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A new Geographic Profiling Suspect Mapping And Ranking Technique for crime investigations: GP-SMART

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Abstract

This study developed and tested a new geographic profiling method for automating suspect prioritisation in crime investigations. The Geographic Profiling Suspect Mapping And Ranking Technique (GP-SMART) maps suspects' activity locations available in police records—such as home addresses, family members' home addresses, prior offence locations, locations of non-crime incidents, and other contacts with police—and ranks suspects based on both the proximity and nature of these locations, relative to an input crime. In accuracy tests using solved burglary, robbery and extra-familial sex offence cases in New Zealand (n = 4511), GP-SMART ranked the offender at or near the top of the suspect list at rates greatly exceeding chance. Highlighting the benefit of its novel inclusion and differentiation of many different types of activity location, GP-SMART also outperformed baseline methods—approximating existing algorithms—that ranked suspects using only the proximity of their activity locations, or home addresses, to the input crime.

KEYWORDS
crime investigation, crime location choice, geographic profiling, police data, suspect prioritisation

1 | INTRODUCTION

A common problem in crime investigations is to prioritise among the many possible suspects who could have committed the crime. Using a collection of analytic methods called 'geographic profiling' (Rossmo, 2000)—or in the UK, geographical profiling (Canter, 2003)—specialist police analysts can examine information in the geography of crimes and suspects to inform investigative activities, including prioritising suspects. This information is particularly telling because people tend to commit crime near places they know from their everyday activities such as where they live, work or socialise—their 'activity nodes' (Brantingham & Brantingham, 1991, 1993).

Often, geographic profiling involves analysing the locations of a series of crimes believed to have been committed by the same unknown offender (e.g., linked by forensic or behavioural evidence), to predict where the offender might have an activity node (Knabe-Nichol & Alison, 2011; Rossmo, 2000). Following this crime-based prediction, suspects can be ranked by the proximity of their known activity nodes to the area predicted as most likely to contain an activity node (e.g., Canter & Hammond, 2007; van der Kemp, 2021) or the prediction score at their known activity nodes (Rossmo & Velarde, 2008). Algorithms automating this prediction process exist, with Rigel (Environmental Criminology Research Inc. [n.d.]) being the most widely used by analysts (Emeno et al., 2016).

A complementary approach to the crime-based one focuses on the suspects, examining their known activity nodes to determine who among them is more likely to have committed a crime in the location of any given crime being investigated. Beneficially, this suspect-based approach can be applied to single crimes; it does not require a series of offences believed to have been committed by the same offender.[1] However, in the absence of a pre-filtered list of specific suspects for a given crime, the potential suspect pool is vast: theoretically, every individual recorded in a police service's crime and intelligence systems. In this situation, manual searches and comparisons between suspects are impossible; automated solutions are necessary. Yet there have been few attempts to automate this suspect-based approach in algorithms that could be used by analysts: we identified only five in the published literature (Bache et al., 2008; Frank, 2012; Gore et al., 2005; Snook et al., 2006; Tayebi et al., 2017) and failed to identify evidence of their use in practice from surveys and interviews of analysts (Emeno et al., 2016; Knabe, 2008; Knabe-Nichol & Alison, 2011; Öhrn, 2019).[2]

Building on these few previous examples, we introduce a new method, the Geographic Profiling Suspect Mapping And Ranking Technique (GP-SMART), which constitutes, to our knowledge, the most comprehensive attempt yet to map and compare suspects' activity nodes in a suspect-based geographic profiling algorithm. In this paper, we describe GP-SMART and test its predictive accuracy in ranking suspects (i.e., where do we find the actual offender in the ranked list of suspects). We first review existing suspect-based algorithms and highlight limitations in their methods and in the way they have been tested, both of which we address in the present study.

2 | SUSPECT-BASED GEOGRAPHIC PROFILING ALGORITHMS

Existing suspect-based geographic profiling algorithms vary in sophistication, but they all calculate the distance between suspects' activity nodes (e.g., known home address, prior offence locations) and an input crime, then rank suspects such that those with nodes closer to the crime rank higher than those with nodes farther from the crime. The logic is grounded in theory—and a common empirical finding: people are more likely to commit crime closer to their activity nodes than farther away (Bernasco, 2019; Brantingham & Brantingham, 1991; Menting et al., 2020; Ruiter, 2017). People with nodes close to the crime are therefore more likely to have committed it than people with nodes farther away. The most basic algorithm merely ranks suspects by the distance between a single node—their home address—and the input crime (Snook et al., 2006). Two others also use only home nodes but apply a distance decay function to estimate a probability of offending at the distance between the suspect's home and the input crime, which informs the suspect rankings (Bache et al., 2008; Gore et al., 2005).[3] Gore et al. (2005) applied distance decay curves derived empirically for each input crime from the other crimes in the dataset but they acknowledge that because the curve (for all crimes in the dataset) is highest in the shortest distance interval (0–250 m), the outcome is 'much the same' as ranking the suspects by distance (p134; as done by Snook et al., 2006). Bache et al. (2008) tested negative exponential and power decay functions, which produced similar accuracy results. Their algorithm additionally adjusts suspects' predicted probability based on their number of prior offences before ranking the suspects, on the grounds that suspects with more prior offences are more likely to have committed the crime. Both Frank (2012) and Tayebi et al. (2017) first estimate each suspect's activity space—the area around and between their nodes, which included home, prior offence locations, co-offenders' homes, and places likely to be commonly frequented by many offenders, such as malls and transit hubs—then rank suspects by the shortest distance from the input crime to this activity space. Like Bache et al., Tayebi et al. additionally adjust the ranks based on suspects' prior offences, in this case ranking higher suspects who have previously committed the same type of offence as the input crime.[4]

We address two limitations of these algorithms. First, they include only a small subset of suspects' activity nodes, but studies have shown that people are more likely to commit crime near any activity node, than farther away (providing crime opportunities are present). These activity nodes include both present and past homes and those of their family members or co-offenders, places of work, where they go or went to school, prior crime locations, and places they purchase drugs or fence stolen goods (Bernasco, 2019; Lammers, 2018; Menting et al., 2016; Pettiway, 1995; Rengert & Wasilchick, 1985). Logically, including more activity nodes in the algorithm should increase the likelihood of identifying one or more of the offender's nodes in close proximity to the input crime and ranking them highly accordingly. Further, a wide range of activity nodes that could be fed to the algorithm are likely to be recorded in police databases. Curtis-Ham et al. (2021a) found that burglary, robbery and extra-familial sex offenders typically had at least 10 activity nodes recorded in a national police database, which included home addresses, family members' home addresses, prior crime locations, places where they had been victims of or witnesses to crime, locations of non-crime incidents police had been called to, and places of arrests, stop and search and other interactions with police.

Second, the algorithms that include different activity nodes treat them equally, and thus ignore relevant variability between activity nodes. People are more likely to commit crime near some activity nodes than others (holding distance equal). Specifically, people are more likely to offend near activity locations they have visited more frequently, more recently, over a longer period of time, and where their activities were more similar to the present offence (Bernasco, 2019; Curtis-Ham et al., under review a, b; Lammers et al., 2015; Menting et al., 2016, 2020; van Sleeuwen et al., 2018). These are places that are more familiar to the offender, and where their prior activities, being similar to the present offence, are more likely to have generated knowledge of good opportunities for that offence (Curtis-Ham et al., 2020). Logically, differentiating between activity nodes in the algorithm—by ranking suspects with high familiarity, high similarity activity nodes near the input crime higher than suspects with less crime-conducive nodes near the input crime—should increase the likelihood of ranking the offender highly.

The accuracy of the existing algorithms, in identifying and ranking the offender highly, has typically been evaluated by running the algorithm for a sample of solved input crimes and a sample of potential suspects, and seeing where the actual offender ranked (Frank, 2012; Snook et al., 2006; Tayebi et al., 2017). However, it is difficult to interpret and compare these results due to differences and limitations in the studies' selection of suspect samples. First, Gore et al., Bache et al., and Frank sampled a relatively small number of suspects including the offender (20[5], 83[6] and 322 suspects, respectively). Their results thus do not reliably indicate how highly the offender would rank in actual investigations where the algorithm would have to prioritise among many thousands of suspects.

Second, all the studies except Tayebi et al. appear to have included suspect activity nodes using records from any time in their data period, including activity nodes that were recorded after the input crime.[7] For example, Frank (2012) included suspects' home addresses and the locations of all their offences during the data period except one offence randomly held back for each suspect to be used as an input crime to test, thus offences committed after the input crime would have been used for prioritising suspects. Further, offenders' home addresses are often not known at the point of investigation and are recorded after they are caught, but they could appear in research data as 'address at offence date' despite having been recorded retrospectively. The studies' results therefore do not reliably indicate how high the offender would rank in actual investigations where the algorithm could only use suspect activity nodes on record at the time of the input offence, as advocated for studying geographic profiling algorithms' accuracy (Goodwill et al., 2014; Rich & Shively, 2004; Rossmo, 2015).

3 | THE PRESENT STUDY

Building on previous suspect-based geographic profiling algorithms, we developed a new method (GP-SMART) that uses a wider range of suspect activity nodes, from police data, to identify and rank suspects for a given crime. We also investigated whether differentiating between suspects' activity nodes, using theoretically salient attributes, would lead to more accurate suspect rankings than simply ranking suspects by the distance from their nearest activity node to the input crime. Further, we assessed accuracy via more ecologically valid methods than previous studies by using (a) a pool of 16,000 potential suspects who had committed a range of offences and (b) only their activity nodes known to police at the time of the given input crime.

4 | METHOD

In this section we first describe the data used in this study, then the GP-SMART process and the method used to test its accuracy. Both the GP-SMART process and accuracy tests were programed in the open-source software R (R Core Team, 2013). An R package ('gpsmartr') implementing the GP-SMART process is available on GitHub at https://github.com/Sophie-c-h/gpsmartr.

4.1 | Data

The data used in this study were extracted from the New Zealand Police National Intelligence Application (NIA). They comprise offenders who committed[8] a residential burglary, non-residential burglary, commercial robbery, personal robbery, or extra-familial sex offence between 2009 and 2018 inclusive; the location and details of their latest offence (of each type); and details of other activity locations (nodes). Data cleaning of offences led to removal of approximately 3% of offence records due to missing or imprecise location or timing information, leaving n = 60,229 offenders.[9]

The activity locations included: home addresses; home addresses of family members (immediate family—parents, children or siblings, current or former intimate partners and other relatives); schools and other educational institutions attended (rarely on record); workplaces (more rarely on record); offence locations; locations where they had experienced crime as a victim or witness; locations of non-crime incidents attended by police (e.g., disorderly behaviour, mental distress, civil disputes); and other police contact locations (e.g., stop and search, intelligence notings, arrests). These locations could reach as far back as the offender's birth date, except for offences, victim/witness events and incidents, which dated from 2004 (due to limited back capture of these records in NIA). Home addresses that are only discovered and recorded after an offender is identified for an offence are typically not backdated in the NIA database, which minimises the risk of including addresses that were not known at the time of investigation, as discussed above. Data cleaning of activity locations involved removal of approximately 12% of activity location records, where: location or timing information was missing or imprecise; preliminary checks showed the prior offence or incident category did not reliably indicate that the person was present at the location of the offence/incident; and the offender was no longer in the offence data following data cleaning of offences. The number of remaining activity locations recorded for each offender as of the date of their latest offence ranged from none to many hundreds, with most offenders having multiple pre-offence activity locations in the dataset.

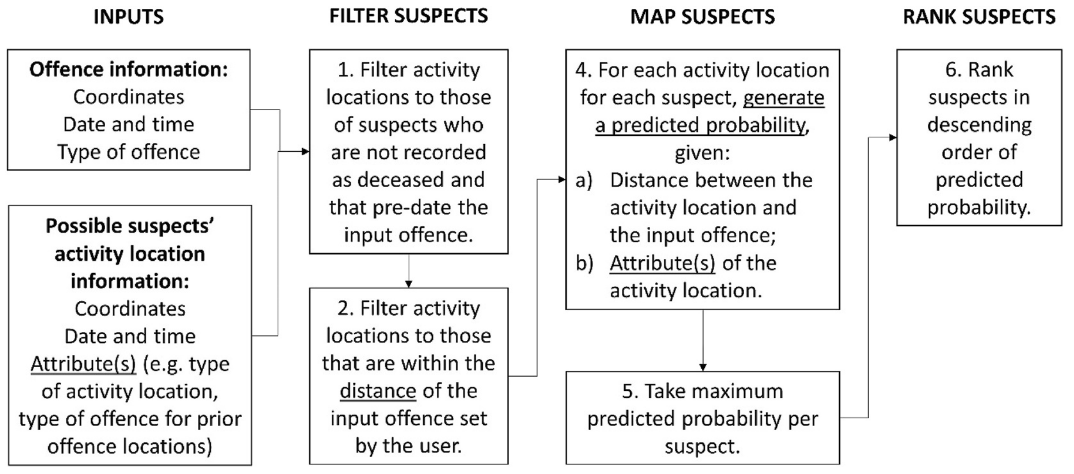

FIGURE 1 Geographic Profiling Suspect Mapping And Ranking Technique process summary

For each crime type we randomly split the offenders into two samples. The first—'calibration'—sample was used to identify values representing the relative likelihood of people offending near activity nodes with different attributes, to use in GP-SMART. The second—'test'—sample was used to test the accuracy of the algorithm in ranking the offender among the top suspects.[10] Separating these analyses prevented the risk of 'overfitting' the likelihood values to the data, which would reduce the algorithm's generalisability to new data and produce inflated estimates of its accuracy (James et al., 2013).

4.2 | The GP-SMART method

Figure 1 depicts a high-level summary of the GP-SMART process that maps and ranks suspects, for a given input offence and list of possible suspects. Here the initial input set of *possible* suspects was all offenders in the test data, which means people who had committed at least one of the offence types included in this research. Although it would have been more ecologically valid to include a wider set of suspects, we were limited to using the data obtained for the programme of research of which this study is one part. However, by including as possible suspects people who had committed a range of offence types (burglary, robbery and sex offences) and not necessarily the input offence type, we recreated some of the noise that would be present with a wider set of possible suspects.

The three underlined parameters in Figure 1 represent configurable elements of GP-SMART dependent on decisions about: which activity nodes attributes to use (and how to measure them), how far to the search for activity nodes 'near' the input offence, and the method for predicting the probability of each suspect offending at the input offence location. In this study we used the activity node attributes theorised by Curtis-Ham et al. (2020) to influence which activity nodes offenders are more or less likely to commit crime nearby. Figure 2 describes the attributes, which were calculated relative to the input crime, such as how recently the activity node was visited prior to the input crime, or whether the activity involved the same offence as the input crime.

After filtering the suspects' activity nodes to only those that pre-date the input crime,[11] and of suspects who were not recorded as having deceased before the input crime, GP-SMART filters to nodes within the user's specified distance: here 10 km. Preliminary analyses showed that 10 km increased the proportion of test cases where the offender was among the filtered suspects from 80% to 93% using 5 km to 86%–96%.[12]

Next, for each activity node for each suspect GP-SMART predicts the probability that the suspect would commit a crime at the input crime's location given its distance to, and the attributes of, the activity node. The prediction

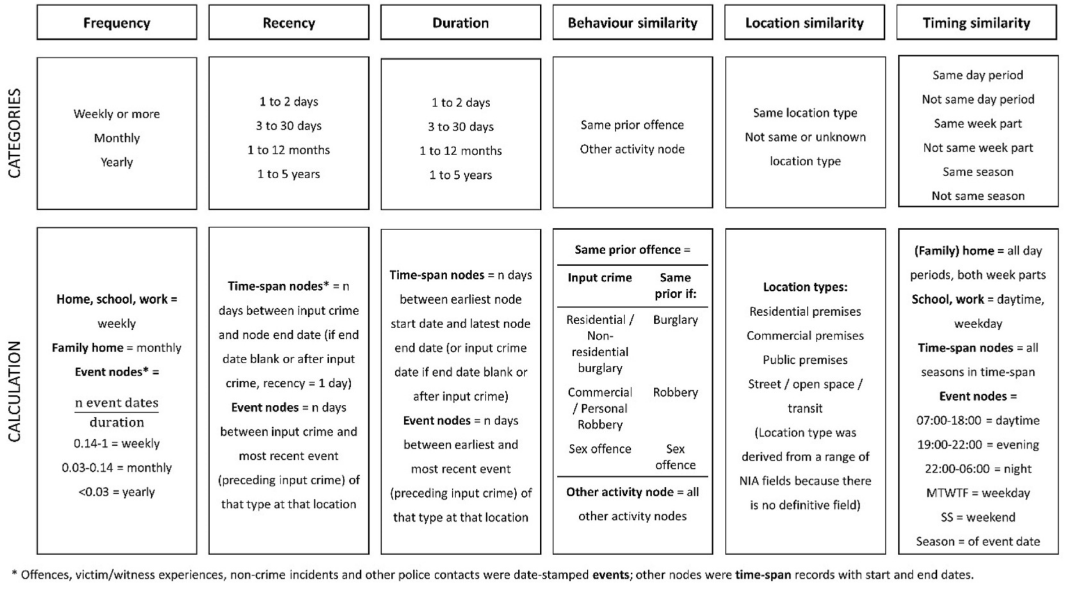

FIGURE 2 Attributes used in Geographic Profiling Suspect Mapping And Ranking Technique to differentiate activity nodes

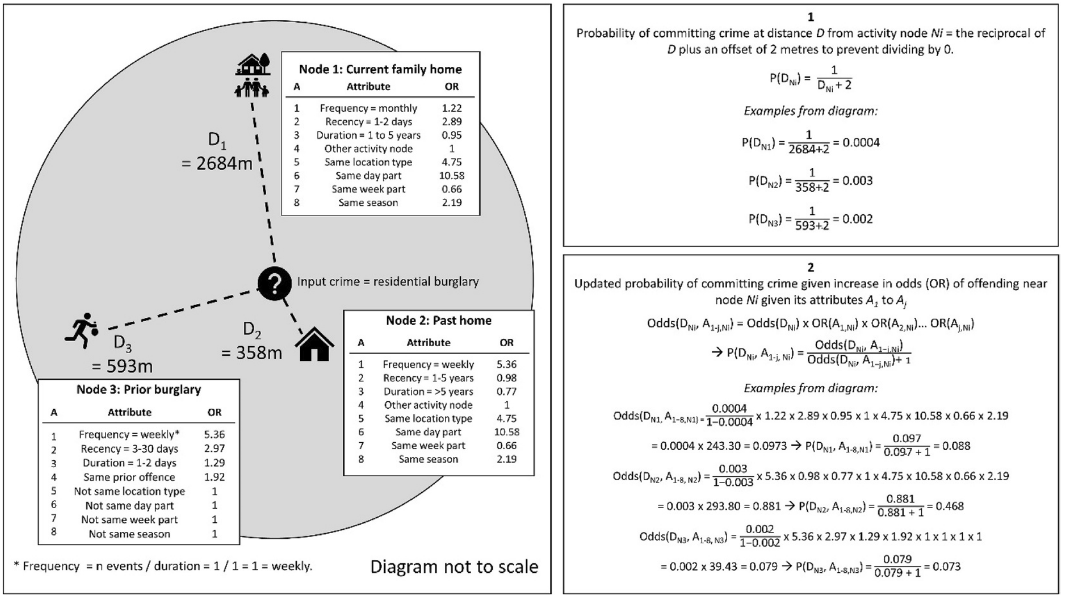

FIGURE 3 Geographic Profiling Suspect Mapping And Ranking Technique prediction method based on distance and attributes of suspects' activity nodes in relation to an input crime

method we implemented in this study follows a Bayesian updating process (Figure 3).[13] The first step is conceptually similar to the application of a distance decay function (e.g., Bache et al., 2008), to estimate the likelihood the suspect would commit the input crime given its distance D from activity node Ni: $P(D_{Ni})$. However, we simply used the reciprocal of the distance between the input crime, which equates to a negative exponential distance decay function $P(D) = D^{-1}$.[14] We convert $P(D_{Ni})$ to odds (the odds of probability P is P/[1 - P]), then update the odds by values representing our beliefs about the increase or decrease in odds of the suspect committing crime near to a node given its attributes A_1 to A_j (frequency, recency and so on): OR($A_{1\text{-j,Ni}}$) before converting the resulting posterior odds back to a probability: P(D_{Ni}, $A_{1\text{-j,Ni}}$). The distance decay function prioritises offenders who have an activity node near the crime location, and the Bayesian updating gives more weight to activity nodes that are important (such as homes) than to nodes that have proven to be less important (such as homes of relatives). In principle, the values by which to update could reflect any a priori belief about the relative likelihood of offending near an activity node, given its attribute(s). In practice, these values will depend on what attributes are available in the dataset, and what is known, or can be ascertained, about the associations between those attributes and crime probability.

For the present study we derived these values by analysing the calibration data to quantify the relative likelihood of offending near an activity node, given its attributes (for the attributes outlined above). Specifically, we applied discrete spatial choice models as described in the Supporting Information S1. In short, these models estimated the increase in odds of an offender committing crime near an activity node with a given attribute over a location where there is no activity node nearby. In our analyses, 'near an activity node' meant in the same neighbourhood, and 'no activity node nearby' meant no node within 5 km of the neighbourhood. For example, the residential burglary offenders were 5.36 times more likely to offend in a neighbourhood[15] containing an activity node visited on a weekly basis and 1.92 times more likely to offend in a neighbourhood where they had committed the same type of crime before (than in neighbourhoods with no activity nodes nearby). These estimates, expressed as odds ratios (ORs), also indicate the *relative* impact of the presence of activity nodes with *different* attributes on the likelihood of committing crime nearby. We therefore adopted these ORs as the updating values for GP-SMART; their application is exemplified in Figure 3. Supporting Information S2 lists the ORs for each node attribute and crime type used in GP-SMART.[16]

The final two steps of GP-SMART (Figure 1) aggregate the predicted probabilities for each activity location into a single prediction for each suspect, then rank the suspects by their predicted probabilities. Initial tests showed that aggregating by taking the maximum yielded more accurate suspect predictions than summing or taking the mean. The maximum appears to sufficiently reflect the presence of higher probability nodes, despite not capturing the cumulative impact of having multiple nodes within the specified distance on likelihood of offending.

4.3 | Accuracy testing method

For each crime type except commercial robbery, we randomly sampled 1000 offences from the test sample for each crime type and ran these through the GP-SMART algorithm to see how often it identified the actual offender in the top ranked suspects, from among all 16,388 possible suspects in the entire test sample. For commercial robbery we used all 511 offences in the test sample. For each sample of input crimes tested, we compared GP-SMART's accuracy with two baseline methods roughly comparable to existing suspect-based algorithms that used only home nodes or included other nodes but weighted them equally. The first baseline method filtered to home addresses pre-dating the input crime (but including both current and past homes), then filtered to home addresses within 10 km of the input crime, then ranked the suspects by the distance between their nearest home address and the crime. The second baseline method was the same as the first but included all activity nodes at each filtering and ranking step.

We used a range of accuracy metrics consistent with previous studies of the accuracy of geographic profiling algorithms in ranking suspects. These were: the proportion of test cases where the offender appeared in the filtered suspects; the proportion of test cases where the offender appeared in the top 1, 5, 10 and 50 and 100 suspects; the median percentile rank of the offender; and the Gini coefficient, a global measure of the concentration of offenders in the top ranked suspects, with coefficients closer to 1 indicating higher numbers of test cases with high-ranked offenders (as per Snook et al., 2006). Suspects with nodes pre-dating the input crime who did not appear in the distance-filtered list ranked by GP-SMART were all assigned a rank at the midpoint of remaining possible ranks. For offences involving multiple offenders, we counted only the highest-ranking offender in the accuracy measures

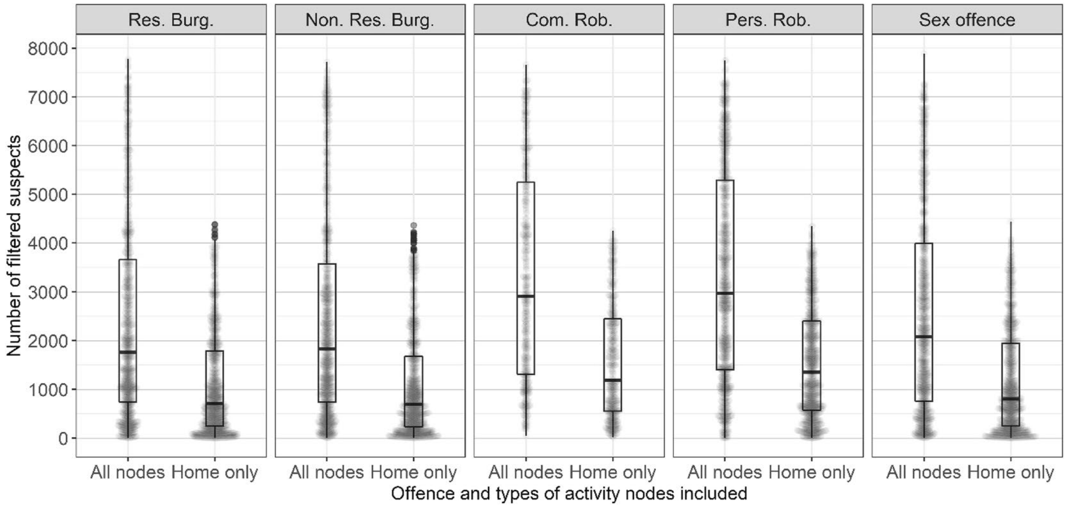

FIGURE 4 Distribution of the number of filtered suspects per test case

TABLE 1 Percent of test cases where the offender appeared in the suspect list

Suspect list	Res. Burg. (%)	Non-res. Burg. (%)	Com. Rob. (%)	Pers. Rob (%)	Sex offences (%)
Any node	100.0	100.0	100.0	99.9	99.8
Home node	98.6	97.9	99.4	99.3	95.3
Any node within 10 km	94.9	93.0	93.9	95.7	85.8
Home node within 10 km	85.2	81.9	86.5	88.4	74.4

(i.e., was at least one of the offenders in the top *k*?). However, most offences involved a single offender (residential burglary: 92% of all offences in the test data, non-residential burglary 89%, commercial robbery 87%, personal robbery 86%, sex offences 99%).

5 | RESULTS

We first consider how many suspects appeared in the filtered list of suspects with prior activity nodes before and after the 10 km filter. Of the 16,388 potential suspects, filtering to only those with at least one activity node pre-dating the input crime resulted in still sizeable suspect pools of at least 15,442 using all nodes and 12,422 using home only. Filtering to nodes within 10 km of the input crime produced median reductions in the number of suspects of between 81% and 89% using all nodes and between 91% and 95% using home only, depending on crime type. Figure 4 shows the distribution of the number of suspects in the distance-filtered lists for each input crime. The bold horizontal lines in the overlaid boxplots indicate the median numbers of suspects, which were in the thousands when including all nodes, but lower when using only home nodes; the underlaid plots provide a more granular representation of the number of cases (points) with different numbers of suspects. In only two test cases (one residential burglary and one personal robbery) were there no suspects with any activity nodes within 10 km of the input crime.

Table 1 shows the proportions of test cases where the offender appeared anywhere in the suspect list, before and after the distance filter, based on any node or home only. In all except 3 cases the offender had a pre-crime activity node on record; the offender appeared in the distance-filtered 'any node' list for 86%–96% of test cases, indicating the utility of applying even a simple distance-based search for suspects with *any* activity nodes within 10 km

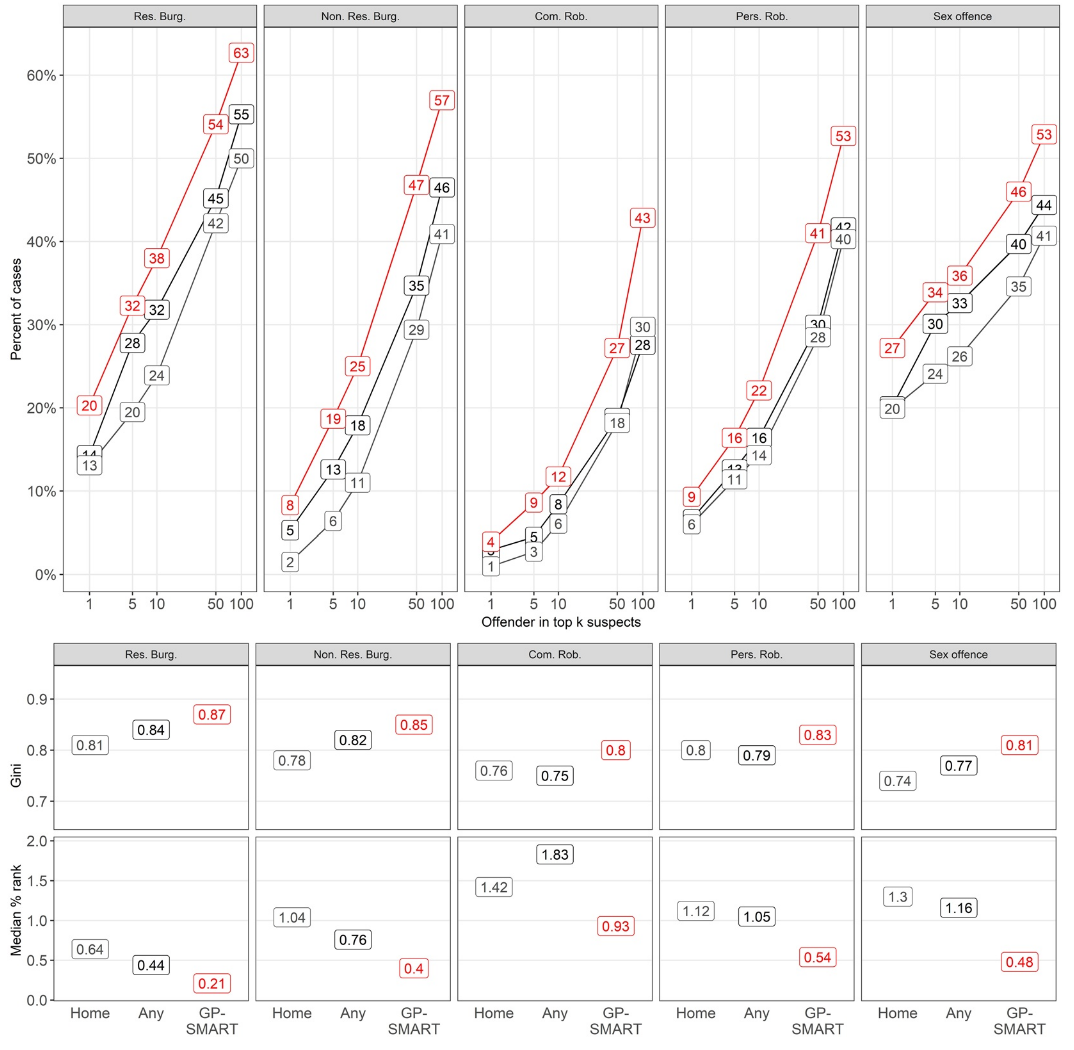

FIGURE 5 Accuracy statistics for ranking suspects using Geographic Profiling Suspect Mapping And Ranking Technique (GP-SMART) (red), distance to nearest activity node (black) and distance to nearest home node (grey)

of a crime. Using only home addresses reduced the chances of the offender being in the distance-filtered suspects by 8%–12%.

Considering the typical number of suspects to differentiate, GP-SMART performed very well. The top panel in Figure 5 shows the proportion of test cases in which the offender appeared in the top *k* suspects for different values of *k*, comparing GP-SMART with the baseline methods ranking suspect by distance to their nearest node or home node. To put these statistics in perspective, the chances of picking the offender as the top suspect if picking randomly—the number of offenders (usually 1)/number of suspects per case—was 0.006% on average for all crime types. GP-SMART ranked the offender at the top in 20% of residential burglary cases: 3240 times the 0.006% expected by chance. Commercial robbery had the lowest accuracy, but even then the offender was ranked first in 4% of cases: 625 times the proportion expected by chance. The proportion of cases with the offender in the top 100 suspects ranged in improvement over chance from a factor of 68 for commercial robbery (43% of cases), to 100 for residential burglary (63% of cases). The Gini coefficients for GP-SMART, ranging from 0.80 to 0.87, indicate that the offenders were highly concentrated in the top ranked suspects (Figure 5 middle panel). On average, GP-SMART placed the offender in the top 0.2%–0.9% of suspects (Figure 5 bottom panel).

GP-SMART's predictions incorporating attributes of the suspects' activity nodes improved on using distance to either any node or home only, across all accuracy measures (in Figure 5, in the top and middle panels higher numbers indicate superior accuracy but in the bottom panel lower numbers indicate superior accuracy). Considering the median percent ranks, for all crime types the offender was about half as far down the ranked list on average using GP-SMART than distance to nearest node (e.g., in the top 0.2% vs. the top 0.4% for residential burglary: see Figure 5, bottom panel). Paired sample Wilcoxon signed-rank tests of difference in offender percentile ranks confirmed that GP-SMART ranked the offender significantly higher up the suspect list than both baseline methods (statistics reported in Supporting Information S3).[17] With robbery offences, the baseline methods yielded similar accuracy as measured by top *k* percentages and the Gini coefficient, suggesting that if the offender appeared in the distance-filtered suspects they were just as likely to appear near the top of the list. But recall that the offender was less much likely to appear in the distance filtered list when using only home nodes than when using any node.

6 | DISCUSSION

This study developed and tested a new suspect-based geographic profiling method, GP-SMART, which prioritises suspects based on both the nature of their activity nodes and their proximity to the crime locations, all derived from police records, under more realistic conditions than previous studies of similar geographic profiling methods. When tasked with prioritising among a large pool of potential suspects and limited to suspect activity nodes pre-dating the input crime, GP-SMART achieved promisingly high accuracy. The probability of finding the offender in the top *k* suspects in our study was 27%–54% and 43%–63% for $k = 50$ and $k = 100$ (depending on crime type: see Figure 5 top panel), which was higher than in the most comparably robust study with 5% and 9% reported by Tayebi et al. (2017). We can also compare the factors by which GP-SMART improves on chance in picking the offender in the top *k* suspects, with those reported for Frank's (2012) suspect-based algorithm, for $k = 1, 5, 10$ and 50. GP-SMART placed the offender in the top *k* ranks between 63 and 4348 times more often than expected by chance (depending on *k* value and crime type); Frank's picked the offender in the top *k* between 3.2 and 7.4 times more often than expected by chance.

The fact that GP-SMART yielded greater accuracy—even under more stringent test conditions—than similar algorithms is consistent with our direct comparisons of GP-SMART and two baseline methods designed to approximate existing algorithms. These comparisons confirmed that including theoretically salient information about suspects' activity nodes (reflecting their familiarity with and likelihood of identifying crime opportunities around their nodes) led to consistently greater likelihoods of finding the offender in the top ranked suspects than using only the distance to their nearest activity node or nearest home address.

GP-SMART's accuracy varied between the crime types studied. Residential burglary and sex offence locations are more strongly associated with offenders' home locations than other offences (Curtis-Ham et al., under review b). Home locations score highly on the attributes used in GP-SMART to adjust the predicted probability of crime near the suspects' activity nodes—especially if recent; GP-SMART thus places high weight on home nodes. So it is unsurprising that the predictions led to greater suspect ranking accuracy for these crime types. Conversely, commercial robbery locations are less strongly associated with offenders' activity node locations, being more constrained by the locations of suitable targets (Curtis-Ham et al., 2021b, under review b). GP-SMART is less accurate for commercial robbery accordingly. Should GP-SMART be extended to other crime types, its accuracy is likely to reflect the strength of associations between people's crime and activity node locations for those crime types.

Our analysis estimated how likely it is that GP-SMART's sifting process will place the offender among the top suspects, but some hefty caveats apply to these estimates due to the limitations of the data and methods used in this study—the percentages listed here can probably not be realised in practice. For example, the suspects were limited to people known to have committed one of the crime types included, providing a relatively high baseline chance of selecting the offender in the top *k* suspects, and likely higher accuracy estimates, in comparison to searching for this needle in the haystack of all possible suspects recorded in NIA.

Additionally, our efforts to limit the suspects' activity nodes to only those on record prior to the input offence were not infallible. For example, offences, victim/witness events or incidents recent to the input crime but only reported to police after the input crime would have counted as 'prior' activity nodes despite not having been in police records yet. Likewise, offences committed shortly before the input crime by a suspect whom the police had not yet caught at the date of the input crime would have erroneously counted as prior activity nodes. Our estimates of the likelihood of finding the offender in the top *k* suspects are therefore also over-estimates of the true likelihood in practice to the extent that recent offence, victim/witness event and incident nodes are only reported to police or attributed to the suspect after a delay, and that suspects' rankings are driven by recent prior offences.

However, we also omitted information that if included in GP-SMART might *increase* its accuracy. We only included a subset of activity nodes that most reliably indicated offenders' activity spaces, with high levels of geocoding accuracy and precision (Curtis-Ham et al., 2021a). It is possible that including even more activity nodes would lead to higher levels of ranking accuracy, even if they were less reliable indicators of offenders' activity spaces (e.g., home addresses of past co-offenders or other associates), or less geographically precise (e.g., traffic offences, which are recorded against stretches of road rather than specific addresses). It is also possible that including these nodes would introduce more noise than signal, and thus reduce accuracy. Additionally, in focussing on only the location and attributes of activity nodes, we did not account for the suspects' likelihood of committing the input crime given their criminal history (c.f. Bache et al., 2008; Tayebi et al., 2017). Higher accuracy could potentially be achieved by adding this information, which could be incorporated into the Bayesian updating step of GP-SMART.

Our operationalisation of the node attributes required many assumptions to fill in gaps in the data, inevitably introducing error. Results will therefore vary, depending on the nature and amount of the data available, and decisions about how to operationalise node attributes using that data, should the GP-SMART method be used in other jurisdictions. Replication is needed to see if the process works as well with data from other jurisdictions, which will vary in the types of activity nodes and attributes available as inputs.

We also recommend some additional tests prior to practical implementation of GP-SMART (or future GP-SMART type algorithms). First, how to apply GP-SMART to a series of offences linked to the same offender warrants further investigation. For example, one could average the suspects' ranks across the series, take their highest or lowest rank, or factor in the proportion of crimes in the series for which they are ranked above a certain threshold. Alternatively, the predicted probabilities for each suspect for each input crime could be combined prior to the ranking step. These methods require testing to see which leads to more accurate rankings. Future research might also provide more specific estimates as to how likely it is that the offender is among the top *k* suspects given the circumstances of an offence, such as the time of day or week, or where it occurred (e.g., a particular city or urban vs. rural area). Lastly, as with any geographic profiling algorithm, field testing is needed to evaluate GP-SMART's utility in operational settings when faced with the true population of potential suspects and information available at the time of a live investigation (Goodwill et al., 2014; Rich & Shively, 2004).

7 | CONCLUSION

The purpose of geographic profiling decision-support tools is not to identify the offender but to help sift through large numbers of suspects (Öhrn, 2019; Rossmo, 2000, 2021). The present study demonstrates the potential for the wide array of suspect activity node information recorded by police to be harnessed to support this suspect prioritisation task, and the benefit of differentiating between activity nodes. Our results suggest that GP-SMART could be a useful 'tool in the toolbox' to support geographic profiling analysis in police investigations, though we also advocate for further research to fully understand its accuracy and utility as next steps towards any practical implementation.

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CONFLICT OF INTEREST

The first author is employed as a researcher at New Zealand Police. This study was not conducted as a part of that employment.

DATA AVAILABILITY STATEMENT

The data used in this research study are not publicly available and were obtained with approval from the New Zealand Police Research Panel (reference EV-12-462). The results presented in this paper are the work of the authors and do not represent the views of New Zealand Police.

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ENDNOTES

[1] For crime series, the suspect-based approach could be applied to each crime individually and the output predictions aggregated such that suspects more likely to have committed multiple crimes in the series are prioritised. We also discuss this point briefly in the Discussion section.

[2] We focus on algorithms whose accuracy has been assessed and published, given that establishing accuracy is a critical step prior to any implementation in practice (Rich & Shively, 2004). Studies describing algorithms without providing evidence of their accuracy were excluded (e.g., Ding et al., 2009).

[3] We refer here to Gore et al. (2005) 'Incident Based Distance Decay Curve filter'. The other two suspect prioritisation methods they report are not suspect-based but instead first predict the offender's home location from the location of a single crime, then rank suspects by the prediction score at their home's location—a process equivalent to the that described above for crime series'.

[4] Other algorithms exist that use suspects' activity node information to predict the location of their next offence, but do not include the step of ranking those suspects by comparing the prediction to an unsolved crime (e.g., Duan et al., 2017). However, algorithms that lack the suspect prioritisation step are not considered herein.

[5] For each of 101 input offences tested, 19 suspects were randomly sampled in addition to the actual offender to create a list of 20 suspects to rank, and 25 samples were repeated for each input offence. This method enabled the authors to identify whether the offender ranked higher on the lists on average than if ranked randomly, according to the aim of the study, but their average ranks are not comparable with studies that employ much larger—and more realistic—suspect samples.

[6] For the dataset of burglary offences tested using offenders' known addresses. Other crime datasets the authors tested did not include the offenders' home addresses, which were instead estimated using a geographic profiling algorithm to predict likely home location, introducing error (given likely inaccuracy in the predictions).

[7] We base this conclusion on the lack of evidence in these studies that suspect nodes post-dating the input the offence were excluded. If they had limited the suspect nodes for each input offence to only those that pre-date that offence, there would have been a different number of suspects ranked for each input crime tested. However, these studies report a single number of suspects, rather than a distribution over the input crimes. In contrast, Tayebi et al. specify that they constructed suspects' activity spaces using data from 54 months preceding the 6-month period in which the tested input crimes were committed.

[8] For whom police had sufficient evidence to support a decision to prosecute, regardless of how the case proceeded (e.g., prosecution or out of court proceeding such as a warning).

[9] Of these, 11,459 appeared in 2 of the offence categories studied separately in this study (e.g., both residential burglary and commercial robbery), 2540 appeared in three, 424 appeared in four, and 27 appeared in all five offence categories.

[10] To ensure complete independence of the two samples, we removed from the test sample (a) offenders who appeared in any calibration sample for another crime type, and (b) offenders whose co-offenders (people with whom they committed their latest offence) appeared in the calibration sample.

[11] For time-span nodes (home, family home, work, school), 'pre-date' meant those with start dates preceding the input crime regardless of when the record was end-dated. For some input crimes and event nodes (offences, incidents, etcetera) the exact timing was unknown and the event was recorded with start and end date-times. For event nodes, to ensure that the event pre-dated the input crime and had likely been reported by the time of the input crime, 'pre-date' meant those with end dates preceding the start date of the input crime. However, for calculating event node attributes relative to (e.g. recency, daypart similarity) the input crime, random date-times between the node and input crime start and end date-times were used, following research establishing that random date-times are a more accurate estimation of the actual timing of unknown timing offences than are the start or end date-time (Ashby & Bowers, 2013; Boldt & Borg, 2016). Time of day was not recorded for the other police contacts, so for these, time-of-day similarity was imputed based on the median over all nodes (being 'same day period').

[12] In developing GP-SMART we also experimented with an additional filter to narrow to suspects with a prior offence of the same type as the input crime, following previous studies that applied a similar filter (Canter & Hammond, 2007; Snook et al., 2006). However, we found that the proportion of test cases where the offender appeared among the filtered suspect reduced to 13%–51%, so we removed the filter.

[13] We also trialled a machine learning approach that trained random forest models with the calibration data to predict the probability of the suspect being the offender, given the distance between a given activity node and the input crime and the attributes of the activity node. GP-SMART applied these models (one for each crime type) to the filtered suspects and their nodes to predict this probability for each suspect and each node for each test input crime (see accuracy testing method below). The random forest model prediction method yielded very similar results to the Bayesian updating method, except for personal robbery where it was less accurate in ranking suspects.

[14] We also trialled the use of distance decay and kernel density estimation functions fitted to the calibration data for each of the different types of node (home, family home and so on), following the methods set out by Levine (2013) that are implemented in the software CrimeStat, as well as the actual proportion of node-crime distances per 0.2 km wide distance band observed in the calibration data. None of these methods performed as well as using the reciprocal of the distance, regardless of the type of input crime or type of node.

[15] Specifically, the same Statistical Area 2 (SA2); see Supporting nformation S1 for detail.

[16] We also trialled a version where we assigned Odds Ratios a priori such that for each attribute the lowest category (e.g., frequency yearly, recency > 5 years, not same daypart) was 1, the next lowest category (e.g., frequency monthly, recency 1–5 years, same daypart) was 2 and so on up to the highest category (e.g., frequency weekly = 3, recency 1–2 days = 5, same daypart = 2). This a priori version produced less accurate suspect rankings than the version we report on that used Odds Ratios empirically estimated from the calibration data.

[17] We compared the percentile ranks rather than absolute ranks to control for the difference in the number of suspects in the list for each case using GP-SMART and the 'any node' baseline versus home only.

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