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Social correlates of specialized versus versatile offending patterns in intimate partner violence: A register-based study in Finland

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ABSTRACT

Purpose: The purpose of the current study was to examine the tendencies toward specialization and generalist offending among intimate partner violence (IPV) offenders and to assess whether some well-known correlates of criminal offending are differentially associated with various offending patterns.
Method: We use large-scale register-based data from Finland including all offenders in police-recorded cases of IPV between 2015 and 2019 (N = 19,030). Two different analytic approaches suggested for research on offense specialization are used: the multilevel item response theory (IRT) approach and latent class analysis (LCA).
Results: Significant tendencies toward both specialization and generalist offending were found in the data using both analysis methods. In addition, the correlates were differentially associated with specialized versus versatile offending patterns. Specialization in IPV was associated with, for example, female gender, older age, higher socioeconomic status, and having an immigrant background. The findings also show IPV specialization and generalist offending to be differentially associated with different victimization types.
Conclusions: The findings suggest that the idea of IPV offenders as specialists who do not engage in violence and crime in other contexts is not empirically fully accurate. Implications for future research, theory, and prevention policies are discussed.

1. Introduction

There is a plethora of research demonstrating that criminality is generally characterized by versatile offending patterns in contrast to specialization in certain types of crime (e.g., Blumstein, Cohen, Das, & Moitra, 1988; Bursik, 1980; Piquero, 2000). Correspondingly, the idea of all deviant and criminal behavior as a manifestation of the same underlying antisocial construct has been incorporated into criminological theory (e.g., Gottfredson & Hirschi, 1990), and there is extensive empirical evidence supporting the generalist models in contrast to type-specific models in explaining a wide range of different offending types (e.g., DeLisi, 2003; Felson & Lane, 2010; van Wijk et al., 2005). In addition to its theoretical implications, the issue of generalist versus specialized criminal careers is critical to policy and practice, as the findings of versatile offending patterns may suggest, for instance, a general, non-crime-specific set of crime prevention strategies (e.g., Piquero, Theobald, & Farrington, 2014).

In the study of intimate partner violence (IPV), offenders are often theorized to be mainly specialists who do not engage in violence and crime outside the intimate relationship or domestic context (e.g., Bouffard, Wright, Muftić, & Bouffard, 2008; Wolbers & Ackerman, 2020). The assumption of IPV offenders as specialists has also been deeply incorporated into IPV prevention and treatment practices (e.g., Gover, Brank, & MacDonald, 2007; Velonis, Mahabir, Maddox, & O'Campo, 2020). Contradicting this idea, several empirical studies have demonstrated versatile offending patterns by IPV perpetrators (e.g., Hilton & Eke, 2016; Ouellet, Paré, Boivin, & Leclerc, 2016; Piquero et al., 2014; Richards, Jennings, Tomsich, & Gover, 2013). Findings of generalist offending among IPV perpetrators are critical to IPV theory, as most IPV-specific explanations that emphasize the unique nature of IPV fail to explain the tendency of IPV offenders to also commit other types of crime (e.g., Bouffard & Zedaker, 2016). However, theoretical and etiological implications of the overlap between IPV and other offenses remain somewhat unclear, as research has mainly focused on describing the observed degree of specialization, and well-known correlates of crime in general have not been integrated into specialization research. Although the most likely explanation for the observed versatility is that IPV and other forms of crime are affected by the same underlying causal

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mechanisms (e.g., Wolbers & Ackerman, 2020), even 100% overlap would not prove this (e.g., Moffitt, Krueger, Caspi, & Fagan, 2000), and additional research is needed to explicate the causes and correlates of generalist offending.

The current study builds on previous work on the issue of specialization versus versatility in the realm of IPV offenders using Finnish register-based data of IPV offenders from all cases reported to the police between 2015 and 2019 (N = 19,030). As studies on specialization in IPV have largely overlooked several potential predictors that could account for different offending patterns, we expand on the previous research by looking into the associations between certain social correlates of crime and the level of specialization/generalist offending among IPV offenders. Moreover, we use two emerging analytic approaches to assess the nature and form of specialization and its correlates.

2. Prior research on IPV and specialization

In IPV research, the view of offenders as specialists is mostly a product of influential theories that see IPV primarily as a consequence of societal-level patriarchy (e.g., Dobash & Dobash, 1979) or other context-specific dynamics (e.g., Straus, Gelles, & Steinmetz, 1980; Wilson & Daly, 1993). By suggesting that the IPV-specific context is central in the etiology of IPV, these perspectives, by and large, fail to explain the tendency of IPV perpetrators to also commit other types of violent and non-violent crime (e.g., Bouffard et al., 2008; Bouffard & Zedaker, 2016; Piquero, Brame, Fagan, & Moffitt, 2006). While findings of generalist offending among IPV perpetrators do not automatically indicate that IPV is reflective of a generally antisocial nature, they do challenge the idea of IPV being distinct from other crime. On the other hand, studies have reported some tendencies toward specialization in IPV (e.g., Bouffard et al., 2008; Wolbers & Ackerman, 2020) or violence more generally (e.g., Osgood & Schreck, 2007), and consequently, any explanation of IPV that fails to take this into account seems at least marginally inadequate.

The issue of specialization versus versatility is inherently an empirical question, but some theoretical solutions have been proposed to explain the mixed views in the IPV literature. Namely, typological explanations that classify IPV into subtypes could account for both specialized and versatile offending patterns. Importantly, the existence of different IPV subtypes and their disproportioned representation in different data sources could explain some contradicting views on IPV and its associations to general violence (e.g., Holtzworth-Munroe & Stuart, 1994; Johnson, 2006). Several studies have suggested that the level of specialization may distinguish different subtypes of IPV perpetrators from each other (e.g., Holtzworth-Munroe, Meehan, Herron, Rehman, & Stuart, 2000; Petersson & Strand, 2020), and generalist offending has been linked especially to perpetration of more severe forms of IPV when compared to IPV-only offenders (e.g., Holtzworth-Munroe et al., 2000). However, the general empirical support for IPV typologies is mixed (e.g., Delsol, Margolin, & John, 2003; Langhinrichsen-Rohling, Huss, & Ramsey, 2000; Waltz, Babcock, Jacobson, & Gottman, 2000), and they have been criticized for being merely descriptive and lacking the ability to inform the explanation of IPV (e.g., Dixon & Wride, 2020).

Similarly, while there is a lot of research describing the degree of versatility in criminal offending generally, much less attention has been paid to whether certain social correlates of crime could explain different levels of specialization (e.g., Mazerolle & McPhedran, 2019; Osgood & Schreck, 2007). Incorporating predictors of crime into specialization research is critical, as there is research suggesting that controlling for relevant background characteristics could account for some specialization patterns (e.g., Armstrong & Britt, 2004). Importantly, research on predictors of generalist offending could shed light on the mechanisms that may generate versatility. Furthermore, correlates of specialization can be highly relevant for criminological theory, as they may inform nuanced processes that affect different types of offending (e.g., Osgood & Schreck, 2007). For instance, it has been suggested that self-defense as a motive for violence could account for specialization in IPV especially among female perpetrators (e.g., Wolbers & Ackerman, 2020), and empirical research on predictors of specialization is needed to validate this assumption.

Although there are surprisingly few established correlates of any pattern of offense specialization, it is evident that the tendency to specialize is not a constant but varies both between (e.g., McGloin, Sullivan, & Piquero, 2009) and within individuals (e.g., Osgood & Schreck, 2007) and also across offense types (e.g., DeLisi et al., 2011). Multiple theoretical frameworks have been proposed to explain this variation—for instance, the rational choice perspective (e.g., Guerette, Stenius, & McGloin, 2005), propensity and opportunity-based models (e.g., McGloin, Sullivan, Piquero, & Pratt, 2007), and even desistance theories (e.g., McGloin, Sullivan, Piquero, Blokland, & Nieuwbeerta, 2011). Notably, research has consistently found offending versatility to be most common among young and early onset offenders and to decline by age (e.g., Mazerolle, Brame, Paternoster, Piquero, & Dean, 2000; Nieuwbeerta, Blokland, Piquero, & Sweeten, 2011; Tumminello, Edling, Liljeros, Mantegna, & Sarnecki, 2013), which is in line with some life-course theories of offending (e.g., Moffitt, 1993). There are also suggestive findings on similar effects of age on the offending versatility of IPV offenders (e.g., Bouffard & Zedaker, 2016). Deriving from desistance theories, the impact of age on offending versatility has been linked to "turning points," such as marriage (e.g., McGloin et al., 2011), that could narrow opportunities to engage in a variety of crime.

On the other hand, some stable individual characteristics, such as gender, have been linked to offending specialization in prior studies (e.g., Tumminello et al., 2013). Importantly, prior research on specialization in IPV has found greater tendencies toward specialization among women than men (e.g., Bouffard et al., 2008; Bouffard & Zedaker, 2016), which has been interpreted in support of explanatory frameworks that suggest different causes for male- and female-perpetrated IPV (e.g., Bouffard et al., 2008). Apart from gender- and age-related factors, prior research on predictors of specialized versus generalist offending patterns is sparse, especially in the context of IPV. Specifically, some well-known correlates of crime, such as socioeconomic or lifestyle factors, have not been well integrated into this research area.

3. Methodological considerations

While earlier research on offender specialization quite consistently reported great tendencies toward generalist offending and little specialization (e.g., Blumstein et al., 1988; Bursik, 1980; Farrington, Snyder, & Finnegan, 1988), more recent studies have detected higher levels of specialization (e.g., Osgood & Schreck, 2007; Sullivan, McGloin, Ray, & Caudy, 2009). These mixed findings may be at least partly attributable to methodological issues. Namely, earlier research has relied on the transition matrix approaches (e.g., Bursik, 1980; Farrington et al., 1988) and the diversity index (e.g., Mazerolle et al., 2000) in measuring specialization. These methods mostly describe the degree of specialization in a given data set but lack a more nuanced ability to describe the nature or form of specialization (e.g., Sullivan et al., 2009). More recently, the latent class analysis (LCA) (e.g., McGloin et al., 2009; Wolbers & Ackerman, 2020) and item response theory (IRT) methods (e.g., Osgood & Schreck, 2007) have emerged in specialization research. It has been suggested that these more recently introduced statistical methods may be more sensitive in detecting specialization than previously used measures (e.g., Sullivan et al., 2009). Moreover, LCA- and IRT-based methods may be more suitable for incorporating explanatory variables into the analysis.

While the diversity of existing methods for studying specialization may sometimes be beneficial for research, it can also appear as a challenge when integrating and comparing findings from different studies (e.g., Mazerolle & McPhedran, 2019). Notably, there is great variation between studies on how the continuum of specialization to versatility is operationalized and measured. Although there seems to be a consensus on the definition of specialization as a tendency to engage in one offending type beyond the chance level, different methods use different metrics to operationalize this tendency (e.g., Osgood & Schreck, 2007; Sullivan et al., 2009). In order to take this into account, applying different methodological approaches in the same data set can be advisable (e.g., Bouffard & Zedaker, 2016) as different methods have their own strengths and limitations in assessing specialization (e.g., Sullivan et al., 2009).

In addition to the chosen statistical method, the observed degree of offense specialization is likely to be very sensitive to several other methodological issues as well, such as the type of data, the time span of the data, and the resolution of the offense grouping. Notably, detecting specialization may be more likely when using self-report data instead of official data (e.g., Lynam, Piquero, & Moffitt, 2004), shorter instead of longer time windows (e.g., McGloin et al., 2007), and broader offense categories instead of a more fine-grained classification of offenses (e.g., Mazerolle & McPhedran, 2019). Clearly, any methodological solution and its potential impact on the results should be openly and carefully assessed in order to avoid biased conclusions.

4. Current study

The purpose of the current study is to analyze the extent and nature of specialized versus versatile offending patterns in a large register-based data set of Finnish IPV offenders (N = 19,030). Specifically, we aim to assess whether specialization in IPV can be detected in the data. In addition, we seek to examine whether certain social correlates of criminal offending could explain different levels of specialization and offending patterns. Moreover, following some previous work in the area (e.g., Bouffard et al., 2008; Bouffard & Zedaker, 2016; Wolbers & Ackerman, 2020), the current study aims to examine different methodological approaches by assessing whether two different methods provide similar answers to our inquiries. Thus, we use two different analytic techniques in analyzing specialization and its correlates: first, a multilevel IRT approach adapted from Osgood and Schreck (2007), and second, LCA. As such, the current study is of methodological relevance, and by integrating results from the two analytic approaches, we seek to shed light on the issue of specialized versus versatile offending patterns of IPV offenders in a manner that has both theoretical and practical implications.

While our study partially replicates the analysis on specialization in domestic violence and its predictors by Bouffard and Zedaker (2016), we also aim for a meaningful contribution to the gaps in the current literature. Specifically, the current study adds to prior research in four main ways. First, studies on specialization in IPV have used a very limited set of predictors of specialization, and the current study expands on that by incorporating explanatory variables that have not been previously used in this research field, such as socioeconomic factors and measures of criminal victimization. Second, we use a large data set that allows, for instance, a more fine-grained classification of criminal offenses than has been used in previous research on the issue. Third, while most specialization research relies on a single statistical method, we use two methods to analyze the degree and form of specialization. Fourth, the majority of all prior research has been conducted in the United States, and assessing whether similar results can be obtained from other country contexts is obviously critical.

5. Data

The data set of the current study draws on data on police-reported crime gathered and maintained by Statistics Finland. The Finnish Police is the initial source for the data on all suspected offenses, but police data alone does not contain reliable information to separate IPV offenses from other offenses of the same penal code (e.g. IPV assaults from other assaults). To address this shortcoming, Statistics Finland has further classified an offense as domestic violence based on auxiliary population register information on the relationship (e.g., kinship, marriage, same household) of the suspect to the victim. Consequently, the classification is not dependent on, for example, the police perception of IPV. The data contain all criminal offenses (except for homicide) between 2009 and 2019 that can be classified as domestic violence or IPV based on official information. In addition to physical and sexual violence (e.g., assaults, rapes), the data include a wide range of other types of personal offenses as well. As the data are based on police statistics, all offenses that the police have recorded as a crime and investigated are included regardless of criminal justice outcomes. Suspects are referred to as offenders for the sake of consistency with prior literature.

For the purpose of the current study, IPV was defined as any offense in the Statistics Finland domestic violence data where the offender and the victim were married, formerly married, co-habiting, formerly co-habiting (in five years prior to the offense), or had a common child. All non-lethal personal offenses (e.g., assaults, attempted homicides, rapes, robberies, extortions, deprivations of personal liberty, menaces, persecutions) toward an intimate partner were defined as IPV. A definition of violence that goes beyond mere physical violence is generally favored in the IPV literature (e.g., Hamberger, Larsen, & Lehrner, 2017), and thus, a broad definition is taken in the current study. The majority of all IPV offenses in the complete data (2009–2019) were assaults.

The final dataset used to define an individual as an IPV offender contains all IPV offenses reported between 2015 and 2019 with complete data on all sociodemographic variables used in the analysis (N = 19,030; exclusion of individuals with missing data reduced the sample size by 2.8%). Missing values are most likely because of individuals not living in Finland at the end of the year, which can cause underrepresentation of this population in the data. As individuals were used as the units of analysis, the reference offense that was used in linking criminal history and other information to the individuals was chosen randomly for those with IPV offenses from several years. The selection was performed randomly instead of choosing the last or the first offense in that time period in order to not systematically skew the data toward more or less prior IPV offenses from these individuals. Complete criminal histories of all criminal law offenses up to five years prior to the reference year (including the reference year) from crime statistics by Statistics Finland were then linked to these individuals. A time window of five years was selected, as it is likely that a very wide time range would bias the results toward a high degree of generalist offending (e.g., McGloin et al., 2009). This solution could, in part, compensate for the observation that specialization may be harder to detect in official data (e.g., Lynam et al., 2004). A sensitivity analysis with a shorter time window was also performed (see 7.4 Sensitivity analysis).

In order to control for the possible risk of offenses associated with the same IPV-related criminal case (as a criminal case may consist of multiple offenses) biasing the results toward a higher degree of generalist offending, all offenses that did not appear in the domestic violence data but were linked to any IPV-related case based on the case identifier were excluded from the criminal histories. “Non-IPV” classified offenses in the criminal histories thus consist of offenses that are not explicitly linked to any IPV offense. This may reduce the risk of classifying individuals who have committed crime against intimate partners only (e.g., both violent and property crimes) on the same occasion as generalist offenders. However, this exclusion could lead to underestimating offending generality, as some versatility-relevant offenses may also be excluded.

In addition to criminal offending, information on criminal victimization during the same preceding five-year period was linked to the data of IPV offenders. Basic sociodemographic information from the previous year provided by Statistics Finland was also linked to the individuals. Descriptive statistics for all the variables are presented in Table 1.

5.1. *Offense categories*

For the purpose of the analysis, IPV offenses were classified into three categories: offenses of physical violence (e.g., assault, attempted

Table 1
Descriptive statistics (N = 19,030).

	%	Mean
IPV		
Physical assaults	88	1.32
Sexual offenses	2	0.02
Other personal offenses	27	0.35
Non-IPV		
Physical assaults	29	0.98
Sexual offenses	2	0.07
Property crime offenses	28	2.89
Drug offenses	13	0.65
DUI offenses	19	0.45
Other traffic offenses	33	1.40
Other criminal law offenses	33	1.71
IPV victimization	35	
Other victimization	30	
Female	23	
Age		39.35
Unmarried	42	
Married	39	
Divorced	19	
High school diploma	14	
Income (€)		20,816
Immigrant background	14	
Urban municipality	75	
Densely populated municipality	14	
Rural municipality	11	

homicide), sexual offenses (e.g., rape, sexual abuse), and other types of personal offenses (e.g., robbery, extortion, deprivation of personal liberty, menace, persecution). Despite the low frequencies of sexual offenses in the data, we decided to separate this category from non-sexual types of violence because of some evidence on relatively high degrees of specialization in sexual offenses reported by previous studies (e.g., Howard, Barnett, & Mann, 2014; Soothill, Francis, Sanderson, & Ackerley, 2000).

Non-IPV offenses were assigned into seven categories. Consistently with the IPV measures, violent assaults and sexual offenses were analyzed as separate offense categories. In addition to these categories, five offense categories were used: property crime offenses (e.g., theft, damage to property, fraud), drug offenses (e.g., unlawful use of narcotics, narcotics offense), DUI offenses (i.e., driving under the influence of alcohol or other intoxicant), other traffic offenses (e.g., endangerment of traffic safety, unlawful driving of a vehicle), and other criminal law offenses. Depending on the analysis, offenses were analyzed either as counts or dichotomous variables.

5.2. Other measures

The criminal victimization measures that were used as dichotomous explanatory variables indicating police-recorded criminal victimization up to five years prior to the reference year were classified into two categories: IPV victimization comprising the same offense types as the IPV-offending measures and non-IPV victimization where all offenses associated with any IPV offenses based on the case identifier were excluded. In addition to non-IPV violent victimization, the second measure included non-violent types of criminal victimization (e.g., property crime victimization). The sociodemographic measures included gender (male/female), age (at the time of the reference offense), immigrant background (yes/no), marital status (unmarried/married/divorced), education level measured as completed high school (yes/no), total yearly income, and the type of the municipality where the individual was living (urban/densely populated/rural).

6. Analytic strategy

We use two analytic techniques to assess the levels and predictors of specialization and versatility in the data: a multilevel IRT approach and LCA. Both methods offer certain advantages when compared to other commonly used approaches in specialization research. Namely, IRT and LCA models provide more insights for examining individual-level differences in specialization in contrast to more conventional methods (e.g., Osgood & Schreck, 2007; Sullivan et al., 2009), and they are both suitable for integrating predictors of specialization into the analysis. However, while the IRT and LCA approaches both model specialization as a latent, unobserved construct, they are crucially different in terms of the fixedness of the framework in which specialization is assessed. Specifically, the IRT strategy requires a fixed framework in which specialization in a specific offense type is investigated, whereas LCA enables a more diverse and data-driven framework that may also lead to detection of unanticipated patterns of offending (e.g., McGloin et al., 2009; Sullivan et al., 2009). LCA, however, needs to operate with dichotomous offense indicators rather than offense counts in order to not confound offense frequency with specialization (Sullivan et al., 2009). Using dichotomized data may, however, lead to losing critical information. The IRT strategy, on the other hand, allows modeling offense counts (e.g., Bouffard & Zedaker, 2016). Overall, both approaches have their own strengths and limitations, and prior research has demonstrated the advantages of combining both of these strategies in assessing the nature and form of specialization (e.g., Bouffard & Zedaker, 2016; Sullivan et al., 2009).

6.1. Multilevel IRT

The multilevel IRT approach used in the current study is adapted from Osgood and Schreck (2007). It has been used for studying specialization in IPV (or domestic violence) by Bouffard and Zedaker (2016) and Bouffard et al. (2008). Overall, the advantages of this method include producing a single metric for the extent of specialization, separating specialization from offense base rates, and defining specialization at the individual level in a manner that permits regression modeling (Osgood & Schreck, 2007). This method is based on a two-level approach that, at level 1, models specialization and versatility as latent variables that vary across individuals and, at level 2, uses individual-level explanatory variables to predict that variation (Osgood & Schreck, 2007). In the current study, the outcome variable at level 1 is the count for each offense type modeled with a negative binomial distribution. Notably, the data are analyzed in a "long format" so that each individual (j) has one item for each offense (i) category (Bouffard & Zedaker, 2016). In the case of the current study, this means 190,300 observations at level 1 (7 non-IPV + 3 IPV items for 19,030 individuals). The level 1 model defines the offense count (η_{ij}) to be dependent of three factors: 1) specialization (β_{1j}) and 2) overall offending (β_{0j})—modeled as random effects—and 3) item base rates (β_{ij}), included into the model as a series of dummy variables (D_{ij}) for each offense type. In addition, a variable (*Spec*) capturing the contrast between IPV and non-IPV offenses is included into the model by assigning IPV offenses a positive value and non-IPV offenses a negative value in a way that averages to zero for all individuals and is not confounded with the overall level of offending by individuals. The mathematical formulation for the model at level 1 can be expressed as:

$$\eta ij = \beta 0j + \beta 1j \; Spec + \sum_{i=2}^{I} \beta ij \; Dij \tag{1}$$

At level 2 of the IRT approach, the specialization parameter (β_{1j}) and the overall offending parameter (β_{0j}) are treated as (latent) outcome variables. The variances of the residual terms (u_{0j}, u_{1j}) from the level 2 null models can be used to assess the overall level of specialization and general offending in the data (Osgood & Schreck, 2007). Importantly, by including individual-level explanatory variables (X_{1j}, X_{2j}…) into the analysis, their associations with overall offending as well as specialization into IPV (versus non-IPV) offenses can be assessed. The level 2 equations for overall offending and specialization are as follows:

$$\beta 0j = \gamma 00 + \gamma 01\ X1j + \gamma 02\ X2j + \ldots + u0j \quad (2)$$

$$\beta 1j = \gamma 11\ X1j + \gamma 12\ X2j + \ldots + u1j \quad (3)$$

6.2. LCA

Unlike the IRT approach described above, LCA is a relatively general and conventional method that is not specific to criminal specialization research but can be applied to diverse research areas. The LCA approach has been previously used in research on IPV specialization by, for example, Bouffard and Zedaker (2016) and Wolbers and Ackerman (2020). It is a mixture model method that allows underlying, unobserved classes to be identified in the data based on a set of observed variables (e.g., Collins & Lanza, 2010; Masyn, 2013). In the case of offending specialization research, LCA is used to detect patterns of offense histories that could reflect underlying tendencies for specialization or versatility (e.g., Bouffard & Zedaker, 2016; Sullivan et al., 2009). These patterns are modeled as exhaustive and mutually exclusive classes (e.g., McGloin et al., 2009). In the case of the current study, the modeling is based on the seven non-IPV criminal history measures entered into the model as dichotomous variables.

The LCA generally proceeds in two steps: first, the model selection across models with different numbers of classes is performed, and second, characteristics of the selected model are inspected by, for example, assigning each individual to their most likely class. In addition to these steps, we also incorporated explanatory variables into the analysis by using multinomial logistic regression analysis to predict the assigned class membership. In this way, the analysis produces information on the correlates of specialist and generalist offending classes and enables interpretational comparison to the results from the IRT analysis.

It should be noted that no consensus exists on the most suitable criteria for determining the correct number of classes in LCA (e.g., Lin & Dayton, 1997; Nylund, Asparouhov, & Muthén, 2007). Although LCA does not explicitly rely on a researcher-constructed framework in which specialization is analyzed (e.g., McGloin et al., 2009), the model selection relies at least partially on researcher subjectivity. Moreover, unlike the multilevel IRT approach, LCA does not produce a single metric that could be used to assess the significance of offending specialization in the data. Thus, the final judgement on the extent to which the model describes tendencies toward specialization or versatility is sensitive to researcher interpretation.

7. Results

7.1. Prevalence of non-IPV offending among IPV offenders

We begin with a brief descriptive overview of the data in terms of the prevalence of non-IPV offending among IPV offenders. In the complete data of all IPV offenders (N = 19,030), 63.0% (95% CI 62.3%–63.7%) of the individuals had been suspected of one or more non-IPV offenses, in addition to one or more IPV offenses, in the five-year period prior to the reference year or during the reference year. For male IPV offenders (N = 14,721), the corresponding percentage was 67.3% (95% CI 66.5%–68.0%), and for females (N = 4309) it was 48.4% (95% CI 46.9%–49.9%)—the difference between the genders being statistically significant ($\chi^2 = 507.07$, $p < 0.001$). In other words, while the vast majority of male IPV offenders had also committed non-IPV offenses, this was remarkably less common among female IPV offenders.

7.2. Multilevel IRT

In the multilevel IRT strategy, we begin by examining whether substantial tendencies for specialization or generalist offending could be detected in the data. According to Osgood and Schreck (2007), the variances of the residual terms from the level 2 null models (=without covariates models) can be used to assess the overall level of specialization and general offending in the data. Specifically, the variance estimate for specialization reflects the degree to which differences between rates of IPV and non-IPV offenses vary across individuals over and above the variation that would be expected by chance. Namely, close to zero variances for specialization or overall offending indicate that these tendencies are not greater than would be expected by chance alone (Osgood & Schreck, 2007).

The results of the analysis indicate the variance estimate for specialization in IPV to be 1.04 (95% CI 0.98–1.10).[1] A non-zero variance implies that there are individual differences in specialization in IPV that are greater than would be expected by chance alone. As for overall offending, the variance was 1.38 (95% CI 1.35–1.42). This, in turn, indicates that there are greater individual differences in the level of overall offending than would be expected by chance alone. Notably, comparison of the estimates indicates the variance for overall offending to be slightly larger than for specialization. This suggests variance in IPV offending to be somewhat more dependent of the overall offending tendency than the specialization tendency. Overall, the structural IRT model indicates individual differences in IPV offending to be dependent of both the specialization tendency and the tendency of overall offending beyond the level of chance. This result justifies the proceeding analysis on the covariates of these tendencies.

In the second level of the IRT strategy, individual-level covariates were incorporated into the analysis in order to assess their associations with specialization in IPV as well as overall offending. Table 2 presents the results of this analysis. Notably, the coefficients for specialization in IPV indicate the relationship of a covariate to the differential between IPV versus non-IPV offending, independent of the overall level of offending of an individual and the offense base rates (Osgood & Schreck, 2007).

Looking at the correlates of specialization and overall offending, being female was positively associated with specialization in IPV and negatively with overall offending, suggesting that women were more likely to specialize in IPV but less likely to offend in general. Age was also positively associated with specialization in IPV and negatively with overall offending. As for the victimization measures, IPV victimization was positively associated with specialization in IPV and negatively with overall offending, whereas other victimization was positively associated with overall offending and negatively with specialization in IPV. Notably, of all the explanatory variables used in the analysis, non-IPV victimization had the strongest (positive) association with overall

Table 2
IRT level 2: linear regression models predicting overall offending and the specialization parameter from the level 1 model. N = 19,030.

	Overall offending		Specialization in IPV	
	Coef.	SE	Coef.	SE
Female	−0.812***	0.024	0.518***	0.033
Age[a]	−0.300***	0.010	0.424***	0.014
IPV victimization	−0.040*	0.020	0.194***	0.027
Other victimization	0.954***	0.019	−1.019***	0.025
Married	−0.011	0.022	0.074*	0.029
Divorced	0.307***	0.025	−0.188***	0.034
High school diploma	−0.352***	0.027	0.430***	0.037
Income[a]	−0.269***	0.010	0.290***	0.013
Immigrant background	−0.349***	0.026	0.470***	0.035
Densely populated municipality	−0.002	0.025	0.003	0.034
Rural municipality	0.012	0.027	0.007	0.037

*** p < 0.001, ** p < 0.01, *p < 0.05.
[a] Continuous variables are scaled and centered.

[1] Unlike Osgood and Schreck (2007), we used confidence intervals instead of Z tests to assess whether the variances are non-zero.

offending (b = 0.954) and also the strongest (negative) association with specialization in IPV (b = −1.019).

When compared to being unmarried, being married was positively associated with specialization in IPV, and but it was not significantly associated with overall offending. Being divorced, on the other hand, was positively associated with overall offending and negatively with specialization in IPV. As for the socioeconomic measures, both income and having a high school diploma were positively associated with specialization in IPV and negatively with overall offending. Immigrant background was also positively associated with specialization in IPV and negatively with overall offending. In this analysis, type of municipality was not significantly associated with either overall offending or specializing in IPV.

7.3. LCA

In the LCA approach, we begin with the model selection process performed among models with 1 to 7 classes. All the models were based on the seven non-IPV offense categories used as dichotomous indicator variables. Table 3 presents the model fit indices for the models. The Bayesian information criterion favored the 5-class solution, and the other fit indices indicated a relatively good fit for that model. As the 5-class model also showed identifiable and distinct classes that were easily interpretable, this model was ultimately selected after carefully inspecting the other solutions as well.

Table 4 presents the estimated class population shares, the offense type probabilities conditional on latent class membership in each class, and the mean number of non-IPV offense types for individuals assigned to their most likely class. To facilitate interpretation, the classes were named based on their most diacritical characteristics. The following five classes were identified:

1. Specialists (57%): In the largest class, probabilities of any non-IPV offenses are low. Of all the non-IPV offense types, the probability of traffic offenses is the highest.
2. Low-level generalists (23%): In the second largest class, probabilities of any non-IPV offenses (apart from sexual offenses) are generally modest. The probability of "other" offenses is, however, relatively high.
3. Low-level generalists with a high level of DUI and traffic offenses (6%): In this class, probabilities of non-IPV offenses are low to modest apart from DUI and traffic offenses, of which the probabilities are remarkably high.
4. High-level generalists with a low level of DUI and traffic offenses (6%): In this class, probabilities of non-IPV offenses are relatively high apart from DUI, traffic, and sexual offenses, of which the probabilities are relatively low.
5. High-level generalists (8%): This class is characterized by the most versatile offending among the classes, as probabilities of non-IPV offenses are all high apart from sexual offenses, of which the probability is low but still the highest among all the classes.

Table 3
LCA: Model fit indices for models with 1 to 7 classes.

N of classes	G^2	BIC	APP[a]	Estimated class population shares
1	19,477.65	130,911.3	1	1
2	2893.77	114,406.3	0.94	0.73 0.27
3	1172.59	112,763.9	0.92	0.67 0.22 0.11
4	361.97	112,032.1	0.87	0.62 0.19 0.11 0.09
5	170.70	111,919.7	0.83	0.57 0.23 0.08 0.06 0.06
6	117.96	111,945.8	0.74	0.42 0.25 0.09 0.09 0.08 0.07
7	94.11	112,000.8	0.75	0.45 0.18 0.12 0.09 0.07 0.06 0.03

[a] Average posterior probabilities for the most likely class in the complete data.

Finally, the correlates of the five classes (based on the individuals in the data assigned to their most likely class) were inspected using a multinomial logistic regression model where the class membership was regressed by the explanatory variables. The specialist class was used as the reference class in the analysis. In addition to the explanatory variables used in the IRT approach, count measures of the IPV offense types (physical, sexual, other) were added to the model in order to examine their associations with the classes of different levels of generalist offending. The results of this analysis are presented in Table 5.

As for the associations between IPV offenses and classes, the number of IPV offenses was positively associated with all the generalist classes (versus the specialist class) for physical and "other" IPV offenses but not for sexual IPV offenses. Looking at the sociodemographic variables, being male was associated with all generalist classes and most strongly with the high-level generalist class. Age and immigrant background were negatively associated with all generalist classes and most strongly with the high-level generalist class. Being married (versus being unmarried) was negatively associated with the low-level generalist class and the high-level generalist with a low level of DUI and traffic offenses class, but it was not statistically significantly associated with the two other generalist classes. Being divorced (versus being unmarried) was, on the other hand, positively associated with all the generalist classes except for the high-level generalist with a low level of DUI and traffic offenses class. As for the socioeconomic measures, both income and having a high school diploma were negatively associated with all generalist classes when compared to the specialist class. While non-IPV criminal victimization was positively associated with all the generalist classes, IPV victimization was negatively associated with the high-level generalist class but not with the other classes in comparison to the specialist class. Type of municipality was associated with the two classes characterized by divergent levels of DUI and traffic offenses: living in a densely populated or rural (versus urban) municipality was positively associated with the low-level generalist with a high level of DUI and traffic offenses class but negatively associated with the high-level generalist with a low level of DUI and traffic offenses class.

7.4. Sensitivity analysis

In addition to the main analysis for the complete data set, we also ran all the analyses for males and females separately. These results can be found in Appendix A. Notably, the male-only and female-only models showed that significant individual-level variation in both specialization and general offending could be found among both females and males despite generally less variation in these tendencies among females. Consistently with the main results, generalist offending was generally less common and specialization more common among females. Also, our analysis suggests substantively slightly different LCA solutions for males (five classes) and females (four classes). While the correlates of specialization and generalist offending among females and males separately were overall largely consistent with the main results on the complete data set, different offending patterns were generally less associated with the correlates among females. Most interestingly, IPV victimization and being married (versus being unmarried) were not significantly associated with any offending pattern for females.

Several additional analyses were run to test the robustness of the reported results. Notably, to assess the sensitivity of the results to the chosen time window for the criminal history measures, we re-run the analyses with a three-year time window (instead of the five-year window in the reported results). While this expectedly affected the prevalence of non-IPV offending among IPV offenders and the level of specialization in IPV in the data, significant tendencies toward generalist offending could still be detected. Moreover, analysis with the shorter time window suggested largely similar correlates for specialization and generalist offending as the reported results.

Additionally, we re-ran the main analyses using several different classifications for the criminal offenses (e.g., separating offenses toward

Table 4
The five-class LCA model. N = 19,030.

		Specialists	Low-level generalists	Low-level generalists with a high level of DUI and traffic offenses	High-level generalists with a low level of DUI and traffic offenses	High-level generalists
Estimated class population shares		0.57	0.23	0.06	0.06	0.08
Probabilities of non-IPV offense types in latent classes						
	Physical assaults	0.095	0.492	0.266	0.674	0.775
	Sexual offenses	0.005	0.036	0.009	0.029	0.076
	Property crime offenses	0.055	0.413	0.308	1.000	0.951
	Drug offenses	0.016	0.097	0.187	0.553	0.691
	DUI offenses	0.041	0.122	0.900	0.153	0.953
	Other traffic offenses	0.170	0.351	0.918	0.255	1.000
	Other criminal law offenses	0.063	0.612	0.321	0.896	0.961
Mean number of non-IPV offense types (0–7) in each class[a]		0.44	2.58	2.94	4.03	5.43

[a] For individuals assigned to their most likely class.

Table 5
Multinomial logistic regression predicting class membership (reference class: IPV specialists). N = 19,030.

	Low-level generalists		Low-level generalists with a high level of DUI and traffic offenses		High-level generalists with a low level of DUI and traffic offenses		High-level generalists	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Intercept	−0.638***	0.073	−1.155***	0.126	−2.279***	0.157	−1.135***	0.129
IPV physical[a]	0.282***	0.023	0.288***	0.031	0.324***	0.037	0.368***	0.027
IPV sexual[a]	0.013	0.020	−0.020	0.034	−0.062	0.049	−0.010	0.029
IPV other[a]	0.433***	0.023	0.235***	0.038	0.477***	0.035	0.495***	0.028
Female	−0.645***	0.058	−1.130***	0.106	−0.973***	0.123	−1.663***	0.108
Age[a]	−0.291***	0.025	−0.253***	0.039	−0.755***	0.061	−0.748***	0.042
IPV victimization	−0.047	0.050	0.008	0.077	−0.094	0.098	−0.213**	0.074
Other victimization	1.392***	0.043	0.775***	0.071	1.802***	0.085	1.913***	0.063
Married	−0.186***	0.052	−0.142	0.082	−0.477***	0.114	−0.021	0.080
Divorced	0.241***	0.060	0.264**	0.094	−0.055	0.136	0.697***	0.090
High school diploma	−0.414***	0.065	−0.474***	0.110	−1.147***	0.197	−1.079***	0.141
Income[a]	−0.203***	0.025	−0.247***	0.040	−1.135***	0.073	−1.150***	0.052
Immigrant background	−0.225***	0.060	−0.399***	0.103	−0.920***	0.134	−1.416***	0.111
Densely populated municipality	−0.090	0.061	0.385***	0.086	−0.769***	0.152	0.167	0.086
Rural municipality	−0.056	0.066	0.288**	0.096	−0.950***	0.178	0.094	0.094

*** $p < 0.001$, ** $p < 0.01$, *$p < 0.05$.
[a] Continuous variables are scaled and centered.

any non-partner family member as its own criminal history measure, combining physical and sexual offenses into one category). This did not remarkably change the interpretation of the main results in comparison to the reported results. Overall, the sensitivity analyses gave additional support for the results from the main analysis, suggesting significant tendencies toward specialization and generalist offending among IPV offenders in addition to supporting the findings of the correlates of these tendencies.

8. Discussion

Are IPV offenders specialists or criminal generalists? As existing empirical literature on this inquiry is relatively sparse (e.g., Bouffard et al., 2008; Bouffard & Zedaker, 2016; Wolbers & Ackerman, 2020), the current study contributes to this area of research by assessing tendencies toward specialization and generalist offending among Finnish, police-recorded IPV offenders and by examining whether certain social factors are associated with different offending patterns. Our findings, by and large, do not suggest that IPV offenders are purely specialists or generalists but reveal that both tendencies exist and contribute to IPV. Moreover, we found that specialization and generalist offending among IPV offenders are associated with different correlates that bear both theoretical and practical importance.

Based on findings from previous studies, it is not surprising that IPV offenders do not simply fall under one single category of either "specialists" or "generalists." While the idea of IPV offenders as specialists remains prevalent in both theoretical and practical understandings of IPV, studies seem to replicate the finding of significant tendencies toward both specialization and versatile offending among IPV offenders (e.g., Bouffard et al., 2008; Bouffard & Zedaker, 2016; Wolbers & Ackerman, 2020). Overall, this may support the more general idea on heterogeneity of IPV suggested by, for example, the typological perspectives (e.g., Holtzworth-Munroe & Stuart, 1994; Johnson, 2006). Yet, determining whether specialist offending is *more or less prevalent* than generalist offending is remarkably more ambiguous than merely discovering whether specialist or generalist offending patterns exist at all. It is evident that the precise degree of specialization detected in empirical data depends on multiple contextual and methodological issues. The partially inconsistent results of the current study demonstrate this clearly: While the results from the IRT-based analysis suggest IPV to be more dependent of the overall offending tendency than specialization, the results from the LCA suggest that most IPV offenders fall into the class characterized by a prominently specialized offending pattern. This further highlights the importance of drawing on multiple statistical methods when studying offense specialization as suggested also by prior research (e.g., Sullivan et al., 2009). As even results derived from the same data set can lead to substantially different conclusions on the dominance of specialization in IPV versus generalist offending, it seems evident that any findings in this research area should be carefully assessed in terms of any methodological choices or other issues potentially affecting the results.

In addition to showing that both specialists and more generalist offenders can be found in the data of Finnish IPV offenders, the findings of the current study also highlight that these tendencies are systematically related to other individual characteristics. The results concerning these differences were rather consistent across the two analytic methods. Consistently with some prior research (e.g., Bouffard et al., 2008; Bouffard & Zedaker, 2016), our findings indicate specialization in IPV to be significantly more common among female than male IPV offenders even when controlling for the offense base rates (Osgood & Schreck, 2007). Importantly, however, our supplementary analyses (see 7.4 Sensitivity analysis and Appendix A) showed that significant individual-level variation in both specialization and general offending could be found among both females and males.

Some theoretical perspectives into IPV suggest that findings on women's specialization in IPV result from defensive violence toward an abusive partner (e.g., Miller, 2001). Interestingly, our results showed the association between specialization and female gender even when controlling for (police-recorded) IPV victimization, and our supplementary analyses (Appendix A) showed that unlike for males, specialization in IPV was not associated with IPV victimization for females. These results are somewhat consistent with the findings by Wolbers and Ackerman (2020) showing no evidence of self-defense, solely explaining specialization in IPV among women. However, the current findings are evidently inconclusive on the role of self-defense or other motivations for violence in addition to other considerable explanations that could account for the gender differences in specialization. For instance, situational opportunities and other lifestyle/routine activity-related factors (e.g., Cohen & Felson, 1979; Mesch, 2000) that may put women and men in different proximities to IPV in relation to other crime could explain why female IPV offenders are less likely to be generalist offenders than their male counterparts.

In addition to gender, the current findings draw out several other correlates of specialization and versatile offending among IPV offenders. Specialization in IPV was consistently associated with older age, marriage, higher socioeconomic status (based on income and completed high school), and immigrant background, whereas generalist offending was found to be associated with younger age, being divorced or unmarried, having a lower socioeconomic status, and not having an immigrant background. While some of these findings are consistent with previous findings on general correlates of offense versatility (e.g., Armstrong & Britt, 2004; McGloin et al., 2011; Nieuwbeerta et al., 2011; Tumminello et al., 2013), they are more or less novel in the context of specialization in IPV. For instance, the association between immigrant background and IPV specialization is interesting as such and could reflect, for example, cultural beliefs on gender equality among some immigrant populations that could affect IPV offending but not necessarily other types of criminality. In addition, the findings on the associations between socioeconomic measures and specialization in IPV (even when controlling for item base rates and overall offending tendency) are, to our knowledge, novel. In addition to obvious theoretical links to the lifestyle/routine activities framework generally, discovering that IPV specialists tend to be of higher socioeconomic status than generalist IPV offenders could also support certain specific explanations into offense specialization, such as the rational choice perspective (e.g., Clarke & Cornish, 1985; Guerette et al., 2005), in that “costs” and “benefits” of IPV versus non-domestic forms of crime (e.g., property crimes, drug offenses) may be perceived differently by different socioeconomic classes.

Interestingly, our findings also indicate different offending patterns to be associated with criminal victimization. While the “victim–offender overlap” as such is a remarkably robust finding in criminological research (e.g., Berg & Schreck, 2021) and can be detected in the current data as a relatively high proportion of individuals with victimization histories (see Table 1), it is noteworthy that the current findings may suggest the association between victimization and offending to be somewhat type-specific. Specifically, non-IPV criminal victimization was found to have a strong positive association with generalist offending but a negative association with specialization in IPV, while IPV victimization was associated with specialization in IPV. In other words, it seems that the specialization tendency extends criminal offending also concerning victimization. While there are prior findings suggesting the victim–offender overlap is somewhat dependent on the perpetrator's relationship to the victim (e.g., Zimmerman, Farrell, & Posick, 2017), the current findings on the association between the overlap and the specialized/versatile offending tendencies are novel. More research is needed to determine whether these findings relate to confounding mechanisms behind certain types of offending and victimization or situational/motivational (e.g., revenge, self-defense) or other factors that could create a continuum between specific types of victimization and offending.

The current study is not without limitations and shortcomings. Importantly, our analysis is based on official data of police-recorded crime that excludes all offenses not known to the police. It should be noted that our definition of IPV suffers from reliance on official data and defining an intimate relationship partially based on housing information. Notably, the IPV measure does not include violence between unmarried partners that have not lived together in addition to violence between unmarried same-sex partners. In addition, it is highly possible that the results are affected by the fact that the criminal histories are likely to be inconclusive regarding crime not reported to the police, and the level of underreporting is likely to depend on the offense type. Moreover, relying on official data may affect our findings on the correlates of different offending patterns. For instance, it is possible that biases in police control or reporting practices could result in crimes committed by some social groups (e.g., socioeconomically disadvantaged individuals) being more comprehensively recorded than crimes by some other groups. Finally, as the current study is cross-sectional and correlational, we are unable to distinguish between selection and causality or within-individual (e.g., age effect) and between-individual (e.g., cohort effect) differences behind the correlates of different offending patterns.

Research on IPV tends to be specialized in studying violence toward partners separately from other crime, but the current study highlights the need for IPV research and theory to take into account the significant tendencies of IPV offenders to also commit other types of crime. Specifically, IPV research could benefit from analysis on IPV under the general criminal career paradigm (e.g., Piquero, Farrington, & Blumstein, 2003) that does not solely categorize individuals as offenders or non-offenders but analyzes offending patterns over the life course. As the current findings link specialization in IPV to several factors commonly associated with the desistance process, such as age, marriage, and income (e.g., Laub & Sampson, 2001), it could also be beneficial to study specialization in IPV in the context of desistance theories and within-individual changes in criminal behavior. In addition, theory and research should acknowledge that IPV offenders are not a homogeneous group in terms of their level of offense specialization. While this has been addressed in the realm of typological IPV research (e.g., Petersson & Strand, 2020), future studies should continue to investigate whether different types of IPV also have separate etiologies as could be expected by remarkably different correlates for specialization and versatile offending suggested by the current study. Importantly, research aiming to establish causal mechanisms behind different offending patterns could also be valuable to crime prevention effects.

IPV prevention and intervention strategies often presume offense specialization at least implicitly in that they focus on IPV and domestic violence and do not generally address violence and crime targeted at non-family members (e.g., Gover et al., 2007; Velonis et al., 2020).

Acknowledging that a significant proportion of IPV offenders are in fact criminal generalists, empirical support for these types of strategies presuming the uniqueness of IPV seems at least partially inadequate. Moreover, recognizing that IPV offenders are not a homogenous group with the same level of general antisocial tendencies, critical attention should be paid to any one-size-fits-all solution for preventing IPV. As suggested by previous research (e.g., Hilton & Eke, 2016; Radatz & Wright, 2016), it is possible that IPV prevention and intervention could benefit from strategies such as the risk–need–responsivity model (e.g., Bonta & Andrews, 2007) that takes into account individual differences in the risk of criminal behavior and in the responsivity to different types of intervention strategies. Overall, being informed by offenders' criminal histories and understanding their implications for assessing the risk of recidivism present some fruitful theoretical and empirical possibilities for both future research and IPV prevention efforts.

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Appendix A. Supplementary analysis for males and females separately

Table A1
IRT structural model variance parameters in male-only (N = 14,721) and female-only (N = 4309) models.

		Variance	95% CI
Males	Specialization	1.33	1.26–1.39
	Overall offending	1.36	1.32–1.40
Females	Specialization	0.87	0.75–1.00
	Overall offending	1.11	1.04–1.18

Table A2
IRT level 2 for males: linear regression models predicting overall offending and the specialization parameter from the level 1 model. N = 14,721.

	Overall offending		Specialization in IPV	
	Coef.	SE	Coef.	SE
Age[a]	−0.320***	0.011	0.454***	0.016
IPV victimization	−0.025	0.022	0.249***	0.030
Other victimization	0.922***	0.021	−0.977***	0.028
Married	−0.027	0.024	0.101**	0.032
Divorced	0.288***	0.028	−0.164***	0.038
High school diploma	−0.418***	0.031	0.492***	0.043
Income[a]	−0.297***	0.011	0.325***	0.015
Immigrant background	−0.361***	0.028	0.477***	0.038
Densely populated municipality	−0.008	0.027	0.003	0.037
Rural municipality	−0.018	0.030	0.047	0.041

*** p < 0.001, ** p < 0.01, *p < 0.05.
[a] Continuous variables are scaled and centered.

Table A3
IRT level 2 for males: linear regression models predicting overall offending and the specialization parameter from the level 1 model. N = 4309.

	Overall offending		Specialization in IPV	
	Coef.	SE	Coef.	SE
Age[a]	−0.186***	0.023	0.302***	0.031
IPV victimization	−0.035	0.044	0.104	0.061
Other victimization	1.071***	0.039	−1.246***	0.054
Married	0.071	0.047	−0.051	0.066
Divorced	0.335***	0.054	−0.322***	0.075
High school diploma	−0.196***	0.049	0.262***	0.068
Income[a]	−0.119***	0.020	0.1410***	0.028
Immigrant background	−0.314***	0.061	0.410***	0.086
Densely populated municipality	0.021	0.056	−0.023	0.077
Rural municipality	0.146*	0.061	−0.216*	0.085

*** p < 0.001, ** p < 0.01, *p < 0.05.
[a] Continuous variables are scaled and centered.

Table A4
LCA for males (N = 14,721): model fit indices for models with 1 to 7 classes.

N of classes	G^2	BIC	APP[a]	Estimated class population shares
1	15,706.40	106,473.2	1	1
2	2244.45	93,088.1	0.94	0.72 0.28
3	929.03	91,849.4	0.91	0.65 0.23 0.12
4	290.66	91,287.8	0.86	0.58 0.20 0.12 0.10
5	149.19	91,223.1	0.81	0.52 0.25 0.09 0.08 0.06
6	107.71	91,258.4	0.75	0.42 0.24 0.11 0.09 0.08 0.07
7	85.43	91,312.9	0.75	0.42 0.19 0.11 0.10 0.08 0.07 0.03

[a] Average posterior probabilities for the most likely class in the complete data.

Table A5
LCA for females (N = 4309): model fit indices for models with 1 to 7 classes.

N of classes	G^2	BIC	APP[a]	Estimated class population shares
1	2876.90	22,451.7	1	1
2	570.57	20,212.3	0.94	0.79 0.21
3	229.87	19,938.5	0.93	0.76 0.19 0.05
4	119.19	19,894.8	0.92	0.74 0.19 0.04 0.03
5	72.83	19,915.4	0.89	0.71 0.19 0.04 0.03 0.03
6	51.86	19,961.4	0.80	0.54 0.25 0.10 0.05 0.03 0.03
7	35.20	20,011.6	0.89	0.73 0.11 0.07 0.03 0.03 0.02 0.01

[a] Average posterior probabilities for the most likely class in the complete data.

Table A6
The five-class LCA model for males. N = 14,721.

	Specialists	Low-level generalists	Low-level generalist with a high level of DUI and traffic offenses	High-level generalists with a low level of DUI and traffic offenses	High-level generalists
Estimated class population shares	0.52	0.25	0.06	0.08	0.09
Probabilities of non-IPV offense types in latent classes					
Physical assaults	0.101	0.478	0.292	0.702	0.784
Sexual offenses	0.008	0.040	0.008	0.040	0.081
Property crime offenses	0.048	0.386	0.301	0.976	0.957
Drug offenses	0.018	0.099	0.197	0.537	0.700
DUI offenses	0.051	0.132	0.941	0.175	0.997
Other traffic offenses	0.199	0.386	0.935	0.362	1.000
Other criminal law offenses	0.065	0.595	0.337	0.920	0.961
Mean number of non-IPV offense types (0–7) in each class[a]	0.44	2.30	2.97	4.10	5.45

[a] For individuals assigned to their most likely class.

Table A7
The four-class LCA model for females. N = 4309.

	Specialists	Low-level generalists with a high level of DUI and traffic offenses	Low-level generalists with a low level of DUI and traffic offenses	High-level generalists
Estimated class population shares	0.74	0.04	0.19	0.03
Probabilities of non-IPV offense types in latent classes				
Physical assaults	0.090	0.105	0.556	0.678
Sexual offenses	0.000	0.004	0.009	0.024
Property crime offenses	0.070	0.370	0.684	0.888
Drug offenses	0.009	0.141	0.215	0.612
DUI offenses	0.019	0.738	0.080	1.000
Other traffic offenses	0.101	0.789	0.159	1.000
Other criminal law offenses	0.068	0.228	0.703	0.942
Mean number of non-IPV offense types (0–7) in each class[a]	0.36	2.63	2.70	5.13

[a] For individuals assigned to their most likely class.

Table A8
Multinomial logistic regression predicting class membership (reference class: IPV specialists) among males. N = 14,721.

	Low-level generalists		Low-level generalist with a high level of DUI and traffic offenses		High-level generalists with a low level of DUI and traffic offenses		High-level generalists	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Intercept	−0.898***	0.044	−2.185***	0.072	−2.99***	0.100	−2.709***	0.078

(continued on next page)

Table A8 (*continued*)

	Low-level generalists		Low-level generalist with a high level of DUI and traffic offenses		High-level generalists with a low level of DUI and traffic offenses		High-level generalists	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
IPV physical[a]	0.252***	0.026	0.309***	0.035	0.356***	0.039	0.377***	0.031
IPV sexual[a]	0.006	0.022	−0.022	0.038	−0.032	0.046	−0.014	0.033
IPV other[a]	0.548***	0.027	0.325***	0.043	0.588***	0.039	0.615***	0.033
Age[a]	−0.227***	0.026	−0.282***	0.042	−0.717***	0.061	−0.760***	0.045
IPV victimization	−0.064	0.053	−0.013	0.084	−0.129	0.103	−0.268***	0.080
Other victimization	1.169***	0.048	0.775***	0.079	1.793***	0.089	1.907***	0.068
Married	−0.126*	0.054	−0.157	0.089	-0.450***	0.116	−0.037	0.085
Divorced	0.246***	0.063	0.297**	0.102	−0.116	0.142	0.654***	0.097
High school diploma	−0.374***	0.068	−0.575***	0.126	−1.404***	0.231	−1.233***	0.160
Income[a]	−0.184***	0.025	−0.268***	0.045	−1.180***	0.078	−1.280***	0.058
Immigrant background	−0.184**	0.062	−0.404***	0.110	−1.093***	0.142	−1.470***	0.116
Densely populated municipality	−0.154*	0.064	0.365***	0.093	−0.596***	0.146	0.141	0.092
Rural municipality	−0.079	0.068	0.288**	0.103	−0.723***	0.165	0.008	0.102

*** $p < 0.001$, ** $p < 0.01$, *$p < 0.05$.
[a] Continuous variables are scaled and centered.

Table A9
Multinomial logistic regression predicting class membership (reference class: IPV specialists) among females. N = 4309.

	Low-level generalists with a high level of DUI and traffic offenses		Low-level generalists with a low level of DUI and traffic offenses		High-level generalists	
	Coef.	SE	Coef.	SE	Coef.	SE
Intercept	−3.330***	0.512	−2.401***	0.323	−4.807***	0.138
IPV physical[a]	0.127	0.090	0.271***	0.043	0.399***	0.060
IPV sexual[a]	−0.527	20.919	0.080	0.063	−0.211	4.848
IPV other[a]	0.119	0.093	0.277***	0.045	0.238***	0.071
Age[a]	−0.049	0.099	−0.239***	0.059	−0.467***	0.121
IPV victimization	0.105	0.216	0.008	0.115	0.132	0.233
Other victimization	0.543**	0.187	1.925***	0.097	2.018***	0.200
Married	0.071	0.219	−0.195	0.122	0.289	0.240
Divorced	0.001	0.268	0.182	0.136	1.059***	0.252
High school diploma	−0.372	0.243	−0.319*	0.135	−0.402	0.285
Income[a]	−0.231*	0.107	−0.315***	0.058	−0.463***	0.120
Immigrant background	−0.978**	0.379	−0.256	0.155	−0.913*	0.384
Densely populated municipality	0.307	0.232	−0.217	0.149	0.360	0.255
Rural municipality	<0.001	0.294	−0.008	0.160	0.931***	0.243

*** $p < 0.001$, ** $p < 0.01$, *$p < 0.05$.
[a] Continuous variables are scaled and centered.

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