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# Using case specific experiments to evaluate fingermarks on knives given activity level propositions



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## ABSTRACT

Bayesian networks have shown to be a useful tool for the evaluation of forensic findings given activity level propositions. In this paper, we demonstrate how case specific experiments can be used to assign probabilities to the states of the nodes of a Bayesian network for the evaluation of fingermarks given activity level propositions. The transfer, persistence and recovery of fingermarks on knives is studied in experiments where a knife is either used to stab a victim or to cut food, representing the activities that were disputed in the case of the murder of Meredith Kercher. Two Bayesian networks are constructed, exploring the effect of different uses of the experimental data by assigning the probabilities based on the results of the experiments. The evaluation of the findings using the Bayesian networks demonstrates the potential for fingermarks in addressing activity level propositions.

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## 1. Introduction

Evaluation of fingermarks given activity level propositions recently became a topic of interest [1,2]. The question which activity led to the deposition of the fingermarks becomes relevant when the source of the fingermark is not in dispute. Research by de Ronde, Kokshoorn, de Poot and de Puit [1] showed that there are multiple variables such as transfer, persistence, direction and pressure that may provide information when evaluating fingermarks given proposed activities that may have led to their deposition. One of these variables is the location of the fingermarks on an object. Based on an experiment with pillowcases, de Ronde, van Aken, de Puit and de Poot [2] have shown the value of the location of fingermarks with regards to assessing evidence for specific activities.

All variables that influence the interpretation of evidence given activity level propositions can be combined in a Bayesian network to evaluate evidence with regards to the relevant activities at stake [3]. A study by de Ronde, Kokshoorn, de Poot and de Puit [1] has illustrated how Bayesian networks can be used for the evaluation of fingermarks given activity level propositions by presenting

examples of Bayesian networks for a fictitious balcony case example. However, in that study, the assignment of probabilities to the conditional probability tables of the networks was left out of scope.

There are several sources of information that can be used to assign probabilities to the states of the nodes of a Bayesian network, mentioned in order of preference [4]. The forensic scientist may perform case specific experiments and base the probabilities implemented in the network on these empirical data. This option is preferred since these probabilities will align most closely with the circumstances of the case. Another possibility is to assign probabilities based on studies reported in literature that used experimental designs that are similar to the case circumstances. If no empirical data are available the probabilities could be informed based on expertise by the forensic scientist. This option, being subjective to a larger extent, is not preferred and puts a burden on the scientist to support their probability assignment. Sources for this could be a systematic review of resulting findings from similar cases, and/or expert elicitation from multiple experts. Whenever data are scarce or based on uncertain assumptions or sources, it is advisable to perform a sensitivity analysis to study the sensitivity of the likelihood ratio to reasonable variations in the assigned probabilities. If data are not available, or the sensitivity analysis determines the evaluation not to be robust, it may be decided that the findings from the evaluation will not be reported.

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In this study, case specific experiments are carried out for a case example in order to show how this information can be used to evaluate fingerprints given activity level propositions. We will first present the case example and present two Bayesian networks that may be used for the evaluation of fingerprints found on a knife given case relevant activity level propositions. We describe the experiments that were performed and the data gained from those. We then demonstrate how the probabilities in the conditional probability tables of the Bayesian networks can be assigned based on the experimental data. Finally, we will show how the networks can be used to evaluate fingerprints given activity level propositions by calculating likelihood ratios for fictitious case findings.

1.1. Case example – the death of Meredith Kercher

On the morning of the 2th November in 2007, Meredith Kercher was found dead on the floor of her bedroom. It appeared that she was stabbed in her neck and torso and it was established that these wounds were the cause of her death. Three suspects were identified: Rudy Guede, Kercher’s flat mate Amanda Knox and Amanda’s boyfriend Raffaele Sollecito. All three were convicted for the murder of Meredith Kercher. Amanda Knox and Raffaele Sollecito were later acquitted [6]. For this case example, we will focus on the claims that the prosecution and the defense made with regards to the knife that was submitted as evidence in the case against Knox and Sollecito.

There was no knife present on the crime scene, raising the suspicion that the murder weapon was removed. A knife was retrieved from a cutlery drawer in the apartment of Sollecito. The knife was tested for DNA, resulting in a matching DNA profile of Amanda Knox on the handle of the knife and a matching low-level DNA profile of Meredith Kercher on the blade of the knife. The knife was tested negative for the presence of blood [5]. The prosecution claimed that the knife was the murder weapon, however; the defense denied this statement and claimed that Knox used the knife for cooking in Sollecito’s apartment.

1.2. Objectives

To the authors’ knowledge, no fingerprint examination was carried out on the knife and only DNA evidence present on the knife was used in this case. For this paper, we investigate what kind of analysis could be performed when fingerprints were obtained from the knife in cases like this. In case fingerprints were found on

the knife, the question in this case may shift from source level to activity level; the source of the fingerprints on the knife would not be disputed by the defense because the suspect provides an alternative explanation for the presence of her fingerprints on the knife, namely cooking with the knife. Therefore, the activity during which the marks were deposited is disputed and it would be of interest to evaluate the findings given the activity level propositions that may be put forward in this case.

2. Bayesian network construction

In this section, we discuss the process of constructing a Bayesian network to address the question whether the suspect Amanda Knox (S) used the knife to stab the victim Meredith Kercher (V) or used the knife to cut food while cooking. In this case, it is disputed whether the knife was the actual murder weapon and therefore we can formulate the following propositions, disputing the activity that is carried out:

$H_p$ : S stabbed V with the knife. S did not use the knife to cut food.

$H_d$ : V was not stabbed with the knife. S only used the knife to cut food.

All networks were built using the software Hugin (version 8.6) and the corresponding .net files can be found in the supplementary material.

For this study, several assumptions have been made:

1. We assumed that the collected evidence represents one fingerprint grip on the knife, consisting of a collection of fingerprints for which is assumed that they are left in one and the same placement of the hand. This means that any handling of the knife prior to the alleged use (like taking it from a drawer or the dish washer) is disregarded.
2. The assumption is made that the source of the fingerprints is known to be the suspect and that no one else touched the knife.
3. The knife in the Kercher case is a 31 cm long knife with a 17,5 cm steel blade and a black, plasticized handle [7]. The knife we used in the experiments is a 22 cm long knife with a 11,5 cm steel blade and a black plasticized handle. We assume that the patterns of fingerprints on the knives resulting from the experiments are similar to those that would be obtained from a slightly larger knife.
4. We assume that the size of the hand of the suspect is an average human hand. The assigned probabilities are based on hands from volunteers ranging from small to large size hands.

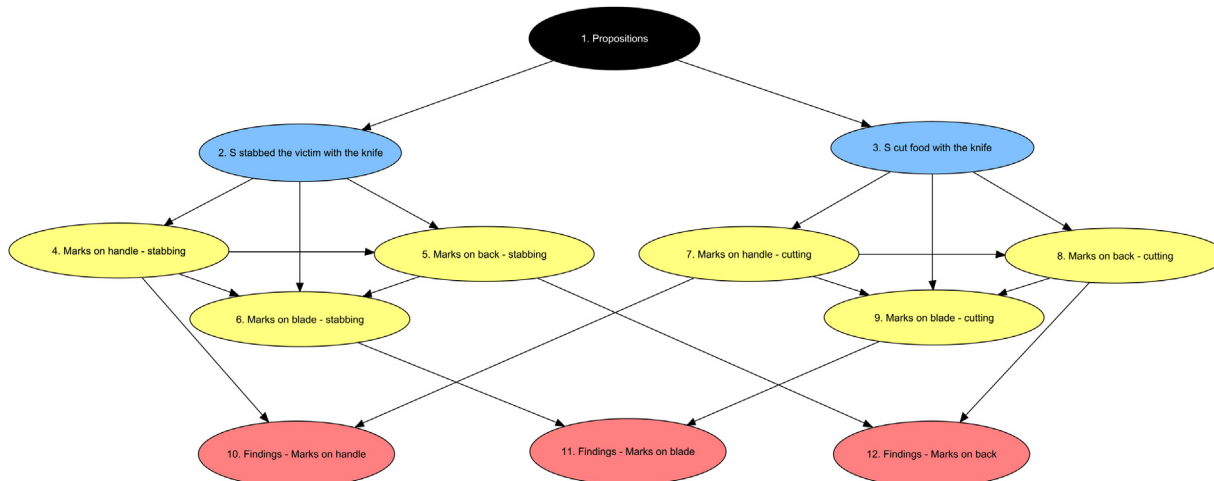


Fig. 1. Bayesian network I and II, focusing on the different locations on the knife.

5. We assume that the purpose of the grip on the knife handle is to use the knife as a tool. There are numerous ways to hold a knife. To use the knife as a tool for stabbing or cutting would make some of those ways improbable. For instance, it would be improbable that somebody would hold the knife with just a finger and a thumb on the handle to stab or cut. However, this is not impossible. Other ways may simply be impossible due to the intrinsic characteristics of both the knife and the hand, for example holding the knife with just a thumb. We assume that all the impossible, as well as the highly improbable ways to hold the knife are impossible in the context of the case. We will discuss this further in Section 4.

If an evaluation as discussed in this paper would be applied to a real case, similar or other assumptions may need to be made [8]. The relevance of the assumptions may be discussed with the mandating authority together with the propositions being set prior to the evaluation being carried out. Also, the impact of such assumptions on the outcome of the evaluation can be addressed in the report.

### 2.1. Constructed Bayesian network

Based on the shape of a knife, it is expected that fingerprints may be observed on different locations of the knife when carrying out different activities. Three separate areas of the knife are therefore distinguished: the handle of the knife, the backside of (the handle of) the knife and the blade of the knife. Fig. 1 shows the constructed Bayesian network, of which two versions (Bayesian network I and Bayesian network II) are presented below, both showing a different use of the experimental data by a different definition of the states of nodes (4)–(12). Bayesian network I focusses on evaluating the presence or absence of fingerprints on particular areas on the knife. Bayesian network II focusses on evaluating the area of friction ridge skin that was left on particular areas of the knife. The networks are created following the procedure described by de Ronde, Kokshoorn, de Poot and de Puit [1], based on the template by Taylor, Biedermann, Hicks and Champod [9]. The presented network in Fig. 1 has a structure that is different from the network for the evaluation of fingerprints given activity level propositions showed in Figs. 1, 4 and 5 presented by de Ronde, Kokshoorn, de Poot and de Puit [1]. In that study, Bayesian networks were constructed for the evaluation of fingerprint grips present on a balcony railing given the activity level propositions that the grip was a result of climbing the balcony or that the grip was a result of leaning on the railing. For the variable location in the balcony example, the balcony railing was divided into four different areas resulting into regions which were bigger than the size of a fingerprint grip. As a consequence, fingerprints found in the regions were considered conditionally independent since the presence of a fingerprint grip in one region was considered not to influence the probability for the presence of a fingerprint grip in another region, given the assumption of a single deposition event that was made. For smaller items, such as a knife, a division of the item into regions may result into areas that are possibly smaller than the size of a fingerprint grip and as such the presence of a mark on the handle of the knife may affect the probability of the presence of a mark on the backside or the blade of the knife. This causes conditional dependencies that should be taken into account, and therefore the nodes representing the transfer, persistence and recovery mechanisms have to be defined for each location region and activity separately. We suggest that for items for which the location is divided into regions that are of smaller size than a grip, additional dependencies have to be taken into account and the Bayesian network should be structured as described in Sections 2.2 and 2.3.

### 2.2. Bayesian network I – location of fingerprints on the knife

The first Bayesian network is constructed to evaluate the presence or absence of fingerprints on the knife.

#### 2.2.1. Node (1) Propositions

The node (1) *Propositions* has two states,  $H_p$  and  $H_d$ , representing the propositions of prosecution and of defense respectively. We assigned an equal prior probability of  $p = 0.5$  to both propositions, as shown in Table 1.

#### 2.2.2. Nodes (2) *S stabbed the victim with the knife* and (3) *S cut food with the knife*

From the node (1) *Propositions*, two activities emerge: (2) *S stabbed the victim with the knife* and (3) *S cut food with the knife*, represented by the blue nodes in Fig. 1. Both nodes have the states ‘true’ and ‘false’. Table 2 and Table 3 show the probability tables for these nodes. Table 2 shows that if  $H_p$  is true, the node (2) *S stabbed the victim with the knife* is true with probability  $p = 1$  and false with probability  $p = 0$ . If  $H_d$  is true, (2) *S stabbed the victim with the knife* is true with probability  $p = 0$  and false with probability  $p = 1$ . Table 3 shows that for the node (3) *S cut food with the knife*, the reverse reasoning holds.

#### 2.2.3. Nodes (4)(7) *Marks on handle*, (5)(8) *Marks on back*, (6)(9) *Marks on blade*

Nodes (4), (5), (6), (7), (8) and (9) represent the combined probability of transfer, persistence and recovery of the fingerprints to a particular location of the knife as a consequence of the activity. This results in the nodes (4) *Marks on handle - stabbing*, (5) *Marks on back - stabbing* and (6) *Marks on blade - stabbing* for the transfer, persistence and recovery of fingerprints to a particular location on the knife for the scenario stabbing and the nodes (7) *Marks on handle - cutting*, (8) *Marks on back - cutting* and (9) *Marks on blade - cutting* for the transfer, persistence and recovery of fingerprints to a particular location on the knife for the scenario cutting food. These nodes each have two states: ‘fingerprints S present’ and ‘fingerprints S absent’.

The conditional dependencies between the three locations should be considered. These dependencies are modelled in the Bayesian network by adding an arrow from node (4) *Marks on handle - stabbing* to node (5) *Marks on back - stabbing*, and arrows from nodes (4) and (5) to node (6) *Marks on blade - stabbing*. The same connection has been made between nodes (7), (8), and (9), as shown in Fig. 1. The probabilities assigned to the conditional probability tables in these nodes are based on the conducted knife experiment, and will be discussed in Section 4.

**Table 1**  
Prior probability table for the node (1) Propositions in Fig. 1.

Propositions	Probability
$H_p$ : S stabbed the victim with the knife. S did not use the knife to cut food.	0.5
$H_d$ : V was not stabbed with the knife. S only used the knife to cut food.	0.5

**Table 2**  
Conditional probability table for the node (2) *S stabbed the victim with the knife* in Fig. 1.

Propositions	$H_p$	$H_d$
S stabbed the victim with the knife:		
True	1	0
False	0	1

**Table 3**  
Conditional probability table for the node (3) S cut food with the knife in Fig. 1.

Propositions	H <sub>p</sub>	H <sub>d</sub>
S cut food with the knife:		
True	0	1
False	1	0

2.2.4. Nodes (10) Findings – Marks on handle, (11) Findings – Marks on blade and (12) Findings – Marks on back

The node (10) Findings – Marks on handle in Fig. 1 is a summary node, representing the presence or absence of fingermarks on the handle of the knife, with the two possible states ‘fingermarks S present’ and ‘fingermarks S absent’. Given the propositions and assumptions that were made, we do not consider marks by other individuals. The nodes (11) Findings – Marks on blade and (12) Findings – Marks on back are similarly defined and represent respectively the presence or absence of fingermarks on the blade of the knife and on the backside of the handle of the knife.

Table 4 shows the conditional probability table for node (10) Findings – Marks on handle. If either (4) Marks on handle - stabbing or (7) Marks on handle - cutting are in state ‘fingermarks S present’, the node (10) Findings – Marks on handle is in state ‘fingermarks S present’ with probability  $p = 1$  and in state ‘fingermarks S absent’ with probability  $p = 0$ . The conditional probability tables for the nodes (11) Findings – Marks on blade and (12) Findings – Marks on back are similarly defined.

2.3. Bayesian network II –area of friction ridge skin on the knife

Thus far, we have dealt with the findings on the knife as presence or absence of fingermarks only. It is up to the scientist to decide which level of detail in the findings will be considered in their evaluation. The choice will often be dictated by the observations made in the case (can certain details be determined?), available data on transfer, persistence and recovery (do the data provide sufficient detail to assign probabilities?), and the contextual information in the case (e.g. does the question that needs answering require a certain level of detail?) [10].

From the knife experiment, we observed that a considerable difference between the two activities stabbing and cutting food was shown in observing particular areas of friction ridge skin on particular locations on the knife. We decided to add this information to network II. The hand that left the fingermarks is divided into three areas of friction ridge skin: the palm, the fingers and the thumb. To each transfer, persistence, and recovery node representing the handle, the backside and the blade of the knife, as well as the three findings nodes, we defined the states based on all possible combinations of the three areas of friction ridge skin, leading to the seven states: ‘palm’, ‘fingers’, ‘thumb’, ‘palm/fingers’, ‘palm/thumb’, ‘fingers/thumb’, ‘palm/fingers/thumb’ and ‘none’. An extra state ‘undetermined’ is added to each of these nodes representing fingermarks for which it is impossible to determine what area of the hand left the mark.

**Table 4**  
Conditional probability table for the node (10) Findings – Marks on handle in Fig. 1. (\*) denotes the fact that these probabilities represent situations which will not occur because the activities stabbing and cutting food are both mutually exclusive (within the context of the example case).

Marks on handle - stabbing	FM S present		FM S absent	
	FM S present	FM S absent	FM S present	FM S absent
Marks on handle - cutting				
Findings – Marks on handle:				
Fingermarks S present	1*	1	1	0
Fingermarks S absent	0*	0	0	1

When combining the variables location and area of friction ridge skin, additional conditional dependencies between these variables should be considered. For example, if a thumb mark is observed on the backside of the knife, this will influence the probability of observing particular areas of friction ridge skin on the handle and the blade of the knife, due to the shape of the knife and the shape of a hand. Since this dependency exists regardless of the activity that is carried out, these variables are considered to be conditionally dependent of each other and should be modelled in the Bayesian network by adding an arrow between them [3]. This results in a Bayesian network that is similarly structured as Bayesian network I but with the states of nodes (4)–(12) defined to include the area of friction ridge skin (thumb, palm, and fingers).

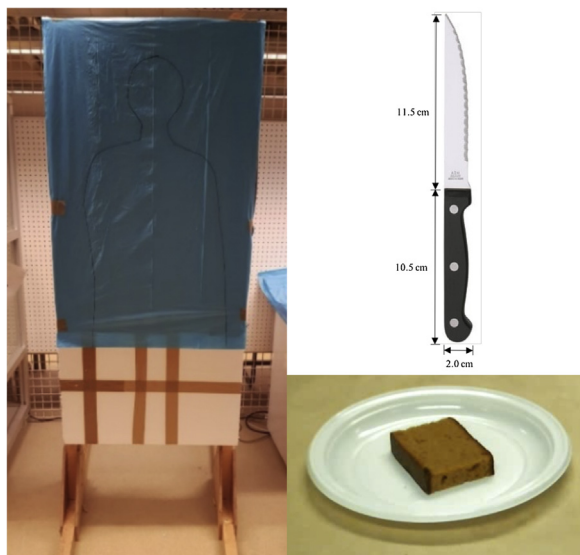
3. Knife experiment

3.1. Experimental protocol

A within-subjects design was used in which each participant conducted the same experimental tasks. Before the start of the experiment, informed consent was obtained from all participants, with which the participants gave permission for the use of their fingermarks for research purposes. A total of 24 students of the Amsterdam University of Applied Sciences (7 males, 17 females, all right-handed donors) carried out two separate scenarios, each with the use of a different knife. In the first experiment, each participant was asked to pick up a knife from the table and to stab three times into a Styrofoam plate on which a silhouette of a person was drawn (Fig. 2). The fingermarks on the knives were directly visualized using cyanoacrylate fuming. In the second experiment, each participant was asked to pick up a knife from a table and to cut a piece of gingerbread into four pieces (Fig. 2), representing the activity cutting food with a knife. Again, the fingermarks on the knives were directly visualized using cyanoacrylate fuming.

The type of material that is being cut may affect the handling of the knife. Different structure or texture, or hardness of the material may affect the amount of force being used (hence impact on the pressure asserted by the individual performing the cutting as well as on the friction between hand and knife resulting from this) as well as the positioning of the hand. Further work is needed to explore the impact of these and other variables on the probability of transfer, persistence, and recovery of marks from friction ridge skin on surfaces. This, however, is outside the scope of the current study.

In this experiment, natural fingerprint samples were used, collected with minimal interference from the researchers to represent the conditions of the case as closely as possible and variables such as duration, pressure, temperature and time between washing hands were not controlled. Between the two scenarios, a week time span was taken. The participants were not provided with instructions on how to handle the knife when carrying out the activities.



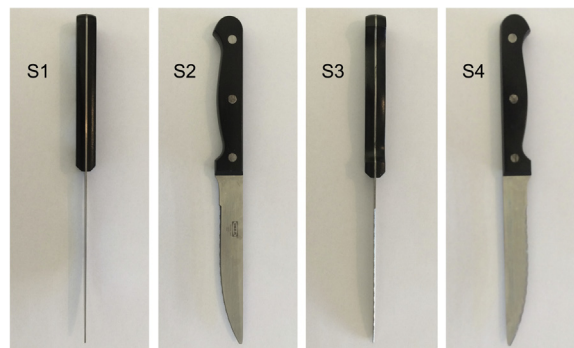
**Fig. 2.** Stabbing construction (left), steak knife used in the experiments (right, up) and gingerbread used for the cutting scenario (right, down).

### 3.2. Materials

For the knives, steak knives of the model SNITTA purchased at IKEA were used (Fig. 2). These are 22 cm long knives with a 11.5 cm blade and a plastic coated black handle. The knives were cleaned with the use of acetone, followed by cleaning with ethanol (70%), rinsing with demi water and drying using Tork paper. For the stabbing scenarios, a Styrofoam plate was placed on a wooden stand and covered with plastic, on which a silhouette of a person with the height of 1.78 was drawn, as shown in Fig. 2. After each stabbing scenario was carried out, the plastic was replaced to prevent a bias for the next participant of where to stab. After the stabbing the knives were put on a table and not covered or packaged. The fingerprints were directly visualized using cyanoacrylate fuming (1,5 g, 120 C) in a MVC3000 fuming system (Foster and Freeman LTD) at 80% humidity. Afterwards, the knives were directly photographed using a Nikon D60. All experiments were filmed using a Logitech C615 HD webcam.

### 3.3. Analysis

During the experiment, two knives were collected for each donor. After visualization, the knives were photographed by taking four pictures of each side of the knife. For the analysis, pictures of the knives and the video footage of the scenarios were scored by a single researcher using a predefined set of variables. During this analysis, the final grip that was used for the activity of stabbing or cutting food was scored. The researcher scored whether fingerprints were visualized (yes/no), which hand they used (left/right), the direction of the knife (overhand/underhand), the rotation of the knife (cutting face of the knife pointing upwards or downwards) and what area of friction ridge skin on the hands were left on which location on the knife. For coding the location and the area of friction ridge skin, the knife was divided into 6 regions: side 1, the topside of the knife handle (S1); side 2, rotating the knife 90 degrees from the topside to the right side of the knife handle (S2); side 3, the downside of the knife handle (S3); side 4, rotating the knife 90 degrees from the downside to the left side of the knife handle (S4); the backside of the knife (back) and the blade of the knife (blade). Regions S1-S4 on the knife handle are shown in Fig. 3.



**Fig. 3.** Division of the knife handle into areas S1, S2, S3 and S4.

For each location on the knife was denoted what area of friction ridge skin was observed in the video footage: palm, fingers, thumb and all combinations thereof. If the area was not touched, the score 'none' was given. For the scoring procedure, the grip used during the activity observed from the video footages, was compared to the pictures of the visualized fingerprints on the knives to determine what area of the hand left the marks present on the knife. The focus of this scoring was not on the quality of the fingerprints, therefore not only identifiable fingerprints were scored but also fingerprints that would possibly not be suitable for identification such as smears or lower scoring fingerprints [11]. To fingerprints for which it was difficult to determine what area of the hand left the mark, a score of NA was assigned. All video footages, pictures and the corresponding scores were double checked by the researcher that scored the files. The videos that were in some respect unclear due to for example movement of the camera were discussed with an additional researcher. In case of agreement, the area of friction ridge skin was assigned, otherwise a score of NA was assigned. This process showed that the coding procedure was a straightforward process with a high degree of intra- and intercoder reliability.

### 3.4. Results

Table 5 and Table 6 show the observations for the experiment in which the participants used the knife for stabbing and for the experiment in which the participants used the knife to cut food, respectively. These tables show that for each scenario and for each donor, fingerprints were visualized on the knife (column FM present = yes).

The video footages showed that there were two optional directions for the grip as a result of holding the knife. The first is to hold the knife in an 'overhand' position such that the wrist is located higher than the elbow and the knife is carried at shoulder height or higher, resulting in a grip in which the thumb is placed near the backside of the knife handle. The second option is to hold the knife in an 'underhand' position such that the wrist is located lower or at equal height as the elbow and the knife is held at stomach height or lower, resulting in a grip in which the thumb is located near the blade side of the knife handle. Table 5 shows that 54% of the donors that carried out the stabbing scenario held the knife in the overhand position. Table 6 shows that the overhand grip was not observed for the cutting food scenario. This seems logical in view of the activity; cutting food with the knife in an overhand position can be considered rather uncomfortable. The results confirm our expectation that the direction of the grip on the knife can be distinctive between the activities stabbing and cutting food.

During the experiment, we observed that two participants rotated the knife during the scenario of stabbing such that the cutting face of the knife pointed upwards (Table 5). This rotation

**Table 5**  
Resulting counts for the scenario stabbing, in which Down = cutting face of knife downwards, Up = cutting face of knife upwards, P = Palm, F = Fingers and T = Thumb.

Donor	FM present	Which hand?	Direction	Rotation	Side 1	Side 2	Side 3	Side 4	Backside	Blade
Donor 1	Yes	Right	Underhand	Down	P/F	P/F	F	F/T	None	None
Donor 2	Yes	Right	Overhand	Down	F	P	P/F	F	None	None
Donor 3	Yes	Right	Overhand	Up	P	F	F	P	T	None
Donor 4	Yes	Right	Overhand	Down	P	P	F	F/T	P	None
Donor 5	Yes	Right	Overhand	Down	F	P	P/F	F	T	None
Donor 6	Yes	Right	Underhand	Down	P/F/T	P/F	F	F/T	None	None
Donor 7	Yes	Right	Overhand	Down	F	P	P/F	F/T	T	None
Donor 8	Yes	Right	Overhand	Down	P/F	P	P	F/T	T	None
Donor 9	Yes	Right	Overhand	Down	F	P	P	F/T	T	None
Donor 10	Yes	Right	Overhand	Down	F	P	P	F/T	T	None
Donor 11	Yes	Right	Overhand	Down	F	P	P	F/T	None	None
Donor 12	Yes	Right	Overhand	Down	F	P	P	F/T	T	F
Donor 13	Yes	Right	Overhand	Down	F	P	P	F/T	None	None
Donor 14	Yes	Right	Underhand	Down	P	P/F	F	P/F/T	None	None
Donor 15	Yes	Right	Underhand	Down	P/T	P	F	F/T	None	None
Donor 16	Yes	Right	Underhand	Down	P/T	P/F	F	P/F/T	None	None
Donor 17	Yes	Right	Underhand	Down	P	P/F	F	F/T	None	None
Donor 18	Yes	Right	Underhand	Down	P/T	P/F	F	P/F/T	P	None
Donor 19	Yes	Right	Underhand	Up	P	F	F	P/T	P	None
Donor 20	Yes	Right	Underhand	Down	P/T	P/F	F	F	P	None
Donor 21	Yes	Right	Overhand	Down	NA	NA	NA	NA	NA	None
Donor 22	Yes	Right	Overhand	Down	F	P	P	F	T	None
Donor 23	Yes	Right	Underhand	Down	P	P/F	F	F/T	P	None
Donor 24	Yes	Right	Underhand	Down	P/F/T	P/F	F	F/T	P	None

**Table 6**  
Resulting counts for the scenario cutting food, in which Down = cutting face of knife downwards, Up = cutting face of knife upwards, P = Palm, F = Fingers and T = Thumb.

Donor	FM present	Which hand?	Direction	Rotation	Side 1	Side 2	Side 3	Side 4	Backside	Blade
Donor 1	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P	F
Donor 2	Yes	Right	Underhand	Down	P/F	F	F	P/T	P	F
Donor 3	Yes	Right	Underhand	Down	P/F	P/F	F/T	P/T	P/F	None
Donor 4	Yes	Right	Underhand	Down	P	P/F	F	P/T	None	F
Donor 5	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P/F	F
Donor 6	Yes	Right	Underhand	Down	P/F	P/F	F	T	P/F	None
Donor 7	Yes	Right	Underhand	Down	P/F	F	F	P/T	P	F
Donor 8	Yes	Right	Underhand	Down	P/F	P/F	F	P/F/T	P/F	F
Donor 9	Yes	Right	Underhand	Down	P/F	P/F	F	P/F/T	P	F
Donor 10	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P/F	None
Donor 11	Yes	Right	Underhand	Down	P	P/F	F	NA	P	None
Donor 12	Yes	Right	Underhand	Down	P/F/T	F	F	P/T	P/F	None
Donor 13	Yes	Right	Underhand	Down	P/F	F	F	P/T	P/F	None
Donor 14	Yes	Right	Underhand	Down	P/F	F	F	P/T	P/F	None
Donor 15	Yes	Right	Underhand	Down	P/F	F	F	P/T	P/F	F
Donor 16	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P/F	None
Donor 17	Yes	Right	Underhand	Down	P/F	F	F	P/T	P/F	F
Donor 18	Yes	Right	Underhand	Down	NA	P/F	F/T	P/T	P/F	F
Donor 19	Yes	Right	Underhand	Down	P/F	P/F	F	P/F/T	F	F
Donor 20	Yes	Right	Underhand	Down	P/F	P/F	F	P/T	P	None
Donor 21	Yes	Right	Underhand	Down	P/F	F	F	P/T	NA	None
Donor 22	Yes	Right	Underhand	Down	P/F	P/F	F	P/F/T	P/F	F
Donor 23	Yes	Right	Underhand	Down	P/F/T	P/F	F	P/F/T	P/F	F
Donor 24	Yes	Right	Underhand	Down	P/T	P/F	F	P/F/T	P/F	None

was not observed for the scenario of cutting food (Table 6), due to the fact that it is impossible to cut food with the cutting face of the knife upwards. Therefore, the rotation of the knife can also be considered as a distinctive feature between the activities stabbing and cutting food.

Important to note is that the variables ‘direction’ and ‘rotation’ of the knife as described here cannot be directly observed in casework and video footages were used in this experiment to observe these features. However, the variables location on the knife and the area of friction ridge skin observed on a specific location indirectly provide information on the direction and the rotation in which the knife was held. For this reason, only the results for the presence of the fingermarks, the area of friction ridge skin and the location on the knife in Table 5 and Table 6 were

used to assign probabilities to the states of the nodes of the Bayesian networks.

**4. Probability assignments and evaluations using the Bayesian networks**

For the probability assignments to the states of the nodes of the Bayesian networks, the probability for state *i* of node *k* with *n<sub>i,k</sub>* observations can be defined as:

$$P_{i,k} = \frac{n_{i,k} + 1}{I + \sum_{i=1}^I n_{i,k}} \tag{1}$$

where  $I$  represents the number of different states for node  $k$  [9,12]. NA observations were considered 'fingermarks present' when assigning probabilities to the states of the TPR nodes of network I, and as 'undetermined' when assigning probabilities to the states of these nodes in network II. We have assumed that each (technically possible) way of holding the knife is equally probable, and as a consequence consider each distribution of friction ridge skin marks on the knife equally probable (a priori). We have therefore assigned the same prior counts to each defined state.

However, some combinations of locations and area of friction ridge skin are impossible to realize in one grip due to the assumptions of our study, the shape of the knife or the restrictions in the movements of the hand. For example, a single thumb cannot be placed on the handle, the backside and the blade of the knife since only single grips are evaluated in this study. We decided to assign a probability of zero to these impossible combinations, denoted by the color grey in the tables in this manuscript and the tables in the supplementary material representing the conditional probability tables for the nodes.

To the authors' knowledge, the knife in the case of the murder of Meredith Kercher was not examined for fingermarks. Therefore, when evaluating findings using the three Bayesian networks, we will consider several fictitious findings that could be obtained in a case like this and we will calculate the weight of the evidence. We note that the values which we calculate with the Bayesian networks in this section, are effectively posterior probabilities. Since we have only two propositions in the proposition nodes, and their assigned prior probabilities are equal, the ratio of the posterior probabilities equals the likelihood ratio. Hence, we refer to the ratio of the posterior probabilities as likelihood ratios (LR) from here on.

#### 4.1. Bayesian network I – location of fingermarks on the knife

Table 7 and Table 8 show the conditional probability tables for the nodes (4) *Marks on handle – stabbing* and (7) *Marks on handle – cutting* in Bayesian network I with states 'fingermarks S present' and 'fingermarks S absent', in which the probabilities are assigned based on the experimental results shown in Table 5 and Table 6. The tables show that observing fingermarks on the knife handle does not provide any information on the activity that is carried out, since the probability to observe fingermarks on the knife handle is equal given the two propositions stabbing and cutting food.

Table 9 and Table 10 show the conditional probability tables for the nodes (5) *Marks on back – stabbing* and (8) *Marks on back – cutting* in network I, respectively. The results show that the probability that fingermarks are present on the backside given that S stabbed the victim with the knife and marks were observed on the handle is considerably lower than the probability that fingermarks are present on the backside given that S cut food with the knife and marks were observed on the handle.

The conditional probability tables for the nodes (6) *Marks on blade – stabbing* and (9) *Marks on blade – cutting* are shown in Table 11 and Table 12. These results show that the probability to observe fingermarks on the blade given that the fingermarks ended up on the knife through stabbing is very low and for almost all participants, fingermarks were absent on the blade. On the

**Table 7**  
Conditional probability table for the node (4) Marks on handle – stabbing in network I.

S stabbed the victim with the knife	True	False
Marks on handle – stabbing:		
Fingermarks S present	0.96	0
Fingermarks S absent	0.04	1

**Table 8**  
Conditional probability table for the node (7) Marks on handle – cutting in network I.

S cut food with the knife	True	False
Marks on handle – cutting:		
Fingermarks S present	0.96	0
Fingermarks S absent	0.04	1

contrary, the probability to observe fingermarks on the blade given that the fingermarks ended up on the knife through preparing food are almost equal if marks are also observed on the handle and the backside of the knife. If marks are only observed on the handle, the probability to observe fingermarks on the blade of the knife is slightly higher than to not observe fingermarks on the blade.

#### 4.2. Network I – exploration I

Instantiating propositions  $H_p$  and  $H_d$  consecutively in network I (supplementary material) shows that the probability for the presence or absence of fingermarks on the knife handle is equal given both propositions, showing that the presence or absence of fingermarks on the knife handle indeed does not provide any evidential value. When evaluating the findings that fingermarks of S are present on all three areas of the knife, the findings support the proposition that the suspect cut food with the knife. If the fingermarks of S are only present on the knife handle and not on the backside and the blade of the knife, the findings support the proposition that the suspect stabbed the victim with the knife. In case we evaluate the absence of fingermarks on the knife, the findings do not add any evidential weight and result in an LR of 1. This can be explained by the fact that this finding was not observed in our experiment.

#### 4.3. Bayesian network II – area of friction ridge skin on the knife

Table 13 shows the conditional probability table for the node (4) *Marks on handle – stabbing* and Table 14 shows the conditional probability table for the node (7) *Marks on handle – cutting* in Bayesian network II. The probabilities are assigned based on the experimental results shown in Table 5 and Table 6, for which the observations in columns Side 1, Side 2, Side 3 and Side 4 are combined to represent the findings on the handle. The results show that for both propositions, the probability to observe the palm, the fingers and the thumb on the handle is the highest. Therefore, the area of friction ridge skin observed on the knife handle provides only little information on the activity that is carried out.

For the nodes (4) *Marks on handle – stabbing* and (7) *Marks on handle – cutting* is determined that the state 'thumb' is considered impossible to achieve due to the fact that placing only the thumb on the handle without the palm or fingers makes it impossible to even carry the knife. This state is therefore removed from the optional states.

The conditional probability tables for the nodes (5) *Marks on back – stabbing* and (8) *Marks on back – cutting* can be found in the supplementary material. Since these nodes are conditionally dependent on the marks observed on the handle, there are again multiple combinations of locations and area of friction ridge skin which are considered impossible given the alleged activities and therefore received a probability of zero (denoted grey in the conditional probability tables). The conditional probability tables for the nodes (6) *Marks on blade – stabbing* and (9) *Marks on blade – cutting* can also be found in the supplementary material. Since these nodes are conditionally dependent on the nodes (4)(7) *Marks on handle* and (5)(8) *Marks on backside*, the location combinations which were already considered impossible for these nodes are



**Table 9**  
Conditional probability table for the node (5) Marks on back - stabbing in network I.

S stabbed the victim with the knife	True		False	
	FM S present	FM S absent	FM S present	FM S absent
Marks on back – stabbing: Fingermarks S present	0.62	0.5	0	0
Fingermarks S absent	0.38	0.5	1	1

**Table 10**  
Conditional probability table for the node (8) Marks on back - cutting in network I.

S cut food with the knife	True		False	
	FM S present	FM S absent	FM S present	FM S absent
Marks on back – cutting: Fingermarks S present	0.92	0.5	0	0
Fingermarks S absent	0.08	0.5	1	1

**Table 11**  
Conditional probability table for the node (6) Marks on blade - stabbing in network I.

S stabbed the victim with the knife	True				False			
	FM S present		FM S absent		FM S present		FM S absent	
Marks on blade – stabbing: FM S present	0.118	0.091	0.5	0.5	0	0	0	0
FM S absent	0.882	0.909	0.5	0.5	1	1	1	1

**Table 12**  
Conditional probability table for the node (9) Marks on blade - cutting in network I.

S cut food with the knife	True				False			
	FM S present		FM S absent		FM S present		FM S absent	
Marks on blade – cutting: FM S present	0.52	0.667	0.5	0.5	0	0	0	0
FM S absent	0.48	0.333	0.5	0.5	1	1	1	14

**Table 13**  
Conditional probability table for the node (4) Marks on handle - stabbing in network II.

S stabbed the victim with the knife	True	False
Marks on handle - stabbing: Palm	0,031	0
Fingers	0,031	0
Palm/Fingers	0,156	0
Palm/Thumb	0,031	0
Fingers/Thumb	0,031	0
Palm/Fingers/Thumb	0,625	0
Undetermined	0,063	0
None	0,031	1

**Table 14**  
Conditional probability table for the node (7) Marks on handle - cutting in network II.

S cut food with the knife	True	False
Marks on handle - cutting: Palm	0,031	0
Fingers	0,031	0
Palm/Fingers	0,063	0
Palm/Thumb	0,031	0
Fingers/Thumb	0,031	0
Palm/Fingers/Thumb	0,75	0
Undetermined	0,063	0
None	0,031	1

removed from the conditional probability table. New combinations which can be considered impossible to achieve with the disputed knife and a human hand are again marked with grey cells and receive a probability of zero.

4.4. Network II – Exploration

The experimental results showed that thumbs were only placed on the backside of the knife in case the knife was held in an

overhand grip, which only occurred for the scenario in which participants stabbed using the knife. Therefore, we are interested in the evidential value provided by the model for this observation. There are four states for the node (12) Findings – Marks on back that incorporate the presence of a thumb on the backside of the knife: the states ‘thumb’, ‘palm/thumb’, ‘fingers/thumb’ and ‘palm/fingers/thumb’. Instantiating one of these states for the node (12) Findings – Marks on back provides a LR in support for the proposition that the suspect stabbed the victim with the knife. The

results from the experiment showed that 13 participants placed their fingers on the blade of the knife while cutting food, whereas for the stabbing scenario, this was only one participant. When evaluating the finding that fingers were observed on the blade, the findings support the proposition that the suspect cut food with the knife. The network also shows that in case no fingermarks are found on the handle of the knife, the only possibility to hold the knife is to hold the knife at the blade with the palm/fingers, palm/thumb, fingers/thumb or the palm/fingers/thumb. Additionally, when no fingermarks are found on the handle of the knife, the only possible finding for the back of the knife is that no fingermarks are observed, since it is considered impossible to hold the knife while only touching the back of the knife and not the handle of the knife.

4.5. Evaluating fictitious findings in the Meredith Kercher case

In this section, we would like to explore the use of the constructed Bayesian networks to evaluate possible findings in the Meredith Kercher case. To the authors knowledge, no fingerprint examination was carried out on the knife in the Meredith Kercher case, causing the evaluations carried out in this section to be solely based on fictitious findings. Suppose that the knife that was retrieved from the apartment of Sollecito contained marks of the fingers, the palm and the thumb on the handle, marks of the fingers on the blade of the knife and marks of the palm and the fingers on the backside of the knife. When evaluating these findings using network I, the state ‘present’ is instantiated for the nodes (10) Findings – Marks on the handle, (11) Findings – Marks on the blade and (12) Findings – Marks on the back, shown by the red bars for these nodes in Fig. 4. This results in a LR of 7 in support of the proposition that the suspect used the knife to cut food. When evaluating these findings using network II, the state ‘palm/fingers/thumb’ is instantiated for node (10) Findings – Marks on the handle, the state ‘fingers’ is instantiated for node (11) Findings – Marks on the blade and the state ‘palm/fingers’ is instantiated for the node (12) Findings – Marks on the back, resulting in a LR of 34 in favor of  $H_d$ . This means that under the propositions stated and the assumptions mentioned in Section 2, the findings are 34 times more probable if the suspect cut food with the knife than than if the suspect used the knife for stabbing.

Now consider that the following fingerprints were retrieved from the knife: marks of the fingers and the palm on the handle, no fingerprints on the blade of the knife and a mark of the thumb on

the backside of the knife. When evaluating these findings using network I, the state ‘present’ is instantiated for the nodes (10) Findings – Marks on the handle and (12) Findings – Marks on the back and the state ‘absent’ is instantiated for the node (11) Findings – Marks on the blade. The resulting LR is 1 demonstrating that with network I the findings are equally probable given both propositions. When evaluating these findings using network II, we obtain a LR of 35 in support of  $H_p$ , as shown in Fig. 5.

One requirement for a formal probabilistic assessment given activity level propositions is that the outcome of the evaluation is robust [13]. To test this, a sensitivity analysis can be performed to assess the impact of reasonable variations in the assigned probabilities on the resulting LR. We refrain from doing so with these fictitious findings in the Meredith Kercher case. For an example of the use of sensitivity analyses we refer the interested reader to Szkuta, Ballantyne, Kokshoorn and van Oorschot [14].

5. Discussion

The purpose of this study was to demonstrate how data resulting from case specific experiments can be used to assign probabilities to the states of the nodes of a Bayesian network for the evaluation of fingerprints given activity level propositions. For this purpose, we conducted an experiment in which a knife was either used to stab a victim or to cut food, representing the activities that were disputed in the case of the murder of Meredith Kercher. Two Bayesian networks were constructed: one to evaluate the presence or absence of fingerprints on particular locations of the knife and one to evaluate the area of friction ridge skin that was left on particular locations of the knife. Probabilities were assigned based on the empirical data resulting from the knife experiment and we explored the LR calculated with the models. We would like to emphasize that the Bayesian networks are a result of many choices made during the process. For example, the choice of how to divide the knife into different locations or how to divide the hand into different areas directly influences the construction of the network. This is often a tradeoff between obtaining as much information as possible from the experimental data versus the amount and quality of the data that are available to inform the probability assignments. For example, based on the collected data for the knife experiment, it could be questioned whether a further division of the knife handle into four separate areas would provide more information. However, when defining more states to a node,

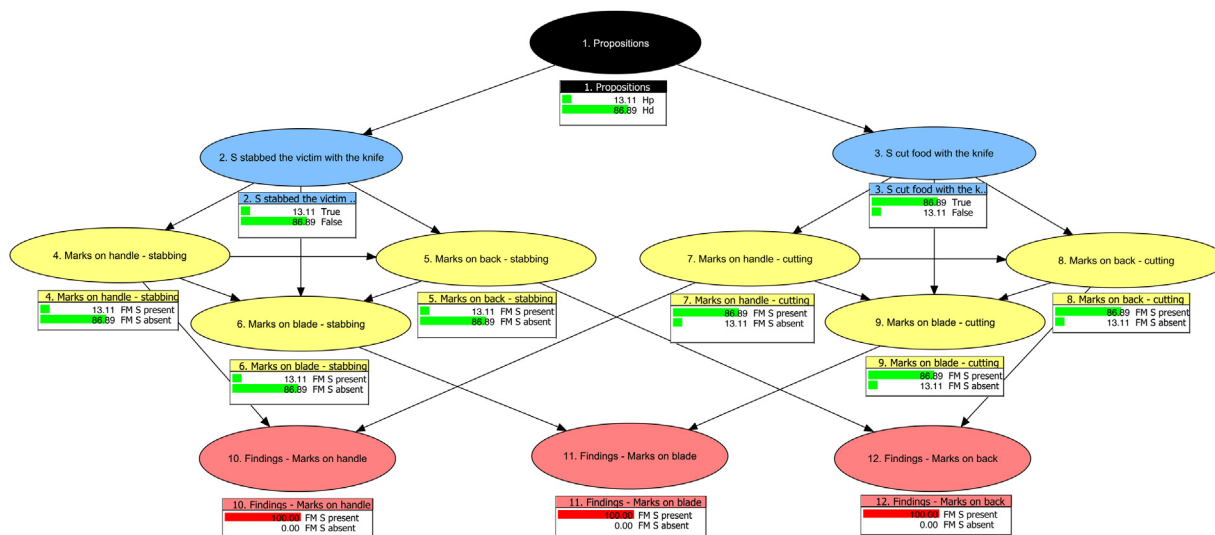


Fig. 4. Bayesian network I for which the findings fingerprints present on the handle, fingerprints present on the blade and fingerprints present on the backside are instantiated.

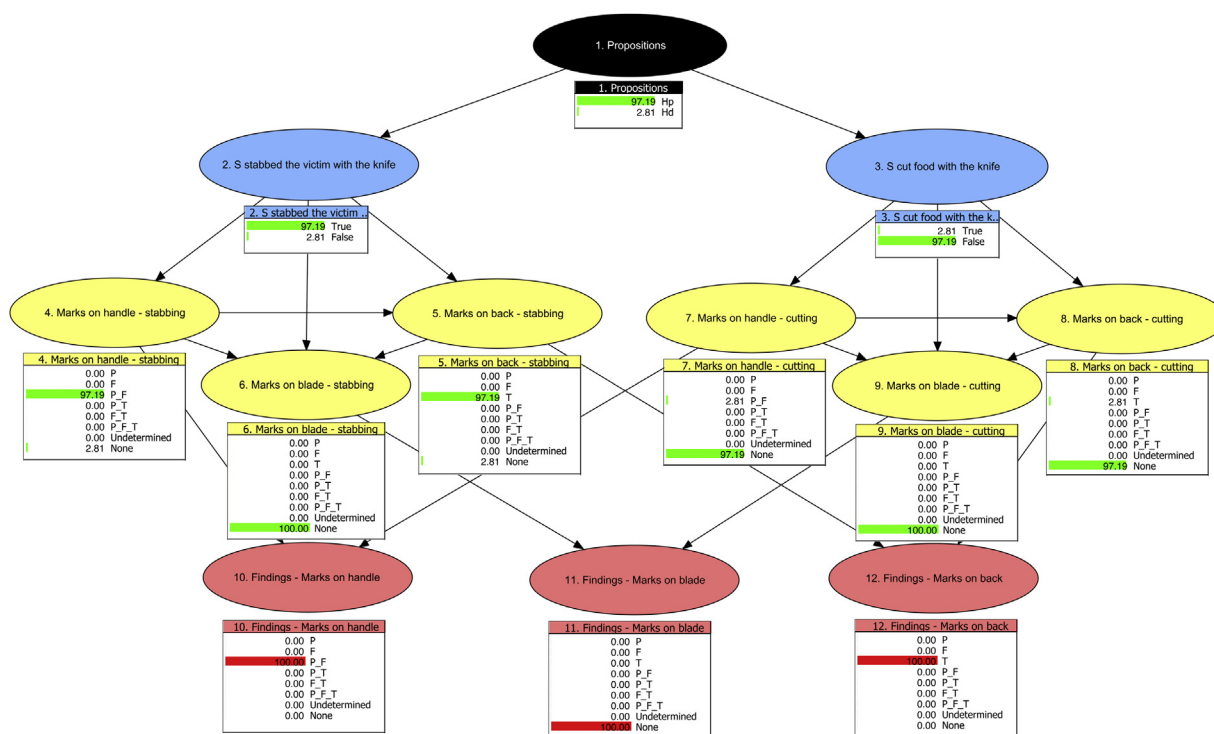


Fig. 5. Bayesian network II for which the findings palm and fingers on the handle, no fingermarks on the blade and thumb on backside are instantiated.

the number of observations for each state will decrease when using the same sample size for the experiment. The conditional probability tables for network II already showed that dividing the knife into three areas caused many states for which no observations were available. Increasing the number of location nodes while assigning the probabilities based on the same sample size will cause the LR to be less informative (e.g. approaching 1). Therefore, the design of the network always depends on data available to inform the probability assignments. In this study, we did not focus on the quality of the fingermarks with regards to source level information, a measure that is nowadays used to select the fingermarks that are collected from a crime scene [15]. For cases in which the donor of the fingermarks remains unknown, network I focusing on the presence or absence of fingermarks on the knives can very well be used to evaluate the fingermarks given activity level propositions since no source level information is required. This may for instance be used in case assessment when the relevance of a particular knife to a criminal activity is debated. For network II, comparison to reference fingerprints from the person of interest is usually required to determine the area of friction ridge skin that left the marks. In our experiment, we used video footages together with photographs taken from the fingermarks on the knives to determine the area of friction ridge skin that left the marks. An advantage of this choice is that smears and fingermarks that are not suitable for identification purposes are also taken into account. A disadvantage of this choice is that these video footages are generally not available in casework, and therefore, the probability to find fingermarks and the ability to assign the area of friction ridge skin to a mark based on this experiment are overestimated compared to case work. A further study focusing on comparing the conducted approach to an approach focusing on the quality of the fingermarks (i.e. grading the fingermarks by using a scale as proposed by Sears, Bleay, Bandey and Bowman [11] or Becue, Moret, Champod and Margot [16]) is needed to point out the implications of the selected method. A limitation of our experiment is that all donors were

right-handed. For left-handed donors, we expect a difference in area of friction ridge skin that will end up on the different sides of the knife handle since the grip would most probably be a mirrored image of a right-handed grip. However, since we have taken all sides of the knife handle together by dividing the knife into the three locations handle, backside and blade in the networks proposed, we do not expect much differences between right-handed and left-handed donors. In case the difference between right-handed and left-handed donors are a topic for further research, we recommend to divide the knife handle into smaller areas (e.g. S1-S4) such that the information which area of friction ridge skin ended on which side of the handle may provide information on the handedness of the donor. The data from the experiments presented here must be carefully considered when used in casework, to make sure the results are also being applicable to the case at hand. For example, all assumptions and evaluations described in this paper are based on the steak knife used in the experiment. The results obtained from the experiment could also be used for knives of similar size and shape as the steak knife used in this experiment. However, if the size or the shape of the knife of interest changes to a complete different knife such as a foldable knife or a cleaver, the results may not be directly applicable since the characteristics of the knife directly influence the possible combination of grips on the knife. When using the data presented in this paper for evaluations in real casework, a careful consideration of the characteristics of the knife, but also the activities at stake, the conducted experiment and the assumptions that were made is required. To be able to use the Bayesian networks for the evaluation of the findings, it is of great importance that all conditional dependencies between the variables are carefully considered. Although these dependencies may result in a complex network, ignoring dependencies that in real life exist may result in an overestimation of the likelihood ratio. For example, if the dependency between the area of friction ridge skin due to the shape of a hand was ignored in our research, this would result in an unjustified higher likelihood ratio. On the

other hand, an underestimation of the likelihood ratio is also possible when probabilities are assigned to combinations of area of friction ridge skin on particular locations on the knife for which is known they are impossible to achieve. If these combinations received a probability, they are considered feasible and combinations that are actually feasible receive a lower probability, resulting in an underestimation of the likelihood ratio. Therefore, we would like to stress the importance of a careful consideration of the dependencies between variables and a careful consideration of the states or combinations of states that are not feasible. Additionally, assigning the prior probabilities to improbable combinations should also be discussed in court since this also directly influences the likelihood ratio. The likelihood ratio values resulting from our calculations can be considered relatively low ( $0.01 \leq LR \leq 50$ ) resulting in a slight or moderate support for one of the propositions [13]. A reason for this is that our experimental sample size was relatively small, i.e. 24 participants for each scenario. Due to the number of possible states for the nodes, this results in many states which stay unobserved in our small sample size while they may receive observations when using a larger sample size. Although the range of LRs obtained in this study might be considered relatively low, this does not mean that an evaluation of fingerprints given activity level propositions is not valuable. This is because the issue that is being addressed at activity level is generally much closer to the deliberations of the court than any source level issues. Depending on the sample size, the data collection strategy, the uniqueness of particular observations for certain activities on the object of interest and other factors, the likelihood ratio value may increase (or decrease) for other scenarios or other objects of interest. Furthermore, when combining the results for fingerprints given activity level propositions together with all other evidence present in a case, this relatively 'low' LR value may still add a considerable value to a case and help a jury or judge in their decision. In this paper, we presented an approach to evaluate fingerprints given activity level propositions in cases like the Meredith Kercher case by using Bayesian networks and a case specific experiment. From the current trends within the field of forensic science, a focus on questioning how and when evidence ended up on a surface is observed [17]. In our opinion, this new focus on the activity that led to the deposition of traces is also relevant for fingerprint evidence. The use of Bayesian networks and case specific experiments to assign the probabilities to transfer, persistence, and recovery of friction ridge skin marks shows great potential for the evaluation of fingerprints given activity level propositions in casework. With the use of this powerful and transparent method, a scientist is able to assist the court in addressing and evaluating their findings given the relevant activity level questions in a case.

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## CRedit authorship contribution statement

**Anouk de Ronde:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Software, Visualization, Writing - original draft, Writing - review & editing. **Bas Kokshoorn:** Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing - review & editing. **Marcel de Puit:** Conceptualization, Funding acquisition, Methodology,

Supervision, Writing - review & editing. **Christianne J. de Poot:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing - review & editing.

## Declaration of Competing Interest

None.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at <https://doi.org/10.1016/j.forsciint.2021.110710>.

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