Behaviour Tracking: Using geospatial and behaviour sequence analysis to map crime

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Abstract

Crime is a complex phenomenon. To understand the commission of crime researchers must map both the temporal and the spatial processes involved. The current research combines a temporal method of analysis, Behaviour Sequence Analysis, with geospatial mapping, to outline a new method of integrating temporal and spatial movements of criminals. To show how the new method can be applied, a burglary scenario was used, and the movements and behaviours of a criminal tracked around the property. Results showed that combining temporal and spatial analyses allows for a clearer account of the process of a crime scene. The current method has application to a large range of other crimes and terrorist movements, for instance between cities and movements within each city. Therefore, the current research provides the foundation framework for a novel method of spatiotemporal analyses of crime.

KEYWORDS: crime; burglary; Sequence Analysis; geospatial anlaysis; methods

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Crimes do not happen in a vacuum, distinct and separate from surrounding actions, events, and locations. To understand the full crime process, from inception through to commission and escape from location, a dynamic method is required. Researchers have developed a number of methods to analyse the temporal dynamics of different crimes, providing investigators with a deeper understanding of the processes involved (Keatley, 2018; Keatley, Barsky, and Clarke, 2017; Taylor et al., 2008). In addition, geospatial research has provided insight into the movements of criminals through space (Ratcliffe, 2010; Chainey and Ratcliffe, 2013). The combination of temporal and geospatial analysis, however, can provide investigators, security consultants, and Law Enforcement Organisations (LEOs) with an opportunity to gain more insight into the commission of a crime, and therefore, places of intervention (Keatley, 2018). The current research provides a novel analytical approach to integrating temporal and geospatial data: Behaviour Tracking.

Burglary is a complex phenomenon that is often overly-simplified (i.e., breaks-enters-steals-leaves sequences) in the research literature (Arntfield, 2016; Keatley, 2018). Of course, burglary is far more nuanced and involves multiple behaviours both temporally and spatially. Residential burglaries, for example, can progress and develop into a number of further criminal behaviours such as where an offender targets dwellings at night for the purpose of accessing or voyeurising the occupants while they sleep, as well as confronting the victims (Arntfield, 2017). This type of burglary, one recently highlighted with the belated arrest of alleged prowler, rapist, and serial killer James DeAngelo in the ‘Golden State Killer’ cold case burglary-murders is just one of six recognised subtypes of residential burglaries that have an often overlooked sexual or fantasy motivation rather than a financial one (Kosir and Drake, 2012). This would in part explain why burglary is also over-represented as a first criminal conviction among violent (both homicidal and non-homicidal) sex offenders (Beauregard, et al. 2017). In other words, it would appear as though burglary has been historically misunderstood as being solely a petty or property-oriented crime and its more paraphilic and predictive dimensions overlooked. The Behaviour Tracking method proposed in the current research allows researchers to investigate and analyse crime in terms of temporal and spatial approaches.

The concept for this integration originally came from applied work conducted by the authors on the movements of police officers about a city through known hot spots and crime zones. The same method is outlined in the current paper, related to a burglary scenario as proof of concept. A burglary was chosen as it provided a relatively contained incident, with clear, thorough data that were not ambiguous, and therefore showcased the method in the current research[i]. Although the data used in the current study were taken from a sample of participants, rather than real-world data, the rationale is because the focus of the current manuscript is on elucidating the Behaviour Tracking method, first and foremost. Evidently, real-world data is ‘messier’ (in terms of steps in sequences being missing); however, the use of a perception dataset in the current study showcases the Behaviour Tracking method. In real-world research, involving sequences that may have missing parts, the method is still useful in two ways: first, by acting as a prompt to investigators, witnesses, or suspects about which parts of the sequence they may be missing or overlooking (Keatley, 2018); second, because in real-world contexts steps in sequences that are missing are not systematic across the entire sample. For example, if sequence 1 has the chain: A→B→D→E (where each letter refers to a behaviour), and sequence 2 has the chain: A→B→C→D→E, then we can still see the ‘missing’ behaviour in other sequences. To date, there is no standard of minimum sample required (Keatley, 2018); however, it is clear that a larger sample will reduce the possibility of missing data misguiding final analyses.

The Rational Choice Perspective (RCP; Clarke and Felson, 2004; Cornish and Clarke, 2016) also provides a theoretical underpinning for the current research approach. A criminal's decision making process and behaviours are the result of complex interactions with the environment they are in. To understand a crime, therefore, means to map the commission of a crime in terms of physical and temporal space and interactions. In this perspective, a criminal's behaviour is purposive and rational; though precipitators may also affect the likelihood of certain behaviours (Leclerc, Wortley, and Dowling, 2016; Wortley, 2016). Furthermore, RCP outlines that crimes occur in sequential stages (Leclerc and Wortley, 2013). The RCP has been a theoretical framework for a variety of different crimes, from school shootings (Keatley, McGurk and Allely, 2018), to terrorism (Gilmour, Hicks and Dilloway, 2017), sexual assault and rape (Leclerc and Wortley, 2013), and theft (Homel, Macintyre and Wortley, 2014). While the decision making process for different crimes may be crime-specific, the general approach to understanding criminals behaviours using RCP can be applied across crimes. An added benefit using RCP to understand the behaviours and decisions of individuals in a crime, is that the same approach can be used to understand victims' responses. For instance, in a fire or terrorist event, victims have the central goal of fleeing or escaping unharmed; therefore, we can begin to understand the motivations of individuals within the scene, and map their behaviours using the Behaviour Tracking technique outlined here in the case of burglary. A hypothetical scripting approach is used in the current research as this has previously been used in temporal methods, such as Crime Script Analysis (Caneppele and Calderoni, 2013; Carroll and Payne, 2014; Leclerc and Wortley, 2014; Haelterman, 2016). The use of hypothetical scripts also allows data to be developed that are similar to real-world data (i.e., police interviews/interrogations), while not breaching privacy and nondisclosure agreements.

Mapping the temporal commission of burglary provides researchers and investigators with the first step towards understanding the crime commission in more detail and perhaps seeing key choice or intervention points[ii]. Behaviour Sequence Analysis (BSA) is a useful method for categorising and analysing the sequential pattern of behaviours (Bakeman and Gottman, 1986; Clarke and Crossland, 1985; Ivanouw, 2007; Keatley, 2018). BSA shows patterns in complex data by analysing the statistical dependencies between behaviours over the course of a time period (e.g., a burglary). BSA is a three-stage method, starting with the *parsing* of behaviours. Police reports, for example, are typically qualitative accounts of the crime, which require breaking down or separating into individual behaviours and events. In the second stage, behaviours are *categorised* according to a classification system and coded together. For example, “breaks-in via back door” and “breaks and enters through rear door” can both be categorised as Behaviour *A*. Inter-rater agreement is used to ensure behaviours and events are categorised consistently, typically resulting in a behaviour coding key. The final stage of BSA involves the analyses of transitions between behaviours. The development of an appropriate coding system or framework is therefore an important part of BSA, such that it captures all behaviours under consideration, and that they are suitably distinct.

Complex actions and interactions can be analysed to show likelihood of transitions between behaviours (Ivanouw, 2007). In the simplest form of BSA, called a *lag-one* sequence analysis, transitions are calculated between behaviours (e.g., breaks glass, moves object) or events (e.g., alarm raised) that directly follow each other. In simple terms, the analysis shows the likelihood, compared to chance, of *A* leading to *B*, and *B* leading to *C* and so on. In terms of burglary, BSA can show the likelihood of breaking-in through the rear door (category *A*) and then proceeding to steal things from the dining room (category *B*) or the living room (category *C*). Therefore, BSA shows investigators whether $A \rightarrow B$ is more likely than chance, compared to $A \rightarrow C$. These behavioural chains are developed into much more complex patterns of behaviour. Clearly, Behaviour Tracking is based on BSA approaches; however, the end result of typical BSA is to create a state transition diagram (a diagram showing the chains of behaviours across a sample). In Behaviour Tracking, including geographic information in a state transition diagram would lead to a complex array of sequences (as chains lead back and forth). Furthermore, it would not be clear how and where to position a spatial location into a sequence, as multiple behaviours could occur in one location. Therefore, the benefit of the Behaviour Tracking method is to take the spatial data and use it to plot a state transition map, which more clearly outlines movements and behaviours throughout different locations.

Behaviour Sequence Analysis (BSA) has been previously used to examine a number of criminal Behaviours and activities, including: serial killers' life histories and murders (Keatley *et al.*, 2018); drink-driving (Keatley, Barsky and Clarke, 2017); violent episodes between people (Taylor, Keatley, and Clarke, 2017); perceived (Ellis, Clarke and Keatley, 2017) and actual rape cases (Fossi, Clarke and Lawrence, 2005; Lawrence, Fossi and Clarke, 2010). In addition to the statistical analysis of Behavioural chains, BSA also provides state transition diagrams to provide visual illustration of the chains of Behaviours. The state transition diagrams are simplified models of the larger transition frequency matrices, and are typically organised in top-down sequential representations. The current research will develop the spatio-temporal *Behaviour Tracking* in terms of burglaries. This is the first step towards developing an integrated method of investigation that incorporates analysis from BSA and more widely used geographic, and geo-spatial analysis in criminal contexts.

Given the novel nature of the present research, no formal hypotheses were made regarding the sequence maps. However, based on previous research in the field, a number of behaviours are likely to occur in the current data. Therefore, a number of expectations can be made, *a priori*. First, sequences are likely to begin with entry to the premises from the rear – this is likely to reflect awareness that burglars attempt to avoid detection (Cornish and Clarke, 1987; Osborne and Capellan, 2017). Furthermore, it is likely that perceptions of burglar's actions will follow rational sequences. Behaviours such as attempting to avoid detection (i.e., wearing gloves; entering properties through rear windows and doors) are likely to occur, similarly, being selective over which items are stolen (based on value and ease of movement with objects) are likely to influence or guide perceptions of burglar's decision making and Behaviours (see Wellsmith and Burrell, 2005). The current research also builds on other 'virtual reality' research in the area of burglary (Nee and Taylor, 2000; Pastra, Saggion and Wilks, 2003; van Gelder et al., 2017). Therefore, while the current research uses participants' perceptions of burglaries, a number of typical behaviours are still likely to occur. While the main focus of the current research is to show a new method for Behaviour Tracking, the results can also be used to inform and support existing and future research in the area of burglary.

Method

Participants

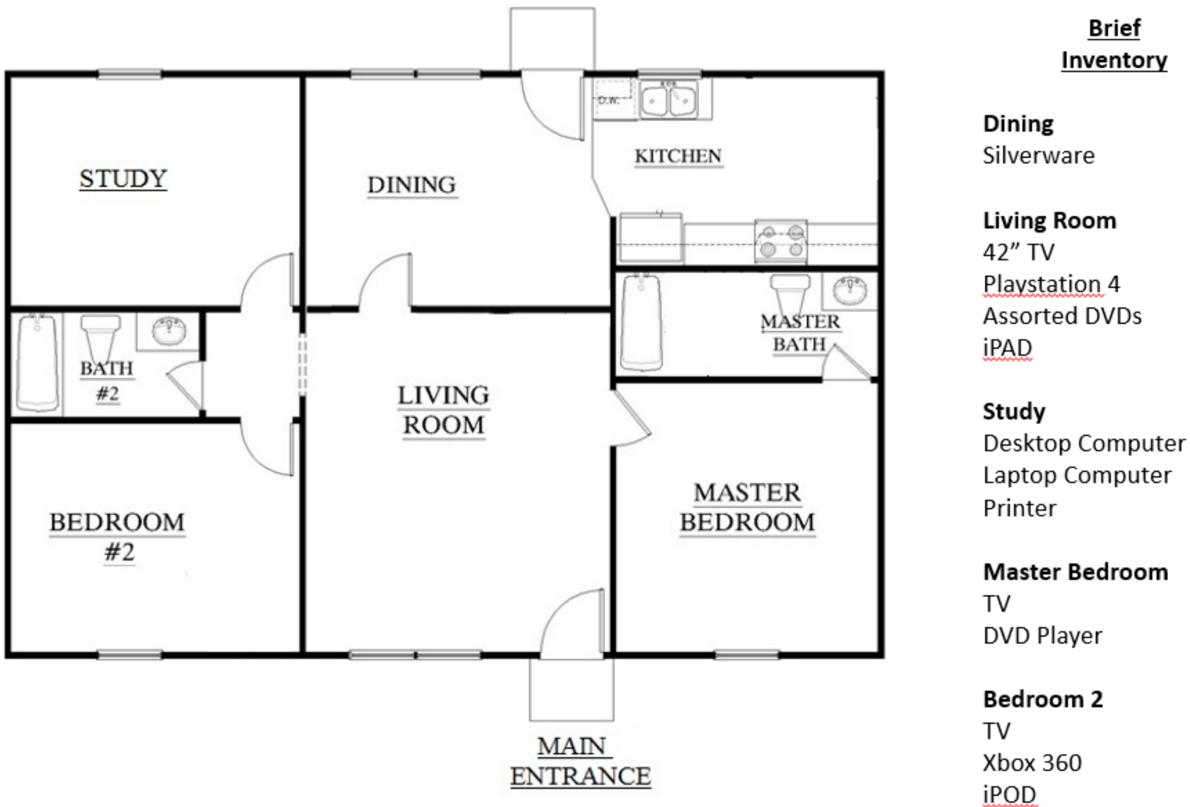
Full access to police records of crimes are typically restricted both in terms of access, and then publication once access is granted. Therefore, the current study used a sample of 41 participants (26 females, 15 males, M_{age} = 21.39, SD = 3.67, range = 19-40 years) to provide data similar to that found in police reports and suspect statements. Participants were selected based on having awareness and understanding of burglaries in the UK. Participants were asked if they had been victims of burglary. The majority of participants (n = 35) were students on a Forensic Psychology course[iii], which had covered various types of crimes including burglary. Therefore, participants were not naïve to burglaries or typical behaviours performed by burglars. All participants gave fully informed consent to participate and for their data to be analysed. The Ethics Review Board at the University of Lincoln approved the current study.

Data

The data consisted of 41 first-person statements taken from participants regarding their perceptions about the particular movements and behaviours an individual would perform while burgling a house. In order to allow more focused accounts, participants were provided with a floor plan of a single-story, ground-floor residential property, which had detailed information about rooms and items in them (see Figure 1)[iv]. Participants were told to give a first-person account of a person's movements and behaviours as they burgled a house, similar to police interrogating a burglar about their actions. Participants were encouraged to be as detailed as possible about all movements and behaviours they would make, so that the analyses could be more detailed with no gaps in the chains – which is similar to police directives in an interrogation to provide detailed accounts. Clearly, participants may not include all information, the same as witness/suspect statements may not; however, this is reduced through the BSA approach (Keatley, 2018). Participants were told the house was empty when burgled, and the burglary occurred at night to avoid possibly entering into mapping sexually-motivated burglaries.

Statements taken from participants about their perceptions were selected for analysis if they were detailed enough to allow for BSA – typically this means 3 or more individual Behaviours (Keatley, 2018). In the current dataset the average length was 17.78 (*SD* = 4.30, range = 11 to 30).

Figure 1. Floor-plan of property being burgled



Coding scheme

Based on participants' responses, a coding scheme was developed to account for all behaviours in the statements. The coding ensured that all categories were mutually exclusive and exhaustive (Bakeman and Gottman, 1986; Bakeman and Quera, 2011), which is a pre-requisite for BSA, to ensure there are no gaps in sequence chains and no overlaps. Multiple coders with experience in BSA research developed and agreed on the coding scheme used to categorise statement transcripts[v]. The coding process was iterated until full agreement and reliability was found. Given the straightforward nature of the case and presentation of materials, there were no ambiguous cases or categories. Finally, a back-translation process was used to recreate statements from codes and check that all important information was still present (Ellis, Clarke and Keatley, 2017). The back-translation approach takes the coded sequence (e.g., A→B→C→D) and turns it back into real behaviours. The reformed behaviour sequence is then compared to the initial participant statement and researchers agree on whether it closely matches the essence and outline of the original sequence without undue loss or biasing. This was the case for all sequences in the current sample.

Statistical Analysis

After statements were coded into sequence chains, data were input into a statistical package R (R Team, 2013), and a program was used to analyse the transition frequencies and standardised residuals. This analysis gave a transition frequency matrix of all significant transitions from antecedent to sequitur. In order to make results more easily interpretable, these transitions were graphically presented in a behaviour map. However, a novel development in the current research is to include spatial place-markers in the sequences, which allow for the state transition diagram to be positioned in a spatially meaningful state space. Instead of simply placing the nodes of the state transition diagram sequentially top-down from start to finish, the nodes were placed spatially in the state space according to locations in the property. Therefore, the current research not only maps temporal progression through the property; but, also spatial movements. BSA also accounts for chance, through Chi-Square statistics and standardised residuals; therefore, it is not simply the total number of transitions (movements from one room to the next and actions therein), but also how likely an offender is to move around a house and perform certain actions, compared to chance.

RESULTS

The first stage of Behaviour Sequence Analysis (BSA) is to consider the frequencies of individual Behaviours and events. Frequency results indicate how closely the current dataset match known or existing datasets, it also provides a first glimpse of the type of individual Behaviours and their prevalence in the current dataset. Table 1 shows the frequency of rooms mentioned in reports, and the items stolen in each room.

Table 1. Frequency of individual categories

Category	**Frequency**
Living room	108
Dining room	79
Back door	59
Study	39
EXIT	41
Same exit	36
Bedroom2	35
iPAD	34
Laptop computer	32
Playstation 4	31
Xbox 360	30
iPOD	26
Master bedroom	23
Silverware	16
Surveil property	13
42" TV	12
DVD player	11
Assorted DVDs	11
Desktop computer; Kitchen	10

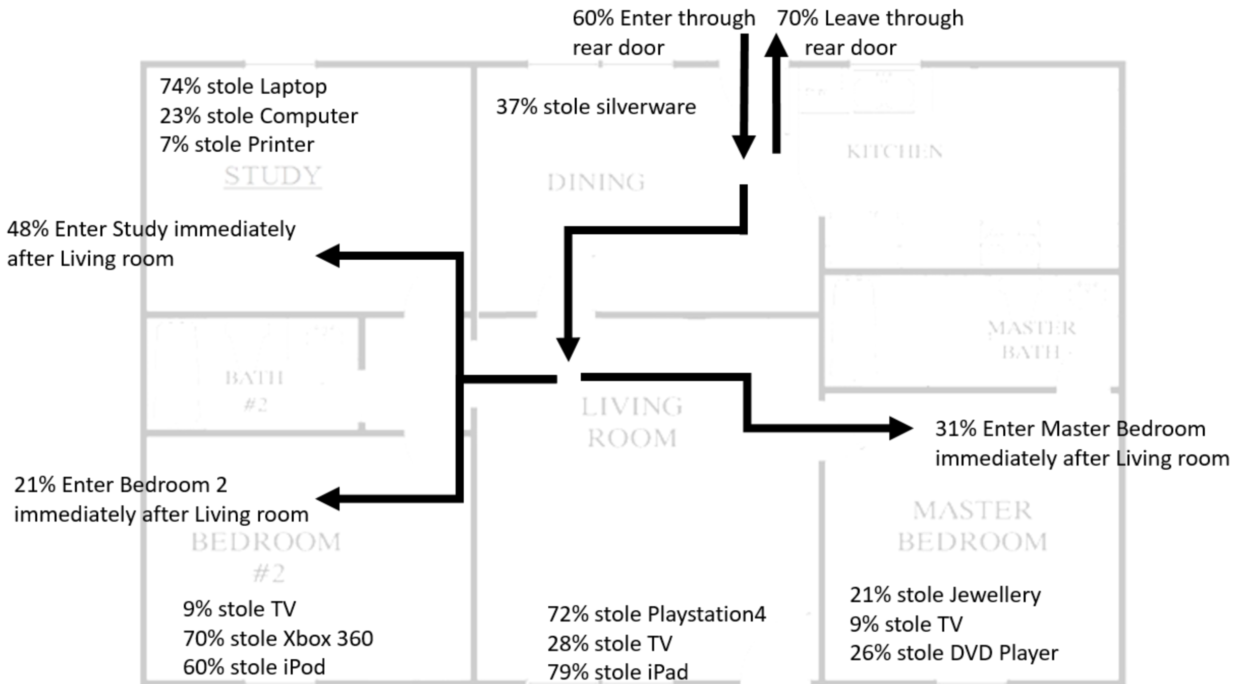
Different exit; Jewellery/watches etc	9
Study window; Wear gloves	7
Kitchen window	6
Main door; TV (MB); TV (BR2)	4
Dining window; Bedroom window; Printer; Bathroom2	3
Check for open door/window; Wear mask; Wipe fingerprints	2
Master bedroom window; Monitor; Cyber crime; Check house for occupants	1

Note. MB = Master bedroom; BR2 = Bedroom #2

The frequency table clearly shows that the living room was the most frequented place in the property, which is likely owing to its position in the centre of the property, and the number of potential items to steal. In terms of items being stolen, smaller items were mentioned more frequently, such as iPad (n = 34) and laptop (n = 32). Finally, while all burglars exited the premises, the majority exited through the same location they entered the building (n = 34).

In order to make the frequency table easier to read, the frequency of movements were mapped on to the property, this is the first step towards mapping movements throughout the property (see Figure 2). Figure 2 shows the main rooms entered, and the main mode of entry and exit: the rear door of the house. For clarity, routes from each room to exit is not mapped on Figure 2. While the frequencies of movements into, around, and out of the property provide some initial awareness of how burglars may move around, it is important to know which of these movements are occurring above the level of chance. For instance, it may be that individuals could randomly move around a property, and by chance end up in one of several rooms. Therefore, to account for chance, BSA was conducted on the chains of movements.

Figure 1. Frequency of movements around the property

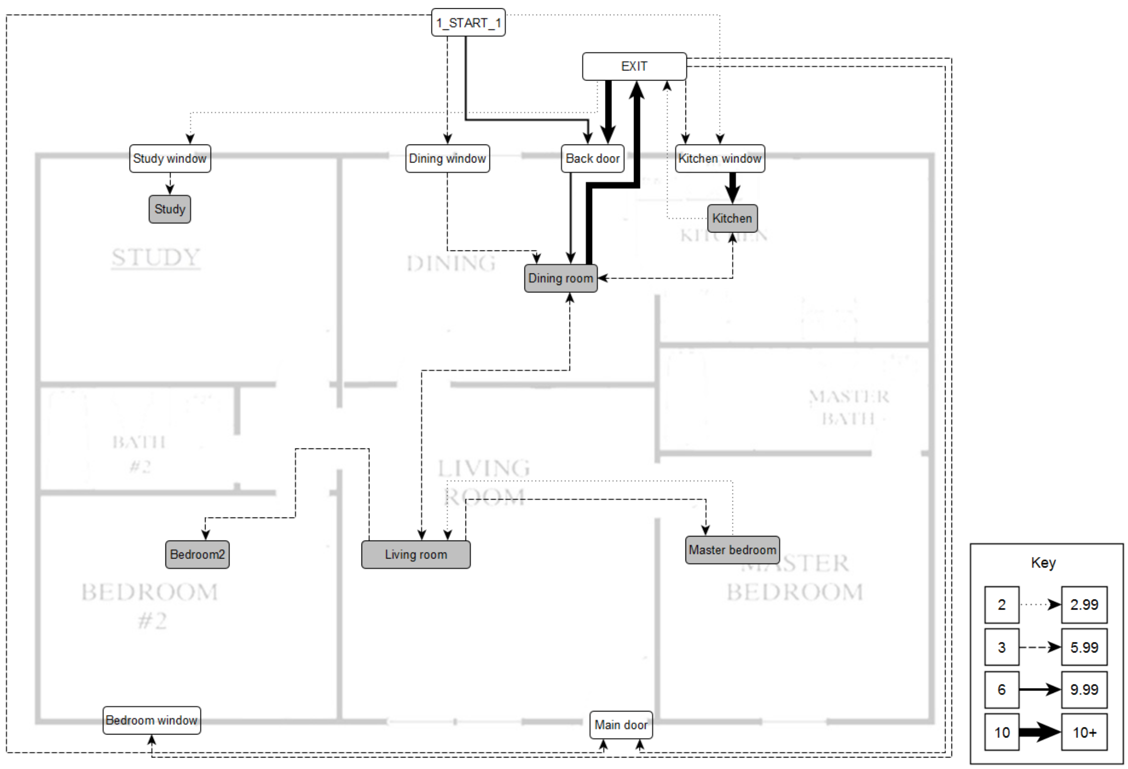


Behaviour Tracking

A lag-one BSA was conducted on the data, to show the transitions of movements and actions in the perceived commission of a burglary. Transitions between all behaviours in the participants' sequence chains were analysed, and transitions occurring more than would be expected by chance, according to Chi-Square analysis (χ^2), were plotted. Two state transition diagrams are included, to show how the analyses can be used to investigate different information at different levels of complexity[vi]. In both diagrams, thicker lines indicate larger standardised residual scores.

In Figure 3, only transitions between rooms are included, to reflect the movement of burglars around the property. This is a rudimentary form of analyses, and is included only to illustrate how the complexity of these diagrams can be increased or decreased to focus on certain crime-scene specific information (for example, this type of analyses could reflect escape paths in other datasets). The transitions clearly show that the dining room is the last room to be used before 'exit' (n = 24, SR = 10.15), and that most exits occurred through the back door (n = 27, SR = 14.08). Conspicuous by their absence of inclusion in the diagram is the master bathroom and second bathroom (bathroom #2)[vii].

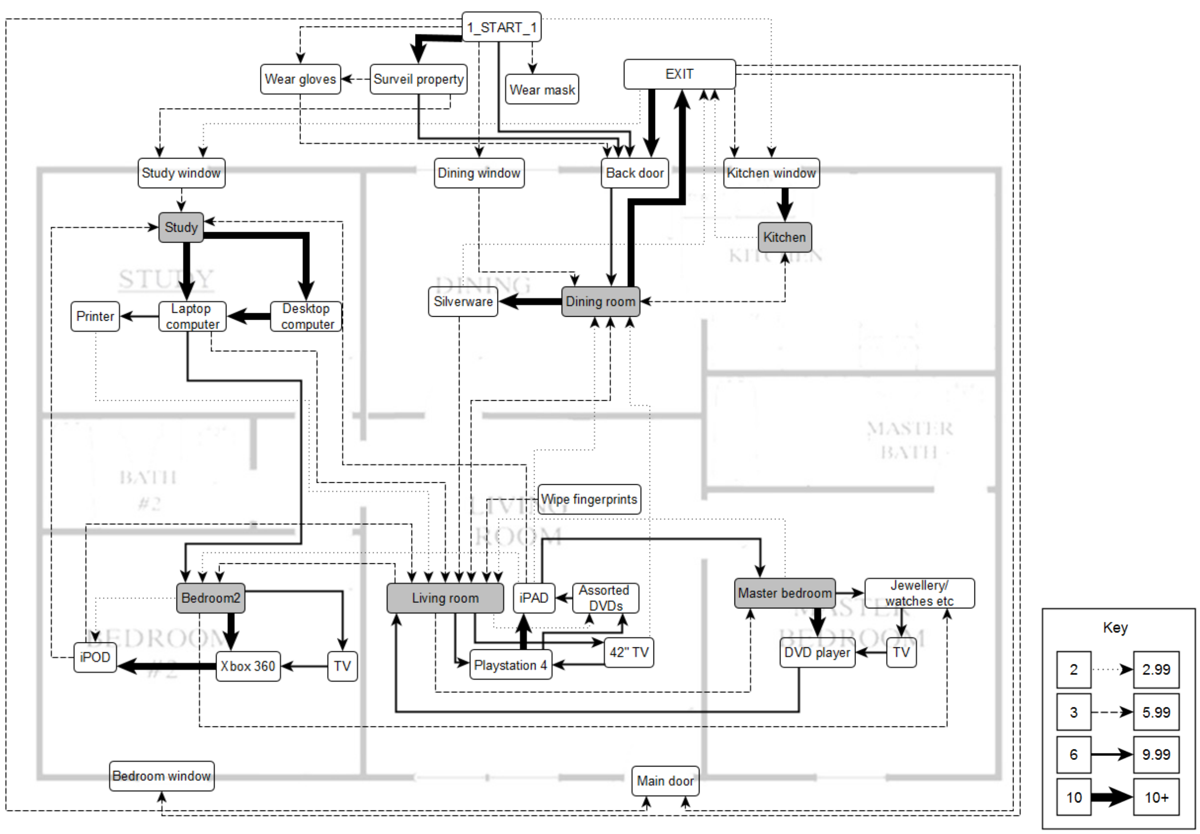
Figure 2. Transition of movements around the property (locations only)



Note: The key indicates the standardised residual scores for transitions between behaviours. Thicker lines indicate higher standardised residuals

Figure 4 provides the complete Behaviour Tracking map of perceptions of movements around the property and items stolen from each room as burglars moved around. Most participants perceived that burglars would enter through the back door and go in to the dining room (n = 27, SR = 8.49). Once in the dining room, silverware was the most likely to be stolen (n = 15, SR = 10.40). In the second bedroom (Bedroom #2), after stealing the Xbox 360, burglars were more likely than chance to steal an iPod (n = 22, SR = 20.81).Whereas movement into the study was not clearly shown in the previous figure (Figure 3), the current findings clearly show that once in the study the desktop computer (n = 10, SR = 13.31) and the laptop computer (n = 23, SR = 16.76) were most likely to be stolen.

Figure 3. Full geospatial BSA of movements around the property and items stolen



Note: The key indicates the standardised residual scores for transitions between behaviours. Thicker lines indicate higher standardised residuals

Discussion

The current study provides a novel approach to spatio-temporal investigation, *Behaviour Tracking*, which takes Behaviour sequence analysis and maps the movements in a geographically meaningful state space. The aim of Behaviour Tracking is to provide a novel method for crime analysis. This method can, and has, been used in a number of applied contexts; however, to show the method to a wider audience, a perception-based dataset of a residential burglary was used. The example data, aimed at replicating police reports of burglary, were used to illustrate how the method and analyses can be used in real criminal datasets. The use of participant perceptions allowed an open dataset that was not restricted under nondisclosure barriers, and therefore allowed the publication of the method for wider distribution and development. The current analyses can be used in the same manner in real criminal cases as well security issues (like exit routes and pathways of people in the event of emergency evacuations).

Although the current dataset used perception based sequences, the findings are consistent with findings in the wider literature (Nee and Taylor, 2000; Wellsmith and Burrell, 2005; Homel, Macintyre and Wortley, 2014; van Gelder *et al.*, 2017). For instance, the majority of participants suggested that burglars would enter through the rear of property, which is typically not as visible as the front of the property. This matches rational choice perspective (Cornish and Clarke, 2016) in that burglars are motivated to enter and exit undetected, which participants correctly perceived as shown by the results. Similarly, participants also suggested that smaller items were more likely to be stolen, which matches rational choice theory predictions and previous research that shows burglars steal smaller goods as they are easier to carry and relatively simple to sell on (Nee and Taylor, 2000; Clare, 2011; van Gelder *et al.*, 2017). This previous research outlines the burglar as an expert in their decision-making (Nee and

Ward, 2015), and the overlap of findings in the current research suggest that the participants' perceptions were an accurate representation of real-world behaviours.

The current findings, however, also highlight that many people are fixated on the archetypal forms of burglary. In every case outlined by participants, the simplified sequence was: enter, steal item(s), leave. This is certainly a type of burglary; but, it is not the only type. For example, no participant mentioned destruction of property or other aberrant behaviours. In the current study, participants were told the house was empty – though if people were present, this would add to more complex scenarios and maps, which the method could be used to outline and highlight similarities across repeated offences (Keatley & Clarke, 2019). For example, in the case of the East Area Rapist /Golden State Killer, the criminal performed a series of similar actions across each crime, Behaviour Tracking could be used to provide clearer outlines of the spatio-temporal similarities between crimes scenes, possibly indicating a similar criminal is responsible.

The current study outlines a key advancement over previous temporal methods of analysis in burglary, such as crime script analysis or standard BSA. The findings indicate not only what behaviours are exhibited in the commission of a crime; but, the location of those behaviours. By including geographic locations in the dataset movements can be spatially as well as temporally located. This is a relatively straightforward and easy development of the BSA method, which has been used in real-world cases. Behaviour Tracking has also been used in real-world applications such as the preparation, attack/abduction location, and disposal of bodies across several homicide cases. This research used locations such as 'indoors' and 'outdoors' as well as killers' *modus operandi* to show types of behaviours in each location. A further application of the method, related to the current research was to analyse several breaking-and-entering crimes that resulted in the sexual assault of the female resident inside the property. Victim statements and forensic information were used for these applications, which did not always provide clear progressive steps; however, main patterns of movements and behaviours emerged, and allowed a foundation framework to begin comparing and analysing future cases. In addition to these cases a further pertinent area this research could be developed to assist with crime prevention strategies is in terms of the recent focus on environment planning for terrorist acts and school shootings (Meyer, 2013; Keatley, McGurk and Allely, 2018). If we could begin to map the movements of criminals through buildings, then crime prevention strategies could be developed to reduce the risk or impede the crime commission.

An obvious limitation of the current study was the use of participants' perceptions, rather than real crime data. However, the use of perception-based data did allow for wider dissemination, and therefore allows the method to be published to a wider audience. Given the overlap between results in the current dataset with existing findings on burglary, the results can be taken as proxy for real criminal behaviours, and therefore the application of the Behaviour Tracking to real crime datasets still holds.

For real-world crime data, evidently CCTV data would provide clear behavioural sequences that can be spatially mapped (cell-phone locations may also provide similar types of geographic locations). However, investigations based on witness or suspect statements are often open to biases in memory or forgetting. Clearly, the Behaviour Tracking method will only be as good as the data used; however, this is true for all memory-derived research (Keatley, 2018). Furthermore, as noted, a benefit of the Behaviour Tracking method over free-recall interview/interrogation approaches is that witnesses create a timeline that may trigger memories through seeing gaps, and investigators can begin to build an 'archetypal' sequence from which to compare witness/suspect statements to assess validity. Therefore, the use of memory recall is not necessarily an unpassable problem for the method of Behaviour Tracking, it simply means that some part of the behavioural chain may be missing. Taking a spatio-temporal approach to analyses may offer investigators an opportunity to see geographical as well as temporal gaps in the information given by suspects or victims/witnesses, and prompt further investigation or allow gaps to be filled with 'most likely' movement chains.

While the current study was evidently made for the purpose of providing a detailed account of the Behaviour Tracking analysis (i.e., step-by-step movements of burglars are not always known), the Behaviour Tracking analysis can take relatively few datapoints (i.e., movements around a home) and still provide maps. The more detailed the account of a person's spatio-temporal movement, the more fine-detailed the Behaviour Map will be; but, having fewer points does not invalidate the method, it simply means we know less of the step-by-step movements. It may be that integrating Bayesian Models (Oatley and Ewart, 2003; Oatley and Ewart, 2011) into the Behaviour Map may provide a means of 'filling' some of the gaps, such that experts in the area provide input into likely movements. Obviously, in real-world data the opposite fact may be the case: very complex datasets. For example, there may be a lot of extra nodes on the diagram (including: presence of owners at home, interpersonal interactions, [guard] dog, burglar alarms, neighbours etc.). The current research purposefully attempted to reduce the complexity of the maps to provide a clearer output. Real-world data are typically messier and presentations using layered animations provides a better presentation of these more complex maps.

The next major step for Behaviour Tracking is to more fully integrate methods from geographic profiling, so that data concerning geographic locations can be more meaningfully included and developed. There are a number of overlapping terms used in both BSA and crime pattern theory, such as *attractors* and *hotspots*. Attractors in BSA are nodes or clusters of nodes that once individuals move in to, they spiral around and are less likely to move away from (such as addiction leading to crime to pay for more drugs, leading to more drugs consumed and then committing further crimes to pay for more drugs etc.). In crime pattern theory, attractors are geographic areas that criminals are more likely to move towards owing to the increase in opportunities for crime. It may be that attractors in BSA state spaces overlap attractors in crime pattern theory locations. Similarly, hotpots in BSA refer to nodes that multiple Behaviours pass through, acting almost like a bottleneck (Keatley, 2018). In crime pattern theory, hotspots are specific locations where the convergence of key elements in crime pattern theory come together (Wortley and Townsley, 2016). Integrating BSA with concepts and analyses from crime pattern theory and geographic profiling leads to a whole new avenue of research, with potentially very important new areas of research. The Behaviour Tracking technique could also be used to map the development of paraphilic behaviours, as outlined by Arntfield (2017), such that different movements and Behaviours around a property indicate where along a continuum an individual is, with regards development of sexual threats and behaviours.

Finally, within the current analyses, the stealing of items was inextricably linked to the rooms items were found in. However, in real-world burglaries a number of alternative actions can be taken in each room (for instance, destruction of property). Therefore, further analyses could be conducted in which behaviours are ‘nested’ within rooms. In a wider approach to Behaviour Tracking this would be akin to mapping movements between cities that a criminal or terrorist may take (major level), and then mapping the behaviours within that city (nested levels), such that we could see at a global level a person moves from City A to City B; but, within those cities a number of sub-behaviours are sequentially performed.

Conclusion

Crime does not happen in a vacuum, separate from any surrounding temporal or spatial influences. Therefore, recently, researchers have attempted to develop spatial analyses and temporal analyses. The current study is the first to integrate Behaviour Sequence Analysis with spatially meaningful locations, as a foundation for future developments in this area. Behaviour Tracking allows investigations to map the spatial and temporal movements of criminals around various locations (e.g., within a building, or through city streets). This allows the crime commission process to be understood in spatio-temporal sequences. The current dataset provided an example of how burglaries may be investigated and mapped using Behaviour Tracking. Future research and collaborative approaches should apply this method to other crimes and use real-world crime data wherever possible. CCTV data will evidently present some of the best forms of data in terms of clear movements; however, the use of qualitative statements in the current data highlight the versatility of Behaviour Tracking to be used on different datasets.

[i] Clearly, real-world data is seldom so 'clean'; however, the current paper is meant to outline the methodological approach, therefore, more detailed data were preferable.

[ii] In other crimes this may be a point at which a suspect is more easily apprehended; or in evacuation scenarios, this could be finding where bottle-necks occur etc.

[iii] There were no systematic differences between those participants that were Forensic Psychology students, and those that were not. Therefore, the sample was analysed as a whole. An alternative approach could have been to create a set of 'dummy' data (as in Keatley & Clarke, 2019); however, to provide a somewhat more realistic dataset based on verbal reports (akin to witness statements), we used participants.

[iv] A floor plan was given to provide some consistency to participants' accounts of crime sequences (otherwise, any number of different properties could be envisioned, and while this would be possible to group and analyse, it was deemed overly complex for the present study). While the floor plan does reduce ecological validity, it does allow for a clearer map to emerge, to show how Behaviour Tracking works. Again, the current article is meant to showcase the Behaviour Tracking method, rather than provide an explanation of burglary, per se.

[v] Although experts in BSA were used in the current study, this was owing to the author team involved. The BSA and Behaviour Tracking method can be conducted by non-specialised researchers, as long as they follow guidelines (see Bakeman & Gottman, 1986; Clarke and Crossland, 1985; Keatley, 2018).

[vi] In computer-generated illustrations the two diagrams can be animated and overlaid. This allows investigators to see global-level movements (between rooms, Figure 3), and nested Behaviours within each room (Figure 4). This would be akin to criminals moving between cities or countries (global movements) and actions within each city (nested Behaviours).

[vii] This is likely a caveat of providing participants with an inventory of each room, a priori; they knew beforehand that the bathrooms provided no items worth stealing. Obviously, in actual crimes, most burglars do not have this foreknowledge. However, this is a limitation of the current data, not the current method. Similarly, real-world data will provide many more nuances and pathways in the dataset (e.g., dogs, people being home etc.). This makes the analyses more complex; but, the basic approach outlined here remains the same.

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