness showed no direct associations with Neuroticism, Extraversion, or Openness.
3. Criminal Cognition (CCS) demonstrated different associations with Reinforcement Sensitivity (RSC) and Agreeableness (AGR) across groups. In the non-violent crime group, criminal cognition was positively associated with Reinforcement Sensitivity (weight = 0.24) and negatively associated with Agreeableness (weight = −0.26). Conversely, in the violent crime group, the negative association between criminal cognition and Agreeableness was weaker (weight = −0.15), and no direct association was observed with Reinforcement Sensitivity.

To further understand the role patterns of psychological characteristics in different crime type groups, centrality measures were calculated to quantify the importance of each variable within the network (Fig. 2). The results indicated significant differences in centrality measures of key variables between the crime type groups. Mindfulness (FFM) exhibited higher values across all centrality measures in the non-violent crime group, particularly in strength. Neuroticism (NEU) showed higher strength, betweenness centrality, and expected influence in the violent crime group. Criminal Cognition (CCS) had higher strength, closeness centrality, and betweenness centrality in the non-violent crime group compared to the violent crime group. Additionally, Openness (OPE) demonstrated higher strength and expected influence in the non-violent crime group.

The stability of the network centrality measures was assessed using the case-dropping bootstrap method (Fig. 3). The results indicated that strength and closeness centrality exhibited high stability in both the violent and non-violent crime groups, whereas betweenness centrality demonstrated poor stability only in the non-violent crime group. Specifically, in the violent crime group, the CS values for strength, closeness centrality, and betweenness centrality were 0.594, 0.439, and 0.206, respectively. In the non-violent crime group, these values were 0.439, 0.362, and 0.051, respectively. To ensure robustness, we additionally computed bootstrapped confidence intervals (CIs) for edge weights and centrality measures, which are provided in the Supplementary Materials (Figs. S3 and S4).

Finally, a permutation-based NCT (1000 permutations) revealed no statistically significant differences in overall network structure ($M = 0.16$, $p = 0.862$), global strength ($S = 1.219$, $p = 0.086$), or individual edge weights.

Bayesian network. Through Bayesian network analysis, we identified significant differences in the conditional probabilities and causal relationships among psychological variables between the non-violent and violent crime groups (see Fig. 4). The main findings are as follows:

1. Mindfulness (FFMQ) directly and significantly influences Neuroticism and Openness in the non-violent crime group, indicating that higher levels of mindfulness are associated with greater emotional stability and cognitive flexibility

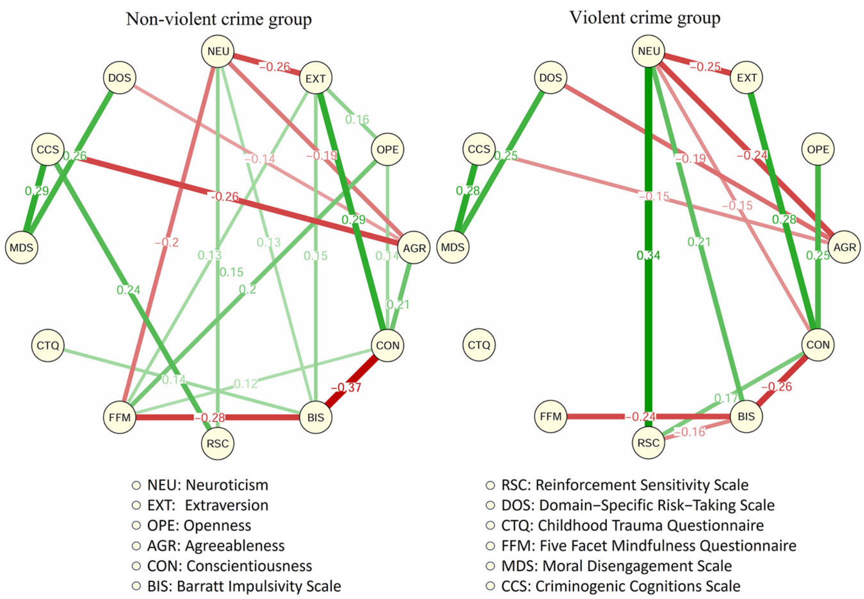

Fig. 1 Two estimated network structures based on non-violent crime group (*n* = 414) and violent crime group (*n* = 335). A threshold of 0.1 was applied to edge weights exclusively for visualization purposes to highlight more substantial conditional dependencies.

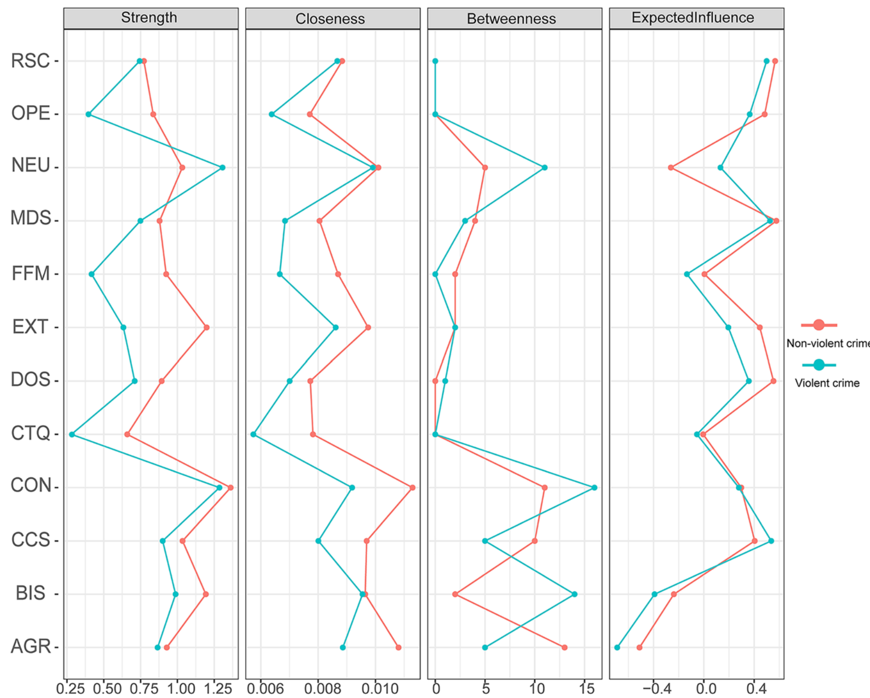

Fig. 2 Centrality indices for the nodes in the non-violent crime and violent crime networks, including strength, betweenness, closeness, and expected influence. Red and blue represent non-violent crime and violent crime networks, respectively.

among non-violent offenders. This pattern was not observed in the violent crime group, suggesting that mindfulness does not have a significant impact on Neuroticism and Openness in violent offenders. This result corroborates the findings from the network analysis, which similarly showed significant associations between mindfulness and Neuroticism and Openness in the non-violent crime group, but not in the violent crime group.

2. Criminal Cognition (CCS) in both groups further influences Risk Attitudes (DOSPERT) through Moral Disengagement (MDS). This indicates that the process by which offenders rationalize criminal behavior through cognitive distortions to reduce self-condemnation is a key psychological mechanism underlying high-risk behaviors. However, in the non-violent crime group, Criminal Cognition is additionally significantly influenced by Agreeableness, whereas in the violent crime group, Criminal Cognition does not form a direct connection with Agreeableness. The network analysis results also exhibited a similar pattern, showing a stronger association between Criminal Cognition and Agreeableness in the non-violent crime group compared to the violent crime group.。
3. In the violent crime group, Reinforcement Sensitivity (RSC) significantly influences Neuroticism, a relationship that was

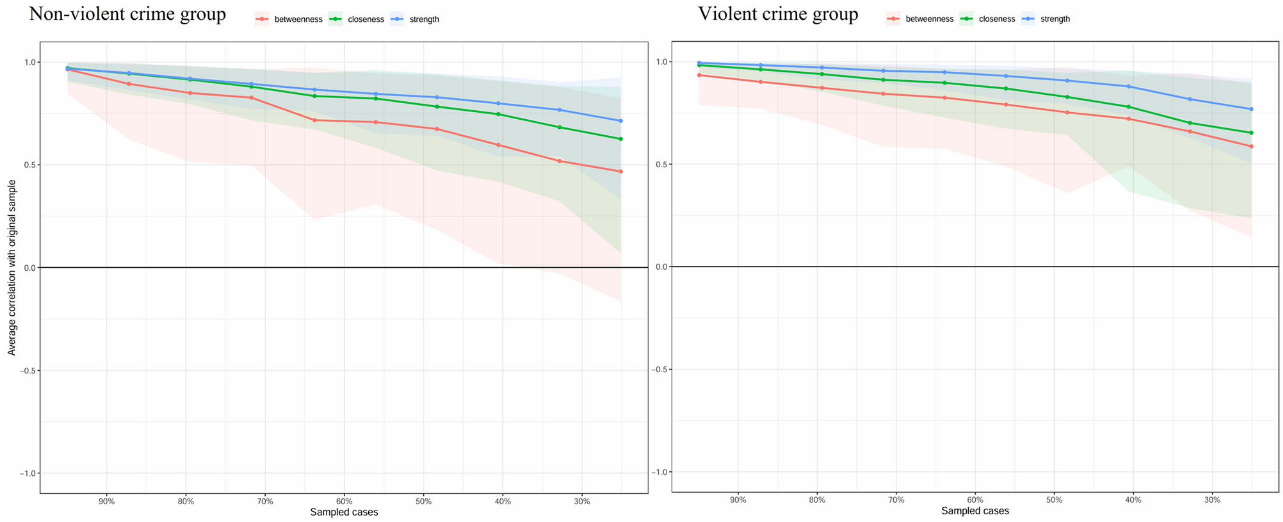

Fig. 3 Stability analysis of centrality measures (strength, closeness, and betweenness) for the non-violent crime group (left) and violent crime group (right). The *x*-axis shows the proportion of sampled cases, and the *y*-axis represents the average correlation with the original sample. Unlike the network analysis, no threshold (0.1) was applied to include all relationships for a comprehensive stability evaluation.

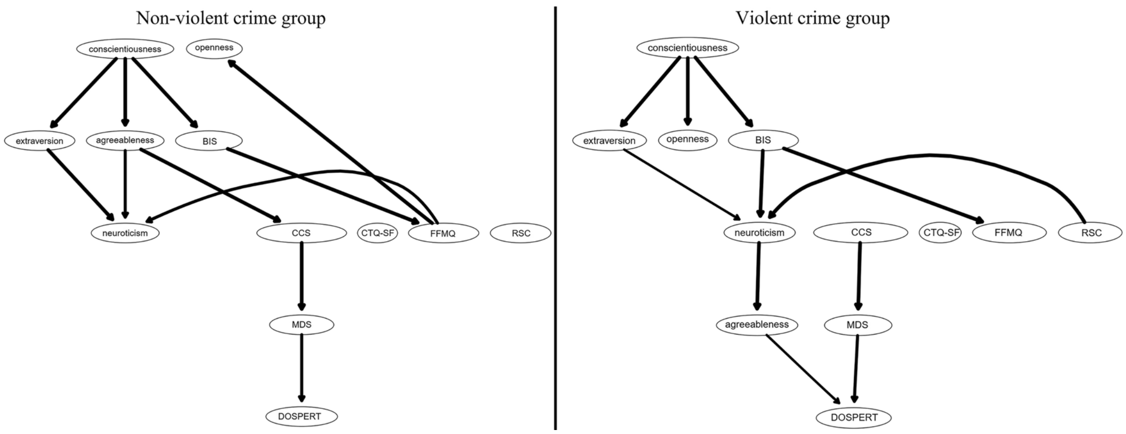

Fig. 4 Bayesian network models of psychological variables in non-violent and violent offender groups. Left panel: non-violent crime sample; right panel: violent crime sample. Ellipses represent variables, directed arrows depict conditional dependencies, and arrow width is proportional to bootstrap edge strength (edges retained when strength > 0.85 and direction consistency > 50 %).

not observed in the non-violent crime group. This finding is consistent with the network analysis, which revealed a more prominent association between Reinforcement Sensitivity and Neuroticism in the violent crime group.

These results are consistent with the findings from the network analysis, further highlighting significant differences in the interaction patterns of psychological variables across different crime types.

Discussion

This study employed network analysis and Bayesian network methodologies to investigate the differences in psychological characteristics and their underlying associative mechanisms between different crime type groups. The results indicate significant disparities between crime types concerning psychological variables, which may influence individuals' patterns of criminal behavior. These findings provide important references for a deeper understanding of the psychological mechanisms of crime and the development of targeted intervention strategies.

The first key finding of this study is that both network analysis and Bayesian network modeling demonstrate that mindfulness significantly influences Neuroticism, Openness, and Extraversion in the non-violent crime group, whereas no direct effects are observed in the violent crime group. This result suggests that mindfulness, by enhancing individuals' emotional regulation capabilities and cognitive flexibility (Ron-Grajales et al., 2021), which is critical to mental health (Ruan et al., 2023), is more applicable to non-violent offenders who exhibit lower psychological distress and higher social adaptability (Haliwa et al., 2021). In contrast, violent offenders may have higher levels of Neuroticism or more pronounced moral disengagement characteristics (Brugués & Caparrós, 2022), which may attenuate the effectiveness of mindfulness in promoting emotional and cognitive improvements. An alternative explanation for the non-significant effect in violent offenders is that they may exhibit reduced responsiveness to introspective interventions, such as mindfulness, due to deeply entrenched cognitive and behavioral patterns. This reduced responsiveness could be related to their emotional dysregulation, moral disengagement, and entrenched cognitive biases (L. Chen et al., 2023). Specifically, individuals with high neuroticism often show negative biases in attention, memory, and interpretation, which may limit the impact of mindfulness on their emotional regulation (L. Chen et al., 2023). In this context, violent offenders' more pronounced emotional biases and cognitive distortions might undermine mindfulness's ability to enhance their emotional flexibility and self-regulation (Utami & Yudiarso, 2023). This finding is consistent with existing literature, which indicates that the effects of mindfulness on individuals' emotional regulation and stress management are significantly influenced by psychological traits and emotional stability (Remskar et al., 2024). Consequently, intervention programs should be tailored to incorporate offenders' psychological characteristics, optimizing the content and format of mindfulness interventions according to different crime types.

The second important finding is that both network analysis and Bayesian network modeling reveal a significant association between Reinforcement Sensitivity and Neuroticism in both groups, with the strength of this association being notably weaker in the non-violent crime group compared to the violent crime group. This result suggests that Reinforcement Sensitivity plays a crucial predictive role in the emotional instability of violent offenders. Supporting the literature, studies have shown that punishment sensitivity is significantly associated with emotional reactivity and aggressive behavior, particularly in individuals with high Neuroticism (Drnas, 2020). Additionally, the higher Reinforcement Sensitivity observed in violent offenders may be related to their heightened responsiveness to threat or punishment cues, thereby exacerbating emotional fluctuations and aggressive behaviors(Espinoza Oyarce et al., 2024; Katz et al., 2020).

Another key finding of this study is that Criminal Cognition influences Risk Attitudes through Moral Disengagement in both groups, albeit with significant differences in the specific patterns of this mechanism. In the non-violent crime group, Criminal Cognition not only significantly affects Moral Disengagement but is also negatively influenced by Agreeableness. In contrast, in the violent crime group, no significant association is observed between Criminal Cognition and Agreeableness. This suggests that criminal cognition in violent offenders may be less dependent on social personality traits such as Agreeableness, and more influenced by deeply entrenched cognitive patterns, including impulsivity and emotional dysregulation. For example, violent offenders are more likely to engage in hostile attribution biases, which lead them to interpret ambiguous situations as threatening, a pattern that may reduce the role of interpersonal traits like empathy in their decision-making processes (Stein et al., 2024). Furthermore, the psychological mechanisms driving violent crime, such as psychopathy, may be more closely linked to cognitive traits and mental characteristics, rather than social personality factors. For instance, research suggests that violent offenders with lower intelligence ($IQ < 85$) are more likely to engage in violent crime, emphasizing the role of individual cognitive features in violent offending (Kim et al., 2024). This result aligns with previous studies showing that violent offenders often develop more rigid cognitive thinking patterns that are less influenced by interpersonal factors like kindness or empathy, instead rationalizing their behavior through dehumanization and other mechanisms of moral disengagement (Brugués & Caparrós, 2022). Furthermore, the mediating role of Moral Disengagement underscores its central position in the formation of criminal behavior, aligning with existing research that indicates Moral Disengagement is a critical mechanism through which offenders rationalize high-risk behaviors and reduce feelings of guilt. Targeted strategies should aim to reduce the influence of Moral Disengagement on the promotion of risk behaviors driven by Criminal Cognition (Gómez & Durán, 2024).

Additionally, this study found significant differences in the association between Criminal Cognition and Reinforcement Sensitivity across the two groups. In the non-violent crime group, Criminal Cognition is significantly and positively associated with Reinforcement Sensitivity, suggesting that non-violent offenders are more inclined to shape their criminal cognition through sensitivity to reward and punishment signals. For example, their perception of potential risks and rewards influences their process of rationalizing criminal behavior (Hahn et al., 2020). However, in the violent crime group, no direct association is observed between Criminal Cognition and Reinforcement Sensitivity, which may reflect that violent offenders' criminal cognition is more driven by emotional dysregulation or external environmental pressures rather than internal reward-punishment sensitivity (Drnas, 2020; Katz et al., 2020).

Although a permutation-based NCT did not detect global differences between the two psychological networks, this null finding should be interpreted cautiously rather than taken as evidence of complete equivalence. First, both violent and non-violent offenders share a common backbone of broad personality traits, so large-scale structural divergence was not necessarily expected. Second, the NCT's statistical power decreases rapidly in moderately dense networks and when sample sizes are unbalanced (Van Borkulo et al., 2023); the present networks retained well over half of the possible edges, a density that can mask subtle but functionally important edge-level distinctions. Finally, the NCT assesses only overall connectivity and the single largest edge difference; it cannot reveal directional or mediating pathways that may still distinguish the groups. Our complementary Bayesian network analysis, therefore, remains crucial for uncovering the specific causal routes through which variables such as reinforcement sensitivity and moral disengagement operate in violent versus non-violent offending.

However, several limitations should be acknowledged. First, the study sample was exclusively composed of male inmates from a single region, lacking representation of female offenders and individuals from other areas, which may limit the generalizability of the findings. Second, the psychological scales used relied primarily on self-reported data, which may be influenced by social desirability bias or response bias, thereby reducing the objectivity of the results. Third, while network analysis and Bayesian network methods are commonly applied to observed variables, our study had to use proxy measures for latent variables. This approach, while widely used in psychological research, may have introduced measurement error and limited the accuracy of the results. Fourth, the moderately dense structure of the present networks limits the statistical power of the NCT, which means that the non-significant global result should be interpreted with caution.Finally, although network analysis and Bayesian network methods reveal complex associations between variables, the cross-sectional nature of the data restricts the ability to establish causal relationships and underlying mechanisms. Future research should incorporate longitudinal data or experimental designs to more accurately validate the causal relationships and mechanisms identified in this study. Furthermore, exploring the role of Moral Disengagement as a moderating factor could provide valuable insights into how this cognitive mechanism influences the relationship between criminal cognition and personality traits over time. Such research could help to better understand the psychological processes that underlie both violent and non-violent criminal behavior and inform the development of more effective, tailored interventions.

Conclusion

By integrating network analysis and Bayesian network methodologies, this study provides an in-depth exploration of the psychological differences and interaction mechanisms between violent and non-violent offenders. The findings reveal that mindfulness significantly enhances emotional regulation and cognitive flexibility in non-violent offenders, but has limited effects on violent offenders. Additionally, reinforcement sensitivity is more strongly linked to neuroticism in violent offenders, highlighting their heightened emotional instability and impulsivity. Criminogenic cognition, mediated by moral disengagement, influences risk-taking behaviors in both groups, though the pathways differ significantly. These results provide important insights for understanding criminal behavior and developing more targeted intervention strategies.

Data availability

The data supporting the findings of this study are not publicly available due to confidentiality restrictions associated with prison data.

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Author contributions

Wang-Cheng Cen conducted data analysis and drafted the manuscript. Cheng-Han Li, Yu-Hao Cui and Wen-Jing Yan reviewed and edited the manuscript and contributed to project oversight and administrative tasks. All authors reviewed and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Ethics approval

All procedures in this study were conducted in strict compliance with the ethical guidelines outlined by the Ethics Committee of Nanjing Normal University (Approval No. NNU202310027). Ethical approval was granted in October 2023. The approved scope covered all planned data collection, analysis, and publication activities involving human participants. All procedures were performed in accordance with relevant guidelines from the Declaration of Helsinki.

Informed consent

Written informed consent was obtained from all participants prior to data collection in November 2023. The consent was obtained directly by the research team from adult participants, and it covered participation in the study, use of data for research purposes, and permission for publication of anonymized data. All participants were fully informed about the purpose of the research, the voluntary nature of their participation, and the measures to ensure anonymity and confidentiality.

Additional information

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