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Measuring recurrent victimization: evaluating operationalization strategies and predictors using the Crime Survey for England and Wales

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ABSTRACT

There is little consensus on how recurrent victimization should be operationalized. This study evaluates alternative measurement strategies and identifies predictors of recurrent victimization using a meta-analytic synthesis of analytic approaches applied to the Crime Survey for England and Wales. Results show that defining recurrent victimization using a Top 10% binary threshold and estimating logistic regression models can lead to biased conclusions. In contrast, operationalizations based on experiencing two or more victimization types or incidents perform better when analyzed using bivariate probit models. Count-based measures, particularly total victimization counts across crime types, also perform well when estimated using negative binomial or zero-inflated negative binomial models. Overall, the findings suggest that categorization-based approaches should be theoretically informed and paired with bivariate probit models, while analyses of victimization volume are better suited to count-based frameworks. Across all approaches, mental health conditions consistently emerge as the strongest correlate of recurrent victimization.

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Introduction

Crime tends to concentrate among a small subset of victims (O et al., 2017), offenders (Martinez et al., 2017), and locations (Lee et al., 2017). This paper focuses on the first group: individuals who are repeatedly victimized. Initially conceptualized as 'repeat victimization' in the late 1970s (Nelson, 1980; Sparks et al., 1977), this phenomenon has since been explored under various terms, including 'chronic victimization', 'multiple victimization', 'polyvictimization', and 'revictimization', each capturing distinct but overlapping constructs (Farrell & Pease, 2014). A recent review of the literature (Krushas et al., 2025) puts all these definitions under the umbrella term of 'recurrent victimization'. In the current study, we follow Krushas et al. (2025) and define 'recurrent victimization' as the experience of more than one victimization within 12-months prior to the

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interview. ‘Repeat victimization’, which is the first type of ‘recurrent victimization’ concerned here, is defined as the experience of the same crime type more than once; while ‘polyvictimization’, which is the second type of ‘recurrent victimization’ concerned here, refers to the experience of two or more *different* crime types. ‘Recurrent victimization’ thus refers to both ‘repeat’ and ‘polyvictimization’ throughout the paper.

Repeat victimization studies focus exclusively on single crime categories such as personal crime (Tseloni & Pease, 2003, 2004), property crime (Osborn et al., 1996), or analyze several crime categories (e.g., property or personal crime) separately in a single study (Tseloni & Pease, 2005). These studies are generally easier to interpret because they focus on a single crime category. However, interpretation is complicated by the fact that early work using the Crime Survey for England and Wales (CSEW) grouped victimization incidents into broad categories (e.g., property vs. personal crime) rather than specific types (e.g., assault). These studies labeled their outcomes as ‘repeat victimization,’ but in practice they may have been capturing ‘polyvictimization’: someone can experience several different incidents within a broad category such as ‘property crime,’ even if the underlying crime types differ. Estimates of ‘polyvictimization’ vary considerably depending on factors such as the number of crime types/categories included to construct the ‘polyvictimization’ variable, the use of binary or count measures, or the operational definitions applied. These variations complicate both the interpretation of findings and the development of cohesive theoretical frameworks. Importantly, both approaches offer only a partial view of individuals’ victimization experiences. While ‘repeat victimization’ focuses on experiences of a single crime type/category, ‘polyvictimization’ focuses on experiences of multiple crime types/categories. A third, integrative approach could combine elements of both, examining repeated experiences across multiple crime types/categories, to provide a more comprehensive understanding of the extent, nature, and concentration of victimization. We define this type of ‘recurrent victimization’ as ‘repeat + polyvictims’ throughout the paper.

Accurate measurement of ‘recurrent victimization’ is not only a conceptual concern but also crucial for practice. Police, victim services, and policymakers rely on consistent indicators to identify those most at risk, allocate limited resources, and design interventions that respond to victims’ patterns of harm. If ‘recurrent victimization’ is measured narrowly, capturing, for example, only repeat incidents within a single crime type/category, practitioners may overlook individuals whose risk arises from exposure to multiple forms of victimization. Conversely, measures that rely solely on a ‘polyvictimization’ category may inflate prevalence while obscuring the intensity or frequency of harm, making it harder to prioritize support for the most persistently affected victims. More precise and theoretically informed measurement helps practitioners detect early escalation, trigger appropriate safeguarding responses, tailor services to victims’ circumstances, and develop prevention strategies that address the full complexity of victimization. Understanding which methods best capture ‘recurrent victimization’ therefore has direct implications for effective practice and for ensuring that the most vulnerable individuals are neither misclassified nor missed altogether. Moreover, precise measurement is a prerequisite for accurately identifying the predictors of ‘recurrent victimization’. Only when recurrent patterns are captured consistently can researchers and practitioners discern which individual, relational, and contextual factors elevate risk. This, in turn, enables the development of evidence-based interventions that not only identify recurrent victims but also address the mechanisms that produce persistent vulnerability.

Therefore, this paper aims to address three main aims:

(1) reviewing and identifying different methods used to measure 'recurrent victimization' in the literature and integrating them into a single study,
(2) identifying robust correlates of 'recurrent victimization' across various statistical models, and
(3) identifying optimal measurement and modeling strategies for investigating predictors for 'recurrent victimization'.

The paper is structured as follows. First, we review existing studies on 'repeat' and 'polyvictimization' to identify the measurement methods used in the literature. Second, we detail the methodology, including the data, outcome variables and their operationalization, predictor variables and the rationale for their selection, the theoretical framework, and the analytical strategy. Third, we present the results from the meta-analytic synthesis of results obtained across analytic approaches. Finally, we discuss the findings and their implications.

Aim 1: review of existing studies

In this review, we first focus on the existing studies that analyzed CSEW data to evaluate how 'repeat' and 'polyvictimization' (i.e., 'recurrent victimization') have been conceptualized, measured, and analyzed. The CSEW is one of the primary sources of data historically used to analyze 'recurrent victimization', and it is also the data source used in our study. We then look at the studies that used other data sources.

Review of studies using the CSEW

This section discusses how previous studies that analyzed the CSEW conceptualized and operationalized 'repeat' and 'polyvictimization'. Among these studies, the focus was mainly on 'repeat victimization', which was operationalized as individuals or households experiencing a single crime category multiple times, such as property crime (Hunter et al., 2021; Osborn & Tseloni, 1998; Tseloni, 2006; Tseloni et al., 2004) or personal crime (Tseloni & Pease, 2015). These studies used count-based measures and applied negative binomial regression. While this method helps to handle the over-dispersed nature of victimization data, it is not without limitations. A limitation of this approach is that because it focuses on a single crime category/type, it does not fully capture the complex dynamics of victimization, where individuals might experience multiple crime categories/types.

An alternative analytic approach used by a previous study that analyzed the CSEW (Osborn et al., 1996) was multinomial regression, where the outcome variable had three categories: non-victims, single victims, and repeat victims of property crime. Osborn et al. (1996) also investigated the predictors of 'repeat victimization' of property crime by applying bivariate probit regression. In the latter case, they argued that victimization should not be analyzed in separate stages – such as estimating distinct logit models for non-victims versus single victims and single victims versus repeat victims. Instead, victimization should be understood as a two-step process: first, overcoming the initial 'hurdle' of becoming a victim, and second, the extent of victimization once that hurdle is crossed (e.g., experiencing it once, twice, or more). A bivariate probit regression is well-suited for this approach, as it jointly models two binary outcomes – one for initial victimization and another for repeated victimization – while accounting for potential correlations between these stages. This allows for a more comprehensive understanding of both the likelihood of victimization and its severity within the recall period. However, while these models effectively analyze levels of victimization within a single crime category/type, they are less equipped to address the co-occurrence of different crime categories/types. In addition, binary categorizations, such as 'victim vs. non-victim', further simplify the complexity of victimization, failing to capture variations in frequency, severity, and type of victimization. These limitations make them less suitable for understanding the overlap and interaction of multiple crime categories/types.

Ignatans and Pease (2016) employed a descriptive technique and identified the top 10% of victims who experienced the largest number of vehicle crime, property crime, and personal crime incidents as 'repeat victims'. However, this method introduces the risk of misclassification, particularly when establishing the threshold for who qualifies as a 'repeat victim'. In addition, Ignatans and Pease (2016) did not investigate predictors of 'repeat victimization'.

Only two CSEW studies examined 'polyvictimization' (Hope & Norris, 2013; Hope et al., 2001). Unlike the above studies focusing on single crime categories, Hope et al. (2001) explored issues of repetition and risk transmission of 'polyvictimization'. They used bivariate probit regression to jointly estimate property and personal crime victimization. This approach differs from Osborn et al. (1996), who used the same method to model victimization levels for a single crime category (property crime). However, Hope et al.'s analysis did not extend to other crime categories/types, such as digital/online crime, limiting its scope. Despite this, their work represents an early effort to understand the interplay between 'polyvictimization' experiences. In short, existing studies using the CSEW have employed negative binomial regression, multinomial regression, bivariate probit models, and the 10% descriptive approach to examine 'recurrent victimization'.

Review of studies using datasets other than the CSEW

In contrast, studies analyzing datasets beyond the CSEW often focus on 'polyvictimization'. Segura et al. (2018), for example, created a count 'polyvictimization' variable by summing binary victimization indicators, and classified individuals as 'polyvictims' based on thresholds such as experiencing two or more different crime types or exceeding the victimization population average. We will refer to this classification approach as the one-above-the-mean method (Finkelhor et al., 2005). While this classification approach offers a straightforward way to quantify 'polyvictimization', it risks oversimplifying the complex nature of victimization experiences. By defining 'polyvictims' solely based on thresholds, this method may fail to capture the severity or frequency of different victimization types, which are important for understanding the full scope of 'recurrent victimization'. Radtke et al. (2024) note that some studies have classified individuals using ordinal categories such as 'non-victim,' 'victim,' and 'polyvictim.' However, to our knowledge, these studies did not apply ordinal regression but instead used logistic regression, chi-square tests, or analysis of covariance.

Gaps in the literature

To our knowledge, no study has comprehensively compared methods for operationalizing and modeling 'recurrent victimization' or assessed how these definitions and statistical approaches influence the identification of key predictors. While Segura et al. (2018) assessed 'polyvictimization' among juveniles, and Radtke et al. (2024) reviewed methods for youth 'polyvictimization', neither study used advanced techniques such as (zero-inflated) negative binomial or bivariate probit regression, nor did they evaluate the stability of predictors across different models. They also did not estimate ordinal regression models although the ordinal nature of multinomial variables (e.g., non-victim, victim, polyvictim) is clear. Importantly, none of the studies integrated both 'repeat victims' and 'polyvictims', which offers a more holistic view of 'recurrent victimization'. These gaps underscore the importance of our study, which provides a systematic review and comparison of various operationalizations of 'recurrent victimization' (aim 1); identifies correlates of 'recurrent victimization' across various statistical models; and proposes optimal modeling strategies for identifying predictors of 'recurrent victimization' (aim 3).

Methodology

Data

The analysis uses data from the 2019/20 CSEW (Office for National Statistics, 2021) to examine the distribution of five overarching crime types available in the CSEW: vehicle crime, burglary, personal theft, violence, and digital crime.[1] The CSEW captures victimization experiences reported by respondents for the 12 months preceding the interview. For this study, data from 32,410 respondents were included after data cleaning process (original $n = 33{,}734$).

Outcome variables

A key strength of this study lies in the construction of multiple 'recurrent victimization' outcome variables from five distinct victimization types (vehicle crime, burglary, personal theft, violence, and digital crime) by synthesizing and applying methods based on previous research. In total, we apply two main methods to construct our two main 'recurrent victimization' outcome variables, and three classification methods to classify recurrent victims and construct several sub-outcome variables based on the two main outcome variables. The following sections explain these methods and our outcome variables (see Table 1).

Two main methods, two main outcome variables

Main method 1: binary summation

Main method 1 treats each victimization type as a binary variable (0 = non-victim, 1 = victim). Summing these binary variables yields the first main outcome variable and we name it 'count of distinct crime types' variable, which ranges from 0 to 5.

Main method 2: count summation

Main method 2 treats victimization types as count variables (e.g., ranging from 0 to 12). Summing these count variables yields the second main outcome variable and we name it 'total count across crime types' variable, which ranges from 0 to 90. This is a comprehensive outcome variable that captures the whole spectrum of victimization including non-victims and the overlap between recurring incidents of the same crime type and the experience of multiple types of crime within a 12-month period. The maximum value of 90 represents either multiple incidents of a single crime type or a combination of repeated incidents across different crime types. This integrated measure allows for a broader understanding of 'recurrent victimization' and provides new insights into the predictors of 'recurrent victimization'.

Three classification methods, several sub-outcome variables

Classification method 1: '2 or more' approach

Using the 'count of distinct crime types' variable (Main method 1), 'polyvictims' are classified as those experiencing '2 or more crime types' (e.g., burglary and personal theft). If using the 'total count across crime types' variable (Main method 2), 'repeat and polyvictims' are those experiencing '2 or more crime incidents' (e.g., repeat victimization or victimization across different crime types).

Classification method 2: 'one-above-the-mean' approach

The 'one-above-the-mean' approach is a classification method commonly used in victimization studies to identify individuals who experience a disproportionately high level of crime (Finkelhor et al., 2005). This method defines thresholds for 'recurrent victimization' based on deviations above the mean number of crime types or incidents among the victim group, aiming to capture those most severely affected. For the 'count of distinct crime types' variable (Main method 1), this approach classifies 'polyvictims' the same as the '2 or more' approach (e.g., '2 or more crime types'). For the 'total count across crime types' variable (Main method 2), 'repeat and polyvictims' are those experiencing '3 or more incidents.' The cut-off points change because of the average victimization among the victim groups based on the outcome variables used.

Classification method 3: top 10% approach

For the 'count of distinct crime types' variable (Main method 1), 'polyvictims' are those in the top 10% of the sample, experiencing '3 or more crime types.' For the 'total count across crime types' variable (Main method 2), 'repeat and polyvictims' are those experiencing '4 or more crime incidents.'

Table 1 provides descriptive statistics for all outcome variables constructed. Supplementary Table S1 summarizes construction of the dependent variables and the model names.

Table 1. Descriptive statistics of outcome variables.

Method 1			
Main variable 1	Mean	Variance	Min-Max
Count of distinct crime types*	0.290	0.355	0–5
Sub-outcome variables	Categories	Frequency	Percent
2 or more (or one above mean)	0 = non-victim	24,966	77.0
	1 = victim	5,904	18.2
	2 = polyvictim (2 or more types)	1,540	4.8
Top 10%	0 = non-victim	24,966	77.0
	1 = victim	7,115	22.0
	2 = polyvictim (3 or more types)	329	1.0
Method 2			
Main variable 2	Mean	Variance	Min-Max
Total count across crime types**	0.443	2.957	0–90
Sub-outcome variables	Categories	Frequency	Percent
2 or more	0 = non-victim	24,996	77.1
	1 = victim	4,883	15.1
	2 = repeat + polyvictim (2 or more incidents)	2,531	7.8
One above mean	0 = non-victim	24,996	77.1
	1 = victim	6,273	19.4
	2 = repeat + polyvictim (3 or more incidents)	1,141	3.5
Top 10%	0 = non-victim	24,996	77.1
	1 = victim	6,763	20.9
	2 = repeat + polyvictim (4 or more incidents)	651	2.0

*Combination of binary vehicle, burglary, personal theft, violence and digital victimization.
**Combination of count vehicle (range = 0–12), burglary (range = 0–90), personal theft (range = 0–15), violence (range = 0–60) and digital victimization (range = 0–50).

Predictor variables and theoretical framework

In addition to the socio-demographic characteristics included in most victimization studies, the selection of predictors was informed by theories such as lifestyle (Hindelang et al., 1978), routine activities (Cohen & Felson, 1979), and social disorganization theories (Sampson & Groves, 1989), which have been previously used to inform 'repeat' and 'polyvictimization' research (e.g., Hope et al., 2001; Hunter et al., 2021; Osborn & Tseloni, 1998; Tseloni, 2006; Tseloni & Pease, 2015; Tseloni et al., 2004). Lifestyle and routine activities theories emphasize how individuals' routine behaviors (e.g., time spent away from home, frequency of social activities) can influence their exposure to crime. Social disorganization theory underscores how community-level factors such as residential stability and economic status contribute to vulnerability to victimization. The variables selected for this study, all of which are included in the CSEW, are described below.

Socio-demographic characteristics

Socio-demographic characteristics included in the study are as follows. **Sex and age**: male and female groups across three age ranges (16–29, 30–59, 60+). **Ethnicity**: White, Mixed/multiple ethnic groups, Asian/Asian British, Black/African/Caribbean/Black British, and Other. **Marital status**: married/civil partnership/cohabiting, single, and separated/divorced/widowed. **Education**: A level or above, below A level, and no qualifications. **Employment**: higher managerial/professional occupations, intermediate occupations, routine and manual occupations, and never worked/long-term unemployed. **Number of Cars**: no car, 1 car, 2 cars, and 3 + .

Guardianship

Guardianship refers to the presence or availability of individuals or social structures that can prevent or deter offending or victimization by increasing supervision and reducing opportunities for crime (Cohen & Felson, 1979). It is a central component of routine activity theory. In this study, **physical guardianship** captures the immediate capacity for supervision within the household, operationalized through the number of adults (1 adult, 2 adults, and 3+). In contrast, **social guardianship** reflects broader forms of community-level supervision and informal social control, approximated by household tenure (owners, social rented sector, private rented sector), accommodation type (detached, semi-detached, terraced, flat), and length of residence (less than 2 years, 2–5 years, 5–10 years, 10+). Together, these measures capture both the direct and indirect dimensions of guardianship that influence opportunities for victimization.

Routine activities

In line with routine activities and lifestyle theories, these variables capture patterns of daily behavior and exposure to potential risk settings that influence victimization experience. **Household composition**: Categories included no children, children, and lone parent households. **Time away from home**: Divided into four categories based on hours spent away: none, 1–3 hours, 5–7 hours, and 7+ . **Frequency of pub and club visits**: Frequency of visits to pubs and clubs was divided into several categories: None, 1-3 times, 4 + .

Mental health

Mental health was treated as a separate domain, distinguishing individuals with and without self-reported mental health problems. Prior research suggests that poor mental health can increase vulnerability to victimization (through reduced capacity for risk avoidance or engagement in risky environments) and result from victimization experiences, highlighting a reciprocal relationship (Pettitt et al., 2013).

Area type

Consistent with social disorganization theory, geographic location (rural, urban, inner-city) serves as an indicator of the broader social and structural context in which individuals live, capturing differences in population density, residential mobility, and community cohesion that influence the capacity for informal social control and the likelihood of crime.

We used these variables in their original versions measured by the CSEW and treated as categorical by coding them as dummy variables for statistical analysis. Descriptive statistics of the predictor variables are presented in Table 2.

Table 2. Descriptive statistics of predictor variables.

Variable	Categories (ref = reference category)	Frequency	Percent
Sex/age	Male 16–29 (ref)	1,829	5.6
	Male 30–59	7,239	22.3
	Male 60+	5,814	17.9
	Female 16–29	2,244	6.9
	Female 30–59	8,728	26.9
	Female 60+	6,556	20.2
Ethnicity	White (ref)	28,879	89.1
	Mixed/multiple ethnic groups	395	1.2
	Asian/Asian British	1,970	6.1
	Black/African/Caribbean/Black British	903	2.8
	'Other' ethnic group	263	0.8
Marital status	Married, civil partnership, cohabiting (ref)	18,197	56.1
	Single	7,211	22.2
	Separated, divorced, widowed	7,002	21.6
Education	A level or above (ref)	17,581	54.2
	Below A level	9,034	27.9
	No qualifications	5,795	17.9
Socioeconomic status	Higher managerial, administrative and professional occupations (ref)	16,022	49.4
	Intermediate occupations	5,805	17.9
	Routine and manual occupations	9,379	28.9
	Never worked and long-term unemployed	1,204	3.7
Number of adults	One adult	10,822	33.4
	Two adults (ref)	16,832	51.9
	Three or more adults	4,756	14.7
Number of cars	No car	6,580	20.3
	1 car	13,708	42.3
	2 cars	9,217	28.4
	3 or more cars (ref)	2,905	9.0
Length of residency	Less than 2 years	5,098	15.7
	2 to 5 years	6,139	18.9
	5 to 10 years	5,010	15.5
	10 or more years (ref)	16,163	49.9
Tenure	Owners (ref)	21,144	65.2
	Social rented sector	5,372	16.6
	Private rented sector	5,894	18.2
Accommodation type	Detached house (ref)	8,038	24.8
	Semi-detached house	10,083	31.1
	Terraced house	9,428	29.1
	Flat and others	4,861	15.0
Household composition	No children	11,226	34.6
	Children	6,733	20.8
	Lone parent (ref)	1,589	4.9
	Household reference person aged 60 plus	12,862	39.7
Away from home	None	904	2.8
	1 to 3 hours	9,344	28.8
	5 to 7 hours	8,758	27.0
	7 or more hours (ref)	13,404	41.4
Pub visit	None	17,369	53.6
	1 to 3 times	9,566	29.5
	4 to 8 times	4,351	13.4
	9 or more times (ref)	1,124	3.5
Club visit	None	30,845	95.2
	1 to 3 times	1,372	4.2
	4 or more times (ref)	193	0.6
Mental health	No, mental health (ref)	30,502	94.1
	Yes, mental health	1,908	5.9
Area type	Rural (ref)	6,995	21.6
	Urban	22,488	69.4
	Inner city	2,927	9.0

Data analysis: regression modelling

This section explains the various regression models employed in this study to examine the predictors of 'recurrent victimization'.

Binary logistic regression

For 'polyvictimization' and 'repeat and polyvictimization' variables with three categories (e.g., 'non-victim', 'victim', 'recurrent victim'), the first and second categories were merged to create a new binary outcome variable (e.g., non-recurrent victims vs. recurrent victims). Binary logistic regression was then conducted on these two-category variables and the predictor variables.

Multinomial logistic regression

This model was used when the outcome variable had three categories, such as 'non-victim,' 'victim,' and 'recurrent victim' (Osborn et al., 1996). After fitting the multinomial models, **bivariate probit regression** models (Hope et al., 2001; Osborn et al., 1996) were also estimated to assess the relationships between the outcome and predictor variables. The current study also employs **ordinal regression** models as a sensitivity check to account for the order within the categories.

Negative binomial regression

For the main variables, 'count of distinct crime types' and 'total count across crime types' negative binomial regression models were applied. These models are suitable for count outcome variables that exhibit overdispersion, as described by Cameron and Trivedi (1986). The current study also estimates **zero-inflated negative binomial regression** models as a sensitivity check.

Each regression model was named systematically based on the outcome variables used. The variable names are followed by an asterisk (*) or two asterisks (**) to indicate the method used for constructing the variable (Main method 1 or 2, respectively). The type of regression model used is indicated in parentheses. For example, 'count of distinct crime types* (negative binomial)' refers to the model that uses the 'count of distinct crime types' main variable constructed using main method 1, followed by a negative binomial regression. This naming convention ensures clarity and consistency in referencing the various measurement and analytic strategies throughout the analysis.

Data analysis: meta-analysis

The second aim of the current study is to identify predictors of 'recurrent victimization' across a range of alternative regression models and to assess the consistency of their effects. To do so, we treat each model specification as providing an estimate of the same underlying effect for each predictor and pool these estimates using a *fixed-effect meta-analytic approach*. Specifically, we express all regression coefficients on a common odds-ratio scale and meta-analyze the corresponding log odds ratios using inverse-variance weighting (i.e., weights equal to $1/SE^2$). The pooled effect size is therefore a precision-weighted log odds ratio, which we exponentiate for presentation.

Although meta-analysis is typically applied to independent studies, here it serves as a within-dataset summary method. The aim is not to generalize across samples but to quantify the stability and robustness of effects across distinct analytical frameworks. The fixed-effect model assumes a common underlying parameter across specifications (Fleiss, 1993; Rice et al., 2018) – a reasonable assumption given that all models draw on the same dataset and measure the same conceptual construct of ‘recurrent victimization‘, albeit operationalized differently.

Inverse-variance weighting is not redundant in this context. Differences in link function, likelihood, and parameterization yield different standard errors for the same predictor. As in standard meta-analysis, weighting by $1/SE^2$ ensures that more precisely estimated coefficients contribute more to the pooled estimate than less precise ones. The resulting meta-analytic estimates can thus be interpreted as precision-weighted summaries of the central tendency of effects across models.

To examine the extent of agreement across models as part of aim 2, we report several standard heterogeneity metrics: **Q statistic**: Indicates substantial variability between effect sizes across models. $\mathbf{I^2}$: Quantifies the proportion of total variation across models attributable to heterogeneity rather than chance. **Higgins** $\mathbf{I^2}$: A modification of the I^2 test that estimates the proportion of variation due to genuine differences between models, beyond random error. $\boldsymbol{\tau^2}$: Estimates the amount of true heterogeneity beyond observed variation. In conventional meta-analysis, heterogeneity statistics quantify between-study variation due to differences in samples or study designs. Here, all estimates come from the same dataset, and heterogeneity instead reflects differences attributable to model specification (i.e., distinct operationalizations of recurrent victimization and different likelihoods and link functions). We use heterogeneity metrics not to generalize across studies, but as diagnostic indicators of specification sensitivity, to quantify how much different analytical decisions alter the estimated effect for each predictor.

Finally, we used the resulting meta-analytic coefficients as reference or ‘true’ effect for each predictor to calculate performance metrics for each analytic approach, which is the third aim of the current paper. **False Positive Rate (FPR)**: The rate at which non-significant predictors are mistakenly identified as significant. **False Negative Rate (FNR)**: The rate at which significant predictors are overlooked. **True Positive Rate (TPR)**: The rate at which significant predictors are correctly identified. **True Negative Rate (TNR)**: The rate at which non-significant predictors are correctly identified.[2] This procedure provides an empirical assessment of how consistently different models identify the same substantive predictors of ‘recurrent victimization’ and helps evaluate the likelihood of false conclusions across analytic strategies.

Data for this analysis can be accessed through the UK Data Service (Office for National Statistics, 2021), and analytic codes are available on GitHub (See Supplementary File).

Results

This section presents the findings from the meta-analytic synthesis of multiple analytic approaches estimated on CSEW data. The regression model results can be found in Supplementary Materials.

The meta-analysis aimed to synthesize the results from the various measurement and analytic approaches and identify the underlying predictors of 'recurrent victimization'. While the term 'meta-analysis' typically refers to the synthesis of results from independent studies, in this context it is used as a within-dataset meta-analysis to provide a precision-weighted summary of coefficients across twenty-one regression models estimated on the same sample. This approach allows us to evaluate the *robustness and stability* of predictors across alternative model specifications rather than to infer population-level effects across independent datasets.

Aim 2: key predictors of recurrent victimization

Figure 1 displays the results of the fixed-effects meta-analysis, which provides the inverse-variance weighted averages of the underlying effects across all twenty-one regressions. The meta-analysis corroborates the importance of certain predictors. **Mental health**: Individuals with mental health conditions are 1.78 to 1.86 times more likely to experience 'recurrent victimization' than those without a mental health condition. **Car ownership**: Households without cars (compared to those with three or more cars) are less likely to experience 'recurrent victimization'. **Education**: Individuals with no

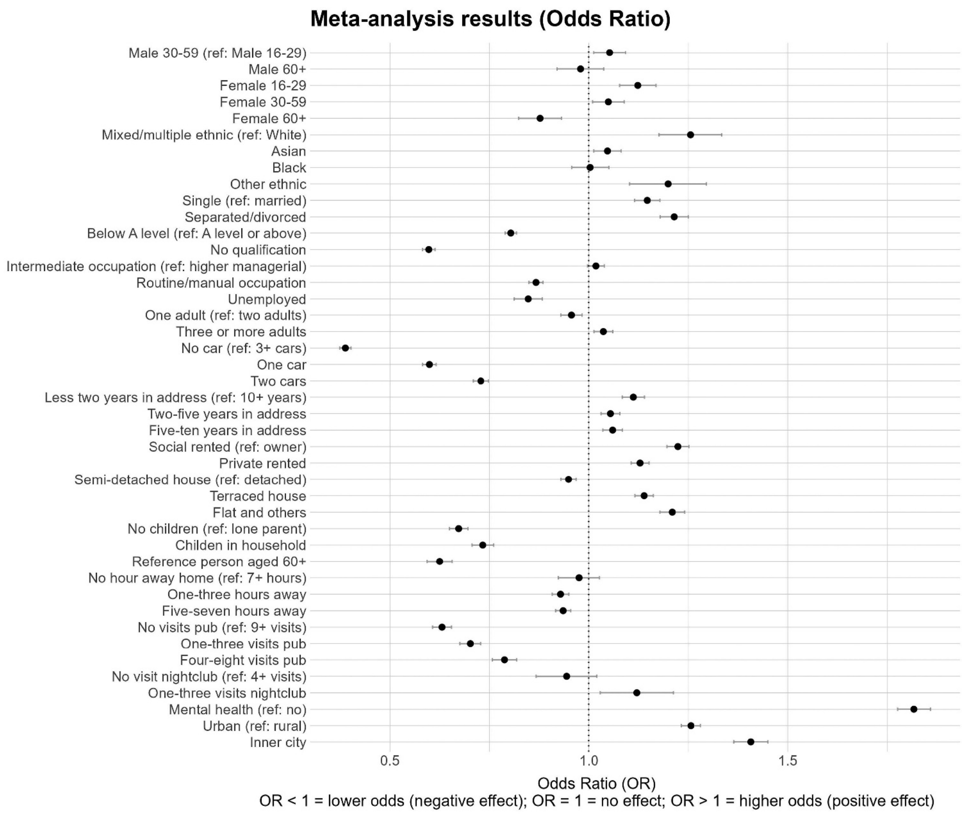

Figure 1. Meta-analysis results (odds ratios and confidence intervals).

qualifications are significantly more likely to become a recurrent victim than those with A-levels or higher education.

While we can confidently assert that certain predictors, such as car ownership, mental health status, and education level, hold consistent significance across all models (see Supplementary Table S2 and Figure 1), predictors that show significance in some models but not others should not be disregarded. Variability in results could arise from factors like measurement error, model specifications, and the statistical power of the models used.

Some other predictors that were not consistently significant across all individual models were identified as significant in the meta-analysis: **Age and gender**: Females over 60 years old are between 82% and 93% as likely as males under 30 to experience 'recurrent victimization'. **Ethnicity**: Individuals from mixed or other ethnic backgrounds are around 1.18 and 1.33 times more likely than White individuals to experience 'recurrent victimization', respectively, although Black ethnicities did not show significant effects. **Relationship status**: Single and separated individuals are about 12% and 18% more likely to become recurrent victims than married individuals, respectively. **Occupation**: Unemployed individuals and those in manual occupations are less likely to experience 'recurrent victimization' compared to those in higher managerial roles. **Social activities**: Fewer pub visits (less than 9 times per month) are strongly associated with a lower likelihood of 'recurrent victimization'. Additionally, spending less than 7 hours away from home on weekdays is weakly associated with lower 'recurrent victimization' risk. **Housing**: Households without children, or with a reference person over 60 are significantly less likely to experience 'recurrent victimization' compared to lone-parent households. **Location**: Individuals living in urban or inner-city areas are more likely to become recurrent victims compared to those in rural areas.

Substantial variability in effect sizes was observed across the models, as evidenced by a significant Q statistics for all variables, suggesting that different regression models yielded varying estimates. The I^2 statistics reveal considerable heterogeneity in effect sizes for predictors such as car ownership (86.8 [no car], 73.7 [one car], and 56.2 [two cars]), pub visits (47.6 [no visits], 21.9 [one-three visits]), mental health (92.3), education level (35.8 [below A levels], 66.7 [no qualification]), and urban residence (42.3 [urban], 61.6 [inner city]). Notably, variables such as car ownership, pub visits, mental health status, education level, and location show I^2 values above 50%, highlighting the susceptibility of these effect sizes to model-specific factors.

Aim 3: optimal measurement and modeling strategies

Beyond identifying predictors, the meta-analysis evaluated the performance of different measurement and analytic approaches in accurately identifying these predictors. Figure 2 shows that the 'Top 10%* (binary logistic)' approach was the only one to show a false FPR greater than zero, indicating it misidentified a variable as significant. 'Top 10%* (binary logistic)' also had the lowest TPR and the highest FNR, suggesting it was the least accurate model. The models with the highest TPR and lowest FNR were '2+/One above mean* (bivariate probit)' and '2 or more** (bivariate probit)'. Other models like 'Total count across crime types** (negative binomial)' and 'Total count across crime types ** (zero-inflated negative binomial)' also performed

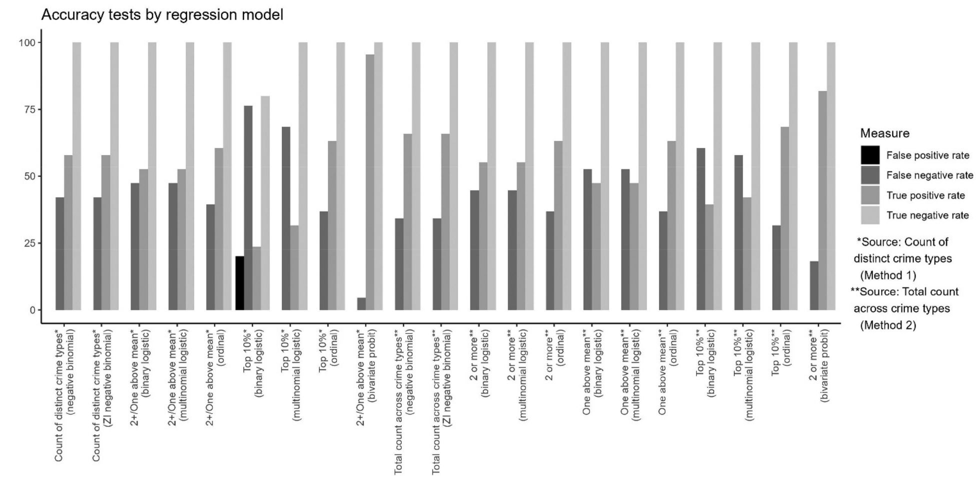

Figure 2. Accuracy tests calculated for each measurement/regression model.

relatively well, with smaller FNRs and larger TPRs than other models. These findings suggest that while certain models are more effective at identifying significant predictors, differences in model complexity and variable inclusion can meaningfully influence apparent predictive strength.

Discussion

This paper aimed to: (1) review and identify different methods used to measure 'recurrent victimization' and integrating them into a single study, (2) identify robust correlates of 'recurrent victimization' across various statistical methods, and (3) identify the optimal measurement and modeling strategies for investigating predictors of 'recurrent victimization'.

Aim 1: review of existing studies

The review of existing studies highlights substantial inconsistencies in how 'recurrent victimization' has been conceptualized, operationalized, and modeled across the literature. Therefore, each method identifies different individuals as recurrent victims (see Table 1), which could lead to variations in understanding the phenomenon and tailoring interventions (Krushas et al., 2025). Research using the CSEW has predominantly focused on 'repeat victimization' within single crime categories, typically using count-based measures and negative binomial regression, with some studies applying multinomial or bivariate probit models to examine escalation or co-occurring risks. Studies using alternative data sources tend to operationalize 'recurrent victimization' through simple thresholds, such as two or more crime types or 'one-above-the-mean' classifications. Importantly, no prior work systematically compares these operationalizations or evaluates how different analytic strategies influence the identification of predictors. This fragmented landscape underscores the need for a unified assessment of measurement and modeling approaches, providing the foundation for Aims 2 and 3 of this study.

Aim 2: key predictors of recurrent victimization

The meta-analytic results provided valuable insights into which predictors most strongly correlate with 'recurrent victimization'. The strongest correlate across all measures was self-reported mental health conditions. This finding aligns with previous studies by Chan (2017) and Tanksley et al. (2020), who highlighted the relevance of mental health in explaining 'recurrent victimization'. Given the high prevalence of mental health conditions among recurrent victims, criminal justice system practitioners, including police, are encouraged to develop targeted interventions for recurrent victims, particularly those with mental health conditions. Research and services supporting victims should receive increased funding, particularly initiatives that address the intersection between mental health and victimization. The development of policies to promote early detection of 'recurrent victimization' in mental health patients is critical.

Aim 3: optimal measurement and modeling strategies

This paper explored how different operationalizations of 'recurrent victimization' affects regression estimates, highlighting that operationalization choices significantly influence both the identification of recurrent victims and their statistically significant predictors and their effect sizes. In particular, we introduced a more holistic approach to measuring 'recurrent victimization' in our second main method, which merges 'repeat victimization' and 'polyvictimization', capturing the whole spectrum of victimization, including the overlap between the recurrence of crime types and the experience of multiple crime types. This method provides a more comprehensive measure of victimization, offering new insights into the sociodemographic characteristics of high-risk victim groups.

The meta-analytic synthesis of results from various operationalizations and regression models revealed that operationalizations based on experiencing two or more victimization categories or incidents performed substantially better when paired with bivariate probit models (i.e., 2+/one above mean* (bivariate probit) or 2 or more** (bivariate probit) models, respectively). Count-based operationalizations, particularly total victimization counts across crime types, also performed well when analyzed using negative binomial or zero-inflated negative binomial models (i.e., Total count across crime categories** (negative binomial) or Total count across crime categories** (ZI negative binomial) models, respectively). For binary outcome variables, models such as the 'Top 10%* (binary logistic)' and 'Top 10%* (multinomial logistic)' were associated with higher risks of false positives and negatives and should be avoided, although 'Top 10%* (ordinal)' and 'Top 10%** (ordinal)' performed relatively well.

Therefore, future research should consider employing theoretically informed category or incident-based 'recurrent victimization' measures analyzed with bivariate probit or negative binomial frameworks. However, we acknowledge that logistic and probit regression models generally yield comparable substantive conclusions, as both reduce outcomes to a binary form and differ primarily in the assumed distribution of the error term. Our inclusion of both models was not intended to suggest fundamental qualitative differences, but rather to assess whether the choice of link function had any practical implications for identifying recurrent victims and their associated risk factors within our sample. Any differences observed are likely attributable to sample characteristics rather than theoretical distinctions between the models.

Conclusions

The findings of this study have important implications for crime prevention policy and practice. The choice of operationalization and modeling strategy directly affects who is identified as a recurrent victim and, consequently, how limited prevention resources are targeted. Using more comprehensive measures, such as those integrating both 'repeat' and 'polyvictimization', can help practitioners recognize individuals and households experiencing multiple or overlapping forms of victimization who might otherwise be overlooked. Similarly, adopting more robust modeling approaches, such as count-based negative binomial models, can provide a more accurate picture of victimization patterns and risk factors, supporting the design of evidence-based interventions that prioritize those at greatest risk. By highlighting how methodological decisions influence the identification of recurrent victims, this study underscores the importance of transparent and consistent measurement practices to ensure that research findings translate effectively into policy design, victim support services, and broader crime reduction strategies. Further research is needed to refine our understanding of 'recurrent victimization', particularly in non-adult populations.

Despite the significant contributions, this study has some limitations as well. Our review primarily focused on adult victimization, while other studies have investigated 'polyvictimization' in children, using different datasets (Fisher et al., 2015; Tura et al., 2023). Unfortunately, the results of our study cannot be generalized to address 'recurrent victimization' in children. In addition, the measurement of mental health issues as a binary variable poses a challenge and should be refined using more nuanced and less stigmatizing measures (Lahey et al., 2022).

Notes

1. Digital crime measures if fraud or cybercrime involved in any incidents mentioned at non-fraud screeners; if personal information or account details used to obtain money or buy goods or services; if tricked or deceived out of money or goods in person, by telephone, or online; If anyone tried to trick or deceive you out of money or goods in person, by telephone, or online; if anyone stole personal information or details held on computer or in online accounts (e.g., e-mail, social media); and if computer or other internet-enabled device has been infected or interfered with e.g., by a virus.
2. These performance metrics were calculated using the following formulae: FPR = FP/(FP + TN); FNR = FN/(FN + TP); TPR = TP/(TP + FN); and TNR = TN/(TN + FP). Where FP represents a false positive, TN a true negative, TP a true positive, and FN a false negative.

Author contributions

Ferhat Tura conceptualized the study, conducted the data analysis, and led the writing of the manuscript. David Buil-Gil and Oluwole Adeniyi contributed to data analysis, manuscript writing, and editing. All authors reviewed and approved the final version of the manuscript.

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Data availability statement

Data can be accessed via the UK Data Service and are cited in the article.

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