Abstract

Fingermarks that have insufficient characteristics for identification often have discernible characteristics that could form the basis for lesser degrees of correspondence or probability of occurrence within a population. Currently, those latent prints that experts judge to be insufficient for identification are not used as associative evidence. How often do such prints occur and what is their potential value for association? The answers are important. We could be routinely setting aside a very important source of associative evidence, with high potential impact, in many cases; or such prints might be of very low utility, adding very little, or only very rarely contributing to cases in a meaningful way. The first step is to better understand the occurrence and range of associative value of these fingermarks.

The project goal was to explore and test a theory that in large numbers of cases fingermarks of no value for identification purposes occur and are readily available, though not used, and yet have associative value that could provide useful information.

Latent fingermarks were collected from nine state and local jurisdictions. Fingermarks included were those (1) collected in the course of investigations using existing jurisdictional procedures, (2) originally assessed by the laboratory as of no value for identification (NVID), (3) re-assessed by expert review as NVID, but with least three clear and reliable minutiae in relationship to one another, and (4) determined to show at least three auto-encoded minutiae.

An expected associative value (ESLR) for each mark was measured, without reference to a putative source, based on modeling within-variability and between-variability of AFIS scores. This method incorporated (1) latest generation feature extraction, (2) a (minutiae-only) matcher, (3) a validated distortion model, and (4) NIST SD27 database calibration. Observed associative value distributions were determined for violent crimes, property crimes, and for existing objective measurements of latent print quality.

750 Non Identifiable Fingermarks (NIFMs) showed values of Log_{10} ESLR ranging from 1.05 to 10.88, with a mean value of 5.56 (s.d. 2.29), corresponding to an ESLR of approximately 380,000.

It is clear that there are large numbers of cases where NIFMs occur that have high potential associative value as indicated by the ESLR. These NIFMs are readily available, but not used, yet have associative value that could provide useful information. These findings lead to the follow-on questions, “How useful would NIFM evidence be in actual practice?” and, “What developments or improvements are needed to maximize this contribution?”

<u>Keywords: fingerprints; non-identifiable fingermarks; AFIS; score-based likelihood ratio</u>

I. Introduction

Currently, those fingermarks that experts judge to be insufficient for identification (Non-Identifiable Fingermarks or NIFMs) are not used as associative evidence. How often do such prints occur? What is their potential value for association? Would they actually impact case investigations or prosecutions in a useful way?

The answers are important. We could be routinely setting aside a very important source of associative evidence, with high potential impact, in many cases; or such prints may be of very low utility, adding very little, or only very rarely contributing to cases in a meaningful way.

At the same time, there are significant challenges to unlocking this potential. Until only recently,[1] a central aspect of fingerprint examination was the restriction of conclusions and testimony to categorical, absolute identifications, or inconclusive.[2-4] In the absence of alternatives, this all-or-nothing approach has been an effective, though imperfect compromise.[5] Methods to measure the associative value (selectivity) of fingerprints are currently under active development,[6-14] but are not yet sufficiently defined and vetted for widespread use and acceptance. However, we can be sure that such methods will not be long in coming.

A second difficulty is that the recovery and examination of NIFMs, and the use of statistical models to interpret them, will require the support of fingerprint practitioners and the courts.[15] A paradigm change is necessary from the current methodology and conclusion scheme and related training, changes in operation and changes in reporting will be necessary.

It will take considerable effort to change these processes. Should this be our priority? New technologies offer a wide range of capabilities for latent print examinations,[16] with expected improvements in documentation, reproducibility of results, quality assurance, and efficiency. Is the potential contribution of NIFMs to investigations and prosecutions sufficiently high that resources should be committed to the work toward these changes?

We currently don't know. We have only minimal information regarding the use of probability models to study NIFMs[15] and no information that is based on either (1) currently available technologies or (2) the utility NIFMs in context of where and how they actually occurred in the case. The first step is to better understand the occurrence and range of associative value of these fingermarks.

The goal of this project was to explore and test a theory that in large numbers of cases fingermarks of no value for identification occur and are readily available, though not used, and yet have associative value that could provide useful information.

This project collected NIFMs from casework in nine jurisdictions within the USA that had fallen below the expert-determined threshold "of value for identification," but that had some clear Level 2 detail (i.e. minutiae) within an area of contiguous ridge flow. An expected associative value (selectivity) of each of these marks was measured (without reference to a putative source) using an AFIS-score model. Whether an AFIS-score based system is the best option to assign the weight to latent print evidence is currently debated,[9,17-19] but regardless of their ultimate suitability for that application, these systems can be validated and calibrated,[20] in a way that allows a means to explore and quantify the potential of using latent prints that are currently left aside in operational practice.

The expected associative values of the NIFMs were categorized by type of crime (violent crimes vs. property crimes) and objective measures of latent print quality.[21-23] Testing for differences among crime categories was of interest because of the possibility that alternative practices such as the extent of crime scene processing or the retention of fingermarks, could result in differences in the distributions of associative value among the NIFMs. Testing for differences correlated with latent print quality measures was of interest as these measures could provide a means to help predict upfront expected associative value.

II. Materials and Methods

A. Collection of Non-Identifiable Fingermarks

Fingermarks (latent prints) were collected from casework produced using existing investigative procedures within the particular jurisdiction. Fingerprints had previously been analyzed by expert latent print practitioners to be of "no value for identification" (NVID), but containing some well-defined minutiae in areas with continuity of ridge flow. To be reasonably representative, marks were collected from nine different jurisdictions within the USA. This variety is important to provide a reasonable overall view because it is known that judgements of NVID will vary with the individual expert,[23] and it is expected that specific laboratory policies or crime scene investigator practices could influence how latent prints are collected and examined. Our research need was for a reasonable cross-section of current practices that would (1) provide a realistic breadth of clarity and quality among the qualifying NIFMs, and (2) ensure that the results are meaningful across a range of jurisdictions and practices.

Qualifying NIFMs for this study needed to show three or more clear and reliable minutiae occurring within an area showing continuity of ridge flow. This quantity of ridge detail was selected as a lower bound representing a rational minimum to be considered.

High quality images [24] of NIFMs meeting these criteria were collected from each jurisdiction, retaining only the latent image itself and the general type of crime (violent crime vs. property crime). To ensure privacy and confidentiality the NIFM images were coded and entered the research project without any record of the agency, case number, suspects, known individuals, or examiners.

Examples of commonly occurring types of NIFMs are given in Figures 1 through 4. Figure 1 (bottom) shows four examples of NIFMs where motion during contact results in smearing of the majority of the mark, leaving only a small portion of ridge detail along the edges. Two other images are shown where the contact area was restricted, resulting in only a small area of ridge detail. Figure 2 shows examples of NIFMs, such as on touchscreens, where only the tip or side of a finger is represented. Figures 3 and 4 show NIFMs on a variety of smaller surfaces, such as on handgun triggers and keys, where the finding of identifiable fingerprints is uncommon.

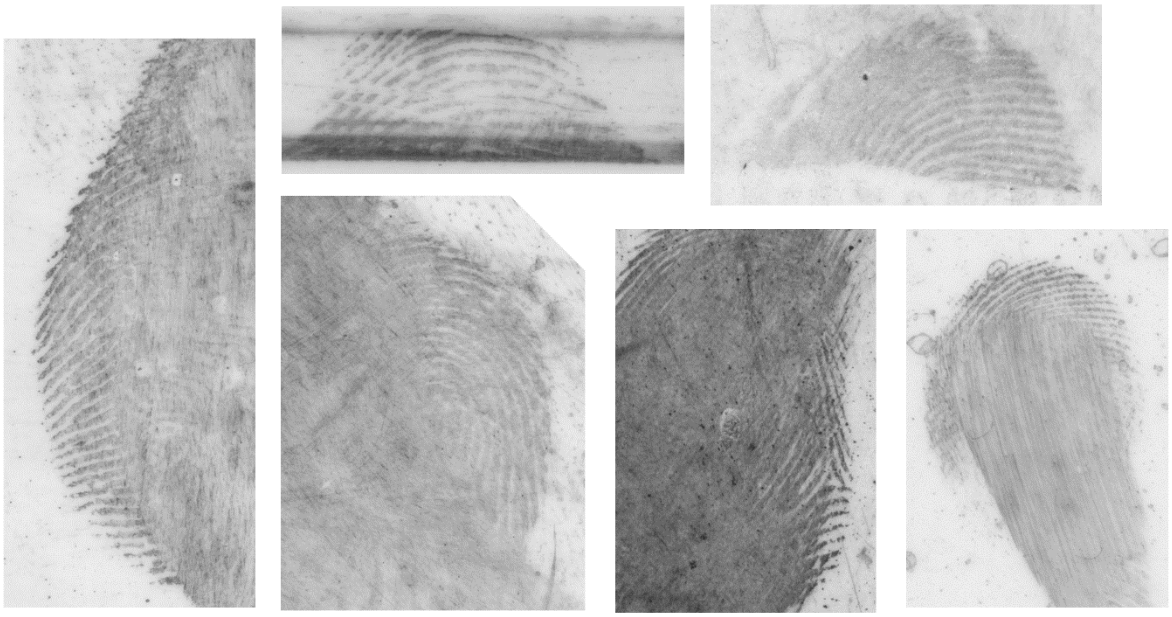

Figure 1. Examples of NIFMs where the mark is clear only at the edges of a smeared print (four lower images), or where the contact area was otherwise restricted (upper two images).

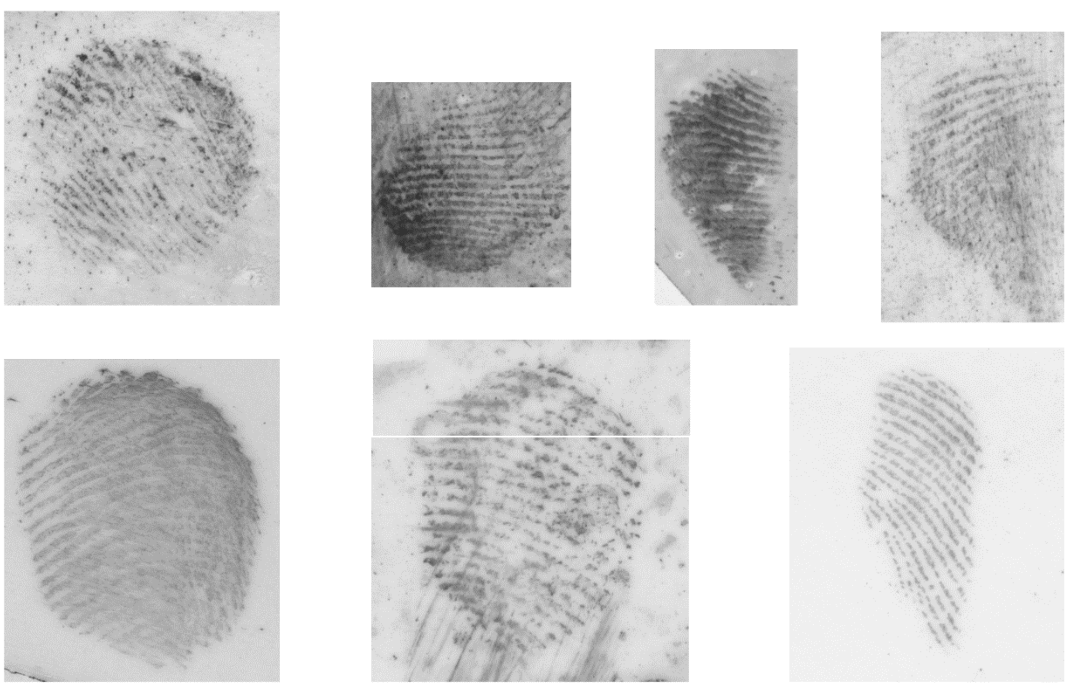

Figure 2. Examples of NIFMs, such as on touchscreens, where only the tip or side of a finger is represented.

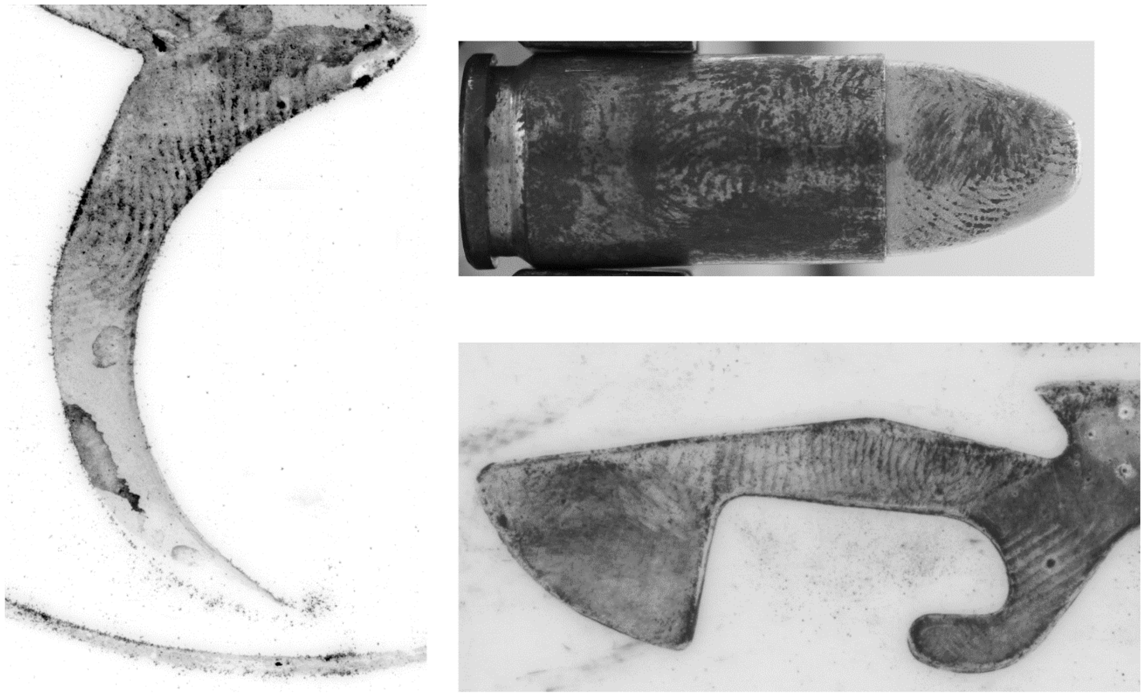

Figure 3. Examples of NIFMs on some smaller surfaces where the finding of identifiable fingerprints is uncommon. Shown are the side a handgun trigger, on the surface of unfired ammunition, and on the side of a bottle opener.

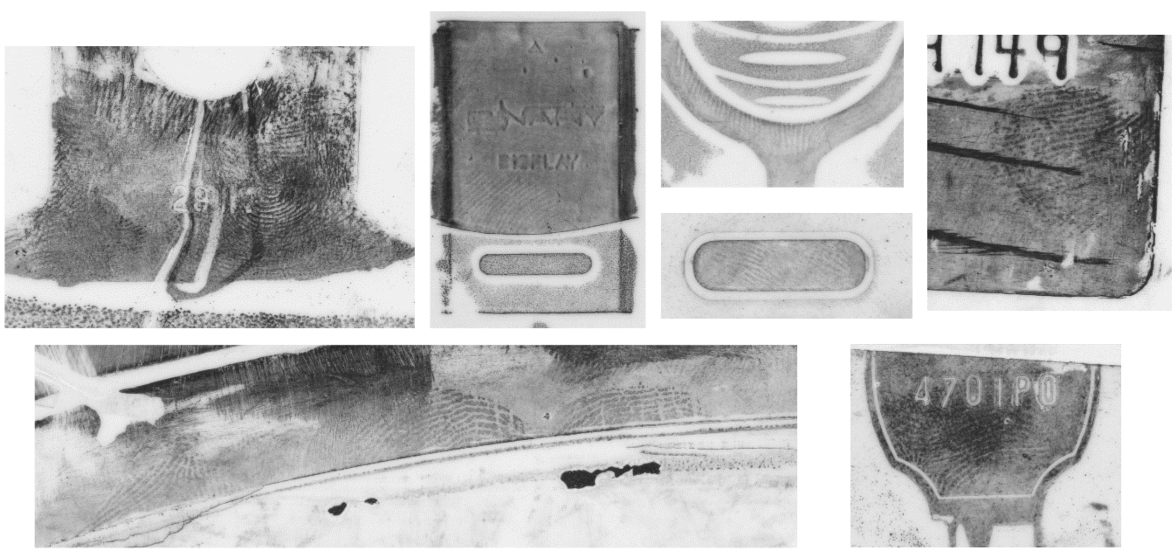

Figure 4. Additional examples of NIFMs on some smaller surfaces where the finding of identifiable fingerprints is uncommon. Shown are a seatbelt tongue (upper left), an automobile door handle (bottom left) and a credit card (upper right). The other images are examples of keys, key fobs and small items with buttons.

NIFMs were screened for minimum qualifications, and normalized (with respect to the NVID decision) using a re-assessment by a highly qualified, certified latent fingerprint examiner (PW). This resulted in the removal of additional fingermarks that were judged to be potentially identifiable. This step was not included as a means of judging or verifying a "correct" determination of NVID, but to normalize the dataset using one expert's determination, thereby reducing variability due to differences in the criteria applied.

B. Measurements of Associative Value

The AFIS-score method used for this study was based on the initial work of Egli [25] with an extension in the form of a distortion model based on Bookstein.[26] It has been further adapted to allow the computation using auto-encoded minutiae and without the need for a reference print. The approach includes the auto-encoding of minutiae and assigns an expected score-based likelihood ratio (ESLR) based on modeling within-variability and between-variability of AFIS scores. This method is used as a means to screen for fingermarks of potential value for identification and is also available for use on-line through PiAnoS (Picture Annotation System).[27] It is further described below.

The latest ELFT-EFS test conducted by NIST [28,29] has shown that auto-encoding of marks using the MorphoBis AFIS system is on par with the manual encoding carried out by fingerprint experts, insofar as it affects the AFIS system performance. (This does not mean that the encoder does an equivalent job; rather, the job that it does results in a comparable effect.) There is indeed a complementarity between auto-encoding and manual encoding, but our objective was to automatize the process as much as possible.

A MorphoBis AFIS system, acquired in 2015, was used on this project. This system is equipped with an encoder in version 11 and matcher in version 10. The system has shown excellent performance in the latest ELFT-EFS test by NIST[28,29] and the Sagem/Morpho matcher is one that considers only minutiae in the matching process. Minutiae meeting Quality Level 11 (a quality metric associated with auto-encoded minutiae) were extracted from the NIFMs and used for ESLR computation. The AFIS system includes a background database of 963,710 fingerprints, stripped from any personal information. These fingerprints are from retired records, purged over 20 years ago by the Swiss Federal Police following an upgrade of their AFIS system. These records have been made available to the University of Lausanne (UNIL) for research purposes only and, according to data protection regulations, cannot be distributed or shared outside UNIL.[25]

Within-variability AFIS scores represent the population of AFIS scores that would result for prints that are actually from the same source. The within-variability was obtained using the scores from the comparison between a set of "pseudolatents" (generated from the NIFM) and the NIFM itself. Pseudolatents are generated using a population of thin-plate spline (TPS) distortion functions. TPS functions, based on the work of Bookstein,[26] define a unique function that maps two sets of paired points on two images. These can be used to distort any set of points from a reference image according to the TPS function. TPS has been already applied to the matching of fingerprint images.[5,30-35]

The TPS distortion functions were computed from a set of 751 cases used as the validation set for [5]. Each case has a crime scene fingermark (latent print) and a set of paired minutiae to a reference finger impression. Each case gives one TPS function that in itself reflects a potential distortion a mark may be subject to. The 751 distortion functions represent the range of distortions each mark can be subject to. For each of the NIFMs in this work, a population of 751 distorted pseudolatents was generated, representing a reasonable range of the expected distortions regularly seen in casework. The TPS method to describe within-item variability follows the approach in [5]. Here the within-source variability distribution is obtained by fitting a log-normal distribution (as in [25]) to the scores obtained from the comparison between the pseudolatents (generated from the NIFM) and the NIFM itself.

Between-variability AFIS scores represent the population of AFIS scores that results for prints that are not from the same source. Between-variability was obtained using the scores from the comparisons between the NIFM and the background database of 963,710 fingerprints, representing a set of unrelated reference prints. For a given NIFM, the between-variability distribution of scores was fitted with a Log-Normal distribution and used as the probability density function.[25]

For a given NIFM, the expected score-based likelihood ratio (ELSR) is obtained by computing the ratio at a given point that we name the “evidence score” of the probability densities of the within-variability and between-variability of AFIS scores. The evidence score used to compute the ESLR is not the score obtained from the comparison of the NIFM and itself but is taken at the point of maximum density of the within-source variability. The “evidence score” then represents the most likely score that would be obtained should a corresponding print be available for comparison purposes.

The process was calibrated as described by Haraksim et al.[20] using a logistic regression method developed by Ramos-Castro et al.[37,38] as applied to the 258 cases from the standard NIST SD27 database.[39]

III. Results

A total of 1668 fingermark images, representing 890 cases, were collected from 9 jurisdictions within the USA. Expert review resulted in removal of 32.4% of the marks on the basis that they were potentially identifiable and removal of another 4.8% of the marks on the basis that they did not meet the minimum requirement of 3 clear and reliable minutiae with clear relationship to each other within the ridge structure. The remaining 1048 NIFMs were auto-encoded and an additional 21.0% were removed as they failed to show the minimum of 3 auto-encoded minutiae above Quality Level 11. ELSRs were measured for the remaining 828 NIFMs.

Figure 5 shows values of Log_{10} ESLR for the 828 NIFM meeting program requirements. Seventy eight of the ESLR values exceed a world population estimate of 77 billion fingers ($Log_{10} >$ 10.88). Figure 6 shows the values for the remaining 750 NIFMs. There is a mean value of Log_{10} ESLR of 5.56 (s.d. 2.29), corresponding to an ESLR of approximately 380,000.

Of the 750 NIFMs, 540 were from property crimes (largely burglaries and thefts), whereas 210 were from violent crimes (largely homicides, robberies and assaults, but including 33 from drug and firearm related crimes). The breakdown in case types and latent prints by laboratory is given in Table 1. Figures 7 and 8 show the distribution of ESLR values for these two subsets of the NIFMs. Possible sources of differences include the extent of crime scene processing, and agency policies regarding the collection and retention of latent prints.

Table 1. Breakdown of NVID Latents by Laboratory and Violent vs. Property Crimes

	Crime Type	
Laboratory	Property	Violent
A	48	0
B	26	37
C	5	4
D	9	1
E	159	17
F	78	56
G	3	16
H	140	42
I	72	37
J	540	210

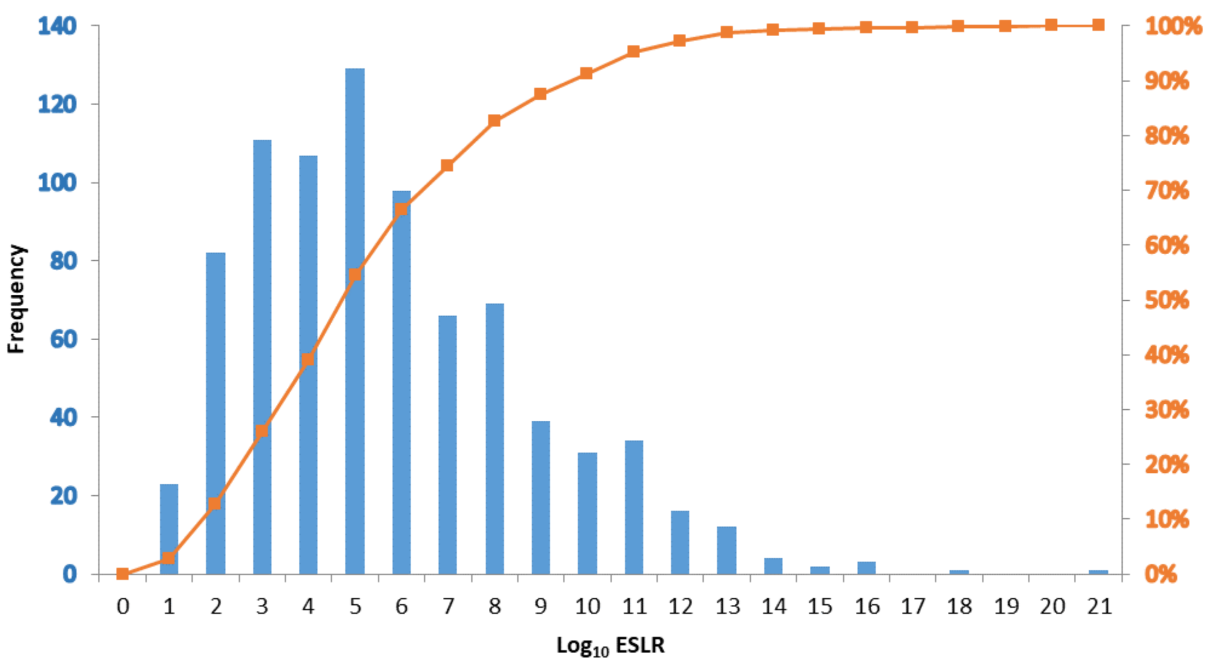

Figure 5. Log_{10} ESLR for the 828 NIFMs meeting program requirements. For example, the bar above the number "5" shows 129 NIFMs. Assuming the selection of the correct individual and a good correspondence with the NIFM print, we would expect an ESLR with a weight of evidence of 10^5 for any of these 129 NIFMs. By analogy, the weight of this evidence would be as if we found matching characteristics that would occur randomly in one in 10,000 individuals (one in 100,000 fingers).

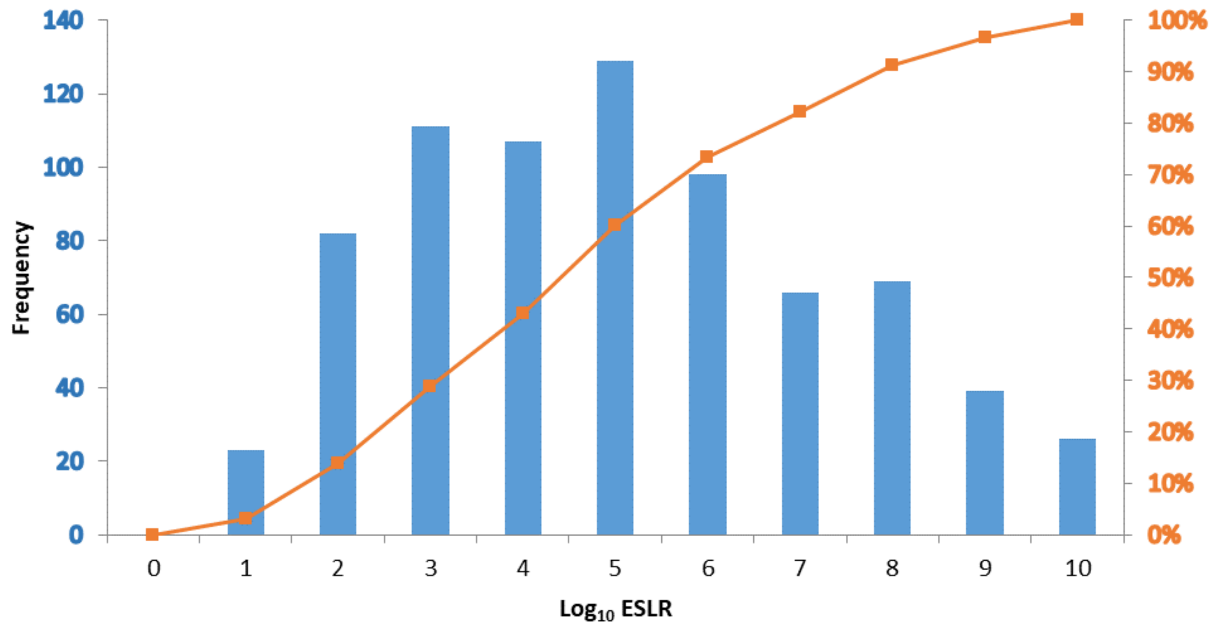

Figure 6. Log_{10} ESLR for the 750 NIFMs with values of Log_{10} ESLR below 10.88.

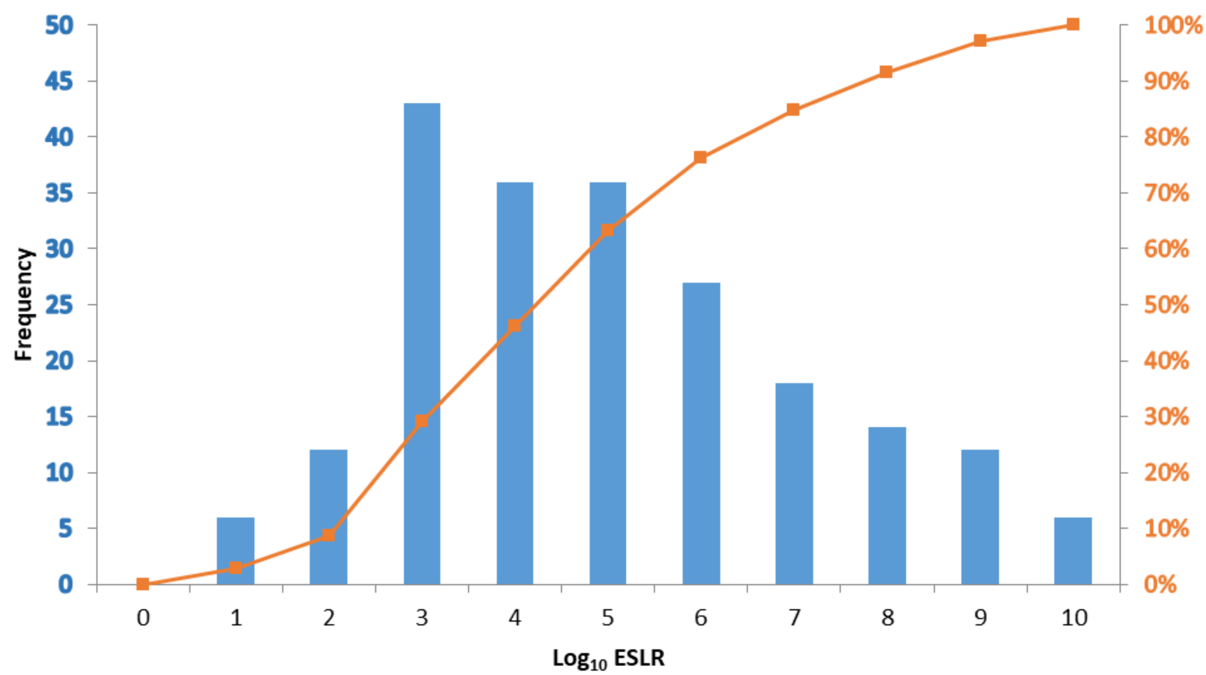

Figure 7. Associative value measurements (Log_{10} ESLR) for the 210 NIFMs from violent crimes with values below 10.88.

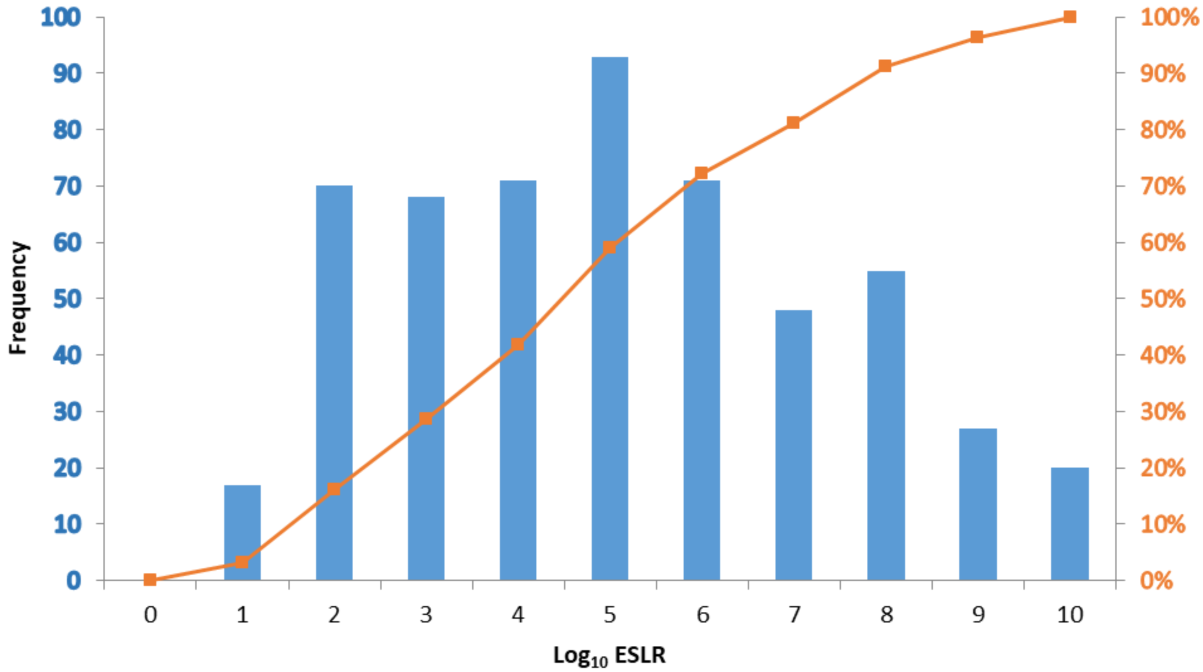

Figure 8. Associative value measurements (Log_{10} ESLR) for the 540 NIFMs from property crimes with values below 10.88.

Figure 9 shows regression analyses of the associative value measurements (Log_{10} ESLR) as a function of four objective quality measurements used as part of the latent print characterization. Although the algorithms of Yoon et al.[21,22] show low positive correlations (adjusted R square values of 0.09 and 0.10, respectively), they show little predictive value. The Universal Latent Workstation (ULW) measures of overall quality and overall clarity [23] show negligible correlation. Given the basis for the calculation of the ESLR value, this is not unexpected. Once minutiae are detected and accepted as a basis for matching (based on meeting a quality threshold of 11) they are used in the computation. The overall quality and clarity of the print does not enter the calculations. With NIFMs we are operating at such a low quality overall that the algorithms tested cannot distinguish easily among these marks.

Figure 10 shows regression analyses of the associative value measurements (Log_{10} ESLR) as a function of the number of the auto-encoded minutiae above quality level 11. Although there is a clear correlation (adjusted R square value of 0.75), there is a wide range in ESLR values for any given number of auto-encoded minutiae. It shows that for a given quantity of minutiae, we can expect a range of ESLR depending on the selectivity of the minutiae.

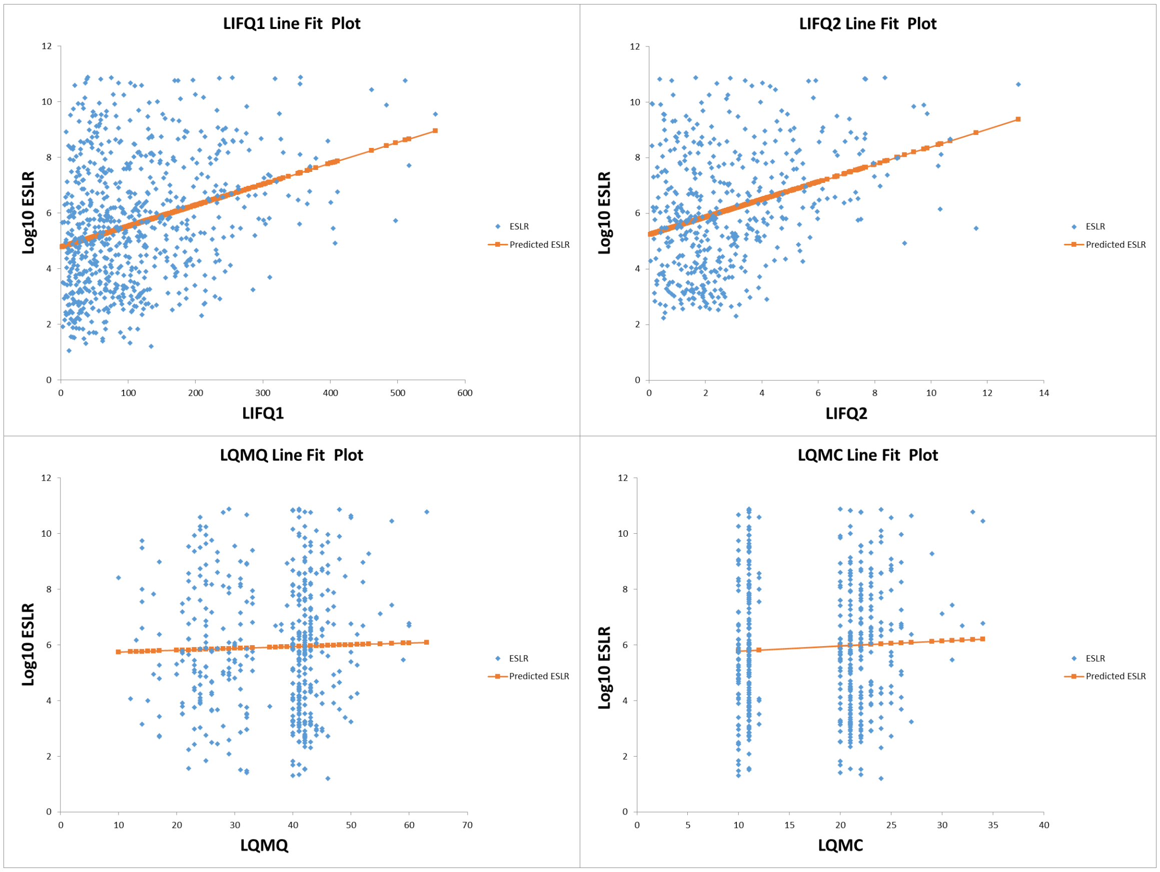

Figure 9. Regression analyses of associative value measurements (Log_{10} ESLR) as a function of four quality measurements. Upper Left: LIFQ1,[21] Upper Right: LIFQ2,[22] Lower Left: ULW measure of Overall Quality (LQMQ),[23] and Lower Right ULW measure of Overall Clarity (LQMC).[23]

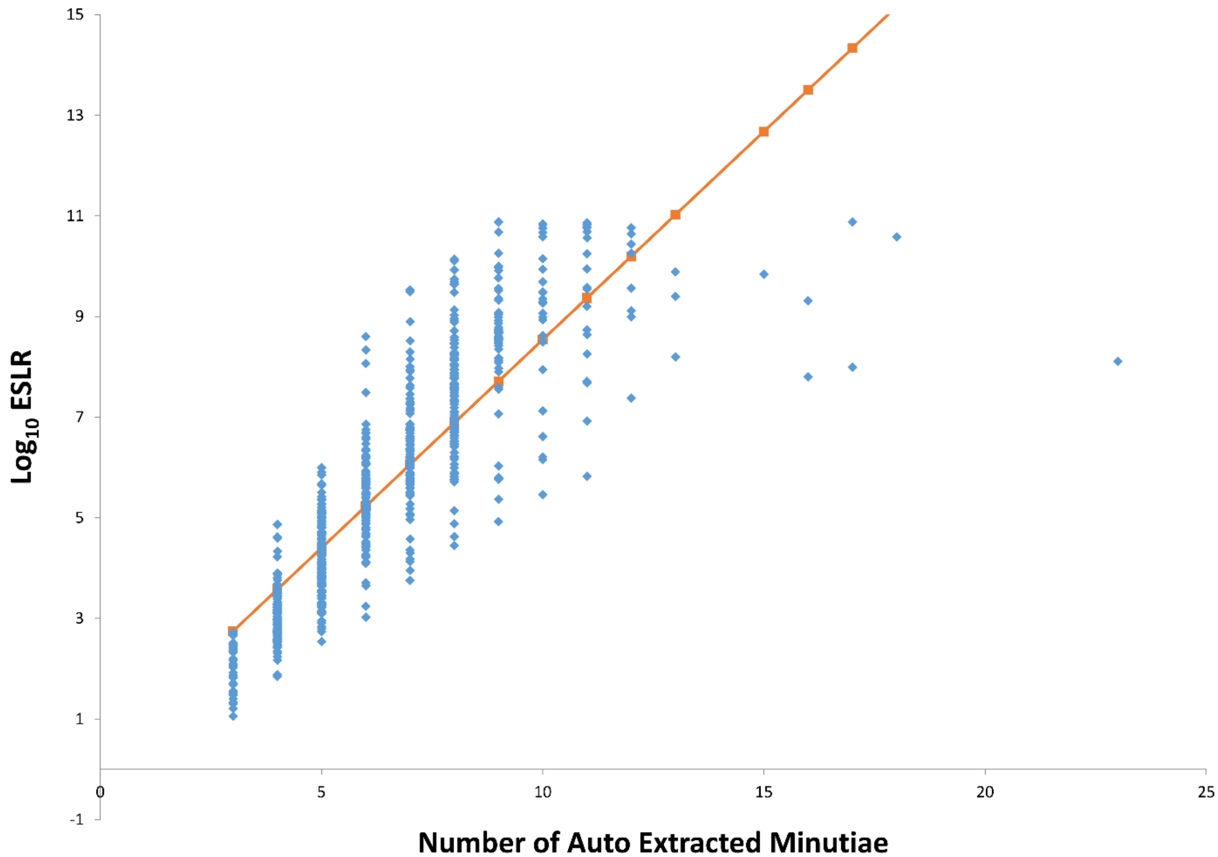

Figure 10. Regression analyses of associative value measurements (Log_{10} ESLR) as a function of the number of auto-extracted minutiae for the NIFMs.

IV. Discussion and Conclusions

It is clear that NIFMs commonly occur. In cases where marks of value for identification occur, there are almost always NIFMs and in greater abundance. While it was not tested, it is likely that NIFMs also occur in cases where fingermarks are not collected for one reason or another (for example, on unfired rounds of ammunition, where past experience indicates that identifiable fingermarks are not to be expected). It is also clear that objective, quantitative measures of associative value, such as the ESLR, can be applied to NIFMs and that there is a strong potential for a high degree of association.

This work selected and applied one method for measurement of associative value, recognizing that such methods are currently under active development,[6-14] and that they are not yet sufficiently defined and vetted for widespread use and acceptance. In particular, whether an AFIS-score based system is the best option to assign the weight to latent print evidence is currently debated.[9,17-19] That being said, we think that any model has its place as long as an empirical validation is carried with it. In this study, we have used the approach developed by Ramos and colleagues using the NIST SD27 dataset.

The auto-encoding of minutiae, use of an AFIS-score model and calculation of an expected likelihood ratio value without resource to a putative source, are major features of the approach used here. These were selected recognizing a research goal for an overall, examiner independent, assessment of the occurrence and value of NIFMs under existing investigative and laboratory practices. An actual evidential assessment of the associative value of a NIFM comparison would reasonably (1) rely on paired features between a fingermark and reference fingerprint, (2) incorporate expert annotation of features (rather than relying solely on auto-encoding of minutiae), and (3) involve a well-defined and vetted method for measurement of associative value. That being said, the method presented here offers a way to assess NIFMs on a systematic basis and to assign priorities and expectations. The method is fully automatic and is independent from the examiner. It can act also as an independent quality measure, part of the mark vetting process used by the laboratory or a secondary triage system.

Apart from the use of a distinctly different method for measurement of associative value, the present work could also benefit from refinements in the approach. These include studies of the variability and reproducibility of the distributions of the ESLR for this dataset; variability in assessments of the ESLR for individual NIFMs introduced by aspects such as contrast, background noise, cropping, sizing and rotation; the understanding of the poor predictive value of current quality metric algorithms; and investigation as to the causes of outliers in the dataset that show high numbers of auto-extracted minutiae (e.g. those with more than 14 in Figure 6).

The work could also be expanded by incorporating more jurisdictions, increasing the number of NIFMs and determining the sensitivity of the measurements to the use of alternative AFIS databases.

The ESLR measurements in our approach were based on the maximum density of the within-source distribution. There are alternative choices and the effects of some of these possible choices on the resulting ESLR values are given in Table 2. One alternative is to use a mean

ESLR from integration of the within probability distribution. Rather than using only the more probable value, this also uses the distortions of the mark giving higher and lower values. Our preliminary investigations show that this approach results in decrease in the ESLR values of approximately 17%. Other alternatives are the use a reasonable lower or upper bound of the distribution of the within variability. Our preliminary investigations show, for example, that using the lower 10^{th} percentile value of the distribution results in a decrease of approximately 41%, whereas using the 90^{th} percentile value results in an increase of approximately 14%. For the purposes of this research, which was to explore and quantify the potential of using latent prints that are currently left aside in operational practice, we chose the maximum density of the within-source distribution. This gives the value which is expected to occur most commonly, given the range of distortions expected in casework. Among the alternatives, we believe this choice is most fit for the present purpose. As noted earlier, when the approach is applied to any actual comparison, there will be an observed value for the distortion, rather than an estimate made from a distribution.

Table 2. Effect on the ESLR of Alternative Choices of Values from the Within-Item Distribution for a Random Sampling of 65 of the NIFMs in this Study

	Maximum Density	Mean	10th Percentile	90th Percentile
Mean	4.38	3.62	2.57	4.98
Standard Deviation	1.68	1.44	1.22	2.04
Range	7.02	5.98	5.58	8.32
Minimum	1.80	1.40	0.46	2.16
Maximum	8.82	7.37	6.04	10.48

There is no reason that the method cannot be applied to marks that are judged by expert examiners to be of value for identification and the ESLRs corresponding to a sampling of such marks could be of interest for comparison to those of the NIFMs. However, any such study would necessarily need to account for the variation among expert examiners in the subjective judgement of sufficiency for identification. A central point of our approach was to use methods that were not dependent of these expert judgements. Toward that end we (1) collected only fingermarks that were previously analysed by expert latent print practitioners to be of "no value for identification," and (2) recognizing the variability among examiners in sufficiency decisions, we conducted an additional normalizing re-assessment by a highly qualified, certified latent fingerprint examiner to remove any that marks that were judged to be potentially identifiable.

Another possible expansion of the present work would be the study of a dataset of marks that are deemed to be NIFMs by expert judgment, but where the true mated source is available. This could incorporate the pairing of features between the fingermark and reference fingerprint and would be as step closer to potential casework applications.

Comparison of auto-extraction and manual encoding of minutiae is also a reasonable line of investigation. However, this would also introduce of a source of subjectivity and manual process that we specifically sought to avoid in this assessment of occurrence and associative value.

While exploration of these refinements and improvements is of value, and they would improve both the accuracy of the methods and our understanding of their limitations, they would not reasonably change the fundamental conclusions of this study. The method used here is sufficiently developed to address the research questions about the occurrence and associative value of NIFMs in this project. As this model, and others, are improved, a re-analysis of the data in this study is likely to produce more accurate measures of the associative values, but is very unlikely to produce differences that would affect the answers to these questions. This research shows that there are many marks, currently declared as not sufficient for identification purposes, which offer the prospect of strong associative evidence. They can provide useful guidance to investigators and to courts.

The finding of large numbers of cases where NIFMs occur with high potential associative value, leads to the follow-on questions, "How useful would NIFM evidence be in actual practice?" and, "What developments or improvements are needed to maximize this contribution?" These developments will include addressing issues common to quantitative assessments of associative value, their reporting and their oral communication.

The findings also indicate that, operationally, it is advisable to consider the collection and retention of NIFMs in casework, anticipating the development and acceptance of methods for measurement of the associative value of NIFM comparisons.

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