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Understanding the Risk of Sexual Reoffending in Adult Men: A Network-Based Model

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Abstract

The predominant approach to understand dynamic risk factors of sexual reoffending has been referred to as the Propensities Model (Thornton, 2016). According to this model, dynamic risk factors can be conceptualized as latent constructs whose change alters the risk of sexual reoffending. Despite its strengths and contributions to research, this model does not offer answers to the question of how dynamic risk factors contribute to the risk of sexual reoffending, or of how sustained change in risk might take place. In this paper we introduce the Network-Based Model of Risk of Sexual Reoffending (NBM-RSR), which addresses several limitations and constraints of the Propensities Model and offers empirically testable propositions regarding the nature and development of the risk of sexual reoffending. The NBM-RSR considers risk of sexual reoffending to involve a self-sustaining network of causally connected dynamic risk factors. Consistent with this, an increased risk of sexual reoffending is characterized through a network that contains more and stronger interconnected dynamic risk factors with a higher strength. Sustained change in risk of sexual reoffending occurs when activity in the network exceeds a critical point resulting in a new self-sustaining network. Propositions based on the NBM-RSR are introduced and translated into testable hypotheses. These propositions revolve around (a) risk of sexual reoffending

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resulting from the construction of a network of causally connected dynamic risk factors, (b) network stability, sudden changes, and critical transitions, and (c) dynamic risk factors' relative influence on risk of sexual reoffending.

Keywords
risk of sexual reoffending, dynamic risk factors, causal network, network approach, sexual recidivism

Introduction

It is of both scientific and social importance to increase our understanding of the processes by which psychological and behavioral variables contribute to the risk of sexual reoffending. An improved understanding of the development and nature of this risk, which can be defined as the probability of future sexual offending by men convicted of a sexual offense, will, ultimately, contribute to increased effectiveness of treatments, risk management plans, and prevention initiatives aimed to assist men with a history of sexual offenses to desist future crimes (Gannon et al., 2019; Ward & Beech, 2015). For example, a better understanding of the nature and determinants of the risk of sexual reoffending, may help treatment providers and program managers better identify and prioritize treatment targets. In addition, increased knowledge of the concept of sexual reoffending could contribute to the development of new risk assessment instruments or help improve existing ones (van den Berg et al., 2022).

Based on the findings of several meta-analyses and two large-scale recidivism prediction studies (Hanson et al., 2007; Hanson & Bussière, 1998; Hanson & Morton-Bourgon, 2004; 2005; Helmus et al., 2013; Knight & Thornton, 2007), Thornton (2002, 2013) introduced the Structured Risk Assessment Need Framework (SRA; see Table 1). The SRA framework contains the following four domains of psychological and behavioral features associated with sexual reoffending: sexual interests, distorted attitudes, relational style, and self-management. These four domains are divided into subdomains. For example, the domain of sexual interests is further partitioned into sexual preoccupation and offense-related sexual interests. The most widely used dynamic risk assessment instruments for adult males with a history of sexual offenses all contain factors from at least three of the four domains of the SRA Need Framework (van den Berg et al., 2018; van den Berg et al., 2020).

According to Thornton (2016), the Propensities Model represent the most well-known conceptual approach to comprehend psychological and behavioral variables directly related to sexual reoffending. However, this model provides a limited theoretical account of the development and nature of the risk of sexual reoffending (Thornton, 2016; Prentky et al., 2015).

To further our understanding of the risk of sexual reoffending and to stimulate theoretical discussion and scientific research on this topic, we present a Network-Based

Table 1. The Structured Risk Assessment (SRA) Framework (Thornton, 2002; 2013), Covering Four Domains of Psychological and Behavioral Features Associated With Sexual Reoffending.

Domain	Subdomain	Meta-analytic Results S= Empirically-supported P= Promising
Sexual interests	Sexual preoccupation • Intense impersonal sexual interests • Sexual coping • Diverse sexual outlets	• Sexual preoccupation (S) • Multiple paraphilias (S) • Sexualized coping (P)
	Offense-related sexual interests • Sexual interest in prepubescent and pubescent children • Sexualized violence	• Sexual interest in children (S) • Sexualized violence (P)
Distorted attitudes	Victim schema • Pro-offending schema about classes of potential victims (e.g., children or women)	• Pro-offending attitudes (S) • Pro-child molestation attitudes (S) • Pro-rape attitudes (S) • Generic sexual offending attitudes (S)
	Rights schema • Excessive sense of entitlement Means schema • Machiavellianism • Violent world schema	Insufficient data to examine the predictive value of more specific attitudes, although all three SRA categories coincided with at least one of the broader categories used in the meta-analyses
Relational style	Inadequate relational style • Dysfunctional self-esteem (inadequate or narcissistic) • Emotional congruence with children	Emotional congruence with children (S) • Painfully low self-esteem was found consistently predictive in the UK, but not in other jurisdictions • Narcissistic self-esteem hasn't been examined in recidivism studies
	Lack of emotionally intimate adult relationships • Lack of sustained marital type relationships • Relationships marred by violence/infidelity	• Lack of sustained marital type relationships (S) • Marital relationships marred by repeated violence/infidelity (S)
	Aggressive relational style • Callousness • Grievance thinking	• Callousness (P) • Grievance thinking (S)
Self-management	Social deviance • Early onset and pervasive resistance to rules and supervision • Lifestyle impulsiveness	• Childhood behavior problems (S) • Juvenile delinquency (S) • Non-sexual offenses (S) • Non-compliance with supervision (S) • Violation of conditional release (S) • Antisocial personality disorder (S) • Impulsivity/recklessness (S) • Employment instability (S)
	Dysfunctional coping in response to stress/problems • Poor problem-solving • Poor emotional control	• Poor Coping (externalizing) (P)

Model of Risk of Sexual Reoffending (NBM-RSR) and elaborate on this model by presenting several empirically testable propositions. The NBM-RSR is inspired by the network approach to psychopathology (Borsboom, 2017; Borsboom et al., 2019; Borsboom et al., 2021; Robinaugh et al., 2019). Following this approach, mental disorders can be understood from a self-sustaining network of symptoms of psychopathology that are causally interrelated through a range of biological, psychological, and social mechanisms (Borsboom, 2017; Borsboom et al., 2021). As an example, from this perspective, Major Depressive Disorder (American Psychiatric Association, 2013) can be considered a system of causally interacting symptoms such as sadness, anhedonia, fatigue, insomnia, concentration problems, and suicidal ideation, instead of as involving some single underlying factor causing these symptoms (e.g., Fried et al., 2017; Wichers et al., 2021). Each individual may experience some of these (interacting) psychological and behavioral features occasionally; for instance, insomnia causing fatigue resulting in concentration problems (Fried et al., 2017). However, when they become strongly enough connected, symptoms may keep each other activated, through feedback processes (e.g., insomnia causing fatigue resulting in concentration problems and sadness leading to insomnia), which may result in and constitute clinical depression. Within the network approach to psychopathology, this stable state of continuous, mutually activating symptoms is referred to as a self-sustaining network or equilibrium (Borsboom, 2017). Ideally, treatment for depression leads to a healthier self-sustaining network characterized by fewer or less strongly connected symptoms resulting in the dissolution of the clinical depression. The shift to a new, in this case healthier, state or equilibrium of the self-sustaining network is referred to as a critical transition (Kossakowski, 2020). Before outlining our NBM-RSR, we will first address and discuss the Propensities Model's approach to understand psychological and behavioral variables associated with sexual reoffending.

The Propensities Model

Central to the Propensities Model are latent constructs, called propensities, which refer to relatively stable intra-individual features that influence an individual's probability of sexual reoffending (Lussier et al., 2020; Prentky et al., 2015; Thornton, 2016). Despite their relative stability, propensities are considered to be amendable to change by treatment or risk management strategies (Mann et al., 2010). Typically, such propensities are referred to as dynamic risk factors (Douglas & Skeem, 2005), criminogenic needs (Andrews et al., 1990), dynamic predictors (Bonta & Andrews, 2017), or psychologically meaningful factors (Mann et al., 2010). Although specific definitions of these constructs vary, they all refer to amendable psychological and behavioral factors, which, when changed, will affect the probability of perpetrating a new sexual offense (Hanson et al., 2020; Prentky et al., 2015; Thornton, 2016). For consistency reasons, we will use the term dynamic risk factor throughout this manuscript.

Although latent constructs cannot be observed directly, depending on their strength and their interaction with the environment, dynamic risk factors may manifest

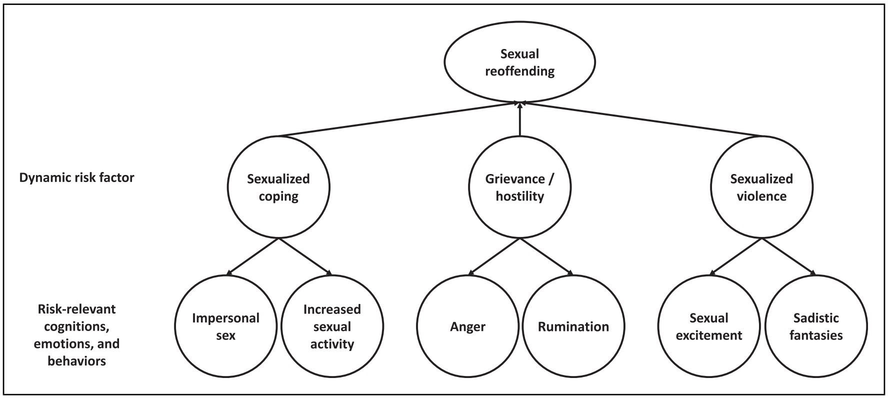

Figure 1. Three dynamic risk factors causally related to sexual reoffending, represented according to the Propensities Model (Mann et al., 2010).

themselves and can be measured through their cognitive, affective, or behavioral expressions, according to the Propensities Model (Mann et al., 2010). These risk-relevant cognitions, emotions and behaviors are not related in a direct way but connected to each other by way of an underlying latent variable (see Figure 1). In the Propensities Model, the short-term probability of sexual reoffending depends on the balance between the extent to which dynamic risk factors are currently active and the degree to which the environment allows for these risk factors to impact offending behavior (Thornton, 2016).

Limitations of the Propensities Model. A number of limitations of the Propensities Model, mostly concerning their incomplete account of the development and nature of the risk of sexual reoffending, have been discussed in the literature (e.g., Prentky et al., 2015; Thornton, 2016). For example, the Propensities Model assert causality of dynamic risk factors but does not provide an explanation for how these factors give rise to the risk of sexual reoffending (Prentky et al., 2015; Thornton, 2016). Also, the Propensities Model does not consider causal interrelationships among dynamic risk factors, or between risk-relevant features within such factors, despite both scientific and clinical observations indicating that psychological and behavioral factors interact with each other (Fried & Cramer 2017; Heffernan & Ward, 2019; Heffernan et al., 2019; Ward & Fortune, 2016). For example in the dynamic risk factor emotional congruence with children, which has been described as an affective and cognitive connection with children expressed through an exaggerated affiliation with childhood by people ascribing child-like characteristics to themselves and experiencing a strong non-sexual liking of children, that is involved in the initiation and maintenance of contact with children (See Figure 2; McPhail et al., 2013; McPhail et al., 2018). Finally, the Propensities Model provides no theoretical account of how sustained change in risk may be achieved (Thornton, 2016).

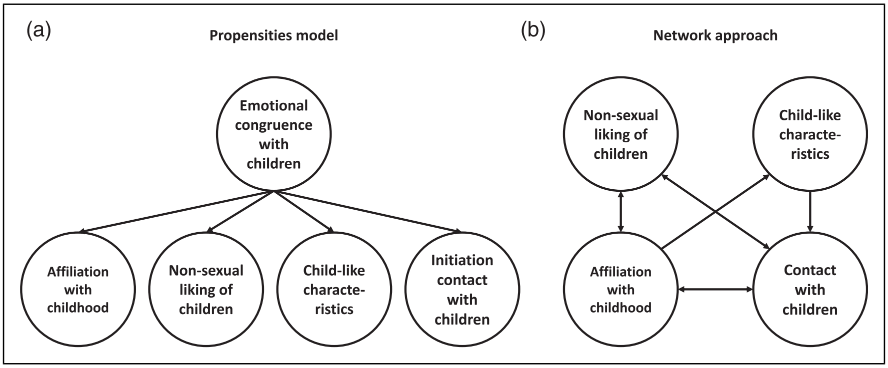

Figure 2. Dynamic risk factor emotional congruence with children presented as (a; left) a latent variable within the Propensities Model, (b; right) a result of causal interacting risk-relevant emotion, cognition, and behavior.

Given these limitations of the Propensities Model, further theoretical work is needed to create a stronger foundation for empirically testable hypotheses concerning the development and nature of dynamic risk factors and how they impact the risk of sexual reoffending (Mann et al., 2010; Paquette & Cortoni, 2021; Prentky et al., 2015). In response to the limitations of the current Propensities Model, we propose a network-based model that provides a coherent and empirically testable account regarding the risk of sexual reoffending. The next section describes the basic theoretical premises of our network approach applied to the risk of sexual reoffending.

Network-Based Model of Risk of Sexual Reoffending (NBM-RSR)

The risk of sexual reoffending is dynamic in nature and varies over time and across contexts (Babchishin & Hanson, 2020; Lussier et al., 2020; Olver & Stockdale, 2020; Nitsche et al., 2022). The NBM-RSR assumes that risk of sexual reoffending:

(A) Results from a self-sustaining network of causally interacting dynamic risk factors (van den Berg et al., 2020; van den Berg et al., 2022),
(B) Is multifactorially determined through the construction of the network (i.e., the network topology; Borsboom et al., 2019).
(C) Varies due to influences from both within and outside the dynamic risk factor network (i.e., the external field).

Risk Resulting From A Network of Causal Interacting Dynamic Risk Factors

In contrast to the Propensities Model – which assume that risk-relevant cognitions, emotions, and behaviors relate to each other through latent variables – the NBM-RSR considers dynamic risk factors as meaningful constellations resulting from causally interacting risk-relevant psychological and behavioral features (see Figure 2 for a graphical representation of the dynamic risk factor emotional congruence with children from both perspectives). According to the NBM-RSR, these cognitions, emotions, and behaviors are risk-relevant due to their nature, persistence, and/or interrelation with other psychological or behavioral features. For instance, a sexual fantasy may be related to sexual reoffending due to its nature (e.g., children, nonconsenting others), persistent occurrence (i.e., high frequency of sexual fantasies) and/or interrelation with other psychological and behavioral features (e.g., using sexual fantasy and behavior to cope with negative emotions).

From a network perspective, dynamic risk factors are theoretically causally connected with each other. When causal connections between dynamic risk factors are suffciently strong, a self-sustaining network will develop (van den Berg et al., 2020).

Risk Determined Through the Network Topology

Within the NBM-RSR, risk of sexual reoffending is conceptualized by and understood from the topology of a self-sustaining network of causally connected dynamic risk factors. Network topology itself is determined by the density (the number of existing connections relative to the possible number), the connectivity (how various parts of a network connect to one another), and the amount and strength (i.e., degree of being presence; degree of activity) of included dynamic risk factors. Increased risk of sexual reoffending is characterized by a network of more and stronger interconnected dynamic risk factors with a higher strength. A sustained change in risk of sexual reoffending occurs when activity in the network exceeds a critical point resulting in a new equilibrium, that is a new self-sustaining network of dynamic risk factors (Kossakowski, 2020; Kuznetsov, 2013; van den Berg et al., 2020; van den Berg et al., 2022). Figure 3 provides an example of self-sustaining networks of dynamic risk factors with distinct risk levels for sexual reoffending.

Dynamic Risk Factors Relative Influence Within the Network. According to the NBM-RSR, the influence of dynamic risk factors on the risk of sexual reoffending cannot be solely understood from their individual direct association with future sexual offending behavior. Their impact on this risk is also determined by the number and strength of causal interrelations with other dynamic risk factors forming a self-sustaining network. Dynamic risk factors with more and stronger connections are hypothesized to have a greater influence on the risk of sexual reoffending (McNally, 2016; van den Berg et al., 2022). See for example the network of dynamic risk factors presented in Figure 4, where adventurous pleasure seeking has a relatively stronger influence on the network

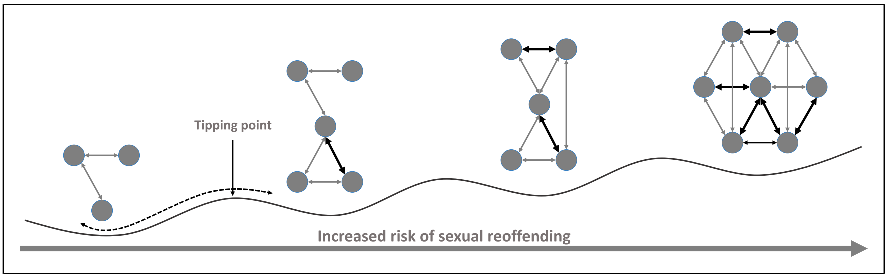

Figure 3. Visual representation of networks of dynamic risk factors with distinct levels of risk of sexual reoffending (increasing in risk from left to right). Sustained change in risk occurs when network activity exceeds a critical point (referred to as a tipping point).

activity compared to impulsive behavior due to its higher number of causal connections. Within the NBM-RSR, dynamic risk factors with relatively higher numbers and stronger connections are described as having a more central position, or higher centrality. Theoretically, a dynamic risk factor can further be influential by forming a connection between two or more communities of dynamic risk factors, called a bridge (e.g., low satisfaction from work in Figure 4).

Communities of Dynamic Risk Factors. Dynamic risk factors with strong causal interrelations group together, forming a community of risk factors (van den Berg et al., 2022). Based on previous findings, the NBM-RSR includes communities of dynamic risk factors relevant to sexual self-regulation, (ability to establish and maintain) emotionally intimate relationships, antisociality, and general self-regulation (Figure 5; Brouillette-Alarie et al., 2016; Hanson & Morton-Bourgon, 2005; Malamuth, 1986; Malamuth, 2003; Malamuth & Hald, 2016; Malamuth et al., 1995; Olver et al., 2021; Stinson & Becker, 2013; Stinson et al., 2016; Stinson et al., 2008; Thornton, 2002; Thornton, 2013; van den Berg et al., 2020; van den Berg et al., 2022). In contrast with Thornton's SRA model (2002, 2013), in which pro-offending attitudes are a separate domain, within the NBM-RSR these attitudes form a dynamic risk factor together with other risk-relevant behavioral and psychological features and are part of one of the four communities. For example, the dynamic risk factor hostility towards women emerging from the causal interactions of hostile beliefs about women, anger, and violent behavior towards women will be part of the community emotionally intimate relationships.

The Impact on Risk of Variables in the External Field

Risk of sexual reoffending is caused by a network of interrelated dynamic risk factors in interaction with variables outside this network, or 'the external field' (Borsboom, 2017; Borsboom et al., 2019). In the NBM-RSR, variables in the external field include biological factors (e.g., genetics, brain structures, hormone

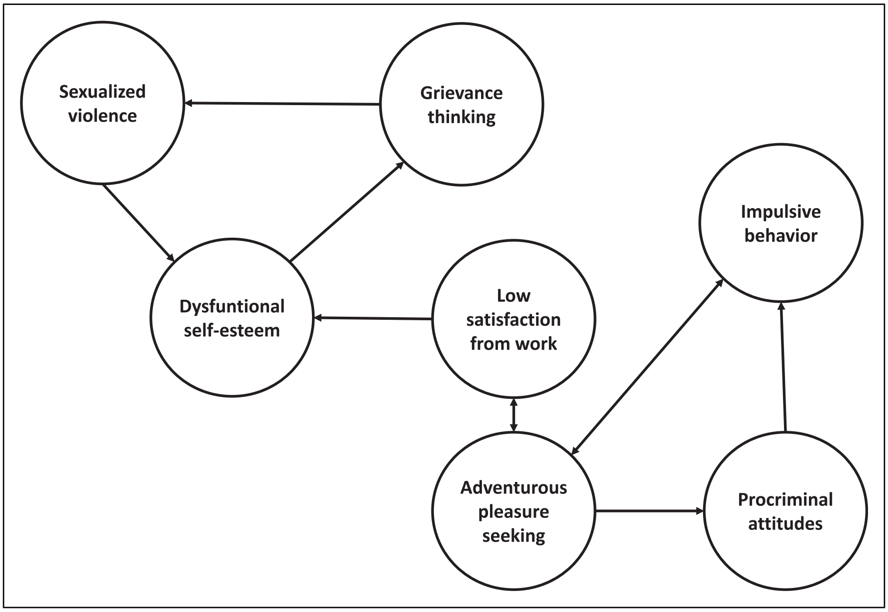

Figure 4. Fictional self-sustaining network of dynamic risk factors representing the risk of sexual reoffending of a man convicted for a series of violent rapes, with low satisfaction from work forming a bridge between two communities of dynamic risk factors.

levels), (early) life experiences (e.g., childhood sexual abuse or neglect), socio-cultural factors (e.g., being part of a masculine (sub)culture or sexualized environment, legal variables), situational factors (e.g., access to potential victims, absence of a guardian, changes in employment), and psychological and behavioral factors (such as human agency, motivation for treatment, intelligence, extraversion, level of social emotional development). The distinction between dynamic risk factors and factors in the external field is their respectively direct or indirect relationship with future sexual offending behavior. The influence between dynamic risk factors and variables in the external field can be mutual. For example, unintentional contact with a boy (situational factor) might trigger deviant sexual interest in a man with a history of sexual offenses against children. And, vice versa, deviant sexual interest in boys might lead to attempts to increase contact with potential victims. However, causal relationships between variables in the external field and dynamic risk factors are not always bidirectional. Causal influence of a single (early) life experience like childhood sexual abuse is unidirectional by definition. Figure 5 provides a graphical representation of the NBM-RSR.

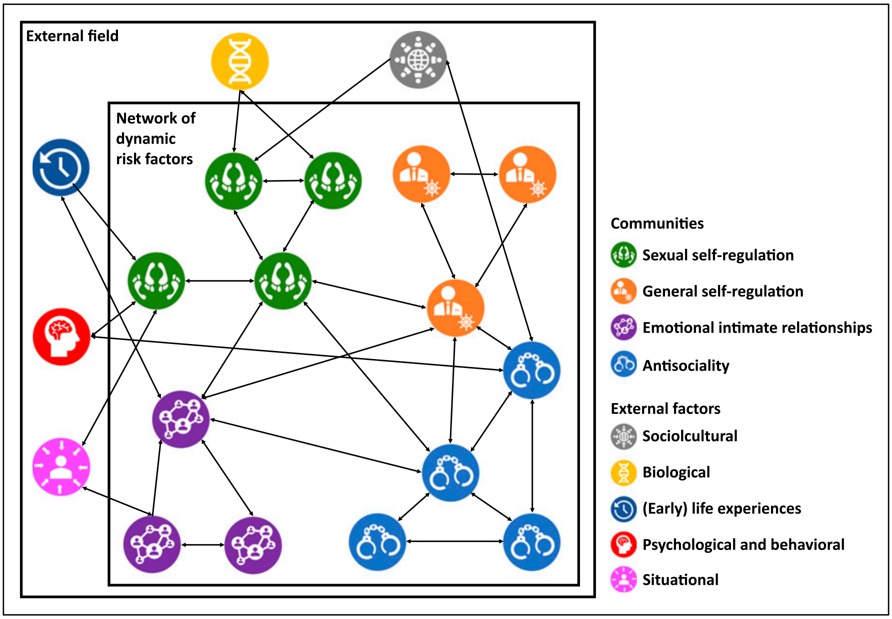

Figure 5. Graphical representation of the network-based model of risk of sexual reoffending (NBM-RSR).

Overview and Discussion

To advance the understanding of the development and nature of the risk of sexual reoffending and to stimulate further theoretical discussion and scientific research on this phenomenon, we propose and introduce a network approach to risk of sexual re-offending. Our NBM-RSR not only aims to provide a coherent account of the development and nature of the risk of sexual reoffending, it also represents a theoretical framework in an effort to overcome the limitations of the Propensities Model. That is, in contrast to this model, the NBM-RSR a) does consider mutual causal interrelationships of risk-relevant features within dynamic risk factors and between dynamic risk factors themselves (Heffernan et al., 2019; Ward & Fortune, 2016), b) provides meaningful information on how dynamic risk factors give rise to the risk of sexual reoffending (Prentky et al., 2015; Thornton, 2016), and c) offers a theoretical account of how sustained change in risk might take place (Thornton, 2016).

According to the NBM-RSR, dynamic risk factors are formed by interacting psychological and behavioral features, which are risk-relevant due to their nature, persistence, and/or interrelation with other psychological or behavioral characteristics. The risk of sexual reoffending in turn arises from a self-sustaining complex network of causally connected dynamic risk factors and is determined by the construction of this network (i.e. the density, connectivity, and the number and strength of included dynamic risk factors). Once the self-sustaining network is formed, variables in the external field affect not only the operation of dynamic risk factors but also the network activity. A sustained change in risk of sexual reoffending occurs when activity in the network exceeds a critical point resulting in a new self-sustaining network of dynamic risk factors.

In addition to contribute to our understanding of the risk of sexual reoffending, the NBM-RSR also has clinical implications. In contrast to the Propensities Model, which may leave clinicians with the impression that all dynamic risk factors must be addressed, individually and consecutively, the NBM-RSR postulates that elucidating key dynamic risk factor(s) at the individual level will allow clinicians to specifically target those dynamic risk factor(s) which, when changed, are most likely to have an effect on other dynamic risk factors and thereby are more likely to reduce the overall probability of sexual reoffending (van den Berg et al., 2022). However, more scientific research into the theoretical framework of the NBM-RSR is needed to allow us to increase treatment effectiveness in men with a history of sexual offenses using individualized networks of dynamic risk factors. In the following section we will present several propositions and hypotheses derived from the NBM-RSR that warrant further research.

Propositions and Hypotheses to be Examined

The NBM-RSR offers a theoretical account of the development and nature of the risk of sexual reoffending and provides a foundation for further research on a number of propositions derived from this model. These propositions revolve around (a) risk of sexual reoffending resulting from the construction of a network of causally connected dynamic risk factors, (b) network stability, sudden changes, and critical transitions, and (c) dynamic risk factors' relative influence on risk of sexual reoffending.

Risk Resulting From Network Topology. Meta-analyses on the predictive value of dynamic risk assessment instruments indicate that the number and strength of dynamic risk factors are predictive of the risk of sexual reoffending (Brankley et al., 2021; van den Berg et al., 2018). However, the NBM-RSR conceptualizes and understands the risk of sexual reoffending not solely from the number and strength of dynamic risk factors; the density and connectivity of the self-sustaining network are also key. From this follows the proposition that increased risk of sexual reoffending is characterized by a network of more and stronger interconnected dynamic risk factors having a higher degree of activity (i.e., being more strongly presence, for example expressed in terms of a higher score on a dynamic risk assessment instrument). Future research could test the following two hypotheses. First, the predictive accuracy of algorithms to estimate the risk of sexual reoffending is expected to be larger when the density and connectivity of the network will be taken into account above and beyond the number and strength of dynamic risk factors. Second, both the density and connectivity of the network of dynamic risk factors is expected to be predictive of reoffending risk in participants matched on number and strength of dynamic risk factors.

Network Stability and Critical Transitions. Recent research involving repeated assessments of dynamic risk factors using the ACUTE-2007 (Babchishin & Hanson, 2020) suggests that although the probability of reoffending may change over time, substantial variability exists in the degree of change. That is, in any given follow-up period the likelihood of reoffending has been found to change for some individuals, while others show a stable risk (Babchishin & Hanson, 2020). From the NBM-RSR, both the relative stability of and changes in risk of sexual reoffending can be understood from self-sustaining networks of dynamic risk factors and their critical transitions (Hayes & Andrews, 2020; Kossakowski, 2020). Future research could examine the proposition of the existence of the relative stability of the self-sustaining network of dynamic risk factors and critical transitions to changed levels of risk. Assuming the existence of critical transitions between two different states in a self-sustaining network, we hypothesize that within-system changes in dynamics indicative of a transition from one state to another – called early warning signals – will be found in the network of dynamic risk factors of adult males convicted for sexual offenses (Kossakowski, 2020; Scheffer et al., 2012).

Dynamic Risk Factors' Relative Influence on Risk. Another proposition can be derived from the NBM-RSR on the relative influence on risk of sexual reoffending of specific dynamic risk factors. According to our model, dynamic risk factors' influence within the network, and therefore their influence on risk, increases due to: (a) an upsurged number of relatively strong interrelations with other dynamic risk factors (i.e. having a higher centrality), and (b) by forming a connection, or bridge, between two or more communities of dynamic risk factors (Castro et al., 2019; McNally, 2016; Opsahl et al., 2010; van den Berg et al., 2022). Simulation studies conducted with 51 cross-sectional psychopathological networks have found moderate evidence to sustain the hypothesis that central and bridge symptoms indeed have a relatively stronger influence (Castro et al., 2019). Future simulation studies could examine to what extent this hypothesis applies to networks of dynamic risk factors relevant to sexual reoffending. An alternative approach to examining the proposition on the relative influence of dynamic risk factors is to test the hypothesis that treatment and risk management strategies focusing on dynamic risk factors with relatively high influence on a network result in a relatively larger reduction in future sexual offending (van den Berg et al., 2022). Assuming future studies indeed demonstrate the relative stronger influence of specific dynamic risk factors on the network of dynamic risk factors (and thus on the risk of sexual reoffending), this can be expected to have not only theoretical but also clinical relevance. After all, devoting attention to these dynamic risk factors in both risk management and treatment of adult men with a history of sexual offenses could result in a substantial decrease in risk of sexual reoffending. The reverse also applies: If future research shows certain dynamic risk factors to have relatively little impact on the risk of sexual reoffending, treatment providers and probation officers might either eliminate or markedly reduce their focus on such factors (van den Berg et al., 2022).

This section presents empirically testable propositions and hypotheses derived from the NBM-RSR. Testing these hypotheses requires a statistical approach that differs from and extends what typically has been done based on the Propensities Model. For this reason, we include a description of how the challenge of statistically detecting interactions among interrelated dynamic risk factors in a network might be addressed.

Detection Interactions in a Network of Dynamic Risk Factors

The NBM-RSR is in part inspired by the network approach to psychopathology (Borsboom, 2017; Borsboom et al., 2019; Borsboom et al., 2021; Robinaugh et al., 2019). Empirical research based on this approach has increased exponentially over the past decade (Burger et al., 2022; McNally, 2021). This research typically uses network analysis to statistically detect interactions within a disorder's symptom network.[1]

To construct and assess the network structure of interrelated dynamic risk factors, first a pairwise Markov random field is estimated (PMRF; Costantini et al., 2015; van Borkulo et al., 2014). A PMRF can essentially be considered a partial correlation network, that is a network in which an association between two dynamic risk factors is conditioned on, or controlled for, all other dynamic risk factors in the network (Isvoranu et al., 2022). In a PMRF, dynamic risk factors connected by edges indicate conditional dependence (Epskamp, Borsboom, & Fried, 2018; Isvoranu et al., 2022). However, some spurious connections may result from sampling error. To control for such spurious connections a technique can be employed that relies on the extended Bayesian information criteria for L1 penalized regularization (Costantini et al., 2015; Epskamp & Fried, 2017). This regularization technique which is used to control the Type I error rate has been shown to result in networks with high specificity and adequate sensitivity (van Borkulo et al., 2014).

Assuming that research on networks of dynamic risk factors will typically include variables at various measurement levels, the appropriate PRMF model to estimate a network of dynamic risk factors relies on the use of mixed graphical models (mgm: Haslbeck & Waldorp, 2020). This is because mgm allows for the existence of not normally distributed data or data which is not measured on a continuous scale. Estimating and visualization of networks as described above can be done with respectively R-Packages graphicalVAR (Epskamp, 2020) and qgraph (Epskamp et al., 2012). However, given the limited sample sizes in research on adult males' dynamic risk factors, there is a reasonable chance that the strength of connections between these dynamic risk factors may not be estimated accurately (Epskamp, Borsboom, & Fried, 2018). This probability increases exponentially when more dynamic risk factors are considered. The next section will describe the current approach to assess the accuracy of estimated networks.

Assessing Accuracy of the Estimated Network. The question which sample size is needed to accurately estimate network structures from psychological data is a subject of debate (e.g., Epskamp, Borsboom, & Fried, 2018; Fried et al., 2018; Williams & Rast, 2020).

Contributing to this discussion, Epskamp and colleagues (2022) outlined several methods to gain insights into the accuracy of edge weights and the stability of centrality indices in the estimated network structure. These methods concern (a) the estimation of the accuracy of edge-weights, by drawing bootstrapped confidence intervals (CIs), (b) investigating the stability of (the order of) centrality indices, and (c) performing bootstrapped difference tests between edge-weights and centrality indices to test whether these differ significantly from each other. The estimation of the accuracy of edge-weights, by drawing bootstrapped confidence intervals (A) should always be performed, while the choice for method (B) and (C) depends on what is important to discover from the network (Epskamp, Borsboom, & Fried, 2018; Constantin et al., 2021). Studies on dynamic risk factors' networks will often use methods (A) and (B) to gain insights into the accuracy of their network estimation because they will especially be interested in strength centralities of dynamic risk factors.

Towards Establishing Causality Within Networks of Dynamic Risk Factors. Networks of dynamic risk factors can be estimated from cross-sectional as well as longitudinal data. Cross-sectional data provides a contemporaneous network indicating to what extent dynamic risk factors are associated within the same window of measurement. These associations suggest at most potential causal relationships. After all, there is no certainty that variation in one dynamic risk factor causes change in the associated dynamic risk factor. Longitudinal data provides a temporal network indicating whether variation in a dynamic risk factor precedes variation in an associated dynamic risk factor in the subsequent assessment (Epskamp, van Borkulo, et al., 2018). As a result, a temporal network might contain causal information on interrelated dynamic risk factors. However, direct causal inference based on temporal networks is not justified because they contain purely statistical associations, and relationships between dynamic risk factors can still falsely appear to be related due to an unseen third variable (Borsboom et al., 2021). To control for third variables, hypotheses regarding causal relationships between dynamic risk factors can be tested in single case experimental designs (SCED; Barlow et al., 2009). SCED are aimed to test the effect of a treatment intervention using a small number of patients (typically one to three) by using repeated measurements (Krasny-Pacini & Evans, 2018). Data of the repeated measurements in turn can be obtained via Experience Sampling Method (ESM; Kuppens & Myin-Germeys, 2022). This type of longitudinal research methodology is a structured self-report diary technique which allows to investigate changes in behavioral, psychological, and contextual features within and in interaction with the real-world context (Csikszentmihalyi & Larson, 1987; Myin-Germeys & Kuppens, 2022; Stone & Shiffman, 1994). Although perturbation by third variables can never be eliminated without Randomized Controlled Trials, as yet the combination of SCED and ESM offers the possibility of making statements regarding causal relationships between dynamic risk factors with a high degree of confidence. For instance, hypotheses on the assumed causal relationships between dynamic risk factors derived from the case formulation of an individual convicted for indecent exposure can be verified by ESM.

Suppose causal links are indeed found between perceived lack of intimate sexual contact, relationship conflicts, stress, and the resulting need to expose genitals to unsuspecting strangers. SCED can then be deployed to examine whether treatment-induced improvement of social relationships skills interferes with the causal chain between these dynamic risk factors. Recent studies show that ESM can indeed be deployed to inform forensic case formulations in clinical practice (Smid et al., 2023; van den Berg et al., 2023).

Although establishing causal interrelationships in dynamic risk factors is of great importance for future development of the NBM-RSR, there are some other challenges. In the next section we will describe current limitations of the NBM-RSR, while offering possible solutions for further development of this model.

Future Steps and Further Development of the NBM-RSR

Some limitations of the NBM-RSR should be acknowledged. First, the network of dynamic risk factors contains variables which empirically have been found to have significant predictive value for sexual reoffending. However, studies on the predictive properties of dynamic risk factors generally do not take the interrelationships among these factors into account. Earlier research on networks combining dynamic risk factors and sexual reoffending has found that most but not all commonly known dynamic risk factors remain related to sexual reoffending after controlling for all other dynamic risk factors in the network (van den Berg et al., 2020; van den Berg et al., 2022). Guided by a more elaborated network topology of the current NBM-RSR, further empirical research might help to determine which dynamic risk factors are causally connected to sexual reoffending and which gain predictive power only through their connection with other dynamic risk factors (and should be considered to be part of the external field). This sophistication of the NBM-RSR might be realized by unraveling empirically validated dynamic risk factors into behavioral and psychological features and causal strains (Heffernan et al., 2019). As described in the former section, hypotheses on the causal interrelationship of these features could subsequently be tested and validated through SCED and ESM or a combination of the two (Burger et al., 2020; Epskamp, van Borkulo, et al., 2018; Pearl & Mackenzie, 2018). Second, sexual reoffending is a collective term for different types of sexual crimes. It covers among others collecting child sexual exploitation material, voyeurism, indecent exposure, child sexual abuse, rape, and sexual murder. Men perpetrating these different crimes share dynamic risk factors but might also have dynamic risk factors typical for their specific offense. (e.g., hostility towards women vs. emotional congruence with children). Therefore, networks of dynamic risk factors regarding to distinctive sexual offenses could differ in their network topology. For this reason, it is recommended to explore networks of dynamic risk factors in different samples based on offense type. Third, most scientific research on dynamic risk factors predictive for sexual reoffending has been conducted in North American heterosexual men adjudicated for sexual offenses. We assume that the core principle of our NBM-RSR applies to people from various backgrounds. Namely, the risk of sexual reoffending stems from the construction of a self-sustaining network of causally connected dynamic risk factors influenced by factors both inside and outside the network. However, differences in the construction of networks of interacting dynamic risk factors might occur in populations matched regarding to for example culture (Helmus et al., 2012), gender (Carvalho et al., 2021), sexual orientation (Tabashneck & Judge, 2021), or being a transgender or gender diverse individual (Jumper, 2021). Future research will have to determine to what extent network construction varies within these groups. Fourth, despite their observed causal influence, the position of protective factors (e.g., characteristics of offenders, their environment, or their situation, that reduce the risk of future criminal behavior; de Vogel et al., 2009) remains unclear in the current NBM-RSR. This is largely due to the proposed mechanisms through which protective factors exert their risk reducing effect. de Vries Robbé (2014) described four mechanisms through which protective factors may have an impact on risk: A risk reducing effect (i.e., a direct causal effect on risk mechanisms); a moderator or buffering effect (i.e., influencing the probability that specific risk factors will lead to offending); a main effect (i.e., offering overall protection for future offending rather than influencing specific risk factors); and a motivator effect (i.e., enhancing or facilitating the later development of other protective factors). Future and more elaborate network models could take protective factors into account and place them within the network of dynamic risk factors or the external field.

Conclusion

We presented a network-based model of risk of sexual reoffending (NBM-RSR) that proposes the development and nature of risk of sexual reoffending to involve a complex self-sustaining network of causally connected dynamic risk factors. In contrast to the Propensities Model, the NBM-RSR provides a theoretical account of the development of dynamic risk factors, how they give rise to the risk of sexual reoffending, and how sustained change in this risk might take place. To further advance our understanding of the development and nature of the risk of sexual reoffending future research should test propositions derived from the NBM-RSR. Assuming future studies demonstrate the relative influence of specific dynamic risk factors on the network of dynamic risk factors, the NBM-RSR also has clinical implications. Based on these studies, clinicians are able to target dynamic risk factor(s) which, when changed, have relatively stronger effect on other dynamic risk factors and thereby are more likely to reduce the overall probability of sexual reoffending.

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Note

1. Statistical networks can be constructed and investigated using the R software environment (R Core Team, 2022). See Borsboom and colleagues (2021) for a more extensive introduction on network analysis in psychological science, Isvoranu and colleagues (2022) for an accessible textbook on network psychometrics for both novices and experienced researchers, and Burger and colleagues (2020) for guidance on reporting network analytic results in a scientific paper. Examples of r-codes to estimate and analyze networks of dynamic risk factors can be found in the supplementary materials of previous studies (regarding cross-sectional data: van den Berg et al., 2020; van den Berg et al., 2022; regarding longitudinal ESM data: van den Berg et al., 2023).

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