

THE INFLUENCE OF ACTIVITY SPACE AND VISITING FREQUENCY ON CRIME LOCATION CHOICE: FINDINGS FROM AN ONLINE SELF-REPORT SURVEY

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Crime pattern theory predicts that offenders commit offences in their activity spaces. We also propose that they most likely offend in the more frequently visited parts. Previous studies used offenders' residential areas or other activity space proxy measures but lacked data on other routinely visited places (e.g., work, school, and leisure activities). A major contribution of this study is the use of an online survey in which 78 offenders reported on their own activity spaces and committed offences (n = 140). Results show that offending is much more likely in offenders' activity spaces than elsewhere, and effects increase with visiting frequency. Although residential area is a good predictor, offenders' more extensive self-reported activity spaces predict much better where they commit offences.

Key Words: crime location choice, crime pattern theory, activity space, visiting frequency, Online Activity Space Inventory Survey (OASIS)

Introduction

According to the geometry of crime in crime pattern theory (Brantingham and Brantingham 1981; Brantingham *et al.* 2017), offenders are more likely to commit offences within their awareness spaces because they know these areas. Besides a home base, most people visit a number of *activity nodes* during their routine activities, such as work, the grocery store and a friend's house. While visiting their activity nodes and spending time there, people acquire knowledge of the area surrounding the nodes. This includes knowledge potentially relevant for committing crime, such as the presence of attractive targets or the absence of surveillance (Brantingham and Brantingham 1993). During their routines, people visit some activity nodes more frequently than others, which probably influences the level of knowledge.

Previous crime location choice studies included offenders' awareness spaces only by assumption, without actually measuring them. Assuming that offenders spend most of their time near their homes, most research has only included (proximity to) offenders' own residential areas as a proxy measure of offenders' awareness spaces (for an overview, see Ruiter 2017). Recently, another offender-specific routine activity node type was included: residential areas of offenders' close family members (Menting *et al.* 2016; Menting 2017). However, all previous crime location choice studies that used the discrete choice framework relied on register data to measure offenders' activity spaces.

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Consequently, these studies included a very limited number of activity nodes, and they did not have information on whether and how frequently offenders actually visited these. These limitations have hampered our understanding of how and to what extent activity spaces affect where offenders commit offences, and crime pattern theory has only been partially tested.

In order to provide a more comprehensive test, we developed the Online Activity Space Inventory Survey (OASIS). In this internet survey, respondents themselves reported about their activities during the three years prior to the survey, the types of location they frequently visited and where, when and how frequently they visited these. We also asked them if, where and when they committed offences. Using OASIS data of 78 offenders, this study is the first to examine the influence of a broad range of regularly visited activity nodes on crime location choice and test whether effects depend on how frequently activity nodes are visited. Using discrete spatial choice models with a spatial choice set of 12,821 areas in the Netherlands, we test (1) whether the presence of an activity node affects the probability an area and areas nearby are targeted; (2) to what extent the inclusion of other activity nodes beyond offenders' residential areas improves our understanding of crime location choices; and (3) whether effects depend on activity node visiting frequency.

Crime Pattern Theory and Previous Research: Offenders' Awareness Spaces

Crime pattern theory's geometry of crime (Brantingham and Brantingham 1981; 1993; Brantingham *et al.* 2017) provides a framework for understanding where offences occur. During everyday activities, people develop a so-called *activity space*: the activity nodes they visit during their daily routines and the paths used to travel between them. The activity space and all areas within visual range form the *awareness space* (Brantingham *et al.* 2017: 101). People acquire spatial knowledge about their awareness space and they generally have little or no information about other areas. According to crime pattern theory, offenders commit offences in areas where the spatial distribution of attractive targets overlaps with their awareness space.

Offenders' awareness spaces at least comprise the areas around their homes. Based on the least effort principle (Zipf 1949), they would prefer to perform their activities close to home because travelling further costs more time and effort. Consequently, they would generally have less information about more distant areas. Although the home location thus seems to be important for understanding where offenders commit crime, Brantingham and Brantingham (1981: 35) emphasize that 'most offenders are not tied exclusively to some home base, but, like other people, are mobile. (...) They develop information about other parts of the urban area through working (...), traveling to school, shopping, or seeking out entertainment and recreation'. Time-use research among a random Dutch population sample shows that many people are involved in common activities such as work, education, shopping and leisure activities on a weekly basis, although some age-group differences exist (Statistics Netherlands 2014). The same is probably true for offenders, as offending generally takes up only a small part of their routine activities (Brantingham and Brantingham 1981; 1993). Other activity nodes such as work or a friend's home thus likely also influence where offenders commit offences, and a sole focus on offenders' home areas would provide an

incomplete picture of their awareness spaces. By spending time in activity node areas, offenders learn whether they could successfully commit an offence there, e.g., because attractive targets are present and surveillance is low (Brantingham and Brantingham 1981; 1993; Brantingham *et al.* 2017). Therefore, all areas with sufficient criminal opportunity that contain an activity node that is regularly visited by a motivated potential offender should have an increased risk of being targeted.

Not only activity nodes themselves are expected to have an increased risk of being targeted by an offender. Distance-decay patterns are described to occur around all major activity nodes and major paths between them (Brantingham and Brantingham 1984). When travelling between activity nodes, offenders also learn about the areas through which they travel. Moreover, while visiting any activity node, offenders could explore neighbouring areas and learn about their characteristics and criminal opportunities. This can be for non-criminal reasons, e.g., while taking a stroll during a lunch break. An offender can also deliberately extend the potential target area and search for new suitable targets for future offences (Rengert and Wasilchick 2000; Summers and Guerette 2018).

All previous crime location choice studies consistently found a strong distance-decay pattern: the likelihood of offending decreases with the distance from the offender's home (e.g., Bernasco and Nieuwebeerta 2005; Clare *et al.* 2009; Bernasco 2010; Baudains *et al.* 2013; Townsley *et al.* 2015). If routines usually take place relatively close to home, it may be argued that (proximity to) the offender's residential area indirectly captures also other parts of the activity space. However, regular activities such as work may occur at some distance from home. Even if nodes are relatively close, proximity to home does not capture the actual node but merely a location near the home node (see Figure 1).

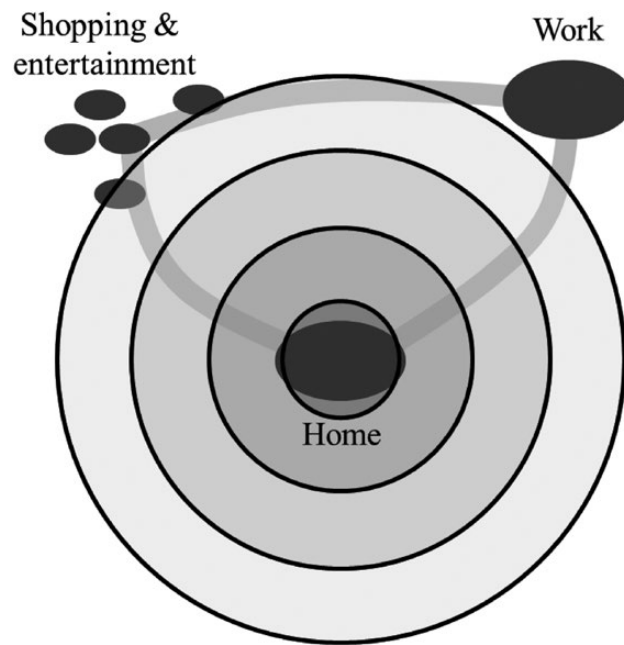


FIG. 1 Hypothetical activity space (based on Brantingham *et al.* 2017) and to what extent and how the full activity space would be covered when only based on (proximity to) the offender's home.

This applies to all contiguous areas in every direction of the home, whereas the direction towards the activity node is likely more important than other directions without activity nodes. Moreover, if distance-decay patterns exist around all major activity nodes and ‘the distance-decay pattern away from home is a simplification’ (Brantingham and Brantingham 1984: 355), the risk of being targeted gradually reduces also for areas around other activity nodes. Only including distance from home implicitly assumes that all crime journeys start from home, but offenders may also start crime journeys from another activity node (e.g., Bernasco 2010). For example, drug-dependent residential burglars’ crime sites were found to also cluster around drug sales areas in addition to their residential areas (Rengert 1996). Therefore, to more rigorously test crime pattern theory, all important activity nodes and their related distance-decay patterns should be explicitly examined.

While controlling for proximity to offenders’ current residential areas, a few other *offender-specific activity nodes* have been found to have an increased risk of being targeted: their former residential areas (Bernasco 2010) and residential areas of their parents, siblings and children (Menting *et al.* 2016; Menting 2017). However, these activity nodes probably constitute only a limited part of offenders’ awareness spaces, without common activity nodes like workplaces, schools and leisure activity locations. Consequently, prior research has tested crime pattern theory incompletely and may have underestimated the proportion of offences committed inside offenders’ awareness spaces.

Previous crime location choice studies did include some measures of *collective activity nodes*: places that attract large numbers of people (e.g., city centre, areas with schools, many retail facilities/employees or bars/restaurants/hotels). These areas had a higher probability of being targeted (Bernasco and Block 2009; Baudains *et al.* 2013; Bernasco *et al.* 2013; Johnson and Summers 2015; Townsley *et al.* 2016; Menting 2017), which suggests that such areas are often also part of offenders’ awareness spaces. Although visited by many people, including potential offenders, they are obviously not equally known to each individual offender. Johnson and Summers (2015), e.g., showed that the presence of schools only positively influenced crime location choices of juvenile but not adult offenders. Proximity to the city centre has also not been a consistent predictor of crime location choice across studies; some found no effect (Bernasco and Nieuwebeerta 2005; Bernasco 2006) or only a positive effect for adult but not juvenile offenders (Johnson and Summers 2015). Although offender-specific awareness spaces often have some overlap with these highly visited collective activity nodes, the level of overlap varies between offenders. Crime pattern theory is thus not rigorously tested with collective measures, as this analytical strategy is based on the untenable assumption that *all* highly visited areas are part of the awareness space of *all* potential offenders and that all other areas, including most areas with residential land use, are not.

In order to provide a more rigorous test of crime pattern theory and better explain offenders’ crime location choices, regularly visited activity nodes of individual offenders and their offending patterns should be mapped more completely. As registration-based data sources do not provide such information, alternative methods are needed. Offenders themselves could be sources to obtain information on their routines and offence locations. Summers *et al.* (2010) interviewed 28 offenders and used maps to study spatial criminal decision-making. They concluded that in contrast to sketch maps (drawn by the offenders), cartographic maps were particularly useful. They suggested that interactive online maps could provide new opportunities. In designing OASIS, we

built on their findings and used Google Maps to help respondents indicate their regularly visited and offence locations.

We test the following hypotheses:

Hypothesis 1: Offenders are more likely to commit offences in areas that include any regularly visited activity node than in otherwise comparable areas without any activity node.

Hypothesis 2: Offenders are more likely to commit offences in areas closer to any regularly visited activity node compared to otherwise comparable areas further away.

We expect that the inclusion of all self-reported regularly visited activity nodes provides a better explanation for where offenders commit offences than when only their residential areas are taken into account. As people probably get at least somewhat familiar with any regularly visited area regardless the reason of visiting, any activity node type is expected to contribute to the explanation of crime location choice. We do not expect that the results would differ substantially for different crime types because familiarity of an area does not affect whether it is suitable for committing a specific crime type, only the distribution of attractive targets does. Although the extent to which a known area is perceived attractive for a specific type of crime can be related to the reason why it is visited (e.g., areas where offenders do their shopping may provide more shoplifting opportunities than their residential area), crime pattern theory provides a generic explanation and offenders are expected to target a known area within their awareness spaces for any type of crime. A recent study also showed that the level of criminal opportunity was less influential in residential areas of offenders and those of their family. These activity node areas were more likely targeted even when opportunity was relatively low, and higher levels of opportunity did not or only marginally increase the likelihood of the area being targeted. Effect patterns were quite similar for violent and property offences ([Menting 2017](#)). We, therefore, include any activity node type and all reported offences in our main analyses.

Influence of visiting frequency

Activity node visiting frequencies vary as ‘human activities occur at varying frequency’ ([Brantingham and Brantingham 1984](#): 350). Some nodes are visited daily (like home), others are visited once a week or only monthly. If knowledge of an area is gradually built each time an activity node is visited—new environmental details can be added to memory and already stored information can be updated—the level of knowledge probably depends at least to some extent on the visiting frequency. This does not only include knowledge of general, static area characteristics that always apply but also time-specific information that applies to the day(s) the area is visited. [Van Sleeuwen et al. \(2018\)](#) argued that offenders’ awareness spaces are time specific: knowledge of an area relevant for committing crime gained on a specific day of the week may not be equally applicable to other days of the week. Visiting an area several times a week would, thus, not only enable a potential offender to better learn general static characteristics but also provide a broader range of time-specific information on which day it would be best to commit crime. Such multi-day time-specific knowledge is generally absent when an area is visited just one (fixed) day a week or less during routine activities, which might be a reason for an offender to target another, more frequently visited part of their activity space.

How frequently an activity node is visited likely also affects the level of knowledge of areas surrounding it: visiting an activity node very frequently also means that areas nearby are more frequently travelled through, and it provides more opportunity to explore contiguous unfamiliar areas. Thus, offenders are not only expected to have more knowledge of the more frequently visited activity node areas, they may also know areas nearby better than areas near less frequently visited activity nodes.

The likelihood of targeting an area should also increase with visiting frequency simply because it is related to how much time the offender spends in an area. It is easy and convenient to commit offences that require some planning while visiting an area for other non-criminal routine activities, and there are more moments to choose the right time from when the area is more frequently visited. Opportunistic offences are also usually committed during everyday activities within the offender's routine activity space (Rengert and Wasilchick 2000). More frequently visited areas would, thus, be more likely targeted than less frequently visited areas.

Because register data do not provide information on visiting frequencies, no study explicitly tested its influence on crime location choice. Nonetheless, a previous finding provides some indirect evidence: family members' residential areas were more likely targeted, but the effect sizes were smaller than those of the offender's own residential area (Menting *et al.* 2016). A potential explanation for this difference is that offenders generally visit their own residential area more frequently than those of their close family members. In the OASIS, we explicitly asked respondents how frequently they visited each reported activity node, which enables us to empirically assess the influence of visiting frequency on crime location choice.

Thus, we expect not only that any regularly visited activity node and areas nearby are at increased risk of being targeted (following Hypotheses 1 and 2), we also expect these effects to be moderated by visiting frequency. This translates into these hypotheses:

Hypothesis 3: Offenders are more likely to commit offences in areas that include a very frequently visited activity node compared to areas that include an activity node that is visited less frequently.

Hypothesis 4: Offenders are more likely to commit offences in areas close to areas that include a very frequently visited activity node compared to areas close to areas that include a less frequently visited activity node.

Methods

Online Activity Space Inventory Survey

Data were collected with the OASIS, developed using LimeSurvey (LimeSurvey 2017). Respondents received the URL of our project's website and a unique personal access code in their invitation letters, which they could use to access the online survey after they had clicked on a link on the project's website. After accessing the survey with this code, respondents received more information on the research, and they could continue with the survey after they had read and agreed with the study's conditions specified in the online consent form. Confidentiality, anonymity and privacy were declared in the invitation letter and survey environment.

The questions were subdivided into five domains based on activities and places commonly reported by young adults in time-use research (Cloïn *et al.* 2013; Statistics Netherlands 2014). The survey included questions regarding the following seven domains: (1) own current and former home locations and other sleeping places, (2) visited homes of others, subdivided into five subdomains: parents, siblings, (ex-)partners, friends and others, (3) victimization locations, (4) offending locations, (5) current and former school locations, (6) work locations and (7) leisure activity locations, in five subdomains: sports, shopping, entertainment (e.g., bars, restaurants, clubs, and cinemas), hangout and other. In order to reduce ambiguity of what behaviours respondents would consider offences (cf. nationwide Dutch victimization survey), the victimization and offending domains were subdivided into crime type subdomains: (1) theft of a car/motor/bicycle, (2) other theft, (3) burglary, (4) vandalism, (5) robbery, (6) violence, (7) trafficking drugs (offending only) and (8) trafficking weapons (offending only). For example, to assess vandalism, we asked whether a respondent had destroyed something of someone else in the last three years. To allow respondents to report about many different combinations of locations, they could report up to 286 different locations in total across all (sub)domains (generally about 10 locations per subdomain). Next to the predefined domains, we asked respondents whether they had regularly visited any other location type, and if so, which type it was. Respondents could also return to previous domains if they wanted to add any activity node they had forgotten to fill out before.

Each (sub)domain contained several general questions about the visited location (e.g., ‘where?’, ‘when?’, ‘how frequently?’). LimeSurvey has a specific feature to assess geographic locations. It allows the user to pinpoint a location using Google Maps, which we used to ask respondents to indicate the locations of their activities. To help them find the right locations, we programmed a search bar based on the Google Places API. That way, respondents could simply type a name of a street or facility and the map would reorient itself to the search result. Detailed instructions on how to select locations were provided with the first mandatory current home location question and in a flyer sent with the invitation letter. Brief instructions were repeated below each map. Longitude and latitude were recorded for all pinpointed locations. With dropdown menus, respondents could indicate the month and year (2013–16) of the reported crime events and the start and end of the period during which the locations were regularly visited. We also asked for every visited location how frequently the respondent had visited it on average during the indicated period. One of six ordinal response categories had to be selected. As respondents were instructed to report only regularly visited locations, defined as at least once per month in a period within the last three years, the lowest visiting frequency category was ‘monthly’. Further options were: ‘a few times a month’, ‘1 day a week’, ‘2–4 days a week’, ‘5–6 days a week’ and ‘7 days a week’.

Respondents

After obtaining permission for our research design by the relevant authorities and a positive advice from the ethical committee of the Law Faculty of the Vrije Universiteit Amsterdam, a random sample of people was drawn from the police suspect information system used by the The Hague Police Service. A reason to use a sample from a

population of former suspects was the consideration that only offenders would provide useful information to test hypotheses on offending locations, and the expectation that a random population or other type of sample would include large percentages of non-offenders. Inclusion in the suspect information system is indicative that considerable evidence is available for prosecution. Blom *et al.* (2005) estimated that more than 90 per cent of suspects in the police database would either receive a transaction (i.e., pay money to the Public Prosecution Service) or would eventually be charged and found guilty.

People were eligible for inclusion in the sample if they were: (1) recorded suspects of an offence in 2014, (2) between 18–26 years old at the time of the sample selection¹ and (3) recorded at a valid and non-secret home address according to the Dutch nationwide population registration system (acronym BRP) at the time of the study in 2016. Invitation letters were sent in three batches in May, June and September to 3,451 individuals (82.5 per cent male). A reminder was sent two weeks after the initial letter. One hundred twenty-four letters could not be delivered because the person appeared to be unknown at the recorded address. Respondents who completed the survey received a 50-Euro gift card. Four hundred thirteen respondents fully completed the survey (response: 12.4 per cent; 76.0 per cent male). The postal mail request to visit our website and online survey may have contributed to the relatively low response rate (De Leeuw 2018). Unfortunately, no other contact information like email addresses or phone numbers was available. For this study, all respondents were included who reported having committed at least one offence in the Netherlands between January 2013 and the study participation month in 2016 while living in the Netherlands. This resulted in a study sample of 78 offenders (87.2 per cent male; mean age = 22.1 years, range = 19–26).

Study area

The entire Netherlands were selected as the study area and neighbourhoods as the spatial unit of analysis. Given the small size of the country—the maximum distance between pairs of neighbourhoods is only 336.7 km—it is possible for individuals to have activity nodes spread across the entire country, and offences may be committed near any of them. Although the vast majority of distances between locations—node to node and node to crime location—reported in the OASIS are rather small, they are occasionally larger than 100 km (maximum: 200 km). Dutch neighbourhoods are the smallest statistical units for which Statistics Netherlands provides detailed information on structural and socio-economic features. Neighbourhood boundaries are defined in such a way that they are internally most homogeneous and generally have one dominant function (e.g., residential, work or recreational areas; Statistics Netherlands 2017a). We used geographical data for all 12,821 neighbourhoods in the Netherlands in 2016, with a median size of 0.68 km² (mean = 2.63, standard deviation (SD) = 5.39, range = 0.01–128.2) and a median residential population of 675 (mean = 1,323, SD = 1,774, range = 0–28,120) (Statistics Netherlands 2017b). Given their size and homogeneous character, Dutch neighbourhoods are expected to be well known to those who regularly visit them.

¹Young adults were selected because awareness spaces often vary with age, with some node types visited more by younger than older people (Brantingham and Brantingham 1981). Young adults are also more likely involved in crime (Hirschi and Gottfredson 1983), and they generally have more experience with online tools such as Google Maps.

Study variables

The 78 offenders in our sample reported a total of 140 offences committed in the study area in the three years (mean = 1.8 per offender, range = 1–8; n per type: 52 violent offences, 46 thefts, 19 acts of vandalism, 16 drug trafficking offences, 4 burglaries, 2 robberies and 1 weapons trafficking offence). To construct the dependent variable, offence locations were geocoded to one of the 12,821 neighbourhoods. For each offence, the neighbourhood in which the offence was committed received a score of 1 and all other neighbourhoods 0.

The activity nodes were coded into several independent dummy variables, using their location geocoded to one of the 12,821 neighbourhoods and the information about the start and end of the period during which they were regularly visited. We first indicated the neighbourhoods in which the offenders were living in the offence month.² These neighbourhoods received the score 1 on the variable *residential area of the offender*, all other neighbourhoods 0. More importantly, other regularly visited locations were also included, indicated by *any activity node*: those neighbourhoods in which the offender reported to have visited at least one activity node of any type—their own residential area or one of the other regularly visited locations—in the month of the offence received the score 1 and those without any activity node 0.

Proximity to the *residential area of the offender* was captured by including mutually exclusive dummy variables (1 = yes, 0 = no), reflecting the spatial lag order of potential target neighbourhoods relative to the offender's residential area: (1) *first-order neighbourhoods* include all neighbourhoods directly contiguous to the residential neighbourhood (first-order spatial lag); (2) *second-order neighbourhoods* are those contiguous to the first-order neighbourhoods and (3) *third-order neighbourhoods* contiguous to the second-order neighbourhoods. Analogously, proximity to *any activity node* was captured by indicating all *first-, second- and third-order neighbourhoods* surrounding the neighbourhoods containing any activity node. When a neighbourhood was simultaneously in multiple spatial lags (e.g., first from work and third from school), the lowest order kept the score 1 to indicate the shortest distance to any node from each neighbourhood, and the higher-order neighbourhood indicator scored 0.

For descriptive purposes and to examine the relative contribution of activity node types, the joint activity node variable was split into four types based on general time-use patterns and observed consistencies in activity type patterns in our survey: (1) residential area of the offender (see above); (2) residential areas of other people known to the offender (e.g., family and friends); (3) school/work locations and (4) leisure activity (e.g., sports, shopping, entertainment and hangout) locations. For each, node neighbourhoods were determined together with their higher-order surrounding neighbourhoods.

To test the influence of visiting frequency, we indicated for each activity node neighbourhood how frequently the node was visited. Whenever there were multiple activity nodes in the same neighbourhood, the highest frequency score was used. Based on

²Former activity nodes may also affect crime location choice due to the dynamic nature of awareness spaces. However, their effects were smaller than those of their current counterparts or sometimes even statistically non-significant (Bernasco 2010; Menting et al. 2016). Respondents in our sample indicated relatively few node neighbourhoods they had *only* visited before the offence. The effect of a dummy variable indicating neighbourhoods with only a *former* activity node of any type added to Model 2 was not statistically significant ($p = 0.09$) and much smaller than those of current any activity nodes and first-, second- and third-order neighbourhoods ($ps < 0.001$). Therefore, only current activity nodes were included.

these scores, two mutually exclusive dummy variables (1 = yes; 0 = no) were used to indicate activity node neighbourhoods that were *very frequently* visited and node neighbourhoods that were *less frequently* visited. *Very frequently* was defined as at least 2–4 days a week, and *less frequently* as monthly up to 1 day a week. *Very frequently* visited activity node neighbourhoods were, thus, visited on multiple different days of the week, and these were not primarily based on the offender's often-daily visited home neighbourhood.

Each higher-order neighbourhood also received one visiting frequency score based on the visiting frequency of the closest activity node, thus considering distance first by using the frequency score of the lowest spatial order. With these frequency scores, mutually exclusive *very frequently* (≥ 2 –4 days per week) and *less frequently* (≤ 1 day per week) dummy variables were generated for each of the first-, second- and third-order neighbourhoods.

Control variables

When examining crime location choice, it is important to take the level of criminal opportunity in all neighbourhoods into account. Therefore, two indicators were included to control for occupancy and activity of people in a neighbourhood, both residents and the working population: *residential population density* and *employee density*. Areas where relatively many people are present per surface unit (e.g., due to the presence of crime attractors or generators; see [Brantingham and Brantingham 1995](#)) have larger concentrations of potential victims and potential offenders but may also have more potential guardians and surveillance opportunities. *Residential population density* was calculated by dividing the number of residents per neighbourhood by area size (in square metres) using 2016 neighbourhood-level data ([Statistics Netherlands 2017](#)). For *employee density*, information was obtained from 2011 LISA data (Dutch: 'Landelijk Informatiesysteem Arbeidsplaatsen'; for more information, see [Steenbeek et al. 2012](#)). LISA data contain information on all businesses and facilities in the Netherlands, which we geocoded to one of the 12,821 neighbourhoods. *Employee density* was calculated by dividing the sum of all people working in a neighbourhood in any facility (part-time employee = 0.5) by the neighbourhood's area size (in square metres). As many types of facilities also attract other people (e.g., customers and schoolchildren), areas with a high employee density generally also have a relatively high visitor density.

Statistical analyses

Conditional logit models were used to test our hypotheses. These models are aimed at testing why a decision-maker (here: offender) chooses a specific alternative (where to commit crime) from a set of alternatives (12,821 mutually exclusive neighbourhoods), given the characteristics of the alternatives and the decision-maker ([Ben-Akiva and Bierlaire 2003](#)). The conditional logit model ([McFadden 1974; 1978a](#)) is derived from random utility maximization (RUM) theory assumptions, which imply that a motivated offender evaluates the expected utility (gain, profits, satisfaction and risks) of each of the possible alternatives and selects the alternative with the largest expected utility. It allows for simultaneous tests of characteristics of the offender relative to the alternatives (e.g., activity nodes) and characteristics of the alternatives (e.g., population density).

Most crime location choice studies have used this model (see overview [Ruiter 2017](#)) after [Bernasco and Nieuwebeerta \(2005\)](#) introduced it into the geography of crime.

Results are presented as odds ratios (OR), the multiplicative effect of a one-unit increase of the independent variable on the odds of choosing a particular target neighbourhood. ORs >1 reflect a positive effect, and ORs between 0 and 1 a negative effect. ORs of binary variables indicating activity node neighbourhoods as well as those indicating neighbourhoods close to activity nodes were expected to be >1. All *very frequently* and *less frequently* dummy variables were also expected to have ORs >1, but effects of *very frequently* visited activity nodes were hypothesized to be larger than those for *less frequently* visited nodes. Effect size differences were statistically tested using Wald chi-square tests. Because offences are sometimes nested within offenders, cluster-corrected standard errors were estimated.

Results

Descriptive statistics

Table 1 shows the number of neighbourhoods that included at least one reported activity node (any node and per type) in the offence month and how many times these were very frequently and less frequently visited. In total, 908 neighbourhoods contained at least one activity node of any type, with a mean of 6.5 (SD = 3.4, median = 6, range = 1–15) neighbourhoods per offence. Offenders often had varying activity spaces; almost two-third of them reported having visited at least one activity node of each of the four types in the offence month. Moreover, **Table 1** shows the number of neighbourhoods that were indicated as a first-, second- and third-order neighbourhood from their respective nearest activity node (any node and per type) in total and per frequency category.

TABLE 1 *Neighbourhoods (n = 1,794,940) indicated as an activity node, first-, second- or third-order neighbourhood, in total, and per visiting frequency category (of the nearest node) of any node type, and of the four types comprising it*

| | Number of neighbourhoods indicated as | | | | |
|-----------------|---------------------------------------|------------------------------|------------------------|-------------|------------------|
| | Any node | Residential area of offender | Residential area other | School/work | Leisure activity |
| Node | 908 | 147 | 402 | 157 | 417 |
| Very frequently | 459 | 144 | 195 | 126 | 155 |
| Less frequently | 449 | 3 | 207 | 31 | 262 |
| First order | 4,454 | 911 | 2,112 | 993 | 2,407 |
| Very frequently | 2,226 | 890 | 1,059 | 786 | 806 |
| Less frequently | 2,228 | 21 | 1,053 | 207 | 1,601 |
| Second order | 8,466 | 2,251 | 4,223 | 2,377 | 5,037 |
| Very frequently | 4,176 | 2,196 | 2,163 | 1,948 | 1,581 |
| Less frequently | 4,290 | 55 | 2,060 | 429 | 3,456 |
| Third order | 12,424 | 4,186 | 7,055 | 3,916 | 7,472 |
| Very frequently | 6,417 | 4,086 | 3,840 | 3,223 | 2,571 |
| Less frequently | 6,007 | 100 | 3,215 | 693 | 4,901 |
| Elsewhere | 1,768,688 | 1,787,445 | 1,781,148 | 1,787,497 | 1,779,607 |

Very frequently: ≥ 2 –4 days per week; less frequently: monthly to 1 day per week.

The cumulative percentage of offences committed within an activity node neighbourhood and within the spatial lags is shown in Figure 2a: 39.3 per cent ($n = 55$) were committed within a neighbourhood with any activity node. This percentage increased rapidly when including higher-order spatial lags surrounding the activity nodes' neighbourhoods; 88.6 per cent of the offences ($n = 124$) were committed within the borders of the third-order spatial lag. Figure 2b shows the cumulative percentages for the two frequency categories: more offences were committed in/near a very frequently visited activity node neighbourhood than in/near a less frequently visited activity node neighbourhood.

Beyond the offender's residential area

Model 1 in Table 2 presents the effects of the residential area of the offender and the respective first-, second- and third-order spatial lags on crime location choice. In line with previous research, the model shows positive effects for offenders' residential neighbourhoods and neighbourhoods nearby. Effects were largest for neighbourhoods of residence (residential node's OR > first-, second- and third-order neighbourhoods' ORs, $ps < 0.01$), followed by the neighbourhoods closest to the neighbourhoods of residence (first-order OR > third-order OR, $p < 0.001$; first- and second-order ORs, $p = 0.18$, and second- and third-order ORs, $p = 0.31$, did not statistically significantly differ). This model in which offenders' activity spaces were only measured by their residential areas had a pseudo- R^2 of 0.304, which indicates that the model fits the data well

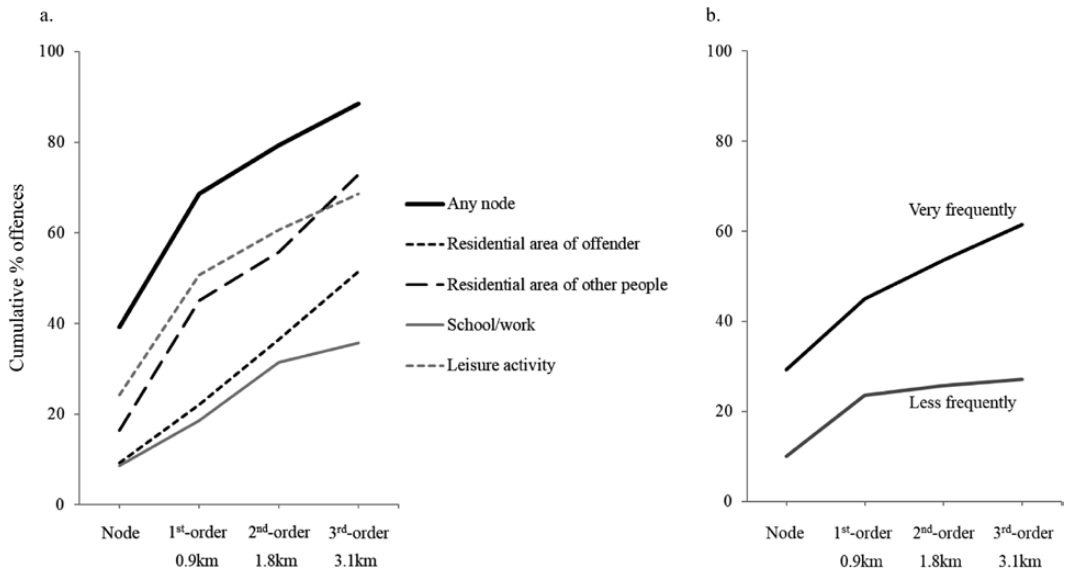


FIG. 2 Cumulative percentage of offences committed within an activity node or first-, second- and third-order neighbourhoods for (a) any activity node ($n = 908$) and the four categories comprising it and (b) any very frequently visited activity node ($\geq 2-4$ days per week, $n = 459$) versus any less frequently visited activity node (≤ 1 day per week, $n = 449$). Note. Distances (in kilometres) are medians between neighbourhood centroids and their first-, second- and third-order spatial lags.

TABLE 2 Conditional logit model testing effects on crime location choice (140 offences; 78 offenders; 1,794,940 neighbourhoods) of (1) the offender’s residential area, (2) any activity node and (3) any activity node split up into very versus less frequently visited

| | Model 1: Node = residential area offender only | | Model 2: Node = any activity node | | Model 3: Node = any activity node, very frequently versus less frequently visited | | | |
|--------------------------------|---|-------|--------------------------------------|---------|--|---------|------------------|----------|
| | OR | SE | OR | SE | OR | SE | Wald $\chi^2(1)$ | <i>p</i> |
| Node neighbourhood | 1,414.0*** | 442.4 | 5,716.1*** | 2,299.0 | | | | |
| Very frequently | | | | | 7,845.3*** | 3,052.9 | 10.7 | <0.01 |
| Less frequently | | | | | 2,253.6*** | 1,159.6 | | |
| First-order neighbourhoods | 340.8*** | 120.5 | 904.4*** | 336.5 | | | | |
| Very frequently | | | | | 906.9*** | 343.6 | 1.07 | 0.30 |
| Less frequently | | | | | 641.0*** | 291.3 | | |
| Second-order neighbourhoods | 162.9*** | 82.0 | 185.2*** | 77.2 | | | | |
| Very frequently | | | | | 278.2*** | 115.3 | 3.47 | 0.06 |
| Less frequently | | | | | 59.0*** | 49.9 | | |
| Third-order neighbourhoods | 101.8*** | 33.3 | 117.1*** | 51.7 | | | | |
| Very frequently | | | | | 180.7*** | 87.2 | 5.14 | <0.05 |
| Less frequently | | | | | 31.3*** | 20.5 | | |
| Residential population density | 1.12*** | 0.02 | 1.05* | 0.02 | 1.06** | 0.02 | | |
| Employee density | 1.09*** | 0.01 | 1.03** | 0.01 | 1.04*** | 0.01 | | |
| Pseudo- <i>R</i> ² | 0.304 | | 0.479 | | 0.490 | | | |

OR = odds ratio, SE = standard error of OR coefficient corrected for clustering within offenders. Wald $\chi^2(1)$ = difference tests between effects of very frequently and less frequently visited per spatial lag order (node, first, second and third order), with *p* of χ^2 -tests.

p* < 0.05; *p* < 0.01; ****p* < 0.001.

(McFadden 1978b: 307), with Akaike Information Criterion (AIC) = 1,856 and Bayesian Information Criterion (BIC) = 1,930.

Model 2 presents the effects of the presence of any activity node in a neighbourhood and its respective spatial lags. Any activity node had a very strong positive effect on crime location choice (OR = 5,716.1). Also first-, second- and third-order neighbourhoods were more likely targeted than neighbourhoods further away. Effects followed a clear distance-decay pattern: the OR of the node itself was statistically significantly larger than the ORs of the first-, second- and third-order neighbourhoods, and first-order neighbourhoods were also more likely targeted than second- and third-order neighbourhoods (all *ps* < 0.001). No statistically significant difference was found between second- and third-order neighbourhoods (*p* = 0.29) though. This model had a pseudo-*R*² of 0.479 (AIC = 1,391; BIC = 1,465), which indicates that including other activity node types to the residential neighbourhood of the offenders considerably increased the model fit. Crime location choices were much better explained in the model with all activity nodes than in the model with offenders’ residential neighbourhoods only.

Additional analyses with each combination of three of the four activity node types showed that excluding any node type always somewhat reduced the node neighbourhood effect sizes and model fit. We conclude that each node type contributes to the explanation of crime location choice. The results were also not particularly driven by a

specific crime type: effects remained positive, statistically significant and overall rather similar across different subsamples of offences (i.e., excluding a specific crime type while including all others). These findings further support the idea that offenders have a strong tendency to commit any offence type within their activity space.

Visiting frequency

Model 3 in Table 2 shows effect differences for *very frequently* visited and *less frequently* visited *any activity node* neighbourhoods (pseudo- $R^2 = 0.490$). Node neighbourhoods that were less frequently visited were much more likely targeted than otherwise comparable neighbourhoods without any activity node (OR = 2,253.6). However, an even stronger ($p < 0.01$) positive effect was found for neighbourhoods with a very frequently visited activity node (OR = 7,845.3). Statistically significant and positive effects were also found for all very and less frequently visited first-, second- and third-order neighbourhoods; these were all more likely targeted than otherwise comparable neighbourhoods that were further away from any activity node. Although very frequently visited higher-order neighbourhoods showed larger effect sizes than less frequently visited higher-order neighbourhoods, the effect differences did not always reach statistical significance, it did only for the third-order. However, the joint test of these three differences between very versus less frequently visited effects was statistically significant, $\chi^2(3) = 9.53$, $p < 0.05$, as was the joint test of the four differences across the node and higher-order neighbourhoods, $\chi^2(4) = 17.8$, $p < 0.01$. This indicates that overall, offenders are more likely to target a neighbourhood with or near an activity node that is very frequently visited compared to a neighbourhood with or near an activity node that is less frequently visited.³

Discussion

Offenders are theorized to commit offences within their awareness spaces (Brantingham and Brantingham 1981; 1993). Particularly, the increased risk applies to activity nodes—where non-trivial amounts of time are spent during routine activities—and to nearby areas. Previous crime location choice studies that used the discrete choice framework have only included proxy measures of some activity nodes, but due to the absence of the required information in register data, the influence of many other activity nodes was never empirically assessed. This study examined whether offenders are indeed more likely to target neighbourhoods that contain any regularly visited activity node (e.g., a friend's home, work and leisure activity location) and to what extent adding additional nodes to offenders' residential areas improves our understanding of crime location choice. To perform a more rigorous test of crime pattern theory than previous register-based studies, data were used from a unique online survey in which respondents were directly asked about where they had spent time and committed offences. These data also enabled us to examine to what extent crime location choices depend on how frequently activity nodes were visited.

³Findings were robust with other cut-off values for visiting frequency. With very frequently defined as ≥ 5 –6 days per week, and as ≥ 1 day per week, effect difference patterns were largely comparable.

Several findings stand out. The 78 young adult offenders in our sample generally visited multiple different neighbourhoods during their routines and reported varying activity spaces with multiple activity node types, similar to what was theorized in crime pattern theory and found in general population time-use research. Including all reported regularly visited activity nodes considerably improved our understanding of crime location choice. The majority of offences were committed within neighbourhoods with any activity node or neighbourhoods nearby. Looking at offenders' residential areas only, these figures dropped considerably. Findings from the conditional logit models confirmed this pattern: the presence of any activity node in a neighbourhood increased the probability of it or the surrounding neighbourhoods being targeted, and including other activity node types substantially improved the model fit compared to a model with offenders' residential areas only. Effects also showed a clear distance-decay pattern: all neighbourhoods near an activity node had an increased probability of being targeted, but this probability was largest for the neighbourhoods of the activity nodes themselves, followed by neighbourhoods surrounding them and then neighbourhoods surrounding those. Each node type contributed somewhat to the joint effect of all regularly visited activity nodes. Findings were robust to excluding any of the reported crime types. Moreover, visiting frequency was influential: any regularly visited activity node in a neighbourhood increased the probability of the neighbourhood being targeted, but, as hypothesized, the effect was significantly larger when the activity node was visited very frequently. Our findings also provide some support that neighbourhoods near very frequently visited activity nodes are more likely targeted than neighbourhoods near less frequently visited activity nodes.

This study corroborates the hypothesis that offenders have a strong tendency to target neighbourhoods, which they regularly visited for non-criminal activities, and that this also applies to neighbourhoods nearby. Expanding offenders' activity spaces based on their residential areas only to those based on all reported regularly visited activity nodes resulted in a much better explanation of crime location choice. This supports crime pattern theory and underscores that a sole focus on offenders' residential areas provides only part of the picture; offenders generally visit more areas during their daily routines and any of those are more likely targeted than areas outside their activity space (Brantingham and Brantingham 1981; 1993). The robustness of the findings across different crime types also indicates that offenders tend to commit crime within their activity space, irrespective of the type. Future research should, therefore, aim to include as much information on individual offenders' activity spaces as possible to explain where any type of crime is committed. Having such information available in larger and diverse offence samples would provide the opportunity to further examine which parts of individual activity spaces are more likely selected for specific crime types. This could be the case when crime-type-specific opportunities might be systematically higher in areas that offenders visit for specific reasons.

The finding that more frequently visited activity node neighbourhoods are more likely targeted than those less frequently visited is also relevant for theory. Offenders are theorized to prefer any known area to unknown areas, but our findings also suggest a distinction among known areas: better-known areas seem to be preferred over less-known areas. By visiting an area very frequently, general and time-specific knowledge levels are expected to be higher. There is also more opportunity to explore the surrounding area and gain more knowledge, also of areas nearby. More knowledge is,

thus, a plausible reason for finding even larger effects of very frequently visited activity nodes. On the other hand, some (more opportunistic) offences may also be committed while just visiting the area for any (non-criminal) reason or along the way, which could make areas in which potential offenders come very frequently also more likely targeted. Although the fact that we found differences within offenders' activity spaces by visiting frequency is itself very relevant for crime location choice research, future research is required to further disentangle why this is and when (e.g., it may differ between crime types), with measures that better capture actual levels of knowledge or motivation behind crime location choices. There may, e.g., be offenders who frequently return to an area *because of* its rich criminal opportunity to specifically search for more gains, but it is yet unclear to what extent, and to which offenders, this alternative strategy applies.

This study not only provides a unique test of a central theory in environmental criminology, it is also methodologically innovative by using an online self-report survey among offenders to assess their activity spaces and crime location choices. Although the research design also had its shortcomings (discussed below), the method provided unique information on individual activity spaces and where offences were committed, regardless of whether offences were known to police. Not only did the OASIS provide information on any type of regularly visited activity node, it is also more likely that offenders actually visited the activity nodes they reported themselves than those that could be derived from register data. OASIS also contains unique visiting frequency information. The online component enabled us to incorporate Google Maps with a search bar to help respondents find the right locations anywhere on earth with the desired level of geographic detail, which improved upon the paper cartographic maps used by [Summers *et al.* \(2010\)](#). The design also provided respondents the opportunity to participate at any desired time and location without the requirement to meet with a researcher, which may reduce the threshold to participate. However, it is important to take into account that online tools might be difficult for some participants. For example, older respondents may be less accustomed to use online tools. This was one of the reasons to only invite young adults in this study. Another challenge is to obtain the information as complete and reliable as possible. Not only do people forget things over time, they might be reluctant to report their (criminal) activities. In face-to-face interviews, researchers could apply techniques that might help respondents remember (details of) past activities and they could also ask additional questions to obtain more information than respondents would report on their own in an online survey.

Some limitations of this study need to be discussed. A relatively small sample of young adult suspects who participated and who reported having committed at least one offence were included in this study. It is unclear to what extent the findings apply to all offenders as not all offenders are known to police and only young adults were selected. Only 12.4 per cent of the invited suspects participated in our survey. However, the nationwide transportation survey of Statistics Netherlands, which also uses a self-report online survey instrument (Dutch acronym: OViN) does not yield a much higher response—18.3 per cent in 2016—among a general population sample invited by letter ([Statistics Netherlands 2016](#)). Nevertheless, participating individuals may differ from those who did not participate, e.g., with respect to our outcome measure. Given that we invited a high-risk sample, the fact that only 78 respondents (19 per cent) reported at least one offence in the study period indicates that the majority of the participating respondents did not commit an offence, forgot about it or were unwilling to report it in

the online survey. We have, however, no reason to expect that potential underreporting of offending implies misreporting. In fact, those who are willing to self-report their offences seem to have little incentive to deliberately provide false information about where and when they had offended. Our findings support this as it is highly unlikely that false information would have yielded such strong effects and high explained variance. In further defence of our data collection strategy, self-reported offences could also include offences that were not solved or reported to the police, whereas previous crime location research has been limited to solved/reported cases only. Moreover, although the study area consisted of all Dutch neighbourhoods, reported activity nodes and offences were more concentrated in urban areas in the western part of the country due to the sampling frame. Findings may not apply equally to offenders from other parts or other countries. In order to increase generalizability, other types of offenders could be asked about their routines and crime locations, e.g., different age groups or incarcerated offenders (who may be more willing to participate and report about offences for which they were convicted).

Furthermore, our online survey likely did not capture information on all activity nodes regularly visited in the three-year period prior to the survey. Although many of the offenders probably reported their most important nodes, some activity nodes might have been forgotten or omitted. Less important activity nodes or those that were visited less often/longer ago may have been underreported. Offenders could also have reported their offences selectively.

Moreover, as with all self-report instruments, the accuracy of reported information is not always certain. Respondents may have had difficulties remembering when they actually visited a location, reported an average visiting frequency that may not optimally reflect the visiting frequency around the time the offence was committed or selected a less specific geographic location. Regarding the latter, by using (often homogeneously defined) neighbourhoods as spatial unit of analysis, lower spatial accuracy is less problematic than when smaller units of analyses (e.g., street segments) would have been used. In fact, we explicitly asked respondents how accurately they had reported geographic locations at the end of each subdomain. 88 offences (63 per cent) were reported with a neighbourhood-/street-/address-level accuracy. Of all reported activity nodes' locations, 77 per cent were on average reported with a neighbourhood-level accuracy or higher. Although the pseudo- R^2 of Model 2 somewhat increased with only the 88 offences with a higher accuracy (pseudo- $R^2 = 0.512$) and reduced with only the 52 offences with a lower accuracy (pseudo- $R^2 = 0.442$), it was consistently very high and effect patterns of node and higher-order neighbourhoods remained rather similar. Accounting for both the accuracy of activity node and offence locations also showed no significant effect size differences between the situation when both node and offence locations were reported at neighbourhood-/street-/address-level accuracy and when at least one of them was reported at a lower accuracy level (all $ps > 0.21$). Thus, not only did the respondents indicate themselves that they had pinpointed the majority of their locations rather accurately, even when taking the accuracy level into account in our models, the location of reported activity nodes of any type explained very well where self-reported offences were committed. By including multiple spatial lags of neighbourhoods surrounding reported node locations, the locations even of those cases reported with lower accuracy were likely still covered. Nevertheless, additional research is desirable to better assess how well activity spaces and committed offences up to three years

ago can be reconstructed with the OASIS, e.g., with cognitive testing or by collecting similar information from other sources.

Furthermore, OASIS only measured activity node locations. This means that there are still parts of the theorized awareness space that are not covered, even when offenders reported all their activity nodes and spent most of their time there. Awareness spaces also include routinely travelled paths between nodes and everything within visible range (Brantingham and Brantingham 1993). By also including neighbourhoods adjacent to activity nodes, parts of the missing awareness spaces are likely covered. However, if an offender travels often through a higher-order contiguous neighbourhood, the knowledge about that particular neighbourhood would likely be higher than that about other neighbourhoods at equal distance. Future studies should, thus, also aim to develop methods to obtain additional individual-level information on awareness spaces, including routinely travelled paths. By using continuous GPS-tracking, e.g., not only a full and detailed picture of all visited activity nodes could be provided but also the travel routes can be determined (e.g., see Rossmo *et al.* 2012). Such new methods, however, do bring along several technical and privacy protection challenges of their own.

Conclusion

In sum, this study's findings indicate that offenders have a strong tendency to commit offences near regularly visited activity nodes, such as residential areas of friends, school, work and leisure activity locations, also if these nodes are outside of their own residential area. The inclusion of more comprehensive information on individual activity spaces improves our ability to explain where offenders commit offences. The more frequently an offender visits a node, the more likely it is to be the locus of an offence.

These insights might be useful in criminal investigations. Unsolved offences may be linked to known (repeat) offenders if police systematically record information on the areas they regularly visit. The findings could also be relevant for urban planning and prevention. By strategically replacing activity nodes that are known to be (very) frequently visited by potential offenders, and by securing and monitoring the broader areas in which they are located, the risk of crime may be reduced.

By asking offenders where they spent time and committed crime, this was the first crime location choice study to more rigorously test and provide empirical support for crime pattern theory with more direct measures of offenders' activity spaces and offences. Additionally, the importance of visiting frequency was introduced and indeed found to be a relevant attribute of activity nodes. More research is needed with larger and more diverse offender samples to examine the generalizability and robustness of our findings. Future crime location choice studies should aim at further increasing the integrality and quality of the assessed parts of individual awareness spaces and offence locations.

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