Everyday Network Exposure to Crime and Victimization and its Association with Commercial Sexual Exploitation

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Journal of Quantitative Criminology
https://doi.org/10.1007/s10940-026-09684-4

ORIGINAL PAPER

Everyday Network Exposure to Crime and Victimization and its Association with Commercial Sexual Exploitation

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Received: 15 April 2026 / Accepted: 7 July 2026

Abstract

Objectives To examine whether exposure to crime within individuals' immediate social networks is associated with the risk of commercial sexual exploitation (CSE) victimization and assess whether this reflects an independent network effect rather than underlying individual or structural vulnerabilities.

Methods A population-based dataset of minors and young adults in the Netherlands (2016–2023) with police-recorded CSE victimization was used and linked to large-scale ego-network data (household, family, school, neighborhood, and work ties). These unique data provided an innovative lens through which to study network exposure and victimization risk. Latent profile analysis identified patterns of network exposure to offending and victimization. Individuals were assigned to profiles using modal classification. Matching weights were applied to adjust for selection into the high-exposure profile based on individual and neighborhood covariates. Next, a set of weighted logistic regression models with doubly robust adjustment estimated associations across three comparisons: CSE victims versus (1) other sex crime victims, (2) other crime victims, and (3) the general population.

Results Across all comparisons, individuals in the high-exposure network profile had a substantially higher likelihood of CSE victimization, also after adjusting for individual risk factors (e.g., prior victimization, youth care involvement) and neighborhood characteristics.

Conclusions Exposure to crime within proximal social networks constitutes a distinct and persistent risk factor for CSE victimization. These findings extend lifestyle and routine activity theories by emphasizing relational, rather than purely situational, exposure to risk. Limitations include potential unmeasured confounding, temporal ambiguity, and classification uncertainty in latent profiles. Future research should further examine causal mechanisms and incorporate network-informed prevention strategies targeting relational environments.

Keywords Sexual Exploitation · Network Exposure · Victimization · Latent Profile Analysis · Matching Weights

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Published online: 31 July 2026

Introduction

Commercial Sexual Exploitation (CSE) is a severe form of violence and abuse where individuals, often minors and young adults, are coerced, forced, or manipulated into sexual activities for financial or other material gain by another person or group. While reliable estimates of the prevalence of CSE victimization in the population are still lacking, it is believed that a substantial number of children and young adults are victimized or at risk. Experiencing CSE victimization is found to be associated with profound and long-lasting detrimental physical, psychological, and social outcomes (e.g., Barnert et al. 2022; Perry et al. 2022). In many countries, CSE of minors and young adults is therefore recognized as a serious and persistent social problem, criminalized as a form of human trafficking involving the sexual exploitation of individuals through coercion, manipulation, fraud, or deceit, with coercion presumed in cases involving minors (UNODC, 2024). To tackle this problem and safeguard young people from future harm, detailed insight into factors contributing to CSE victimization is pivotal.

The emphasis of extant empirical studies into CSE has been on individual-level characteristics that are associated with an increased likelihood of experiencing CSE (de Vries & Goggin 2020; Franchino-Olsen 2021; Laird et al. 2020). An emerging body of research however, has begun to highlight the socially embedded nature of CSE (de Vries et al. 2024; de Vries et al. 2025a, b; de Vries & Cockbain 2024; Weston & Mythen 2023). CSE is a form of sexual victimization that is by definition non-incidental and often occurs within broader contexts of peer, family, and community crime and violence (de Vries et al. 2025a, b; de Vries et al. 2020, 2024; Reed et al. 2019; Reid et al. 2015). Qualitative studies indicate that individuals are often recruited into CSE through pre-existing social ties, such as family members, intimate partners, or friends, rather than strangers (de Vries et al. 2025a, b; Reed et al. 2019), whereas findings from scarcely available quantitative research suggest that exposure to victimized or offending peers might also be associated with increased risk of experiencing CSE (de Vries et al. 2024; de Vries et al. 2025a, b). To fully grasp the dynamics of CSE victimization, research therefore needs to move beyond individual-level risk factors and broaden its empirical focus to include relevant features of the social environment.

The present study seeks to unravel how social exposure to crime within different types of everyday networks relates to experiencing CSE, and whether this association reflects a genuine network effect or, instead, captures underlying structural conditions that shape both exposure and vulnerability (i.e., individual and contextual risk factors). To examine how exposure to crime within everyday social networks influences the risk of CSE, this study draws on innovative population-based administrative datasets about ego network contacts spanning household, family, neighborhood, school and workplace (Bokányi et al., 2023; Bos et al. 2022). These data were obtained for a sample of police-reported minors and young adults who reported experiences of CSE in the Netherlands between 2016 and 2023, and three comparison groups (sex crime victims, other crime victims, and a general population) The availability of data on both police-reported CSE victimization and offending, together with comprehensive information on ego networks composed of ordinary contacts makes the Netherlands a uniquely suited setting for this research. To date, the empirical foundation of the networks-and-crime literature has been built largely on more constrained data, including information on ego networks obtained from surveys, including the Add Health,, and self-reports or administrative data from singular contexts such as street gangs, co-offending groups and incarcerated samples (e.g., Haynie 2001; Morselli 2009; Papachristos 2009; Sarnecki 2001). The data drawn on here link virtually every individual registered in the Netherlands to their household, family, neighborhood, school and workplace contacts, providing a new lens on how crime and victimization are socially distributed. The use of these data enables the first robust examination of whether exposure to police-reported crime within everyday ego networks increases the likelihood of experiencing CSE victimization relative to individuals who experience other forms of (sexual) victimization and to individuals in the general population, where victimization rates are substantially lower.

By focusing on exposure to crime within everyday social structures, this study adds to the broader networks-and-crime scholarship. Much of that scholarship, including foundational work on social contagion and network exposure to violence is based on co-offending networks or has converged on peer exposure as the central relational mechanism for explaining crime involvement (e.g., Haynie 2001; Charette and Papachristos 2017; Morselli 2009; Papachristos, et al. 2015a, b; Sarnecki 2001; Schreck et al., 2004; Turanovic 2022). With new data on everyday contacts across five different network layers, the present study is uniquely positioned to test which other relational contexts can transmit victimization risk.

In doing so, this study also contributes to the evaluation and refinement of established victimization theories emphasizing lifestyle exposure, routine proximity to crime, and target attractiveness (Cohen & Felson 1979; Fattah 2000; Hindelang et al. 1978; Meier & Miethe 1993; Miethe & Meier 1990), offering new insights on social vulnerability for victimization. More specifically, this study advances our understanding of CSE risk by shifting attention away from the individual-level vulnerabilities that dominate much empirical literature on CSE toward the social mechanisms that transmit risk across interpersonal networks. A networked account of victimization should do more explanatory work for some crimes than for others and its leverage is likely greatest for victimization that is relational and non-incidental, that is sustained within ongoing ties rather than arising from chance encounters, of which CSE is a paradigmatic case (Kulig & Cullen 2021). Studying CSE therefore offers a useful test of the exposure-victimization link, while the comparison with other forms of victimization allows us to begin mapping how that link may vary across crime types more generally. Practically, if a crime exposure-victimization link is indeed confirmed in the case of CSE, this would indicate that prevention and intervention strategies should target the social contexts and relational mechanisms that transmit vulnerability (de Vries et al. 2025a, b; Reed et al. 2019), and focus particularly on the types of social relationships that most profoundly – and most consistently – heighten one's vulnerability to victimization.

Background

Rethinking Risk for CSE: From Individual Vulnerabilities to Social Contexts

Previous research has mostly emphasized the importance of individual-level risk factors for CSE, such as previous experiences of victimization, previous contact with youth services running away, truancy, or a history of school dropout (see, for systematic reviews, Choi 2015; de Vries & Goggin 2020; Franchino-Olsen 2021; Laird et al. 2020). Although this focus has generated valuable insights into personal pathways to exploitation, it also contributed to a conceptualization of CSE risk that is primarily individualized and psychological and behavioral in nature. This, in turn, reflects a wider trend in public health and child maltreatment research to ‘privatize risk’; that is, to emphasize personal – and to some extent family-level – factors rather than interrogating the social environments that produce and reproduce *social vulnerability* (Karatekin et al. 2022; Rockhill 2001).

Recently however, CSE studies have begun to acknowledge the limitations of narrowly focusing on individual experiences and behaviors. These studies, for instance, highlight that previous work has largely overlooked heterogeneity in backgrounds of young people harmed by CSE, by drawing attention to a substantive group of CSE-involved individuals who lack prior histories of abuse or running away (Reid et al. 2019), or for whom such individual experiences and behaviors do not predict their elevated risk of experiencing CSE compared to other forms of abuse and violence (de Vries et al. 2020). Previous work also often overlooks factors like peer and family relationships, even though emerging evidence suggests that CSE and its related dynamics are deeply shaped by the social contexts in which they occur (de Vries et al. 2024; de Vries et al. 2025a, b; de Vries & Cockbain 2024; Weston & Mythen 2023). More generally, a strong focus on individual-level risk factors downplays the broader social and structural conditions in which exploitation occurs, leading proxies for the latter to have been insufficiently incorporated in prior empirical research on CSE risk.

Notable exceptions include qualitative studies aiming to unravel the mechanisms through which family members, peers, or intimate partners recruit or facilitate recruitment of young people into CSE (de Vries et al. 2025a, b; Reed et al. 2019). These studies provide valuable initial insights into *which* types of contacts may matter and *why* – for example, by identifying exploitative relationships or grooming processes within family, peer and school-based networks. However, by design, such qualitative approaches cannot provide a formal test of the crime exposure-victimization link.

A small number of quantitative studies has also begun to examine how exposure to delinquent peers or to CSE itself relates to personal experiences of CSE (de Vries et al. 2024; de Vries et al. 2025a, b). Using administrative data from child welfare services in the U.S., these studies find that exposure to victimized or offending peers significantly increases the likelihood of subsequent CSE victimization. Data limitations, however, have constrained the scope of these previous analyses, either in terms of specifying the types of network contacts involved or by focusing exclusively on high-risk individuals (e.g., de Vries et al. 2024, 2025a, b).

Consequently, there remains a need for quantitative research capable of distinguishing between different types of everyday social ties – such as family, household, school, workplace, and neighborhood networks – to identify how exposure to crime within these networks shapes vulnerability to CSE.

Theorizing the Everyday Network Exposure-Victimization Link

While in early childhood most minors are primarily exposed to family and caregiver relationships, extrafamilial connections become especially important during adolescence and early adulthood, as minors and young adults increasingly depend on and engage with peers and others outside of family and caregiver settings (Steinberg & Silverberg 1986). During this developmental period, peers and other social contacts strongly shape individuals' perceptions, behaviors, and choices, and, consequently, their exposure to risk (Berger et al. 2019; Sentse et al. 2013; Stubbs-Richardson et al. 2018).

These insights also feature prominently in classical criminology: Differential association and social learning perspectives hold that criminal definitions and behaviors are acquired primarily through intimate association (Akers 1998; Sutherland 1947), and decades of subsequent research confirm peers as among the most consistent correlates of adolescent offending (Haynie 2001; Sarnecki 2001; Warr 2002). Adolescents' social networks may serve as conduits for crime, victimization, or exploitation, for example, by normalizing risky behaviors or providing routine proximity to offending or victimized peers. To explain the role of network exposure to crime on the probability of personal victimization, previous research has relied on social contagion theory which posits that behaviors, experiences and attitudes can spread through social networks, much like viruses in a population (Christakis & Fowler 2010, 2013). Applied to victimization, this perspective suggests that exposure to crime within one's social network can increase an individual's own likelihood of involvement in crime and victimization (Forsyth & Gibbs 2020; Green et al. 2017; Papachristos et al. 2012; Papachristos et al. 2015a; Papachristos et al. 2015b; Sentse et al. 2013; Tracy et al. 2016; Turanovic 2022). This contagion perspective has been developed most fully within the networks-and-crime tradition, where studies of co-offending, gang violence, and the diffusion of gunshot victimization have repeatedly shown that an individual's risk of victimization is patterned by the offending and victimization of those with whom they co-offend (e.g., Charette & Papachristos 2017; Fox et al. 2021; Papachristos 2009; Papachristos et al. 2015a, b; Papachristos et al. 2015a, b). However, data limitations have impeded much of the existing networks-and-crime literature from considering the importance of exposure to crime in everyday, ordinary networks.

Network Exposure to Crime in Everyday Contexts as an Independent Mechanism of Individual Victimization Risk

Although peer exposure has dominated the network-and-crime literature, the theoretical perspectives examined here point to mechanisms that extend well beyond the peer group. Specifically, lifestyle-exposure, routine activity, and structural-choice accounts locate victimization risk not in criminal or delinquent peer association as such, but in the broader patterning of everyday life – the ordinary contexts of household, family, neighborhood, school, and workplace in which individuals are routinely embedded, and through which they may be brought into proximity with motivated offenders and deprived of capable guardianship. It is this wider, multi-contextual conception of exposure to crime in everyday life that the present study foregrounds.

Lifestyle-exposure theory and routine activity theory (RAT)—two of the most advanced early victimization theories—offer complementary explanations of victimization risk. Both frameworks emphasize that patterns of daily life, including where people go, when they are present, and with whom they interact (i.e., their everyday networks), create the situational contexts in which criminal opportunities arise and victimization may occur (Fattah 2000; Meier & Miethe 1993).

According to lifestyle theory (Hindelang et al. 1978), people's likelihood of encountering risky and harmful situations is determined by the extent to which their personal lifestyles and daily activities, including work, leisure, and social activities, position them in proximity to crime (Fattah 2000; Meier & Miethe 1993). In the context of CSE, relevant lifestyle patterns may include spending time in unsupervised online spaces, engaging in street-based activities (e.g., after running away from home) or maintaining relationships with peers or adults involved in exploitative or criminal networks. These activity patterns not only imply greater likelihood of exposure to potentially exploitative settings, but also an increased risk of being embedded within social networks where crime in general, or exploitation specifically, is normalized and transmitted through daily contacts (e.g., family, peers or neighbors) (de Vries et al. 2025a, b; Reed et al. 2019).

Routine Activities Theory complements this view by emphasizing that victimization is more likely to occur when motivated offenders, suitable targets, and the absence of capable guardians converge in time and space (Cohen & Felson 1979; Felson 1987; Felson & Clarke 1995; Felson & Cohen 1980). In the context of CSE, everyday social networks shape each of these elements. Peers, for example, may act as facilitators or recruiters (motivated offenders), normalize unsafe environments (increasing target suitability), or fail to provide protection or intervention (reducing guardianship) (de Vries et al. 2025a, b; Reed et al. 2019). Especially in environments characterized by potentially exploitative or unstable ties, such as unsafe household settings, certain school contexts, or informal hangout places, routine activities can heighten the likelihood of victimization through repeated exposure to motivated offenders. Empirical research finds that offering alternative forms of affection and love, or material support in the form of shelter, food, drugs or money are common tactics used by traffickers to draw individuals into CSE (Dank et al. 2015; de Vries et al. 2025a, b; Greenbaum 2020; Kennedy et al., 2007; Reed et al. 2019; see also Kulig & Cullen 2021). Furthermore, traffickers may also exploit the vulnerabilities that put young people in situations of exposure to harm in the first place, by using intimidation, isolation, and sometimes actual violence, to maintain control and dependence of trafficked individuals (e.g., Dank et al. 2015; see also Kulig & Cullen 2021). Over time, repeated exposure to crime may not only heighten youths' vulnerability to exploitation, but also normalize coercive or criminal exchanges within the group, blurring the distinction between survival strategies, opportunism, and victimization (Dank et al. 2015; de Vries et al. 2025a, b; Reed et al. 2019). As such, victims may come to view involvement in the sex industry as a promising or even empowering opportunity, while psychological manipulation by motivated offenders can further distort their sense of autonomy or self-worth (Dank et al. 2015; de Vries et al. 2025a, b; Kulig & Cullen 2021; Reid et al. 2015).

Building on lifestyle-exposure and routine activity perspectives, the structural-choice model of victimization integrates both structural and situational determinants of victimization risk (Meier & Miethe 1993; Miethe & Meier 1990). It posits that victimization risk arises from two interrelated processes: Broader structural conditions that shape individuals' exposure to crime, and situational choices that affect how offenders select their targets. According to this framework, proximity to motivated offenders and exposure to high-risk environments create the opportunity structure for crime, while target attractiveness and the level of guardianship influence whether an offender targets a specific individual. In the context of CSE, this means that certain environments, such as dysfunctional family settings, unstable housing, unsafe school settings or substance-using networks, constitute structural conditions that may repeatedly expose individuals to exploiters. Notably, living with older romantic partners, peers or family members involved in the sex trade, or running away from home or caregiver settings are well-documented risk markers for CSE vulnerability, as they heighten youths' visibility and accessibility for traffickers (Choi 2015; de Vries et al. 2020, 2024; Franchino-Olsen 2021; Reid 2014). These social contexts erode effective guardianship and increase the likelihood that victimization becomes enduring rather than incidental. As Kulig and Cullen (2021) observe, while many crimes are episodic encounters between offenders and victims, CSE is relational and sustained – rooted in patterns of repeated exposure, dependence, and coercion (de Vries et al. 2025a, b; Reed et al. 2019).

In sum, these lifestyle-exposure and routine activity perspectives interpret social networks as independent mechanisms linking an individual's risk of victimization to the offending or victimization of others within their network. In this view, network effects operate alongside structural opportunities and exert an influence above and beyond individual experiences and contextual conditions. These mechanisms also imply that the explanatory weight of network exposure should vary across crime types. Classic lifestyle and routine activity formulations were developed largely for predatory, direct-contact offenses, where victimization turns on the momentary convergence of offender, target, and absent guardian in time and space (Cohen & Felson 1979; Hindelang et al. 1978). For episodic or stranger-perpetrated crimes, situational proximity and opportunity may dominate, and the composition of one's enduring ego-network may matter comparatively less. By contrast, for crimes that are relational and sustained, like CSE, but plausibly also other forms of exploitation, interpersonal violence, and group-embedded violence such as gang conflict, victimization is bound up with ongoing relationships, so exposure within everyday networks should be a far more central mechanism. On this logic, a network account is a specification of when relational, rather than situational, exposure carries the most risk.

Network Exposure as a Proxy for Structural and Meso-Level Conditions

An alternative explanation is that network exposure to crime may function as a more refined proxy for underlying structural or meso-level conditions than conventional neighborhood-level dynamics. Criminological research has long underscored the importance of neighborhood-level factors, such as concentrated disadvantage, social instability, or socioeconomic inequality as key correlates of crime, including victimization (Berg & Loeber 2011; Foster & Brooks-Gunn 2013; Keel et al. 2024; Miethe & McDowall 1993; Sampson 1985; Van Wilsem et al. 2006). Yet, much prior work has relied on aggregated neighborhood attributes, often overlooking how intermediate social contexts, such as family, school and workplace networks, may shape victimization risk. Structural environments may be conducive to crime not only by creating opportunities for crimes to occur, but also by conditioning social interactions, shaping guardianship, and embedding individuals in community dynamics that can either protect against or perpetuate harm. As such, exposure to crime and higher local offending rates may both signal underlying structural criminogenic conditions.

Still, neighborhood-level indicators may fail to capture the everyday social and institutional contexts in which exposure and vulnerability unfold. For example, an individual may reside in a generally disadvantaged neighborhood but on a relatively safe street within it or attend a high-risk school but be embedded in a lower-risk classroom. In such cases, exposure to criminally involved peers may capture variation in structural context that neighborhood-level aggregate measures obscure. This logic is particularly relevant for CSE, where victimization often occurs through offenders within a victim's immediate social networks and in the context of broader patterns of abuse and violence, for example within the family context (de Vries et al. 2025a, b; Reed et al. 2019).

Building on this logic, network exposure to crime may offer a more sensitive indicator of structural conditions than either geographic proximity or traditional neighborhood-level metrics. By mapping the structure and composition of individuals' immediate social environments, network exposure captures the meso-level contexts, such as peer groups, school classes, or social clusters, through which structural inequalities and opportunities for crime become manifest. In other words, who one is connected to, and how those connections are organized, can serve as a more precise account of the structural conditions in which crime and exposure unfold (Campana 2023; Faust & Tita, 2019; Papachristos et al. 2012), shaping both opportunity and vulnerability to victimization. This may be particularly important in the case of everyday networks, such as those formed through residence, schooling, or neighborhood proximity, which are often constrained by structural forces rather than the result of mere individual choice. To the extent that network exposure operates as a structural proxy, its apparent effect should diminish – or even disappear – once broader contextual conditions are accounted for.

Current study

The central objective of the current study is to better understand whether exposure to others involved in crime, either as offenders or as victims, is associated with an increased risk of subsequent CSE victimization, or whether this association primarily reflects underlying individual and contextual vulnerabilities that jointly shape both network composition and victimization risk. Although criminological research has extensively examined the role of social contexts in heightening vulnerability to victimization, much less attention has been devoted to understanding how everyday social relationships shape victimization experiences, particularly for severe and non-incidental crimes such as CSE. The current study addresses this gap by examining whether exposure to crime, through everyday social relationships with family members, peers, classmates, coworkers, and neighbors, heightens the risk of experiencing CSE. By distinguishing exposure to crime across qualitatively distinct contexts and identifying which relational contexts most strongly, and most consistently, elevate the risk of CSE, we also seek to contribute to the networks-and-crime literature that has tended to treat exposure to crime as a single, undifferentiated quantity. In addition, the design also speaks to how the exposure-victimization link may differ across crime types. Because CSE victims are compared not only with the general population but also with victims of other sex crimes and of other, non-sexual crimes, the analyses can indicate whether network exposure is a generic correlate of victimization or is especially pronounced for a relational, non-incidental harm such as CSE, providing an empirical entry point for theorizing exposure effects across the broader victimization literature.

Specifically, we test two competing hypotheses. The first posits that exposure to victims or offenders in one's everyday social network is positively associated with the likelihood of subsequent victimization, even after accounting for relevant individual-level characteristics (e.g., prior victimization histories) and neighborhood-level structural conditions (e.g., disadvantage and residential instability). Persistence of this association would be consistent with a relational mechanism through which victimization risk is transmitted across social ties, above and beyond compositional differences in individual vulnerability and neighborhood context. The second hypothesis conceptualizes exposure as a proxy for individual-level experiences (e.g., previous victimization) or broader meso-level structural conditions (e.g., concentrated disadvantage or social instability). From this perspective, the association between exposure and subsequent victimization is expected to be substantially attenuated once individual-level characteristics and neighborhood-level structural conditions are accounted for. Under this explanation, apparent exposure effects primarily reflect shared underlying vulnerabilities or contextual constraints that influence both network connections and victimization risk, rather than an independent effect of exposure itself. By contrasting these explanations, the current study seeks to clarify whether exposure contributes uniquely to victimization risk or whether its apparent effect is better understood as a proxy for individual and structural sources of vulnerability that cluster within social networks.

Methods

The stratified analytical sample consisted of 6,797 minors and young adults (between 12 and 27 years), approximately one quarter of whom were identified as victims of commercial sexual exploitation (CSE) based on police reports. To be included, individuals had to be registered in the Dutch population register (‘Basisregistratie Personen’, BRP) with reported ego networks in the year prior to the reported victimization (or the matched year, see below) during 2016–2023.[1]

Sample Construction

The sample was constructed using a total of 17 different population-level administrative datasets from the Social Statistics Datasets (SSB) from Statistics Netherlands (*Centraal Bureau voor de Statistiek,* CBS), the national statistical office of the Netherlands, which maintains and links longitudinal administrative registers across various domains such as demographics, socioeconomic status, and criminal justice contacts.[2] SSB contains virtually all administrative government registers on individuals to which CBS has access as part of its statutory task. Using a pseudonymized linkage key, individuals can be linked across registers, allowing the assessment of trends and patterns across a wide range of background characteristics. First, police-reported victim data was used to identify the complete population of reported victims of CSE. From January 1st 2016 through December 31st 2023,

[1] These years were chosen because 2015 was the first year in which the police registrations at Statistics Netherlands included a reliable number of police-reported victims of CSE; 2023 was the last year possible for matching the ego network data.

[2] Access to these pseudonymized data is available for scientific research against payment. While researchers do not have access to identifying information (each record has received unique person identifiers), individual-level data across many domains (e.g., security, social welfare, education) are provided and can be combined for anyone registered in the Netherlands. Researchers can access these microdata in a secure working environment for analyses.

the police had registered 1,403 minors and young adults as victims of CSE.[3] From this sample, 432 individuals were excluded because they lacked a BRP registration prior to or on the date of reported victimization or because no relationships were reported for them at all, which primarily concerned individuals born outside the Netherlands. Although police records documented their victimization, the absence of a BRP registration precluded linkage to information on other network and socioeconomic characteristics. As a result, the CSE subsample included 971 individuals.

Next, three comparison groups were constructed using the police-reported victimization file and the administrative demographic data for all individuals registered in the Dutch population registers (BRP) during 2016–2023. These comparison groups include minors and young adults (between 12 and 27 years old) randomly sampled from 1) a population with other reported sex crime victimization experiences; 2) a population with reported victimization experiences other than CSE and sex crime; and 3) the general population, a group characterized by substantially lower baseline rates of victimization. To avoid duplicate observations, individuals already included in the victimization-based groups were excluded from the general population sample. Including these comparison groups allows us to distinguish between risk factors specifically associated with CSE versus those that are also linked to sex crime victimizations or other types of victimizations more generally. Comparing individuals with CSE to the general population captures characteristics associated with vulnerability more broadly. Comparison groups were matched at a 1:2 ratio to those with CSE victimization experiences to obtain balanced samples and include minors and young adults between 12 and 27 years of age who had reported ego network contacts in the year before their included victimization (or year of matching in case of the comparison group drawn from the general population).

Ego Network Data

Population-level administrative ego network datasets provided detailed information on the social relationships of minors and young adults included in the analytical sample for the year prior to victimization (or, for individuals in the general population comparison group, the year prior to the matched year). CBS has made these ego-network data available for all individuals registered in the BRP, covering multiple relational layers using distinct administrative sources (see also Bos et al. 2022). To date, these network datasets have not been used to examine exposure–victimization associations (for an exposure–offending link, see Bos et al. 2022). Data has been made available in the form of edge lists and include relationships between individuals across five different layers: household members; family members; neighbors; classmates; and colleagues. CBS derived household relationships (e.g., family members or unrelated individuals sharing a residence) from a combination of population address data and tax records, which identify individuals forming a shared household. While many households consist of family units, particularly among minors and young adults, households may also include non-kin,

[3] The current sample is limited to police-reported victims only; the exclusion of victims reported by other organizations (e.g. service providers) could introduce bias if these organizations come across substantively different victims than police and did not report victimization concerns to police. Unfortunately, data linkage from the main service coordination provider in the Netherlands was not possible due to privacy concerns, which also precluded us from assessing potential differences between police-reported CSE and CSE reported by other organizations. Nonetheless, it is important to note that police were the most prominent reporter of CSE of minors and young adults throughout the study period).

Table 1 Descriptive statistics for ego networks of individuals with at least one contact (N=6,797)

Network Type	N	Percentage	Mean	Median	SD
Known Contacts (All)	6797	100	180.41	162	129.028
Known Contacts (House)	6346	93.365	8.629	3	69.539
Known Contacts (Family)	6339	93.262	20.994	17	16.261
Known Contacts (Neighbors)	6627	97.499	42.779	43	9.753
Known Contacts (Classmates)	4907	72.194	83.246	46	107.629
Known Contacts (Colleagues)	4148	61.027	84.665	100	30.844

such as friends, roommates or cohabiting partners. Family relationships are constructed using registered parent–child linkages in the Basic Population Register. These linkages allow for the identification of a wide range of kinship ties, including parents, children, siblings, grandparents, grandchildren, aunts, uncles, cousins, and co-parents. To minimize duplicate relationships, we excluded family members who were also household members from the family member layer, and kept these relationships only included in the household member layer (see also Bos et al. 2022).[4] Next, using the Basic Register of Addresses and Buildings (BAG) and the BRP, CBS defined neighbors as the members of the ten geographically closest households within a radius of 50 m (random selection was used for those households located at equal distances). Classmate relationships are derived from educational registers spanning primary to tertiary education. CBS defines classmates as individuals enrolled in the same school, in the same educational program and academic year. When more than 100 classmates were identified for an individual, a random selection of 100 classmates was retained. Colleague relationships were constructed by CBS using tax records on wage employment, which identify the employing organization of each worker in the Netherlands. Individuals employed by the same organization are considered colleagues. Because some firms can be very large and may operate across multiple locations that are not distinguishable in the data, CBS restricted the colleague network layer for firms with more than 100 employees to the 100 coworkers living closest to the individual, increasing the likelihood of actual acquaintance. Table 1 reports the overall summary statistics for ego networks, which had an average size of 180 contacts per person, with varying network sizes depending on the network layer.

Individual-level and Neighborhood-Level Datasets

To supplement the network and victimization data, several additional datasets from Statistics Netherlands were used to obtain information on exposure to crime, individual-level characteristics of all individuals included in the sample, and characteristics of the neighborhoods in which they resided. These data are available for all individuals registered in the Dutch population register (BRP) and were linked to the analytical sample used in this study. Rather than relying on a single baseline year, information from the relevant reference

[4]A small number of duplicate ties remain because individuals can appear in multiple other network layers (e.g., a neighbor may also be a family member). These duplicates were retained, as their frequency was too low to warrant modeling multiplexity.

year (e.g., the year of victimization or the corresponding matched year) was linked to each individual's record. This included police victimization records provided by Statistics Netherlands to identify prior reported victimization, while police suspect records were used to capture individuals' criminal histories. These were obtained for individuals in the analytical sample and members of their ego networks.

Additional datasets used to construct individual-level covariates (discussed below), covered involvement in special education involving people with cognitive disabilities, learning delays due to illness or other special care needs; school dropout histories; household composition; socioeconomic status of individuals and their parents; historical track record of addresses; and previous contact with youth service agencies. Additionally, residential address information, which was pseudonymized with unique address and municipality codes using the Basic Registers of Addresses and Buildings, was gathered to assess number of times moved. Using these addresses and municipality codes, two publicly available datasets were used to derive neighborhood socioeconomic indicators (obtained from *Kerncijfers wijken en Buurten*, KWB) and crime reports (obtained from the police open data initiative).

Measures

Outcome Measure: Experiencing CSE Victimization

Our primary outcome measure indicates whether an individual had experienced CSE victimization (1 = "Yes"; 0 = "No"). To assess whether the factors associated with CSE victimization differ from those associated with other (sex) crime victimizations, we conduct our analysis across different subsamples. Specifically, we examine exposure effects on CSE victimization compared to (1) those who experienced another form of sex crime victimization, (2) those who experienced other crime victimization (not CSE and not sex crime); and (3) the general population.

Key Independent Variable: Exposure to Reported Suspects and Victims in Ego Networks

Our main hypothesis is concerned with the relationship between network exposure to crime and individual CSE victimization risk. Therefore, we constructed multiple measures of exposure to suspects and victims within individuals' ego networks by linking each ego network member to police records to determine their crime histories. In total, ten exposure measures were created, capturing exposure to suspects *or* victims across the five relationship types (i.e., households, family members, neighbors, classmates, or colleagues), allowing for a more detailed analysis of how varying types of social relationships relate to victimization risk. Each exposure measure indicates whether an individual in the analytical sample had any ego network contacts in the previous year who had been involved in crime – either as suspects or victims – during the preceding five-year period. Because ego network sizes vary substantially across individuals, we transformed absolute counts of crime-involved alters into relative exposure measures, expressed as the percentage of ego network contacts with a history of crime involvement relative to the total number of ego network contacts.

Table 2 presents the mean relative exposure to crime across the various subsamples, indicating that reported victims of CSE have significantly higher mean exposure to victims and

Table 2 Mean exposure to suspects or victims within ego networks as a proportion of total number of members in an ego network

	Total	**CSE (N=971)**	**Sex Crime (N=1,942)**	**Other Crime (N=1,942)**	**General Population (N=1,942)**
Variable	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**
Exposure to any victims	13.538 (6.646)	16.672 (8.452)	11.995 (6.013)***	14.658 (6.129)***	12.394 (5.946)***
Exposure to any suspects	5.973 (7.177)	11.309 (13.169)	5.039 (5.276)***	5.818 (5.638)***	4.395 (4.054)***
Exposure to any victims within the household	16.557 (26.686)	24.436 (29.554)	15.343 (25.398)***	17.326 (27.896)***	13.063 (24.256)***
Exposure to any suspects within the household	7.279 (19.247)	18.084 (28.35)	5.950 (16.832)***	6.431 (18.426)***	4.053 (14.188)***
Exposure to any victims within the family network	13.448 (12.722)	16.268 (15.458)	13.186 (12.046)***	13.945 (12.858)***	11.802 (11.394)***
Exposure to any suspects within the family network	5.755 (10.744)	9.655 (15.04)	5.726 (10.653)***	5.638 (10.184)***	3.950 (7.94)***
Exposure to any victims who are neighbors	12.280 (7.175)	12.275 (7.911)	11.943 (6.898)	13.009 (7.233)*	11.892 (6.947)
Exposure to any suspects who are neighbors	4.107 (4.403)	4.913 (5.44)	3.934 (4.212)***	4.284 (4.275)***	3.699 (4.066)***
Exposure to any victims who are classmates	8.233 (11.133)	11.812 (16.246)	7.334 (9.126)***	8.647 (11.291)***	6.931 (9.068)***
Exposure to any suspects who are classmates	5.076 (11.194)	11.025 (19.472)	4.380 (8.605)***	4.690 (10.294)***	3.185 (6.877)***
Exposure to any victims who are colleagues	9.612 (10.159)	7.933 (9.934)	7.369 (9.435)	12.572 (10.705)***	9.733 (9.654)***
Exposure to any suspects who are colleagues	3.594 (5.898)	3.404 (5.655)	2.476 (4.295)***	4.872 (7.322)***	3.530 (5.556)

*SD=Standard deviation. *: p-value<0.05; **: p-value<0.01; ***: p-value<0.001 (test results for differences between the CSE group and any of the comparison groups are based on t-tests given the continuous nature of the data)*

particularly to suspects than other reported (sex crime) victims and the general population. This difference can largely be attributed to substantially higher levels of exposure to crime within the household, family, and classmates ego networks.

Individual-Level Covariates

Motivated by previous research highlighting the importance of individual-level experiences and behaviors as potential risk-enhancing factors (de Vries et al. 2020; de Vries & Goggin 2020; Franchino-Olsen 2021; Kulig & Cullen 2021), and to assess whether exposure effects persist even after accounting for such factors, we included several individual-level covariates particularly relevant for minors and young adults and which were available in the CBS registers. To clarify, our aim was not to capture all possible individual-level vulnerabilities, but rather to examine exposure effects while adjusting for those individual-level experiences that have consistently been identified as risk-enhancing in both international and national literature.

Specifically, we included several demographic characteristics to assess potential differences between the sample of CSE victims and the comparison groups. *Sex* was included as a dichotomous variable (1 = "Female"; 0 = "Other"); age was included as a continuous variable; and migration background represents whether the individual or at least one of the parents was born outside of the Netherlands (1 = "Yes"; 0 = "No").

To assess potential vulnerabilities and risk-increasing factors on the individual level, we included variables indicating whether individuals had experienced *previous victimizations* (1 = "Yes"; 0 = "No") and *previous offending* (1 = "Yes"; 0 = "No"), measured as the number of any victimizations or offending, respectively, recorded within the five years preceding the year of CSE/sexual/any victimization (or the matched reference year for the general population). In addition, we constructed a household composition measure indicating whether individuals *lived without parents or caregivers* (1 = "Yes"; 0 = "No"). To account for educational circumstances, we included two binary measures indicating *whether an individual had attended special education at some point before the year of victimization* (1 = "Yes"; 0 = "No"), and whether an individual had any *school dropout history* (1 = "Yes"; 0 = "No") up to that year.[5] Furthermore, we also accounted for several other factors that could indicate vulnerability or instability throughout a youth's lifespan by assessing the number of times an individual had *moved* up until the year of victimization (or matched year), whether one or both of their parent(s) had received *public benefits* (including unemployment benefits, social assistance welfare benefits, social provisions, and sickness and disability benefits) (1 = "Yes"; 0 = "No"),[6] and whether or not they previously had *contact with youth service agencies* (1 = "Yes"; 0 = "No"), for example due to behavioral concerns or concerns in their living situation. A '0' on all dichotomous variables was interpreted as there were no reported concerns for a given variable.

Neighborhood-Level Covariates

In addition to individual-level vulnerabilities, broader contextual factors may play a role in shaping risks of victimization (Turanovic 2022). Neighborhood-level information was operationalized at the *wijk*-level, an officially defined administrative district in the Netherlands that comprises multiple smaller residential areas and is commonly used as a representation of the broader neighborhood context. We used this spatial scale to capture structural and contextual neighborhood characteristics that extend beyond individuals' immediate residential surroundings and reflect shared social and institutional environments.

Specifically, using data from the year preceding the year of victimization or the matched reference year, we accounted for neighborhood *population size* (log-transformed) and several proxy measures for concentrated disadvantage, drawn from publicly available CBS neighborhood statistics. These included the *average income across income recipients (log-transformed), ethnic heterogeneity* (operationalized as the percentage of non-Western migrants, excluding Europe, North America, Oceania, and Indonesia) in each neighborhood (see Steenbeek & Hipp, 2011), and the proportion of *rental housing* as an indicator of

[5] We excluded a variable indicating whether or not an individual went to school in the year preceding victimization (or the matched your), because it correlated too strongly with age across the models.

[6] We included the socioeconomic status of parents instead of the individuals themselves because the sample included many minors who were not employed yet. The socioeconomic status of parents is more comparable across sampling groups.

Table 3 Descriptive statistics for covariates (N = 6,797)

Variable	N (Total)	% (Total)	Mean	SD
Reported Sex	4552	66.97	-	-
Age	-	-	19.59	4.35
Migration Background	2042	30.04	-	-
Previous Victimizations	2047	30.12	-	-
Previous Offending	1163	17.11	-	-
Lives at home but not with two parents or caregivers	1292	19.01	-	-
Attends school	4475	65.84	-	-
Special education at all	813	11.96	-	-
School drop out	975	14.34	-	-
Times moved	-	-	4.97	3.61
Parent receives public benefits	2198	32.34	-	-
Previous contact with child services	2247	33.06	-	-
Population Size	-	-	17,265.92	19,471.49
Population Size (Log)	-	-	9.31	0.99
% Migrants Non-western background	-	-	15.26	14.59
Mean income for income recipients	-	-	32.59	6.96
Mean income for income recipients (Log)	-	-	3.47	0.19
% Rental Homes	-	-	44.15	17.25
Crime rate	-	-	49.44	54.02

residential instability. Lastly, we included *crime rate* per 1,000 neighborhood residents to assess differences in local crime exposure across neighborhoods while accounting for variation in population size. Table 3 presents the descriptive statistics for all covariates.[7] Missing values in 16 observations across key level-2 variables were imputed using information from observed values in other variables via multiple imputation by chained equations (MICE) implemented in R using the *mice* package (Buuren & Groothuis-Oudshoorn 2011).

Analytical Strategy

As shown in Fig. 1, we maintained a four-step analytical approach to examine the relationship between exposure to crime and the likelihood of experiencing CSE victimization compared to (1) those who experienced another form of sex crime victimization, (2) those who experienced other crime victimization (not CSE and not sex crime); and (3) the general population.

First, to capture heterogeneity in individuals' exposure to crime within their ego networks, we applied a person-centered latent profile approach using Gaussian finite-mixture modeling as implemented in the *mclust* package in R (Scrucca et al., 2023). Using all ten exposure

[7] All descriptive statistics are calculated at the individual level, consistent with the estimation sample for regression analyses. Level-2 variables therefore reflect the average exposure of individuals in the data. Standard errors in subsequent regression models are clustered at the neighborhood level.

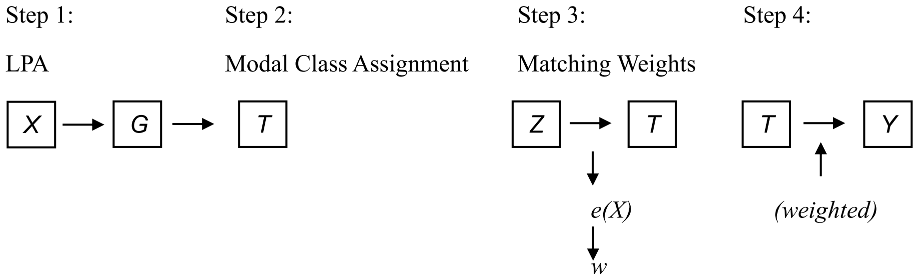


Fig. 1 Schematic overview of analytical steps

variables discussed above, this approach identifies subgroups of individuals who show similar combinations of exposure across multiple network layers. Latent profiles were based on exposure indicators such that $P\,(G|\,X)$, where X refers to the observed exposure indicators and G represents the latent profile group. We initially considered using general exposure measures (e.g., any exposure to suspects or victims) when modelling CSE risk. However, these measures can obscure meaningful differences in *where* exposure occurs (e.g., household vs. school vs. work). Including all ten exposure variables in a multivariate model was also not an option as this caused multicollinearity issues, left little room to add a set of important covariates and did not address the question which combinations of layers are important to understand the exposure-victimization link. A latent profile approach addresses these limitations by modeling co-occurring exposure patterns directly. Profiles were estimated on the full analytical dataset to ensure that the derived profile definitions are comparable across all individuals. Because a latent profile approach using *mclust* is sensitive to a random initialization, a set of 500 different models using different initialization seeds were used to identify the most optimal model with the lowest BIC, which is commonly interpreted as having the best fit.

Second, we assigned individuals to profile groups with the highest posterior probability as follows:

$$\widehat{G}_i = \arg\,\max_{g} P(G_i = g \mid X_i) \tag{1}$$

Here, $\widehat{G}_i$ refers to the modal assignment, while G_i denotes the true but unobserved latent profile membership. The modal assignment is defined as $\widehat{G}_i = \arg\,\max_g P(G_i = g \mid X_i)$, where X_i represents the vector of observed exposure indicators for individual i, g indexes the set of latent profiles, and $P\,(G_i = g|X_i)$ denotes the posterior probability of belonging to profile g given these indicators. The profile with the highest overall exposure to crime (discussed further below), which also included the highest number of reported victims of CSE was used as the treatment group T_i in subsequent analyses to assess the exposure-victimization link:

$$T_i = \mathbb{I}(\widehat{G}_i = \text{high-exposure profile}) \tag{2}$$

Third, to address potential selectivity in the exposure effects – operationalized as individuals' assignment to a high-exposure profile derived from the latent profile analysis[8] – we

[8] In several robustness analyses, we assess exposure effects through assignment in other exposure profiles derived from the latent profile analysis.

employed a propensity score weighting approach targeting the Average Treatment Effect in the matched sample (ATM). Propensity scores were estimated using logistic regression, and matching weights were applied to emphasize individuals in the region of common support. This approach assigns greater weight to individuals with comparable exposure probabilities while downweighing those with extreme propensity scores. Matching weights were selected because they approximate the estimand of propensity score matching while retaining the full analytical sample. Compared with conventional inverse probability weighting, matching weights are less sensitive to skewed propensity score distributions and reduce the influence of poorly comparable units, leading to improved covariate balance and more stable effect estimates without requiring arbitrary trimming or caliper specifications (Yoshida et al. 2017). Matching weights have been adopted as a favorable strategy in several studies using observational data to address selection into treatment, particularly when propensity score distributions are highly skewed and to avoid sample loss (see, for example, Deuren et al., 2021; Bea et al. 2025).

The propensity score for individual i can be denoted as e_i=$P(T_i = 1 \,|Z_i)$, in which T_i indicates treatment status (i.e., being assigned to the high-exposure profile in the latent profile analysis) given a set of individual-level and neighborhood-level covariates Z_i. The matching weights (w_i) are then computed as follows.

$$w_i = \begin{cases} \frac{\min(e_i,1-e_i)}{e_i}, if T_i = 1 \\ \frac{\min(e_i,1-e_i)}{1-e_i}, if T_i = 0 \end{cases} \tag{3}$$

Under this weighting scheme, observations with substantial overlap in covariate distributions receive greater weight, thereby targeting the population for which treated and untreated individuals are most comparable. This approach improves covariate balance while attenuating the influence of extreme propensity scores. Unlike propensity score matching, matching weights retain individuals with propensity scores near 0 or 1, although such observations receive minimal weight (Yoshida et al., 2017). In the current study, the propensity score represents the conditional probability of assignment to the high-exposure profile given all observed covariates, including demographic characteristics, prior experiences (e.g., previous victimization or offending), family characteristics, prior contact with youth care agencies, and neighborhood characteristics.[9] Matching weights were implemented using the *WeightIt* package in R (Greifer 2025).

Fourth, to estimate the effects of membership in a high-exposure profile on the likelihood of CSE victimization, we employed weighted logistic regression, using the matching weights as probability weights in survey-based regression designs:

$$\begin{gathered} logit\left[P\left(Y_i = 1\right)\right] = \alpha + \beta T_i + \gamma' Z_i \\ \text{with weights } w_i \end{gathered} \tag{4}$$

Because our objective was to examine specific pairwise contrasts for all three comparisons (CSE versus 1) other reported sex crime victims; 2) other crime victims; and 3) the general population), three separate binary logistic regressions using the same outcome measure

[9] Neighborhood-level variables (including percentage measures) were mean-centered prior to analysis to facilitate interpretation of regression coefficients.

(CSE victimization) were conducted for each comparison. Lastly, we report doubly robust estimates that combine matching weights with regression adjustment to further reduce bias from residual covariate imbalance and robust standard errors were clustered at the neighborhood-year level to account for residual dependence in the data. Multilevel models were not pursued because there was insufficient between-neighborhood variance to justify hierarchical modeling.

Findings

Latent Profiles for Exposure to Crime

Using model-based clustering to identify latent exposure profiles, a four-profile solution provided the best fit to the data based on 500 models estimated with randomized initialization (log-likelihood = −66,063.03; df = 236; BIC = −134,208.6; ICL = 126,936.4). In addition to providing the best statistical fit, the four-profile solution yielded substantively distinct and interpretable patterns of crime exposure across the different social network layers. Solutions with fewer profiles combined heterogeneous exposure patterns, whereas solutions with additional profiles primarily subdivided existing groups without producing meaningful new exposure configurations. The classification quality in our latent profile model was exceptionally high (M = 0.974, median = 0.999, IQR = 0.991–0.999), indicating low classification uncertainty, and the model was estimated across 500 random seed initializations to ensure a stable global solution, further reducing the likelihood that classification error meaningfully affected our results.

As illustrated in Fig. 2, profile 4 (n = 1,035) represented the high-exposure profile, displaying substantially higher mean exposure levels across several crime exposure indicators relative to the other profiles. Exposure was particularly elevated for victimized and offending family members, household members, and classmates. Unlike the other profiles, this group reflects pervasive exposure spanning multiple social contexts rather than concentration within a single network layer. A total of 329 CSE victims were classified in this profile, representing the largest proportion of CSE victims across the four profiles (31.79% of total *n* in this profile; 33.88% of reported CSE victims).

To compare, profile 1 ($n = 1{,}520$) was characterized by the highest mean exposure to victimized household members, but relatively low exposure to victimized or offending classmates, and moderate exposure within other network layers. Relative exposure should be interpreted in light of the generally smaller average household and family sizes compared to other network layers, which may help explain the larger relative exposures observed within these layers. This profile therefore captures individuals whose crime exposure is concentrated primarily within the household rather than extending broadly across their wider social networks. A total of 242 reported CSE victims were grouped in this profile (15.92% of total *n* in this profile; 24.92% of reported CSE victims). Profiles 2 ($n = 1{,}901$) and 3 ($n = 2{,}341$) were both characterized by relatively low overall exposure to crime, although profile 2 was marked by no exposure to victimized or offending colleagues, no exposure to offending household members, and low exposure to victimized and offending classmates. Profile 3, in contrast, was characterized by no exposure to victimized or offending household members. Thus, although both profiles represent relatively low-exposure groups, they differ in the

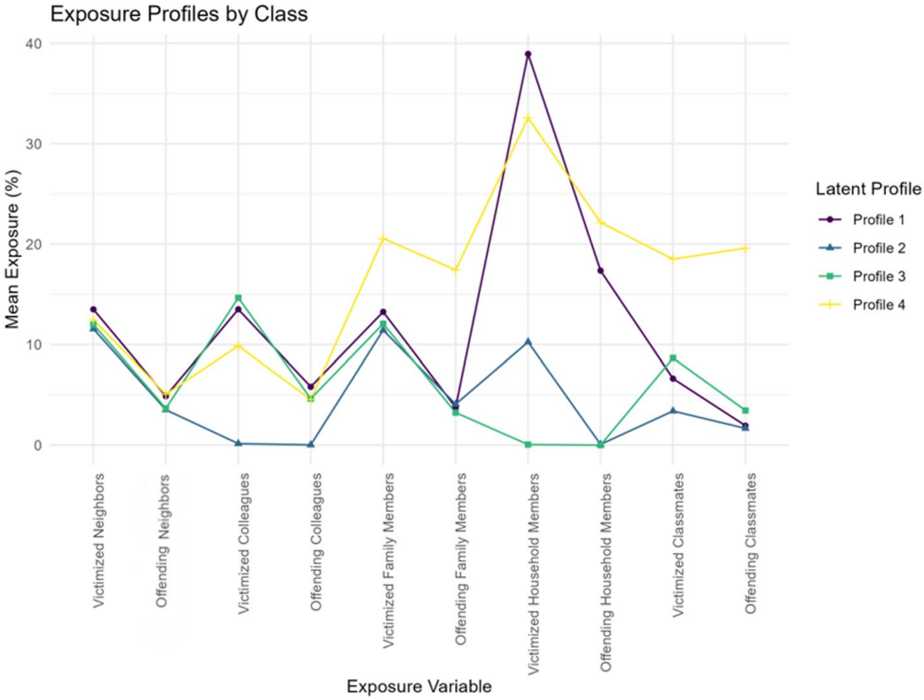


Fig. 2 Latent profiles and mean exposure to crime within each profile

social contexts in which exposure is absent, distinguishing individuals with limited household exposure (Profile 3) from those with particularly limited workplace and household offending exposure (Profile 2). A total of 212 reported CSE victims were assigned to Profile 2 (11.15% of total *n* in this profile; 21.83% of reported CSE victims) and 188 reported CSE victims to Profile 3 (8.03% of total *n* in this profile; 19.36% of reported CSE victims). The high-exposure profile (Profile 4) was used as the treatment group in the subsequent analyses employing matching weights, as discussed in the following section.[10]

Findings from the Matching Weights Regression Models

To examine whether exposure to victims or offenders is indeed associated with an increased likelihood of CSE victimization and whether such exposure distinguishes CSE victims from other victim groups and the general population, we applied matching weights to construct balanced samples of individuals with high exposure (i.e., membership in the high-exposure latent profile, profile 4) and lower overall exposure. This procedure was conducted separately across the three comparison groups: (1) CSE victims versus other sex crime vic-

[10] We also considered applying multi-group matching weight procedures, in which all latent profiles are treated as multiple potential treatments within a single model, using one profile as the reference category. However, diagnostic tests indicated a poorer model fit. This appears to stem from the fact that the latent profiles represent conceptually distinct categories that are influenced by the included covariates in different ways. We therefore treat each profile as a separate treatment in distinct analyses. Although we focus primarily on the effects of membership in the high-exposure profile, we also examine the effects of membership in the other profiles in additional sensitivity analyses.

tims, (2) CSE victims versus other crime victims, and (3) CSE victims versus the general population.

Initial covariate balance diagnostics indicated substantial selection into the high-exposure profile. Specifically, covariate balance plots, shown in Fig. 3, revealed substantive absolute mean differences between highly exposed and less exposed individuals across a range of individual- and neighborhood-level covariates, suggesting that the two groups differed prior to weighting, on a number of individual-level variables (especially age, previous victimization, number of times moved) and several neighborhood-level indicators (population, % non-Western population and % rental housing), depending on the specific comparison made. Applying matching weights substantially improved covariate balance; the standardized mean differences for all covariates fell within the commonly accepted range for adequate balance (generally below |0.10|), indicating that the weighted samples approximated balanced comparisons between the highly exposed and less exposed groups.

Table 4 reports the Effective Sample Sizes (ESS) for both the treated (high-exposure) and untreated (lower-exposure) groups across the three comparisons. Because matching weights alter the contribution of each observation to the analysis, classical sample size and degrees of freedom are less meaningful for assessing the statistical information in the weighted data. Instead, an ESS is more commonly used as a diagnostic of the amount of information retained after weighting. ESS is calculated as:

$$\text{ESS} = \left(\sum w_i\right)^2 / \sum w_i^2 \tag{5}$$

where w_i denotes the matching weight assigned to observation i. The ESS for the treated group exceeded 95% of the original treated sample in every comparison, indicating that individuals in the high-exposure profile received relatively stable weights and contributed strongly to the weighted analyses. For the untreated group, ESS remained above 40% of the original sample across all comparisons, indicating a moderate but still acceptable reduction in information due to the down-weighting of poorly comparable units. Taken together, these diagnostics suggest that the matching weights produced a well-defined overlap population for estimating exposure effects.

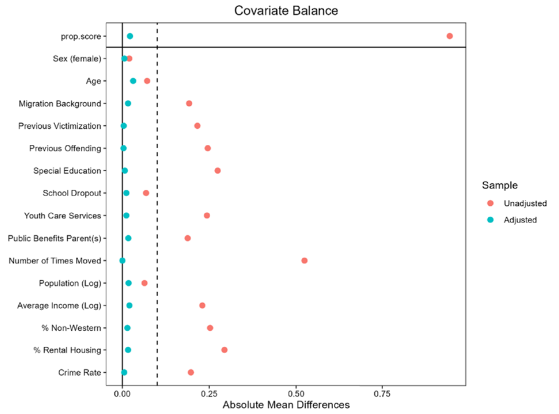
The matching weights were subsequently incorporated as probability weights in weighted logistic regression models estimating the association between exposure and CSE victimization. Robust standard errors were clustered at the neighborhood–year level to account for potential residual dependence in the data. The models, shown in Table 5, additionally included covariates used in the propensity score model, resulting in doubly robust estimates that combine propensity score weighting with regression adjustment.

Across all three outcome comparisons, membership in the high-exposure profile was consistently and significantly associated with an increased likelihood of CSE victimization. When comparing CSE victims to other sex crime victims, individuals in the high-exposure profile had 1.712 times higher odds of CSE victimization (OR = 1.712, 95% CI [1.359, 2.158], $p < 0.001$). The association remained significant in comparisons with other crime victims (OR = 1.372, 95% CI [1.042, 1.807], $p < 0.05$). and the general population (OR = 1.742, 95% CI [1.244, 2.437], $p < 0.01$).

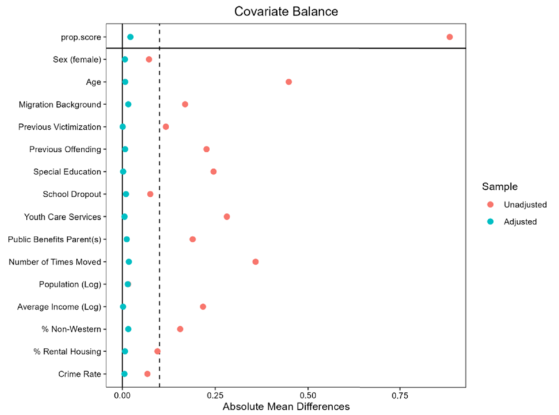
These findings indicate that elevated exposure to victimized or offending individuals within one's household, family, or school environment is consistently associated with a

Fig. 3 Covariate balance plots representing unadjusted and adjusted mean differences between treatment (high-exposure profile) versus other

a) Subsample (N = 2,913) comparing reported victims of CSE with reported victims of *other sex crimes*



b) Subsample (N = 2,913) comparing reported victims of CSE with reported victims *of other crimes*



c) Subsample (N = 2,913) comparing reported victims of CSE with *the general population*

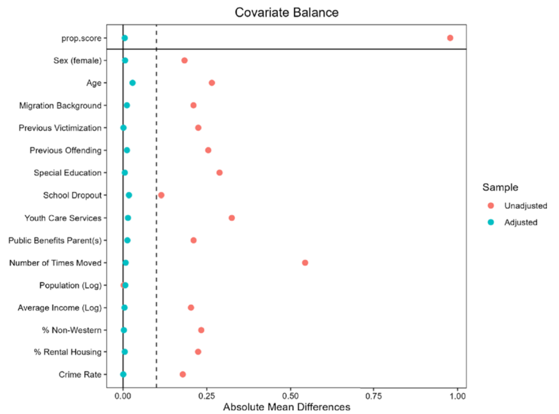


Table 4 Effective sample sizes (ESS)

	CSE versus Sex Crimes	CSE versus Other Victimization	CSE versus General Population
Unadjusted N Treated Group (High Exposure Profile)	578	620	495
ESS Treated (% of Original N)	552,78 (95,64%)	598,425 (96,52%)	471,640 (95,28%)
Unadjusted N Control Group	2335	2293	2418
ESS Untreated (% of Original N)	1108,443 (47,47%)	1190,968 (51,94%)	1001,020 (41,40%)

ESS is the Effective Sample Size, which indicates the size of the overlap (matched) population

higher likelihood of CSE victimization. Importantly, the effect persists across different comparison groups, suggesting that such exposure distinguishes CSE victims from other victimized individuals and the general population.

Although the primary focus of the analysis was on the exposure-victimization link, several individual-level covariates remained significantly associated with CSE victimization in the weighted regression models. These associations were most pronounced in the comparison between CSE victims and the general population, where individual characteristics – especially being female, having a migration background, having previous reports of victimization and offending, being enrolled in special education, receiving services from youth care, and increased number of times moved – consistently and significantly increased the odds of experiencing CSE victimization. By contrast, neighborhood-level covariates showed little consistent association with CSE victimization after weighting and adjustment, suggesting that contextual neighborhood factors contributed relatively little to the remaining variation in the likelihood of CSE victimization.

Sensitivity Analyses

Additional sensitivity analyses were conducted in which the treatment variable was redefined as membership in each of the other latent profiles rather than the high-exposure profile. Specifically, the matching weights procedure and subsequent weighted regression models were repeated using profile 1 (Appendix Table A.1), profile 2 (Appendix Table A.3), and profile 3 (Appendix Table A.5) as the treatment group.

When either profile 1, characterized by relatively high mean exposure to victimized household members, or profile 2, characterized by relatively low mean exposure levels, were used as the treatment groups, no significant associations with CSE victimization were observed across any of the four comparison groups. Using profile 3, with low mean exposure levels, as the treatment group, yielded a consistent negative association with CSE victimization across all comparisons. Membership in this profile was associated with lower odds of CSE victimization when compared with other reported sex crime victims (OR = 0.791, 95% CI [0.628, 0.995], $p < 0.05$), other crime victims (OR = 0.640, 95% CI [0.500, 0.820], $p < 0.001$), and the general population (OR = 0.668, 95% CI [0.509, 0.876], $p < 0.01$).

Table 5 Results from doubly robust logistic regression analyses using matching weights (Treatment Condition = Profile 4)

Variable	Sex Crime Victimization		Other Victimization		General Population	
	β (SE)	OR [95% CI]	β (SE)	OR [95% CI]	β (SE)	OR [95% CI]
Intercept	−6.264*** (0.597)	0.002 [0.001–0.006]	−3.844*** (0.589)	0.021 [0.007–0.068]	−6.047*** (0.639)	0.002 [0.001–0.008]
High Exposure Profile (Profile 4)	0.538*** (0.118)	1.712 [1.359–2.158]	0.316* (0.140)	1.372 [1.042–1.807]	0.555** (0.171)	1.742 [1.244–2.437]
Female	1.588*** (0.311)	4.894 [2.658–9.010]	3.606*** (0.228)	36.824 [23.534–57.620]	3.644*** (0.295)	38.240 [21.458–68.146]
Age	0.113*** (0.023)	1.120 [1.071–1.171]	−0.087** (0.025)	0.917 [0.872–0.963]	−0.003 (0.027)	0.997 [0.946–1.051]
Migration Background	0.606*** (0.138)	1.833 [1.399–2.401]	0.409** (0.153)	1.505 [1.115–2.030]	0.447* (0.187)	1.564 [1.084–2.257]
Previous Victimization	0.807*** (0.134)	2.241 [1.722–2.916]	0.289 (0.150)	1.335 [0.994–1.793]	0.870*** (0.187)	2.386 [1.654–3.442]
Previous Offending	0.747*** (0.144)	2.110 [1.590–2.800]	0.596*** (0.165)	1.814 [1.313–2.506]	1.091*** (0.218)	2.978 [1.943–4.564]
Special Education	0.618*** (0.145)	1.856 [1.396–2.467]	0.700*** (0.190)	2.013 [1.388–2.920]	1.075*** (0.229)	2.929 [1.870–4.587]
School Dropout	0.500** (0.167)	1.649 [1.188–2.289]	0.289 (0.177)	1.335 [0.944–1.888]	0.209 (0.226)	1.232 [0.791–1.919]
Youth Care Services	0.796*** (0.184)	2.217 [1.545–3.180]	1.289*** (0.178)	3.628 [2.557–5.148]	1.714*** (0.205)	5.553 [3.715–8.300]
Public Benefits (Parents)	0.033 (0.128)	1.033 [0.803–1.329]	−0.060 (0.145)	0.941 [0.709–1.250]	0.317 (0.179)	1.373 [0.968–1.949]
Number of Times Moved	0.076*** (0.017)	1.079 [1.044–1.115]	0.149*** (0.024)	1.160 [1.106–1.217]	0.155*** (0.026)	1.168 [1.109–1.229]
Population (log)	0.071 (0.073)	1.074 [0.932–1.238]	0.078 (0.079)	1.081 [0.927–1.262]	0.166 (0.092)	1.180 [0.985–1.414]
Average Income (log)	−0.045 (0.084)	0.956 [0.810–1.127]	−0.170 (0.083)	0.844 [0.713–0.999]	−0.122 (0.104)	0.885 [0.722–1.086]
% Non-Western	0.036 (0.093)	1.037 [0.864–1.246]	0.050 (0.099)	1.051 [0.865–1.278]	0.006 (0.132)	1.006 [0.777–1.302]
% Rental Housing	−0.091 (0.105)	0.913 [0.744–1.122]	−0.283 (0.117)	0.754 [0.599–0.950]	−0.142 (0.133)	0.868 [0.669–1.126]
Crime Rate	0.099 (0.065)	1.104 [0.972–1.253]	0.143 (0.075)	1.153 [0.995–1.336]	0.006 (0.088)	1.006 [0.847–1.195]

Standard errors (SE) are clustered on the neighborhood-year combinations (N = 6,797). OR = Odds Ratio. CI = Confidence Interval. *: p-value < 0.05; **: p-value < 0.01; ***: p-value < 0.001

Across these sensitivity analyses, the effects of individual-level covariates were broadly similar to those observed in the models using the high-exposure profile as the treatment condition. Additionally, several neighborhood-level variables, particularly the percentage of rental housing, average neighborhood income, and neighborhood crime rates, appeared statistically significant in some models. However, these effects were not consistent across treatment definitions or comparison groups, suggesting limited robustness of neighborhood-level associations.

Discussion

This study set out to examine whether everyday exposure to crime within individuals' immediate social networks is associated with an increased risk of commercial sexual exploitation (CSE) victimization, and whether this association reflects a distinct network effect or instead captures underlying structural vulnerabilities. We used a unique and innovative population-based dataset containing information on minors and young adults who reported experiences of CSE in the Netherlands between 2016 and 2023, combined with comprehensive information on ego networks composed of housemates, family members, neighbors, classmates and colleagues (Bokányi et al. 2023; Bos et al. 2022). These data – population-scale, multi-relational ego-networks spanning household, family, neighborhood, school, and workplace ties – allow us to move beyond the single-layer peer and co-offending data on which the networks-and-crime literature has largely relied, and to ask not simply whether network exposure matters but which everyday relational contexts transmit it, and with which intensity. Across all model specifications and comparison groups, the findings provide consistent and robust evidence that individuals embedded in high-exposure networks, defined by a relatively large proportion of offending and victimized alters within households, families and schools, face a significantly elevated likelihood of CSE victimization. Crucially, this association persists even after accounting for selection effects of individual and neighborhood-level risk factors on having high-exposure networks, suggesting that network exposure represents a meaningful and independent dimension of vulnerability to victimization.

Additionally, the association between network exposure to crime and CSE victimization risk was persistent across all comparison groups, including comparisons with other sex crime victims, other crime victims, and the general population. This comparison structure provides an important insight into the specificity of the observed association. Had the high-exposure profile merely captured a general propensity toward victimization, we would expect the association to attenuate substantially when comparing CSE victims with other victimized individuals. Instead, the effect remained similar in magnitude across all comparisons, suggesting that high-exposure networks capture a dimension of vulnerability that is particularly relevant to CSE rather than simply reflecting elevated victimization risk more broadly. This is a notable finding, given that CSE often involves processes such as grooming, coercion, and exploitation that are inherently relational and non-incidental (de Vries et al. 2025a, b; Kulig & Cullen 2021; Reed et al. 2019).

One plausible interpretation is that certain types of social ties, particularly those within households, families, and school environments, play a critical role in structuring access to victims and shaping vulnerability. These social contexts are characterized by repeated interaction, trust, and dependency, which may be exploited by offenders. Moreover, exposure to victimization or offending within these close everyday relationships may normalize harmful dynamics, reduce perceived risks, or create pathways through which exploitation can occur. In line with prior work (e.g., de Vries et al. 2025a, b; Reed et al. 2019), such relational mechanisms may facilitate both direct and indirect transmission of vulnerability, including through social learning, coercive control, or network-based recruitment. Importantly, individual-level vulnerabilities (e.g., being female, and being enrolled in special education) are still important correlates for elevated victimization risk.

Neighborhood-level structural conditions such as disadvantage and residential instability on the other hand showed limited and inconsistent associations with CSE victimization risk, suggesting that broader contextual characteristics may play less of a direct role than often assumed, at least in the current European context. This further supports the interpretation that proximal social environments, rather than broader structural contexts, are the primary channels through which risk is transmitted. In terms of the two accounts outlined at the outset, this pattern aligns more closely with network exposure operating as an independent dimension of risk than as a mere proxy for neighborhood-level structural conditions; had exposure primarily captured concentrated disadvantage or residential instability, its association with CSE should have attenuated once these conditions were accounted for. It also aligns with the ecological perspective that distal contexts exert their influence largely through more immediate relational settings.

Theorizing Victimization Risk Through a Network Lens

Our findings offer important contributions to established victimization theories, particularly lifestyle-exposure and routine activity frameworks (e.g., Cohen & Felson 1979; Hindelang et al. 1978; Miethe & Meier 1990). Traditionally, these perspectives conceptualize victimization risk as a function of individuals' lifestyles, routine activities, and proximity to motivated offenders, alongside target suitability and the absence of capable guardianship (Cohen & Felson 1979; Fattah 2000; Felson 1987; Felson & Clarke 1995; Felson & Cohen 1980; Hindelang et al. 1978; Meier & Miethe 1993). However, these frameworks tend to emphasize spatial and behavioral proximity and overlook the fact that individual routines are structurally embedded within enduring social relationships. Based on our analyses, we suggest that proximity to crime may be more accurately understood as relational rather than merely situational. In other words, individuals in high-exposure network profiles are not merely encountering risk in situational contexts, rather they are embedded in social environments where crime and victimization are part of everyday relational structures and interactions. These relational structures suggest that exposure is cumulative and persistently operating through social ties, thereby amplifying vulnerability beyond what traditional measures of routine activity capture. In this respect, our findings converge with social contagion and networks-and-crime perspectives, which hold that crime and victimization are patterned by the offending and victimization of those to whom one co-offends with (e.g., Charette & Papachristos 2017; Fox et al. 2021; Papachristos 2009; Papachristos et al. 2015a, b; Papachristos et al. 2015a, b). The findings also contribute to that literature by moving away from treating exposure as a largely undifferentiated quantity (e.g. a count of delinquent peers) to distinguishing between exposure across qualitatively distinct everyday contexts, with household, family and school exposure emerging as especially consequential for CSE victimization.

In addition, our findings call for a refinement of what is understood by target attractiveness (Fattah 2000; Meier & Miethe 1993). Rather than viewing attractiveness solely as an individual attribute (e.g., vulnerability or visibility), which is the dominant perspective in victimization research, including CSE studies (see, for systematic reviews, Choi 2015; de Vries & Goggin 2020; Franchino-Olsen 2021; Laird et al. 2020), our results suggest that vulnerability may be socially conferred. That is, embeddedness in high-risk networks may signal vulnerability to potential offenders, reduce guardianship, and increase visibility within exploitative contexts. Target suitability, therefore, may, for an important part, be relationally produced rather than individually inherent. As such, the conceptualization of CSE victimization risk should move away from solely scrutinizing individual vulnerabilities and also focus on the social environments in which social vulnerability arises; providing empirical support for a recent call in the literature on CSE (de Vries et al. 2024; de Vries et al. 2025a, b; de Vries & Cockbain 2024; Weston & Mythen 2023).

More broadly, the notion of social vulnerability resonates strongly with ecological systems theory (Bronfenbrenner, 1979), which posits that individuals are most profoundly shaped by their most proximal environments such as the family, household, and school contexts. The present findings corroborate this principle by showing that precisely these proximal network domains are where exposure to offending and victimization consistently translates into heightened CSE risk. In other words, the micro- and mesosystems appear to be critical loci through which vulnerability is produced and reproduced (see also de Vries et al. 2024, 2025a, b).

Implications for Prevention and Intervention

Our findings carry important implications for prevention and intervention strategies. If vulnerability to CSE is transmitted through social networks, then efforts to prevent exploitation must extend beyond individual-level interventions to also address the relational contexts in which risk is embedded. This includes focusing on the social environments where exposure is most concentrated, particularly in households, families, and school-based peer networks. Strengthening protective relationships and enhancing guardianship within these settings may be especially critical. This may involve supporting caregivers, improving school-based monitoring and support systems, and fostering prosocial peer connections that can counterbalance exposure to harmful influences (see also de Vries et al. 2025a, b; Finigan-Carr et al. 2019; Firmin 2020; Greenbaum 2020).

Recognizing that exploitation often occurs through trusted individuals or within seemingly normative relationships, prevention efforts should also more explicitly target the relational mechanisms that facilitate abuse. This includes equipping young people with the skills to identify grooming behaviors, boundary violations, and subtle forms of coercion, particularly when these occur within friendships, romantic relationships, or family networks. At the same time, caregivers, teachers, and other guardians need training to recognize early warning signs of relational exploitation – such as sudden shifts in peer networks, secrecy, or dependency on specific individuals – and to respond in ways that do not inadvertently isolate victims further (see also de Vries et al. 2025a, b for similar recommendations). Interventions should also promote open communication and trust, so that young people feel able to disclose concerns about individuals within their immediate social circles without fear of stigma or disbelief. While exposure to crime was most profound within households, families, and schools, and not so much within neighborhoods and work settings, it may be neighbors or colleagues who could potentially offer a helping hand to leave an exploitation situation, especially when housemates, family members or classmates are involved (see also de Vries et al. 2025a, b).

More broadly, these findings point to the potential value of network-informed interventions. Rather than focusing solely on individuals deemed “at risk,” such approaches would identify and engage key actors within social networks (e.g., influential peers or family members), who may either facilitate or help prevent victimization risk. For example, peer-led interventions could be designed to shift group norms, increase collective guardianship, and disrupt pathways through which exploitative behaviors are normalized or transmitted. Similarly, mapping risk within networks (e.g., identifying clusters of vulnerability or shared exposure to high-risk individuals) could help practitioners target interventions more strategically, intervening not only with victims but also with the relational structures that sustain exploitation. Taken together, a network perspective suggests that effective prevention requires not only strengthening individuals but also reshaping the social ties and environments through which vulnerability is produced and reproduced.

Limitations and Future Directions

Despite the use of innovative large-scale ego network data and a rigorous analytical framework to examine the association between network exposure and CSE victimization across multiple comparison groups, this study comes with several limitations. First, unmeasured individual and contextual factors may still bias the estimates. Although a wide range of observed characteristics was considered, unobserved vulnerabilities or unmeasured neighborhood dynamics may simultaneously shape both network exposure and the risk of victimization. This concern is a general one for observational network research, where it is notoriously difficult to separate a genuine exposure effect from latent homophily and from shared environmental conditions that lead similar individuals both to cluster together and to be victimized (Shalizi & Thomas 2011). Our design addresses selection on observed individual and neighborhood characteristics but cannot rule out that unobserved homophily contributes to the estimated association; the independence of the network effect should therefore be read as conditional on the covariates considered rather than as definitive. Second, despite the use of a causal inference approach, causal interpretation should be approached with caution. While exposure was measured in the five years preceding the year of police-reported victimization, the actual exploitation may have occurred weeks, months or even years prior to reporting. As a result, the temporal ordering between exposure and victimization cannot be established with absolute certainty. Although increased exposure is consistently associated with elevated risk across models, future research is needed to further unpack the causal relationship, ideally incorporating more precise timing and additional confounding factors. Additionally, future work could also further unpack exposure effects across varying demographics, including gender, race/ethnicity and age, to further understand if exposure to crime has different effects for different populations.

Third, another limitation of the current study concerns the use of modal class assignment derived from the latent profile analysis. Although this approach is commonly applied in practice, it does not account for classification uncertainty, which may attenuate effect estimates, particularly when classification accuracy is low (e.g., Bolck et al. 2004;Lê et al., 2025). In the present study, however, classification quality was high, as indicated by elevated posterior probabilities and limited dispersion, suggesting that the extent of misclassification (and therefore potential measurement error) is likely modest. Moreover, the implementation of existing methods that aim to account for classification uncertainty (e.g., three-step correction methods as proposed by Lê et al., 2025) is less straightforward when used in combination with weighting approaches such as matching weights. Applying classification uncertainty corrections with a matching weights approach risks introducing model dependence, particularly because it would require using the same set of covariates in two distinct weighting mechanisms, one addressing classification uncertainty in the LPA analysis and one addressing confounding in the matching weights regressions (and again in doubly robust regression models). These weights, however, are not independent and both derived from the same underlying model, which risks introducing additional model dependence and complicates the interpretation of the estimated effects. Nevertheless, we acknowledge that – despite the observed classification quality in this study – some degree of classification uncertainty remains, and future research could further explore the sensitivity of the results to alternative approaches that explicitly account for this uncertainty.

Fourth, the network data used in this study do not capture either the quantity or the quality of specific social relationships. As a result, network exposure should be interpreted as a proxy for potential social interaction rather than direct evidence of interpersonal influence. Given the way the data were constructed, it remains unclear whether individuals actually interacted with offenders or victims within their network. Instead, exposure likely reflects broader proximity to crime and the general risk level of an individual's social environment. Future research could therefore complement the current findings with survey-based (ego)network data to obtain more precise measures of actual social interaction, although such approaches are often limited in scalability. Relatedly, the network indicators used here are primarily quantitative and do not capture qualitative aspects of relationships, such as tie strength or emotional closeness. Incorporating these dimensions would provide a more nuanced understanding of how network processes contribute to victimization risk.

Lastly, our findings may be influenced by potential spotlight effects. Individuals connected to known offenders or victims may receive increased law enforcement attention, making their behavior and victimization more likely to be detected, regardless of actual risk. This selective visibility could inflate associations between network exposure and victimization. More broadly, our key measures (exposure, victimization) are derived from police records and may reflect patterns of enforcement rather than underlying behavior, particularly if policing is unevenly distributed across social or geographic contexts (e.g., disadvantaged neighborhoods). Although neighborhood-level controls partly account for such patterns, they cannot fully eliminate bias due to differential detection. This is a general limitation of administrative police-reported crime data but may be particularly salient in network studies when social network exposure measures are also constructed from police-recorded events. If law enforcement attention is disproportionately concentrated within particular social networks or neighborhoods, this may not only increase the likelihood that CSE victimization is detected but also shape the observed relationship between network exposure and victimization by increasing the visibility of both exposure and outcome within the same populations. We therefore interpret our findings as reflecting associations observed within police-recorded data. Future research could address this by incorporating alternative data sources, such as self-reports, victimization surveys, or complementary big data sources (e.g., online advertisements or forums), to better disentangle exposure effects from artifacts of law enforcement practices.

Conclusion

This study leverages large-scale ego-network data and a rigorous causal inference approach to demonstrate a robust link between network exposure to crime and CSE victimization. In sum, drawing on population-scale, multi-relational ego-network data and a selection-adjusted design, the study identifies network exposure to crime as a robust, context-specific correlate of CSE victimization, concentrated in household, family, and school ties and persistent across comparison groups. The persistence of this association across all comparison groups suggests that high-exposure networks capture a form of relational vulnerability that is not reducible to general victimization risk, highlighting the distinctive role of social network context in understanding CSE. While individual vulnerabilities, such as prior victimization and contact with youth care, remain important, our findings identify network exposure as an independent and persistent risk factor. In doing so, this study moves beyond the predominantly individual-level focus in CSE literature and highlights the importance of structurally embedded social environments. These results also extend lifestyle and routine activity perspectives by demonstrating that proximity to crime is not merely situational but embedded in enduring social ties. This underscores the need to conceptualize and measure victimization risk as a networked process.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10940-026-09684-4.

Acknowledgements The authors are grateful for valuable feedback on earlier versions of this paper received from the audience at the yearly conferences of the American Society of Criminology in Atlanta, United States (2024) and the European Society of Criminology in Bucharest, Romania (2024).

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