JURY PERCEPTION OF EXPLAINABLE MACHINE LEARNING AND DEMONSTRATIVE EVIDENCE

by

Rachel Edie Sparks Rogers

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Rachel Edie Sparks Rogers, Ph.D.

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Adviser: Susan Vanderplas

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DEDICATION

Dedicated to...

ACKNOWLEDGMENTS

Thank you to all my people!

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1.1 Introduction

There are many forms of forensic evidence that have been generally accepted for use in court cases as unique and identifying (without proof). There are even some methods - such as bite mark analysis - that have been used in the courtroom as evidence, but would later be shown to not be scientifically valid (PCAST, 2016, p. 86). When a defendant's future hangs in the balance of such evidence, we must know that the type of evidence being presented is something that can be relied upon, and that the jury can weigh it appropriately when reaching a conclusion. One way to assure that these goals are met is through the use of statistical methods in analysis, which allows for the quantification of comparisons and the establishment of accurate error rate calculations. However, several studied have indicated that these statistical methods are more difficult for jurors to understand. By testing jury perception in bullet matching, and developing tools for assessing jury perception, we hope to expand what can be learned about jury perception in order to present statistical methods in a way that can be understood and used to make decisions by the wider public. Bullet matching has a history similar to many areas

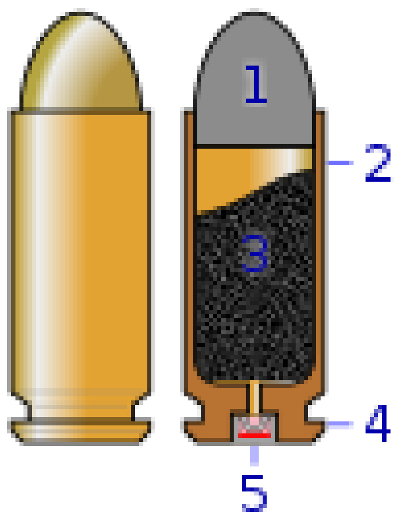

Figure 1.1: Image of bullet structure. 1 indicates the bullet, 2 indicates the cartridge casing, 3 indicates the powder, 4 indicates the head of the cartridge casing, and 5 indicates the primer.

of forensic pattern evidence, and we have to statistically validate its use before it should be used in the courtroom or treated as reliable evidence. However, we must also establish that jurors can treat the evidence with appropriate weight.

1.2 Bullet Matching Background

In firearms evidence, there are two pieces of fired evidence that may be evaluated: the cartridge casing and the bullet itself. The structure of the bullet is shown in Figure 1.1, provided by Glrx (2021). Striation marks are created on the bullet as it travels down the barrel due to rifling, defects, and impurities (Hare, Hofmann, Carriquiry, et al., 2017), while the head of the cartridge casing is marked by the breech face and aperture sheer (Chapnick et al., 2021).

The practice of bullet matching is based on the concept that rifling in a

Figure 1.2: Cross section of a gun. The rifling is the spiral pattern of lands (raised portions) and grooves (indented portions).

gun barrel can produce uniquely identifying marks on bullets fired from the gun, due to random variation (PCAST, 2016, p. 104). Rifling is defined as the spiral ridges in a gun barrel that stabalize the bullet, as shown in Figure 1.2 , from baku13 (2005). The raised areas are known as lands, while the depressed areas are known as grooves.

When a bullet is fired, it travels down the gun barrel and marks from the rifling are scratched into the bullet's surface.

This results in indented areas that correspond to the land impressions, as shown in Figure 1.3 , provided by Gremi-ch (2009).

The diagram in Figure 1.4 from Hare et al. (2017) demonstrates the structure of these land and groove impressions on a bullet. As there are multiple lands on a gun barrel, this results in multiple land impressions on a fired bullet.

Striation marks, or scratches in the bullet surface caused by the rifling, can be seen on these land impressions, as shown in Figure 1.5 (provided by

Figure 1.3: Fired bullet. Indented portion correspond to the gun lands.

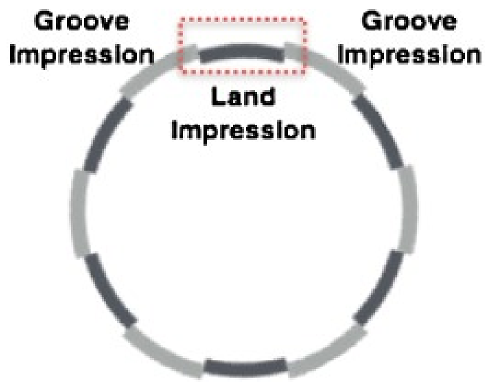

Figure 1.4: Fired bullet. Indented portion correspond to the gun lands.

Hare et al. (2017)). Firearms examiners can compare these striation marks across bullets in order to determine if they were fired from the same gun.

Firearms examiners use comparison microscopes, such as Figure 1.6, to compare these striation marks between two bullets, shown in the top right of the figure.

An early attempt to distinguish guns based on the rifling can be found in two issues of "The Saturday Evening Post" from 1925, in an article entitled "Fingerprinting Bullets". Stout describes the wrongful conviction and subsequent exoneration of Stielow, who was accused of murder (Stout, 1925a). At the trial where Stielow was found guilty, an expert for the prosecution stated

Figure 1.5: Fired bullet. Indented portion correspond to the gun lands.

Figure 1.6: Image of a comparison microscope and aligned bullets

that there were nine abnormalities on Stielow's gun that corresponded with marks on the fired bullet (Stout, 1925a, p. 7). It was later found that the bullet found at the crime scene indicated the gun was missing a land – leaving a distinctive pattern – while the alleged gun showed no such evidence; the alleged gun also showed evidence of not being fired in more than 3 years (Stout, 1925a). While this trial did not require 'uniquely identifying' marks to rule out the alleged weapon (only a mismatch in lands), it motivated Charles Waite to attempt to catalog the manufacturing methods of guns by various companies around the country, with the goal of connecting a gun to its manufacturer. Waite soon encountered issues due to the multitude of guns produced abroad, as well as "cheap knock-offs" with no clear record, making it difficult to trace a gun or bullet to its manufacturer (Stout, 1925b). While Waite's early attempt to match barrel markings to specific gun brands was focused on the creation of a 'database', more recent firearms identification methods have relied on the direct comparison of bullets, such as comparing fired evidence to a suspected gun.

1.3 Issues in Pattern Analysis

1.3.1 Subjectivity of Comparisons

One of the issues listed in the article still resonates today: disagreement among experts; this can be especially problematic in countries that use the adversarial judicial system, where experts can testify on the side of the prosecution or the defense (Stout, 1925a, p. 6). This could lead to multiple experts with differing conclusions on the same comparison, and are not guaranteed to be unbiased. Because there is no quantitative score describing the strength of a bullet match, it is possible for experts to use different criterion when making a conclusion about the same evidence. Disagreement among experts concerning strength of evidence can be found within a single lab, where experts undergo the same training, use the same equipment and operate under the same procedures, as demonstrated by Montani, Marquis, Egli Anthonioz, & Champod (2019). Montani et al. (2019) discuss the importance of independent verification, and how to present results when experts do not agree. They suggest that, when experts disagree, a third expert should be consulted, and all conclusions should be documented and presented as evidence. In the case of bullet comparison studies, researchers ask examiners to make conclusions regarding the comparison of several bullets or cartridge cases, and experts do not always agree. NRC (2009) states that subjectivity is involved in determining "sufficient agreement" among firearms (NRC, 2009, p. 155). This issues is also reflected in Imwinkelried (2020), who suggest that bullet identification is based more on personal experience than on the scientific method. In plain terms, there is not a set standard for what constitutes sufficient agreement between compared evidence.

Procedural issues may also lead to differing expert opinions across laboratories; one system may not allow an exclusion to be documented if the class characteristics match, while another system may not have such a limitation (Baldwin, Bajic, Morris, & Zamzow, 2014, p. 6). In their study, this led to 45 of 218 examiners labeling all different source comparisons as inconclusive, and 96 examiners labeling none of the comparisons as inconclusive (Baldwin et al., 2014, p. 16). Without a standardized procedure, experts may evaluate the evidence similarly when comparing two bullets, but must draw different conclusions based on the procedures of their laboratory. This results in inconsistencies in results based on location, which are compounded with inconsistencies that may arise due to the subjectivity of bullet comparisons.

Aside from the difference in evaluation, subjectivity can lead to bias in pattern recognition. The need for an unbiased method of evaluation is aptly demonstrated by the case of the Madrid bombing, in which the FBI incorrectly matched a latent fingerprint to the incorrect individual, despite the use of a verification process (Stacey, 2005). The individual incorrectly identified was a Muslim from Oregon who had been on an FBI watch list (Kassin, Dror, & Kukucka, 2013, p. 42). Kassin et al. (2013) suggest that this incorrect conclusion may relate to confirmation bias, and outline other contributing factors, such as extraneous details, external pressures, and order of presentation. While this example is based on fingerprint analysis, the same issues of subjectivity are present in bullet matching.

Research has been conducted to better understand the factors that drive firearms examiners to make their conclusions. The use of virtual comparisons allowed Chapnick et al. (2021) to investigate what examiners considered important when evaluating cartridge cases by including a feature to highlight important aspects of comparisons. They found that examiners generally tended to highlight the same features when making match conclusions (Chapnick et al., 2021, p. 8). However, not all examiners who correctly identified the samples used 'irregularly shaped marks' to distinguish the known matches: the number was around 60%-70% (Chapnick et al., 2021, p. 6). This is far from a unanimous consensus on important features for determining a match in this type of firearm evidence.

While there are issues in subjective bullet matching, there have been attempts to quantify the method. Biasotti (1959) suggests that statistical methods can be used in order to determine whether two bullets were fired from the same gun. He concludes that evaluation of individual striation marks (or striae) is not sufficient, but counting the number of consecutively matching lines may provide enough information to distinguish between matching and non-matching bullets, in the case of the .38 Special Smith and Wesson revolvers used in this study (Biasotti, 1959, p. 37 – 47). Biasotti (1959) hoped that such methods may lead to a statistical model for evaluating firearms (47). The idea of consecutively matching striae (CMS) was addressed again in S. G. Bunch (2000), but a completely standardized or quantifiable method of examination has yet to be developed. According to Weller (2021), consecutively matching striae is still used today by some examiners (pg 48). However, the use of consecutively matching striae has not been nationally adopted. Biasotti (1959)'s idea of using consecutively matching lines is used and extended in the bullet matching algorithm developed by Hare et al. (2017).

1.3.2 Scientific Validity

In recent years, the scientific validity of many forensic science methods have been called into question, as shown in the NRC (2009) and PCAST (2016) reports on feature comparison methods. General concerns in both reports include foundational evidence for scientific validity, general inability to determine error rates for conclusions, and subjectivity in analysis methods. Some issues outlined by PCAST (2016) are the circular nature of the identification guidelines put forth by the Association of Firearm and Tool Mark Examiners (AFTE) and the lack of appropriately designed error rate studies

[104]. AFTE defines sufficient agreement as "…the examiner being convinced that the items are extremely unlikely to have a different origin" (PCAST, 2016, p. 104). Thus, items are classified as having sufficient agreement if they agree sufficiently enough to conclude that they did not come from different sources. This guideline is in itself subjective - there are no benchmarks for determining what one means by "extremely unlikely to have a different origin". Both NRC (2009) and PCAST (2016) suggest a move away from subjective methods. PCAST (2016) states the importance of the development of an objective method for firearms comparisons (113).

These reports also highlighted the lack of studies that produced accurate error rates due to several issues, such as the reporting of inconclusive decisions as well as simple design issues (PCAST, 2016, p. 104 - 112). For example, Chapnick et al. (2021)'s report does not include inconclusive results as a potential source of error. They reported three errors (false positives) in their study, and reported a false negative error rate of 0%, ignoring the wide range of inconclusive decisions. For known matches of participants from the US and Canada, 38 of 491 comparisons were reported as inconclusive, while 254 of 693 comparisons were reported as inconclusive for know non-matches (Chapnick et al., 2021, p. 6). The issues of error rate calculation are addressed by Hofmann, Vanderplas, & Carriquiry (2021), particularly with regards to whether or not inconclusive decisions are treated as errors in calculations. They suggest to not consider inconclusive decisions errors for the calculation of examiner error rates, used in the lab setting; but to consider inconclusive decisions as errors for process error rates, used for determining if the evidence is relevant enough for judging the guilt of the suspect. This distinction would allow an examiner to report an inconclusive finding without a negative reflection on their work, as inconclusive decisions are sometimes necessary. But it would also provide jurors with relevant information in terms of evaluating the reliability of firearms evidence.

In another evaluation of inconclusive results, Dror & Scurich (2020) describe different ways in which inconclusive results are produced. They differentiate between inconclusive decisions based on the amount of evidence present; an examiner reaching an inconclusive decision when there is not sufficient evidence to reach a conclusion would be correct, whereas an examiner reaching an inconclusive decision when there is sufficient evidence to reach a conclusion would be incorrect. This definition relies on a quantifiable amount of evidence necessary to reach a conclusive decision. By failing to distinguish between correct and incorrect inconclusive decisions in research studies, examiners may opt for the inconclusive choice on hard conclusive comparisons, resulting in error rates that are only valid for easy comparisons when inconclusive decisions are not considered an error(Dror & Scurich, 2020, p. 336). Dror & Scurich (2020) would consider those inconclusive choices to be "incorrect" - there is enough evidence to reach a conclusion. Similarly, another potential error would be the examiner reaching a conclusive decision when there is not sufficient evidence to reach a conclusion (Dror & Scurich, 2020, p. 334). This delineates conclusion and errors into distinct categories, which are not seen in error rate studies. Both inconclusive and conclusive results for the same analysis cannot be correct – there either is enough evidence to make a conclusion, or there is not enough evidence to make a conclusion; to say otherwise may deflate actual error rates (Dror & Scurich, 2020, pp. 334–335). Dror & Scurich

(2020) indicate that this inconclusive issue is more prominent in studies than in casework, as inconclusive decisions are more common in error rate studies. However, this distinction between correct and incorrect decisions are not commonly made in studies due to a lack of a quantifiable method for separating the two categories, leading to inconclusive decisions contributing lowering the error rate in some studies.

Other issues in the computation of error rates include the use of closed set studies, which result in significantly lower rates of inconclusive decisions and false positives (PCAST, 2016, p. 109). In closed set studies, the source gun is always present, and examiners are asked to match a set of known bullets to a set of unknown bullets - allowing for them to use a process of elimination to make matches; conversely, open set studies do not include all source guns (PCAST, 2016, pp. 108–110). The Ames Laboratory study is described by PCAST (2016) as an appropriate closed set black-box study (111). These types of analyses are classified as black-box studies because reported match results are based on an examiner's subjective opinion rather than a list of objective steps (PCAST, 2016, p. 5). When comparing closed-set studies to non closed-set studies, PCAST (2016) found that closed-set studies had a much lower rate of inconclusive decisions as well as false positives (111).

1.3.3 Scale of Conclusions

This debate regarding scientific validity continues to this day, as Vanderplas, Khan, Hofmann, & Carriquiry (2022) shows. In this declaration, they discuss the current issues with error rate studies, in which they conclude that, until valid error rate studies have been conducted, they cannot support the use of firearms analysis in the courtroom (Vanderplas et al., 2022, p. 10). Others have called to scale back conclusions that attest to "individualization" in the courtroom due to the inability to tie a specific piece of evidence to a specific source, to the exclusion of all other sources (Imwinkelried, 2020; NRC, 2009). There has been some resistance to scaling back conclusions, however, as demonstrated in a memo sent out by Jim Agar II, an FBI attorney. They stated that less conclusive language would not be truthful on the part of the firearm expert and to ask firearms examiners to use this language would result in perjury (Agar II, 2021), despite the reliance on subjective methods with unclear error rates.

There has also been some push back against the conclusions of PCAST (2016), as shown in OSAC (2016) (provided by the Firearms and Toolmarks subcommittee. According to Davis & Baker (2014), the Organization of Scientific Area Committees (OSAC) subcommittees are "generally composed of 70% practitioners, 20% researchers, and 10% research and development technology partners and providers". OSAC (2016) argue that a false positive error rate is not necessary for determining foundational validity, and that closed set error rate studies are fine for calculating error rates. OSAC (2016) also suggests that PCAST (2016) ignores the importance of peer review in studies that instruct firearms examiners to work alone, and that black box studies may not properly reflect casework. However, in order to accurately represent casework, blind testing (where the examiner does not know they are being tested) would be needed - but due to logistical issues and case load, this may not be feasible (PCAST, 2016, p. 59). OSAC (2016) argues that AFTE language is not circular - the basis of a practical impossibility is based on knowledge of best known non-matches conveyed through training. Here decisions are based on "knowledge and experience", which does not counteract the subjective nature of this decision making. Despite these disagreements OSAC (2016) also promotes the use of more objective methods.

These differing views are represented in Swofford & Champod (2022). Swofford & Champod (2022) interviewed 15 individuals with a range of expertise in forensic science and the court system in order to assess their feelings about the use of algorithms and the presentation of probabilistic reporting, as opposed to categorical reporting and traditional analysis methods. They found that prosecutors interviewed supported the use of match terms such as "identification" and "individualization" instead of probabilistic terms, but two of the prosecutors also rejected the use of terms that convey "absolute certainty" (7). All participants felt that that examiner testimony should accurately reflect scientific limitations, although there was not a consensus on whether this practice was in fact followed in the courtroom - defense attorneys felt that the examiners usually do not uphold this expectation, while lab managers expressed frustration on the part of the court (19). The scale to which firearm evidence is used in the courtroom is rather contentious, and views may differ based on occupation.

In general, individuals want to guarantee that the information presented in the courtroom is accurate and valid, without causing too much imbalance between the limitations and the categorical conclusion. However, there isn't agreement on where the balancing point between these two factors are - somewhere between giving too much credit with a match of "absolute certainty", and introducing unfounded reasonable doubt by overstating the limitations.

If accurate numerical information on error rates or an objective method of evaluation that can be described to the court were available, it may be possible to have factual statements of limitations and scope of evidence that both sides of the argument would find satisfactory. In an investigation on the effect of the inclusion of error rate on either voice or fingerprint evidence, B. L. Garrett, Crozier, & Grady (2020) found that the inclusion of an error rate reduced convictions for fingerprint evidence presented categorically, but had no effect in the case of voice comparison (a less established science) or when the fingerprint comparison was presented as a likelihood ratio. They state, "This suggests that error rate information is particularly important for types of forensic evidence that people may assume are highly reliable." (1206). It seems that including error rates for evidence methods seen as reliable may call into question some assumptions participants make about the science, resulting in a closer consideration of the facts presented at trial.

Quantifying both the limitations in terms of error rates and the analysis method with set cutoffs would leave the language used by experts when presenting evidence as a variable that can be manipulated. While there is much debate over the language used in these conclusions, B. Garrett & Mitchell (2013) found that the specific language used to describe the strength of the match (when a match was present) had little effect on participants' judgement of guilt. They tested 11 different forms of match language, such as 'individualization', 'match', or 'very likely that the defendant was the source', as well as language that included match conclusions 'bolstered' by certainty or likelihood language (B. Garrett & Mitchell, 2013, p. 489). McQuiston-Surrett & Saks (2009) also found that there was not a significant difference in participants' view of the likelihood the defendant committed the crime when the examiner presented the conclusion as a 'match' compared to presenting the conclusion as 'similar in all microscopic characteristics.' B. Garrett & Mitchell (2013) suggests that this lack of difference may relate to the overall view of firearms evidence as reliable, meaning that even a weak match basically boils down to being a match in the eyes of the participants (507). They also found some tempering effect of the expert admitting the possibility that their conclusion was made in error (507). Thus, the use of accurate error rates may moderate the reliability of experts for a more considered weighing of evidence. In fact, in the Ninth Judicial Circuit Court, there are jury instructions regarding the need for juries to treat firearms and other 'expert' testimony in the same manner as other opinion testimony, in which they must decide how much weight the testimony should receive (United States Courts for the Ninth Circuit, 2019). United States Courts for the Ninth Circuit (2019) also suggest to avoid labelling such testimony as expert testimony, since it may cause jurors to give the testimony undue weight. One way to fix these issues of subjectivity is by developing a more objective method of evaluation. One objective method introduced to the forensic sciences is bullet matching algorithms, such as the one described in Hare et al. (2017).

1.4 Quantitative Methods

1.4.1 Bullet Matching Algorithm

This bullet matching algorithm was developed by Hare et al. (2017) and uses a random forest in order to determine a match score (Hare et al., 2017, p. 2352). This algorithm can be described as follows:

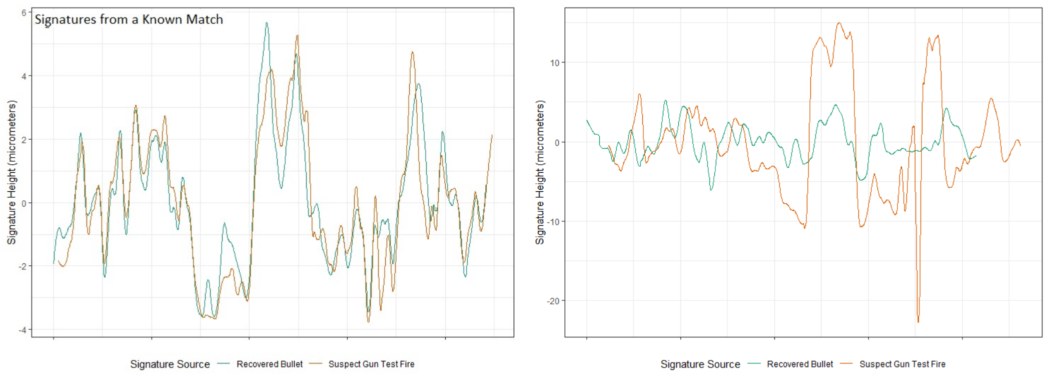

Figure 1.7: Left image depicts two matching signatures, while the right image depicts two non-matching signatures. These were generated by the author.

The algorithm first takes a 3D scan of the two bullet lands, then identifies a cross section, or a stable area of the bullet land that can be used in comparison. This cross section is used in order to identify the signatures of the bullets, or a 2D line that captures the marks scratched onto the bullet's surface. First the shoulders (the raised area on either side of the scratched pattern) must be removed from the cross section. Then a loess smoothing is applied twice in order to remove the curvature of the bullet. What is left is the bullet land's signature (which will show the peaks and valleys produced by the barrel of the gun). The two signatures are compared using a variety of attributes, such as consecutively matching striae and the relative height of the peaks/valleys, as shown in Figure 1.7.

A random forest is used to compare the two signatures and come up with a match score for the lands. Lands are then aligned across the bullet for the maximal random forest score, and this number would be considered the match score for the bullet. Figure 1.8 shows two grids of land match scores computed in two different bullet comparisons.

In multiple tests, it was found that the algorithm is able to successfully

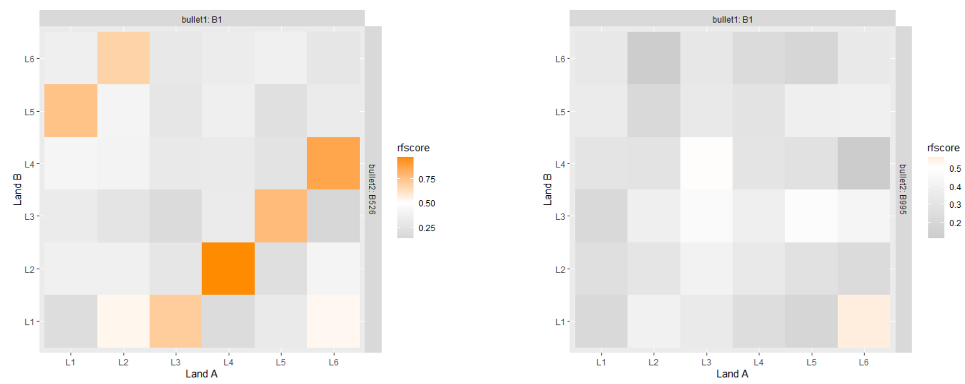

Figure 1.8: Left image depicts two matching bullets (indicated by high land-to-land match scores in a diagonal formation), while the right image depicts two non-matching bullets.

distinguish between known matches and known non-matches without the use of an inconclusive decision (Vanderplas, Nally, Klep, Cadevall, & Hofmann, 2020, p. 10). If the bullet is not fit for algorithmic comparison, then an ‘inconclusive’ result may still be reached. This may be the case for gun types that have not been tested for the algorithm. The use of an algorithm allows for quantification of bullet matching, for cases where the algorithm has been verified.

There are some concerns about implementing algorithms for forensic evidence in the courtroom, due to the issue of explaining complex methods to jurors. B. L. Garrett & Rudin (2023) explain one main issue that may result from “black box” algorithmic methods: the results from the algorithm may not be accurate, and this may be difficult to discern when individuals do not understand the method used. They instead suggest the use of “glass box” methods, where the algorithm’s model is interpretable (people can see how it works, and what information is used to make decisions). B. L. Garrett & Rudin (2023) state that “…interpretability is particularly important in legal settings, where human users of a system… cannot fairly and accurately use what they cannot understand.". This brings up a particularly salient point in jury trials - jurors should understand the pattern comparison process if they are making decisions based on its results. In a combination of computerized results and human interpretation, Montani et al. (2019) suggest presenting the algorithm as a "second independent expert" whose comparison and conclusion can be compared to and presented alongside the examiner's. Supplementing the decision of the forensic expert with an algorithm would allow for verification of results in two independent methods. The three laboratory managers interviewed by Swofford & Champod (2022) suggested using algorithms as a supplement to the forensic examiner (6), similar to Montani et al. (2019)'s suggestion. The three prosecutors varied in their feelings of algorithms in the courtroom: one thought that they would add unnecessary complications, while two suggested that the algorithms may be useful for the forensic expert (Swofford & Champod, 2022, p. 8). The three defense attorneys, as well as the three judges, also supported the use of algorithms as empirical evidence, while stating concerns of transparency (Swofford & Champod, 2022, pp. 10–13). Three academic scholars supported the use of algorithms, so long as the algorithms can be understood, have been validated, and do not include factors that may cause systematic biases (Swofford & Champod, 2022, p. 16). Swofford & Champod (2022)'s study demonstrates the variety of opinions on algorithm implementation throughout forensic science, although most support the use of algorithms.

1.4.2 Quantitative Results

Quantitative methods of examination can lead to quantitative results. In this case, the quantitative results are in the form of a match score, but in other cases, results may be presented as a likelihood ratio. For example, John Song, Chen, Vorburger, & Soons (2020) proposed a likelihood approach for a cartridge case comparison method that uses congruently matching cells. This is a change from the match language usually used by forensic examiners, but these likelihood ratios may have some benefit. Marquis et al. (2016) suggest that the use of a likelihood ratio requires examiners to consider what they are including when weighing the strength of evidence, and provides a value that can be consistent across disciplines (4). This quantitative approach, even while conducting a subjective evaluation, is meant to prevent examiners from being biased by information provided outside of their direct examination (S. Bunch & Wevers, 2013, p. 223). The approach also asks examiners to consider both the null and alternative hypotheses, and may make it less likely for either the examiners or jurors to transpose the conditional, which may happen in the case of reporting probabilities (Evett, 1998; Marquis et al., 2016, p. 3).

As an example of transposing the conditional, suppose an examiner were comparing a bullet from the suspect's gun to a bullet recovered from the crime scene. The examiner may find that there is significant agreement between the two bullets. They may then conclude that "the probability of seeing such significant agreement between the two bullets *given that another gun fired the bullet at the crime scene* is small". In this case, the examiner is making a statement regarding the amount of agreement between the two bullets (P(Correspondence|Different Source)). If the conditional is transposed, the statement would become "the probability that another gun fired the bullet at the crime scene *given the significant agreement between the two bullets* is small" (P(Different Source|Correspondence)). Here, the conditional part of the statement has been switched, so that the examiner is making a statement regarding the gun being fired at the crime scene instead of a statement with regards to the bullet comparison. By stating a likelihood ratio, such as “the bullet comparison provides strong support for the proposition that the two bullets came from the same gun rather than the proposition that the two bullets came from different guns”, both the null and alternative hypothesis are clearly stated, and the focus of the statement is on the bullet comparison, rather than the gun’s presence at the crime scene.

As shown above, the likelihood ratio directly compares the null and alternative hypotheses in a case, which is not accomplished by considering a single probability (Nordgaard, Ansell, Drotz, & Jaeger, 2012, p. 6). Likelihood ratios also allow for the integration of evidence from multiple sources, and individual likelihood ratios may be multiplied together to calculate an overall likelihood ratio. Meuwly, Ramos, & Haraksim (2017) suggested guidelines for validating both score- and feature-based likelihood ratio methods, so this form of result presentation could be more widely accepted. These methods included validation criteria for all variables considered in a likelihood ratio, where validation criteria can be considered in several ways: a comparison with current “state of the art” methods, detection error trade-off graphs to measure discriminating power, and performing validation on a validation data set.

1.4.3 Explainability in the Courtroom

One roadblock in the use of quantitative methods and results, such as likelihood ratios, in the forensic sciences is the necessity to explain such methods to jurors so that they can understand the method and results well enough to make informed decisions in court cases. Association of Forensic Science Providers (2009) stated that opinions and conclusions should be expressed in likelihood ratios when outlining guidelines for forensic experts (163). Participants in Swofford & Champod (2022) expressed concern that probabilistic reporting (as opposed to categorical reporting) would be confusing and easily misinterpreted, when compared to the alternative of categorical reporting (18). In order to gauge how quantitative methods are perceived in the courtroom, we can consider fingerprint and DNA analysis. B. Garrett, Mitchell, & Scurich (2018) studied the use of FRStat for fingerprint matching in the courtroom. The FRStat language presented to the study participants is as follows: "The probability of observing this amount of correspondence is approximately [XXX] times greater when the impressions are made by the same source rather than by different sources" (language from Defense Forensic Science Center, 2018). B. Garrett et al. (2018) used ratios from 10 times greater to 100,000 times greater, and found that the likelihood that the subject committed the crime according to the participants did not change significantly. This demonstrates that potential jurors may have trouble accurately interpreting statistical results, including likelihood ratios.

In DNA research, Koehler (2001) found that participants were more likely to believe the subject was the source of the DNA when presented with a probability instead of a frequency. When asked about how many individuals would match DNA for a given match proportion in a population of 500,000, 60.7% of participants who received a frequency and 42.1% of individuals who received a probability answered correctly (Koehler, 2001, p. 503). When asking these individuals to determine the guilt or innocence of a suspect, the percentage of participants who correctly interpreted the DNA results seems relatively low. Jurors are also prone to find evidence to be weaker when frequencies are presented as whole number (1 out of 100,000) compared to a decimal number (0.1 out of 10,000), even though the frequencies represent the same value (Koehler & Macchi, 2004, p. 544). These studies show that individuals struggle with interpreting numerical results, and assigning appropriate weight to likelihood ratios.

In addressing these issues of interpretation, attempts have been made to assign a verbal scale to be used alongside a likelihood ratio, such as the European recommendations for reporting forensic science put forth by the European Network of Forensic Science Institutes (ENFSI, 2016). A sample of phrasing from their recommended scale has been recreated in Table 1.1. Verbal values range from no support to extremely strong support, and correspond to a numerical output. This type of scale would present jurors with both the quantitative result as well as a brief interpretation, so they are not solely relying on their own perception of what the likelihood ratio qualitatively means. It also offers a numerical scale that may encourage consistency across examiner reports.

Table 1.1: Sample language from ENFSI (2016) (17)

Likelihood Ratio	Verbal Equivalent
1	The forensic findings do not support one proposition over the other
2 - 10	The forensic findings provide weak support for the first proposition relative to the alternative

Likelihood Ratio	Verbal Equivalent
10 - 100	...provide moderate support for the first proposition rather than the alternative
100 - 1,000	...provide moderately strong support for the first proposition rather than the alternative
1,000 - 10,000	...provide strong support for the first proposition rather than the alternative
10,000 - 1,000,000	...provide very strong support for the first proposition rather than the alternative
1,000,000 and above	...provide extremely strong support for the first proposition rather than the alternative

A similar scale is also suggested by Evett (1998), with verbal values of "Limited support", "Moderate support", "Strong support", and "Very strong support" (201). These values approximately correspond to the scale above, but consists of fewer categories. Marquis et al. (2016) suggest against providing the full verbal scale to participants, because participants may use other terms on the scale in order to orient the likelihood ratio in comparison to the full scale (7). However, this ability to orient relative to other values may assist jurors in accurately judging the strength of evidence presented.

While verbal scales are useful for clarification, individuals may not always interpret them consistently. For example, Budescu & Wallsten (1985) asked participants to rank common probabilistic words (such are "rarely" or "usually") on three separate occasions, finding that individuals typically gave consistent rankings across time points, but there was variation in rankings between individuals. In an earlier study, Lichtenstein & Newman (1967) asked individuals to assign numerical probabilities to probabilistic words, finding that eight of the eleven mirror terms (such as "quite likely" and "quite unlikely") demonstrated asymmetry - positive terms (such as likely) scored lower than their mirrored negative terms (unlikely). For example, "quite likely" and "quite unlikely" had median values of 0.8 and 0.1, respectively (Lichtenstein & Newman, 1967, p. 564).

Martire, Kemp, Watkins, Sayle, & Newell (2013) studied the use of a verbal scale similar to ENFSI (2016) in a courtroom setting, in the case of shoe print evidence. They found a "weak evidence effect", in which findings that provided "weak support" for the proposition that the defendant's shoe left the print resulted in decreased likelihood scores of guilt, compared to likelihood scores collected before the introduction of forensic evidence. Martire et al. (2013) did not find this trend when the evidence was presented numerically as a likelihood ratio; in this case, participants tended to think of the defendant as more guilty after hearing the forensic evidence (as expected). They did not, however find that the reverse was true: those who received "weak support" for the proposition that the defendant did not leave the shoe print resulted in increased likelihood scores in favor of innocence, as expected. Martire et al. (2013) hypothesize that this demonstrates that the participants are engaging in a "criminal justice perspective" by weighting the evidence toward the defendant's innocence (since the burden of proof rests on the prosecution). This inconsistency of interpretation between the numerical scale and the verbal equivalent may act as evidence against implementation of a solely verbal scale.

Examiners also show evidence of inconsistency in scale interpretation. Mattijssen, Witteman, Berger, Brand, & Stoel (2020) asked examiners to use a verbal scale for degree of similarity and support when digitally comparing cartridge cases. When using a verbal scale for degree of similarity/support, Mattijssen et al. (2020) found that the between-subject and within-subject reliability was moderate to high (11). Mattijssen et al. (2020) asked 10 examiners who regularly used likelihood ratios to provide both a verbal degree of support along with a likelihood ratio. They found that the verbal degrees of support were in general an overestimation when compared to the likelihood ratios (8). While this is a small non-representative sample, it suggests that verbal scales do not always correspond to quantitative scales across subjects. Thompson & Newman (2015) investigated the amount of weight participants gave either DNA or shoeprint evidence when it was presented as a likelihood ratio, verbal equivalent, or random match probability. While individuals updated their response as expected when the strength of evidence was changed in all cases of the DNA condition, participants did not produce significantly different estimates when shoe print evidence was presented as a likelihood ratio or verbal equivalent, but they did produce different estimates in the case of the random match probability. These results indicate that participants may weigh evidence differently depending on the presentation method. Thompson & Newman (2015) hypothesize that the difference between the DNA results and the shoe print results may stem from the perception of DNA analysis as highly scientific. By combining the quantitative analysis with a verbal translation, it may be possible to present quantitative results in a manner that is understood consistently by laypeople.

This mix of quantitative language alongside more categorical terms is supported by subjects in Swofford & Champod (2022). Almost all participants expressed concerns about the interpretation of the probabilistic language, and many recommended a combination of both methods (Swofford & Champod, 2022). The prosecutors interviewed thought that match language was sufficient by itself, and did not wish to complicate testimony with probabilistic language (Swofford & Champod, 2022, p. 8). McQuiston-Surrett & Saks (2009) studied the use of match language versus probabilities with both judges and juries. Both groups assigned higher probabilities to the defendant committing the crime when presented with qualitative evaluation or a single probability for the hair comparison, as compared to frequency methods of reporting. McQuiston-Surrett & Saks (2009) found that participants were more sure of the guilt of the defendant when qualitative language was used as opposed to a subjective probability. While match language may give jurors more confidence, it could have the effect of shifting the consideration of evidence from the jury (who in a quantitative approach would need to determine whether or not they feel a likelihood ratio is large enough to indicate that the subject is the source) to the forensic expert, who can declare a match.

1.4.4 Demonstrative Evidence

Aside from result language or scales used, another important factor in jury decision making is demonstrative evidence. Images can supply helpful context in describing complex forms of analysis, but they may also introduce bias in the form of “truthiness”, an official term introduced by comedian Stephen

Colbert. He described truthiness as the quality of something *seeming* true (Colbert, 2005). In this video, Colbert talks about "thinking with your head vs. knowing with your heart", where some information may feel true, regardless of the facts. Bornstein & Greene (2011) found a "truthiness" effect in the courtroom - jurors tend to remember evidence that align with their previous beliefs (65). This concept can apply to images that make people more likely to feel like a statement is true, even when they do not contribute new evidence. Kellermann (2013) suggests that the truthiness or "falsiness" of non-probative visual images should be carefully considered before using images in the courtroom "…both to prevent backfire effects and to capitalize on every possible tactic that can be used to persuade jurors…" (40). While the concept of truthiness can be used to benefit either side in an adversarial justice system, trial outcomes should be based on factual evidence, rather than feelings that evidence is factual. In the case of images in trials, it is important to balance the benefit of providing additional information to the jury via images without increasing truthiness.

The impact of photos on an individual's perception can be rather large, as investigated by Cardwell, Henkel, Garry, Newman, & Foster (2016). They asked individuals to "give" or "take" food from an animal, represented by a word. Subjects were later asked to identify whether or not they gave food to an animal – either accompanied by an image or not. Individuals were more likely to say that they gave food to an animal if it was accompanied by an image (Cardwell et al., 2016, p. 887). They found that images had an effect for positive associations such as giving food, but not negative associations such as taking food (Cardwell et al., 2016, p. 883). In this case, the use of images may make it easier for individuals to visualize a scenario (giving food), and thus makes them more likely to remember the event - whether it happened or not.

In a study of perception, McCabe & Castel (2008) presented a variety of graphics alongside articles relating to cognitive neuroscience. The graphics all contained the same information, which was already presented the accompanying article. They found that participants gave higher ratings of scientific reasoning to articles that included a brain image with activated areas, as opposed to a bar chart, topographical brain graphic, or no graphic. Participants were also more likely to agree with the conclusion of an article when the brain image was present, compared to when it was absent. Although the information presented in the articles did not change throughout these conditions, the brain image appears to add more “truthiness” to the articles, causing individuals to find them more scientific than articles with other graphics or no graphics.

In the courtroom, studies have been conducted to evaluate the effect of images of the brain. Gurley & Marcus (2008) studied the use of brain images when arguing the defendant is not guilty by reason of insanity. In a study on introduction to psychology university students, they found that the inclusion of images showing a brain lesion increased the odds of the participants finding the defendant not guilty by reason of insanity. MRI scans were presented with additional information regarding impulse control for the damaged area, so the effect may not be caused by the images themselves but rather by the additional information. Schweitzer et al. (2011) investigated whether images of the brain presented alongside expert testimony with regards to a mental disorder effected the participant’s verdict of the defendant’s mental state. In this case, no additional information was provided alongside the neuroimage, allowing the effect of the image itself to be studied. They found that the inclusion of neuroimages did not significantly effect the judgement of the participants. The influence of images on individuals remains unclear, and may be situationally dependent.

1.5 Response Methods

There are many different ways to measure participant responses. Verbal scales, such as those used in the ENFSI guidelines described in the last section, are often used to record participant responses. Likert scales can be used to evaluate several factors, such as the reliability, understanding, and scientific quality of the forensics expert, the algorithm, and the testimony in general. It is therefore important to ensure that participants' views are accurately recorded with Likert type scales, which can vary in the number of categories used. Several researchers found that the 7-point scale may perform or represent the participants' true views better than the 5-point scale (Finstad, 2010; Joshi, Kale, Chandel, & Pal, 2015). Participants often preferred more categories, such as 7, 9, or 10 (Komorita & Graham, 1965; Preston & Colman, 2000). However, Preston & Colman (2000) found that reliability decreased with more than 10 categories. This indicates that 7, 9, or 10 point scales should be adequate for reliable responses that accurately represent the participant's views.

Other methods have also been used to evaluate participant responses, such as asking participants to give a likelihood ratio or a probability of guilt. Thompson, Kaasa, & Peterson (2013) asked participants rate the chance of guilt on a scale from: with values generally on a log 10 scale (ex. 1 in 100; 1 in 1,000); a middle value of a fifty-fifty chance; and extreme values of "Certain to be guilty" and "Impossible that he is guilty". They compared results from participants to Bayesian conditional probabilities based on provided likelihoods of a match and error rates in order to consider how much weight participants were giving DNA evidence. Their results mainly showed no significant difference between Bayesian and participant estimates (meaning that the estimates were "in the right ballpark"), with some conditions producing estimates either greater than or less than what was expected.

In another study of the relationship between how examiners present evidence (likelihood ratio, verbal equivalent, or random match probability), Thompson & Newman (2015) applies the same multiple choice scale for selecting the chance that the defendant committed the crime for half of the participants, while the other half of the participants were asked to supply how many more times likely it was that the defendant was guilty as compared to not guilty, or vice versa (based on a response scale found in Martire et al. (2013)). The likelihood statement was worded as follows: "Based on the available evidence I believe it is _____ times more likely that Mr. Kelly is guilty than not guilty." (Thompson & Newman (2015), 5). In comparing responses from these two scales, Thompson & Newman (2015) found that individuals were more likely to give higher estimates on the categorical log scale than when they were asked to provide a likelihood - resulting in the categorical log scale being more consistent with the expected result when using Bayesian methods of calculation. This indicates an inconsistency in results based on the response method used.

1.6 Conclusion

In order to ensure that the US justice system is just, we must be confident that the evidence presented in the courtroom is scientifically valid, and that the evidence is presented in a way that gives jurors the ability to appropriately judge its strength. This includes the use of accurate error rates as well as quantitative responses. One way to facilitate error rate calculation and quantitative results is through the use of algorithmic or statistical methods. These methods must, however, be explained in a manner that is understandable to those without a statistical background, while limiting any of the potentially biasing effects of “truthiness”.

Chapter 2

Jury Perception of Bullet Matching Algorithms and Demostrative Evidence

2.1 Background

2.1.1 Firearms Examiners

The foundational belief in bullet comparisons as a form of identifying evidence is that guns can leave unique striation marks on a bullet as an artifact of the rifling process (PCAST, 2016, p. 104). Striation marks are left on portions of the bullets known as “lands”, due to contact with the rifling as the bullet is fired. These marks are compared by examiners across bullets in order to identify if bullets were fired from the same source. These examinations are subjective, as they are based on the firearms examiner’s experience and judgement (NRC, 2009, p. 153). This can lead to issues of bias in analysis (Kassin et al., 2013). In 2019, the PCAST report highlighted common issues with traditional bullet matching methods, such as the lack of appropriately designed error rate studies and the circular nature of AFTE’s bullet matching guidelines (PCAST, 2016, pp. 104–112). Issues in error rate studies have been discussed in several articles (Dror & Scurich, 2020; Hofmann et al., 2021).

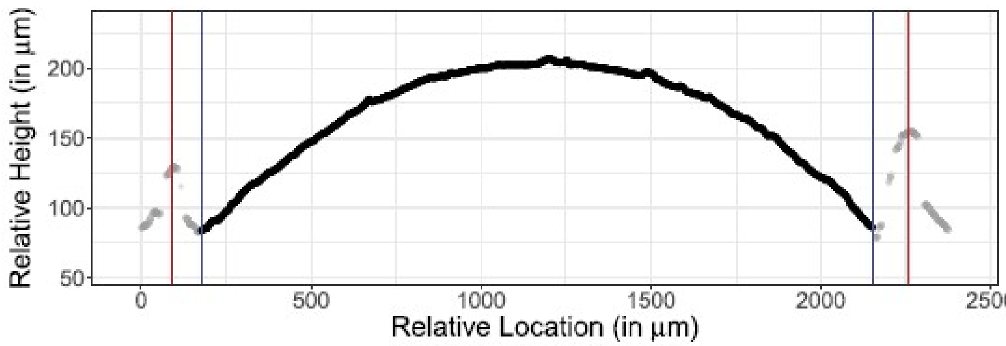

Figure 2.1: The land is shown in the center. Shoulders are shown outside of the vertical lines.

PCAST emphasizes the importance of the development of an objective method for firearms comparisons (PCAST, 2016, p. 113). The use of an automatic, objective method would contribute to quantifiable presentation of evidence and would lower the effort required to identify the method's error rate.

2.1.2 Bullet Matching Algorithm

Following PCAST's publication, many methods of statistical matching have been developed and evaluated, such as Hare et al. (2017), Vanderplas et al. (2020), J. Song et al. (2012), and Vorburger, Song, & Petraco (2015). In this study, the bullet matching algorithm used was developed by Hare et al. (2017). The algorithm can briefly be described as follows:

1. A 3D scan is taken of each bullet land (containing striation marks to be compared), a stable cross-section is extracted, and shoulders (without relevant striation marks) are removed, as in 2.1, an image from Hare et al. (2017).

Figure 2.2: Two aligned signatures for a known match. Image generated from Houston dataset by authors.

2. A smoothing function is applied twice in order to extract the signature, a pattern of high and low points on the bullet's surface corresponding to the striation marks. The signature can then be compared to land signatures from other bullets, as in 2.2.

3. Traits, such as consecutively matching striae and depth of grooves, are then used in a random forest to produce a match score (ranging from 0 to 1) for the lands. The random forest consists of decision trees that consider a combination of variables and responses in order to predict if two signatures were created by the same gun. The decision trees in a random forest each consider a subset of variables and observations to

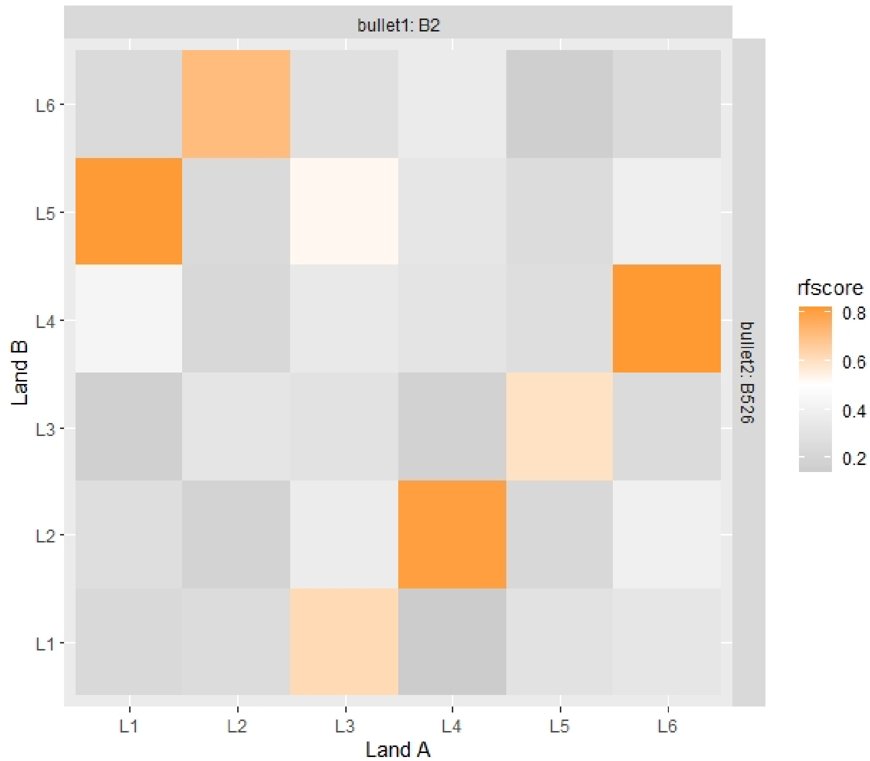

Figure 2.3: Diagonal correspondence (in orange) among lands indicate a match, as shown here. Image generated from Houston dataset by authors.

> decide whether or not the lands match. The decisions of these trees are combined to produce the match score. Lands are then aligned across bullets in order to compute an overall match score for the bullets, as in 2.3.

```
include_graphics(path = "images/Test_Fire_F526.jpeg")
```

This algorithm was trained on Hamby's Consecutively Rifled Ruger Barrel Study data sets 252 and 173 (Vanderplas et al., 2020), and the final random forest was able to correctly predict all matches and non-matches (Hare et al., 2017, p. 2350). Three sets were then used to verify the algorithm: Hamby set 44, Phoenix PD, and Houston FSC (Vanderplas et al., 2020, p. 5). The algorithm performed well for undamaged bullets, and was able to completely distinguish between matches and non-matches when a cutoff value was individually chosen for each data set (Vanderplas et al., 2020, p. 10).

2.1.3 Explainable Machine Learning - Previous Research

Jurors' ability to interpret statistical methods and language is in doubt; in a study conducted by Koehler (2001) with regards to the probability of a random match in DNA evidence, they found that jurors had different interpretations when the probability was presented as 1 out of 1,000 versus 0.1 out of 100, where those presented with a decimal number were more likely to view the probability of a random match as smaller. In another study, B. Garrett et al. (2018) asked jurors to evaluate evidence that used the following FRStat language, typically used in fingerprint analysis: "The probability of observing this amount of correspondence is approximately [XXX] times greater when the impressions are made by the same source rather than by different sources" (language from Defense Forensic Science Center, 2018). When asked for the likelihood the defendant committed the crime when presented with the above FRStat language, participants did not provide significantly different likelihoods for values ranging from 10 times greater to 100,000 times greater. This may demonstrate a lack of understanding when jurors are presented with numerical results for statistical evidence. ENFSI (2016) proposes a verbal scale to supplement likelihood ratios, which may alleviate some of the burden of statistical interpretation from potential jurors. This scale ranged from weak support, corresponding to a likelihood ratio between 2 and 10, to very strong support, corresponding to a likelihood ratio greater than 10,000 (ENFSI, 2016, p. 64). When interviewing judges, lawyers, forensic scientists, and forensic researchers, Swofford & Champod (2022) found that many expressed concern regarding the interpretation of probabilistic language, and several suggested a combination of both match and probabilistic language. Hare et al. (2017)'s algorithm differs from previous presentation methods in that its output is a match score, as opposed to a likelihood ratio. In this study, potential jurors may encounter both the algorithm's match score alongside the categorical match language of the examiner.

2.1.4 Demonstrative Evidence

Images are often used to assist individuals in understanding non-image information. However, images may have an effect of making a scenario more believable, as demonstrated in a study by Cardwell et al. (2016) which involved "giving" or "taking" food from animals with or without images. Images are also mentioned as a factor that can influence how truthful individuals view statements in the courtroom - even if no new information is presented through the presence of the image (Kellermann, 2013). Therefore, the use of images in a courtroom should be studied for an effect with regards to how subjects perceive the evidence presented - namely, if there is a difference in how reliable or credible they feel the experts are, based on the presence or absence of images. Because the images are intended to aid only in interpretation, we would hope for an increase in understanding across all other conditions, while reliability and credibilty stay the same. However, based on previous research, it seems probable that the presence of images would increase the perceived reliability and credibility of the evidence and expert, respectively.

2.2 Methods

2.2.1 Study Format

First, participants are presented with a short scenario based on B. Garrett, Scurich, & Crozier (2020): a bullet is the only evidence recovered from an attempted convenience store robbery, and is tested against a gun found in Richard Cole's car in a routine traffic stop. Participants are informed that the store clerk was unable to identify the robber because they were wearing a ski mask, and that the testimony presented represented all relevant information. They were also advised that they would be unable to re-read testimony, and a notepad was provided for their convenience. Participants are then asked to read a transcript of mock court testimony, and rate their impression of the evidence presented, as well as their impression of the experts. This document included expert testimony, cross examination, and questions from the jury conveyed through the judge regarding error rates. The expert testified to their qualificiations, as well as the process of bullet matching. They then described comparing the fired evidence to a test fire from the defendant's gun, and the results of the comparison. When the algorithm was included, the firearms examiner also described the algorithm's match score resulting from this comparison. Cross examination included questions regarding the ability to uniquely identify the source of the bullet, as well as the subjectivity of the comparison.

When the algorithm was included, an algorithm expert then testified. They also listed their qualifications and involvement in the development of the algorithm. The expert would then describe the process for obtaining a match score (similar to the algorithm description in the previous section). They also spoke to the publication history of the algorithm, the code availability, and the algorithm's applicability to the type of firearm considered in the case. Cross examination included questions on the newness of the algorithm, as well as subjective aspects of calibration, and limitations with respect to the types of bullets that it can evaluate.

The testimony was based on actual court testimony provided by forensics experts lawyers, and judges, shown in Appendix A.

After reading the transcript, participants were directed to respond to some questions regarding the testimony. They were first given information about their responsibility as jurors to choose whether or not to convict, and the 'beyond reasonable doubt' threshold was established before asking participants for their conviction decision. Participants were also asked to estimate the probability that the defendant committed the crime, and the probability that the gun was involved in the crime. These questions were followed by several Likert scales on the strength of evidence, the credibility of the examiners, reliability and scientificity of the evidence, and understanding of the procedures.

Two attention check questions were asked, in order to ensure that participants were reading both the testimony and the subsequent questions. The first attention check asked participants to identify the caliber of bullet recovered from the crime scene, while the second attention check asked participants to select a specific value from a Likert scale.

The study includes three independent variables: presence or absence of the algorithm, presence or absence of demonstrative evidence (images), and conclusion (match, exclusion, or inconclusive). In the case of the algorithm, two testimonies were presented: that of the firearms expert (Terry Smith), and that of the algorithm expert (Adrian Jones). The firearms expert presented the algorithm results for the case alongside their own analysis, and suggests that the algorithm's results supports their conclusion. By presenting the algorithm results with the interpretation suggested by the firearms expert, we hoped that potential jurors could use the firearms expert's explanation and conclusion to guide their understanding of the algorithm's results. The algorithm expert then describes in greater detail the algorithm's process, and its validity for this particular case. When demonstrative evidence is present, images of rifling (baku13, 2005; Gremi-ch, 2009), a bullet comparison, and algorithm images (such as those shown above) were included alongside the testimony. In terms of the conclusion: a "match" indicated agreement in individual and class characteristics; an "exclusion" indicated an agreement of class characteristics, but disagreement in individual characteristics; and an "inconclusive" indicated an agreement in class characteristics, but not enough agreement in individual characteristics to state that there was a match.

The number of survey questions that respondents received depended on the scenario; participants who received the algorithm were asked more questions than those who did not receive the algorithm. For example, participants who did not receive the algorithm were asked about the reliability of the forensics examiner's bullet comparison and the reliability of the field of firearms as a whole. Those who received the algorithm were asked about the reliability of the forensics examiner's bullet comparison, the reliability of the algorithm's comparison, the overall reliability in the case (which includes both the algorithm comparison and the forensics expert's comparison), as well as the reliability of the field of firearms as a whole. This same format was used when asking participants about credibility and scientificity.

2.2.2 Prolific

Participants were recruited using Prolific, an online survey-taking website. From the Prolific website, participants were directed to a link containing our survey, created using RShiny. We selected options to recruit a representative sample of individuals located in the United States, and asked that participants self-screen for jury eligibility before completing the survey. Jury eligibility was defined as US citizens over the age of majority in their state who had not been convicted of a felony, were not active law enforcement, military, emergency response, or a judge, and who did not have a disability that would prevent them from serving on a jury. They were also required to have normal or corrected to normal vision, due to the images used in the study. Participants were compensated with \$8.40 for completing the study, for an hourly compensation rate of about \$27.79 (median completion time of approximately 18 minutes). Individuals who did not include their Prolific identification number and an individual whose notes indicated that they had progressed far enough into the survey to get a separate scenario before restarting were excluded from analysis.

Figure 2.4 depicts completion times (from completion of the demographics information to the end of the survey) by conditions for unique fingerprints (n=559), excluding 5 observations greater than 75 minutes. In general, it appears that those who received the algorithm condition took slightly more time on average than those who did not (median values of 19.134 minutes and 13.716 minutes, respectively). This is unsurprising, given the increased length of the algorithm condition.

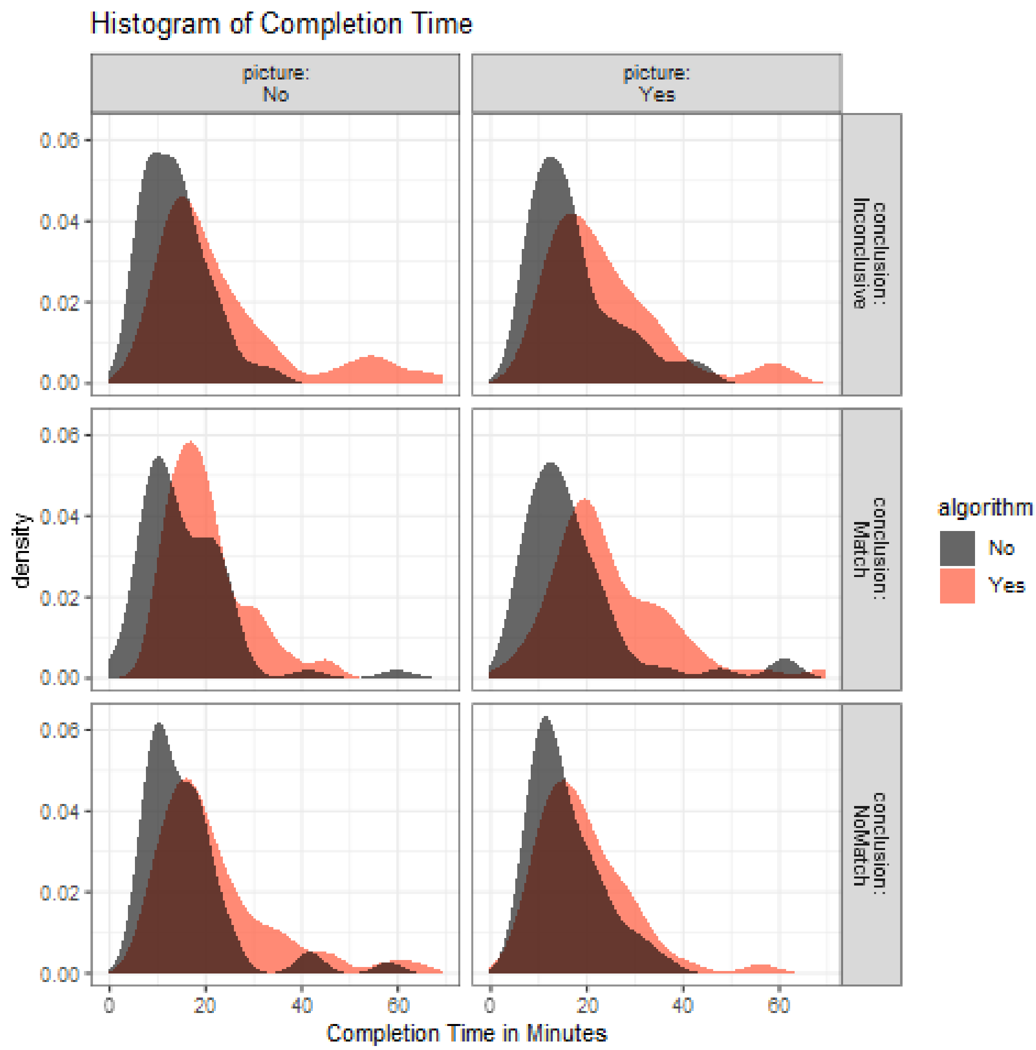

Figure 2.4: Completion Time by Condition for all unique fingerprints

2.3 Results

Due to scale compression, no statistical analysis was performed on this data.

2.3.1 Participants

Of the 636 participants with Prolific ID's who started the survey, there were 324 female participants, 307 male participants, and 5 non-binary partic-

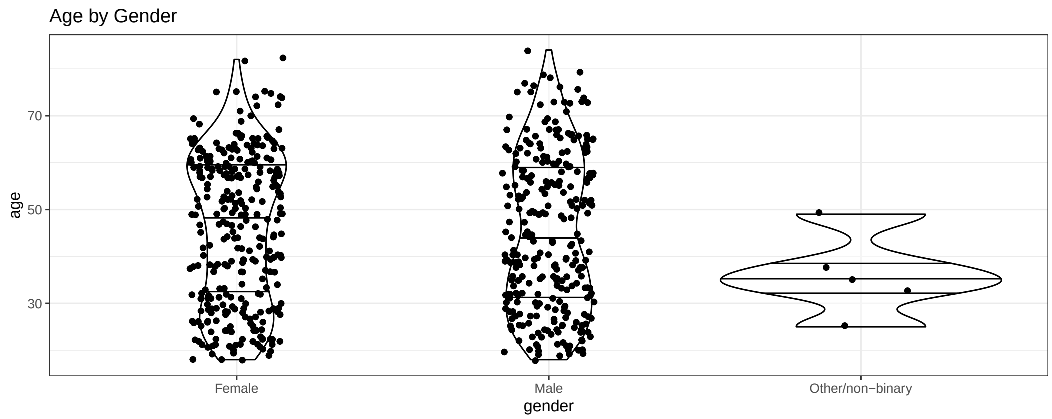

Figure 2.5: Demographic Information

Table 2.1: Attention Check Information

	Reading Correct	Reading Incorrect
Caliber Correct	569	12
Caliber Incorrect	10	0

ipants. These participants are a representative sample (in terms of age, sex and ethnicity, based on census data) of Prolific participants who are located in the United States. The median age was 45. Age and gender are shown in Figure 2.5. An age of 0.2 was excluded due to implausibility and lack of study completion. 591 participants eligible for analysis completed the survey, and 569 participants correctly answered both attention check questions. In two instances, participants reported being removed from the survey website prior to survey completion, which may have happened in other cases where the participants did not complete the survey. The division of correct answers on the attention check questions are shown in Table 2.1. These 569 participants were considered for the following analysis.

2.3.2 Overview

Participants were asked a variety of questions in order to assess their thoughts and feelings on the case and the evidence presented. Two questions related to probability: respondents were asked to provide a value for the probability that the gun was at the crime scene, and to provide a value for the probability that Richard Cole (the defendant) committed the crime. Another question asked participants if they would convict Cole, based on the evidence. Questions of credibility, reliability, and scientificity were assessed using a 7-point Likert scale (eg. "Extremely unscientific" to "Extremely scientific"). Understanding was ranked on a 5-point Likert scale ("I understood nothing" to "I understood everything"). Participants were also asked about uniqueness of firearm toolmarks, as a simple yes/no question. Strength of evidence was ranked on a 9-point Likert scale ("Not at all strong" to "Extremely strong"). The perceived frequency with which firearms examiners made mistakes was assessed on a 7-point Likert scale ("Never" to "Always").

2.3.3 Probability

There is a difference in the perceived probability that Cole committed the crime as well as the perceived probability that the gun was present at the crime scene based on the examiner's decision, as shown in Figure 2.6. The match condition resulted in high probabilities, while the non-match condition resulted in low probabilities, indicating that participants reacted to the examiner's testimony. A wider range of probability values were observed for the inconclusive decision, without the high peaks that were present for conclusive decisions. Definite conclusions of match or not a match resulted in higher peaks at more extreme values for the probability that the gun was at the crime scene, compared with the probability that Cole committed the crime. This may indicate that some individuals are distinguishing between evidence that the weapon was used and evidence against Cole. The inconclusive decision resulted in a more spread out distribution that is practically the same for both the probability that the gun was at the crime scene and the probability that Cole committed the crime, with participants generally selecting values below 50%.

For both Cole and the gun, values are slightly more concentrated toward the lower end of the scale when the algorithm is absent for the non-match condition, and the inconclusive decision produced similar densities across both algorithm conditions. In the case of the gun's involvement, values are more concentrated toward the higher end of the scale when the algorithm is present for the match condition. There is no real difference between match distributions for the probability that Cole committed the crime. The vertical lines indicate the match score presented by the algorithm (0.034 or 3.4% for the non-match condition, 0.34 or 34% for the inconclusive condition, and 0.989 or 98.9% for the match condition). These are displayed in order to visually assess whether the subjects are anchoring to the given match score when assessing the probability of the gun being present at the crime scene. Because the match score is on a scale of 0 to 1, this value could be misinterpreted as a probability for the gun being used in the crime. It does not appear that the participants are anchoring to this value, however, as the distributions do not correspond more to the line when the algorithm is present.

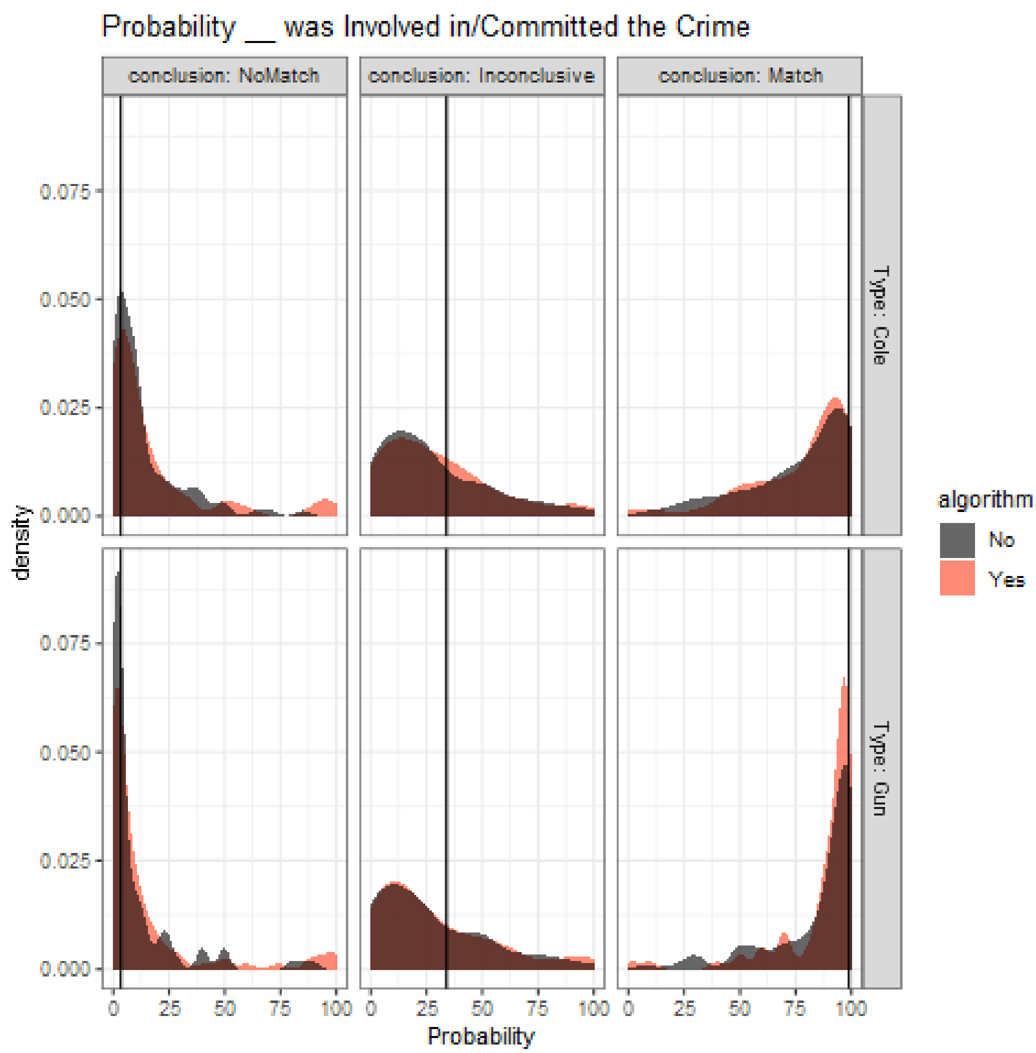

Figure 2.6: Probability the gun was used in the crime, or that Cole committed the crime. Black lines indicate bullet match scores for the algorithm.

2.3.3.1 Probability and Guilt

After reading the testimony, the participants were given the following question: "The State has the burden of proving beyond a reasonable doubt that the defendant is the person who committed the alleged crime. If you are not convinced beyond a reasonable doubt that the defendant is the person who committed the alleged crime, you must find the defendant not guilty. Would you convict this defendant, based on the evidence that you have heard?" 10 out of 196 individuals in the non-match category, 13 out of 191 individuals in the inconclusive category, and 112 out of 182 individuals in the match category chose to convict, despite the bullet matching being the only evidence against Cole in the crime. As 2.7 illustrates, across all categories individuals who chose to convict generally assigned a higher probability to Cole committing the crime than those who did not choose to convict. The same general trend of higher probability values for those who chose to convict and lower probability values for those who chose not to convict is also seen for non-match and inconclusive conditions when discussing the probability that the gun was used in the crime. However, in the case of the match condition, those who did not convict gave a generally higher probability that the gun was used in the crime than the probability that Cole committed the crime, resulting in comparable values (albeit with more variability) to those who chose to convict.

2.3.4 Credibility

Through all conditions, the level of credibility remained approximately the same for both the firearms examiner and the algorithm expert. As Figure 2.8 demonstrates, "Extremely credible" was by far the most selected category for

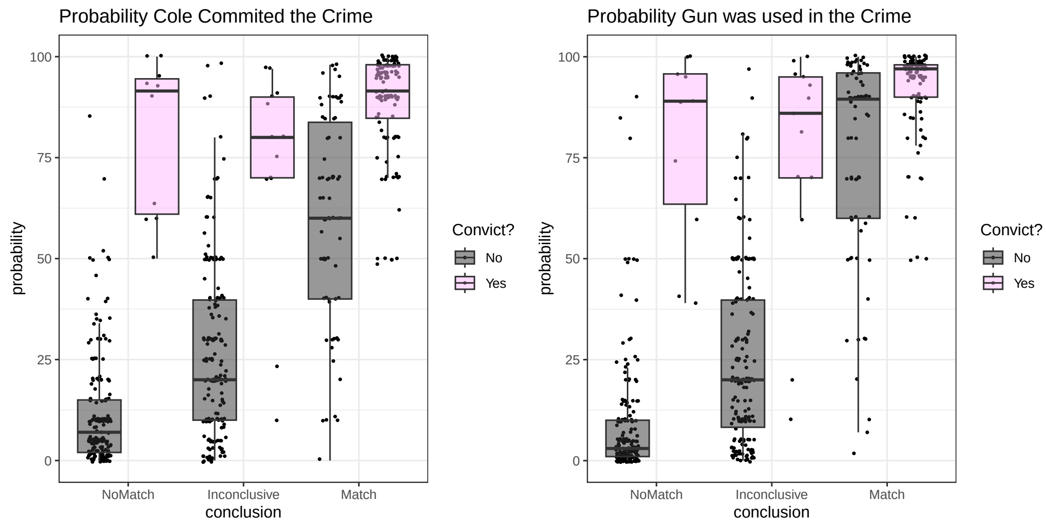

Figure 2.7: Probabilities based on whether the participants thought the defendant was guilty

the firearms examiner, with some people selecting “Moderately credible”, while the other categories quickly drop off in responses. This trend was also reflected in the data for the algorithm expert, and can be seen in most histograms resulting from this study (leading to a question of scale compression). The lack of difference based on examiner decision, image, or algorithm (in the case of the firearms examiner) provides a hopeful indication that the credibility of expert witnesses is not necessarily swayed by the facts of the case or the presence of images, when their written testimony remains the same.

2.3.5 Reliability

In terms of reliability, participants appeared to find the case evidence less reliable when an inconclusive decision was given than they did when a conclusive decision was reached, as shown in Figure 2.9. Note that this question was only answered by participants who received the algorithm condition and is meant to encompass both the examiner’s comparison and the algorithm com-

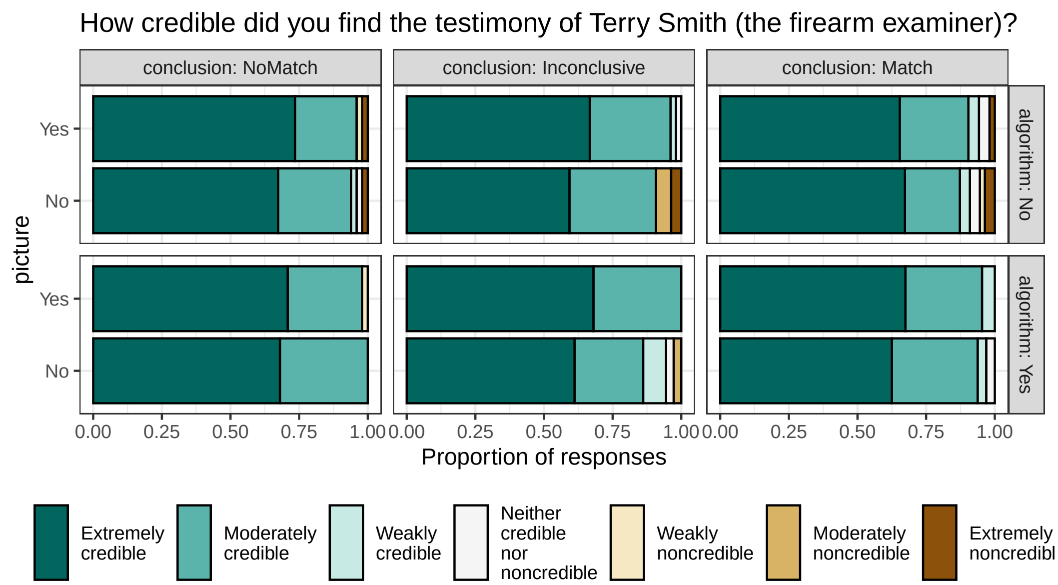

Figure 2.8: Histogram of Firearms Examiner Credibility

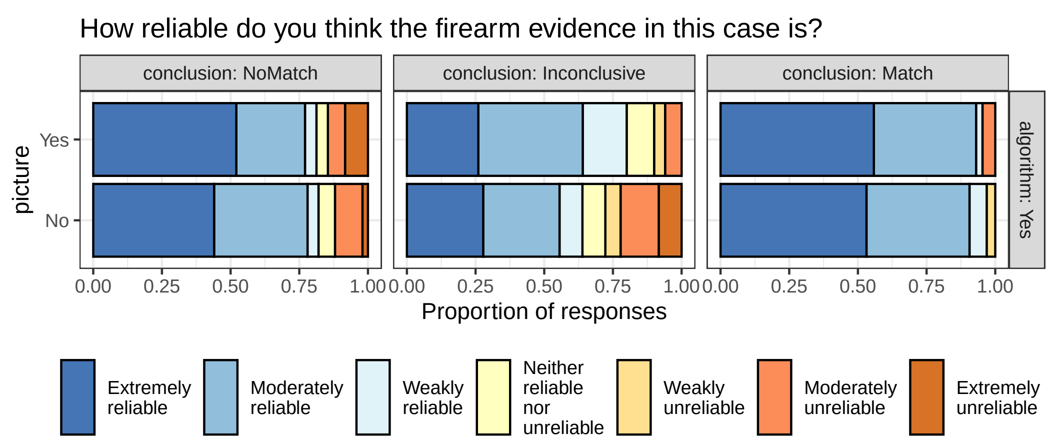

Figure 2.9: Histogram of overall case reliability

parison. As with the credibility condition, the majority of individuals selected the two highest conditions, “Moderately reliable” and “Extremely reliable”, across all categories of conclusions. In the case of an inconclusive decision, the highest proportion of participants selected “Moderately reliable”, while for the conclusive decisions, the highest proportion of participants selected “Extremely reliable”.

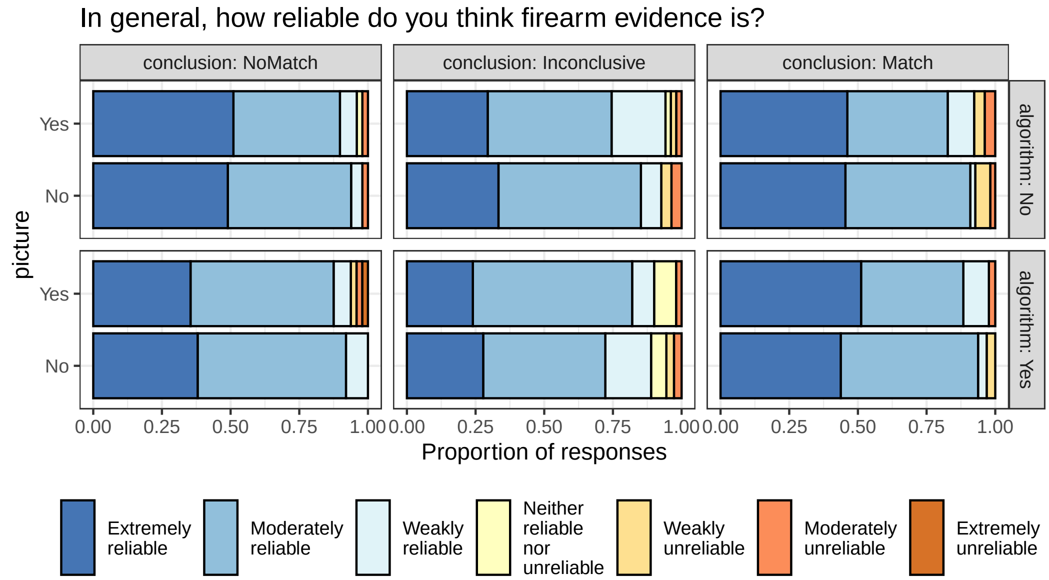

Figure 2.10: Histogram of perceived firearm reliability as a field

Individuals were also asked to rate the general reliability of firearms evidence as a field (Figure 2.10). As with case reliability, those who received an inconclusive condition were more likely to select “Moderately reliable” than they were to select “Extremely reliable”. This trend is also shown in the non-match condition when the algorithm is present. However, it is not reflected in the match condition. When the algorithm is absent, both the match and the non-match conditions appear to produce approximately equal proportions for the two highest categories of reliability. As with previous responses, all other categories are sparsely populated.

In all conditions, participants were asked to rate the reliability of the examiner’s subjective opinion of the firearm evidence (Figure 2.11). Participants from both the algorithm and non-algorithm groups gave similar reliability ratings in the non-match condition: most chose “Moderately reliable” or “Extremely reliable”, with more choosing “Extremely reliable”. For inconclusive

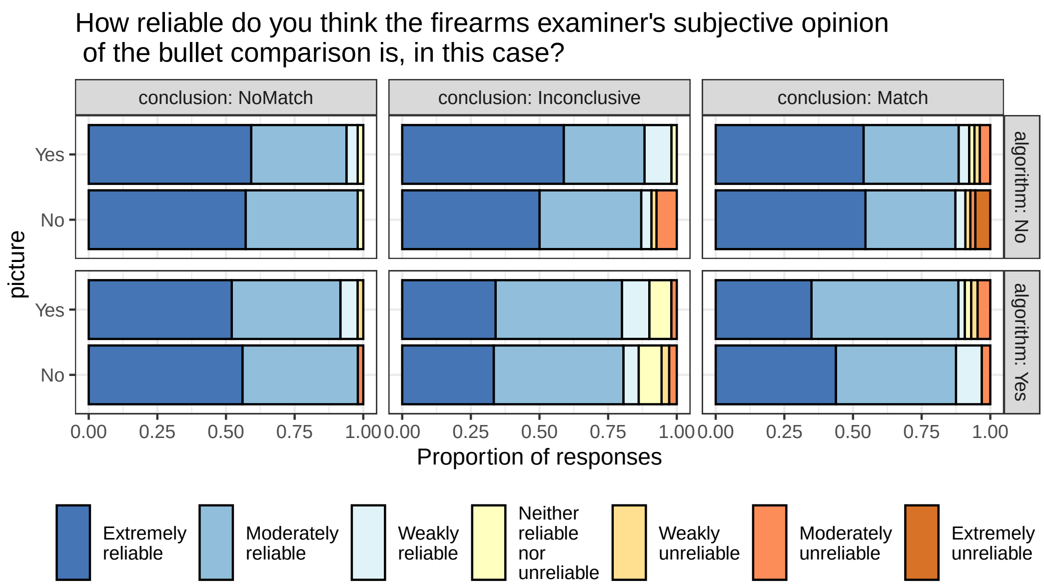

Figure 2.11: Histogram of perceived firearm exam reliability

and match conditions, there is a difference in proportions of which category is selected based on the presence or the absence of the algorithm. When the algorithm is absent, the trend is fairly similar to that in the non-match condition: between the two highest categories, the majority chose “Extremely reliable”. However, in the case that the algorithm was present, this trend was flipped: more participants chose “Moderately reliable” over “Extremely reliable”.

Individuals who received the algorithm were also asked to rate algorithm reliability, responses are shown in Figure 2.12. The responses were in many ways similar to those given in the case of general reliability: those who received an inconclusive decision were more likely to give a lower reliability rating, and the two highest categories were by far the most selected. Both also demonstrated a higher selection of “Weakly reliable” when individuals were presented with an inconclusive decision.

In most cases, individuals gave lower reliability ratings when an inconclu-

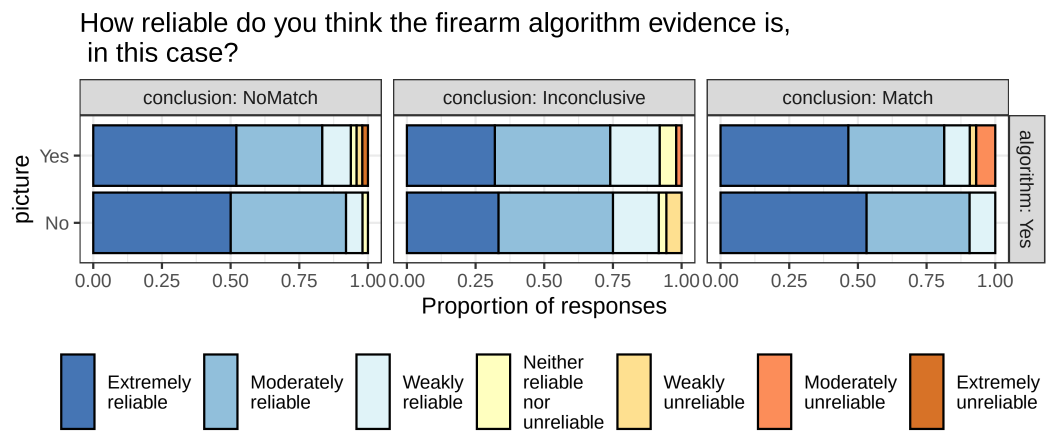

Figure 2.12: Histogram of perceived algorithm reliability

sive decision was reached. They also tended to select the two highest reliability categories, “Moderately reliable” and “Extremely reliable”, regardless of other conditions. The presence or absence of images did not have a noticeable effect on reliability ratings. The presence of the algorithm is related to a slight reduction in reliability ratings for the firearms examiner’s personal bullet comparison, in the case of an inconclusive or match decision.

2.3.6 Scientificity

Participants were also asked about how scientific they felt the process was, in a similar four-question format to reliability. These results bore some similarity in responses to reliability across questions. As previously stated, images did not appear to have a large effect and the two highest categories were by far the most selected. When asked about their rating of how scientific the evidence was in the case overall, those receiving the inconclusive condition were less likely to select “Extremely scientific” compared to their counterparts given conclusive conditions.

In terms of firearms evidence as a field, results are shown in Figure 2.13.

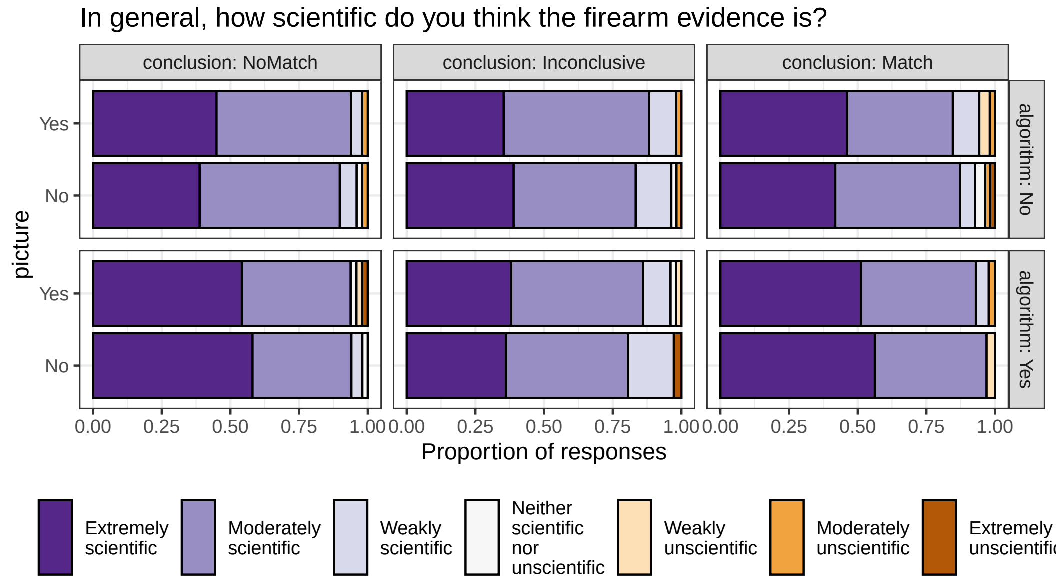

Figure 2.13: Histogram of perceived firearm scientificity as a field

Here, as before, those who received the inconclusive decision were more likely to select "Moderately scientific" over "Extremely scientific" for both cases of the algorithm. A higher proportion of individuals selected "Extremely scientific" for conclusive decisions when the algorithm was present compared to when the algorithm was absent.

Regarding how scientific individuals found the examiner's comparison, the algorithm only seemed to have an effect when individuals were presented with an inconclusive decision (2.14). When the algorithm was not present, people were more likely to select "Extremely scientific", resulting in a proportion on par with conclusive results. When the algorithm was present, however, "Moderately scientific" became the most popular choice for those who received an inconclusive decision, which reflects the general trend of the majority of participants selecting the second highest category for inconclusive results. Results for conclusive categories are fairly similar across algorithm conditions, with a

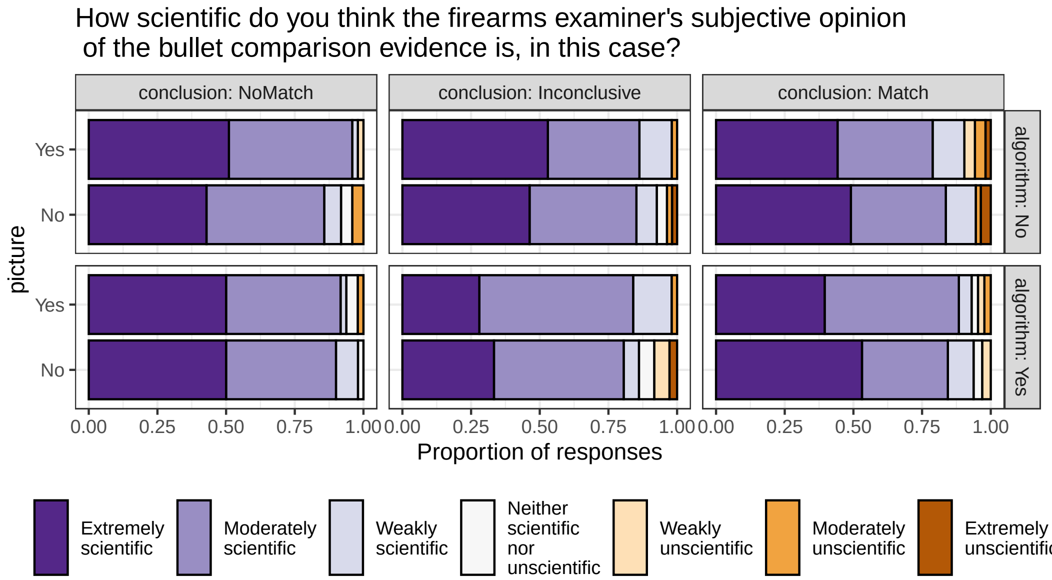

Figure 2.14: Histogram of perceived scientificity of the bullet comparison of the firearm examiner

close split between “Moderately scientific” and “Extremely scientific”.

Participants gave the algorithm a high rating in scientificity across all categories of conclusions, as shown in Figure 2.15. Here, all decisions had the highest proportion of respondents select “Extremely scientific”. The proportion selecting “Moderately scientific” was noticeably lower than the proportion selecting “Extremely scientific”. The use of demonstrative evidence did not have a visible effect.

In summary, the algorithm is related an an increase of perceived scientificity for the field of firearm evidence as a whole when individuals were presented with a conclusive decision, and “Extremely scientific” was the most selected category when evaluating the scientificity of the algorithm evidence regardless of conclusion. As for how individuals rated the scientificity of the algorithm expert’s comparison, the algorithm only appeared to influence results

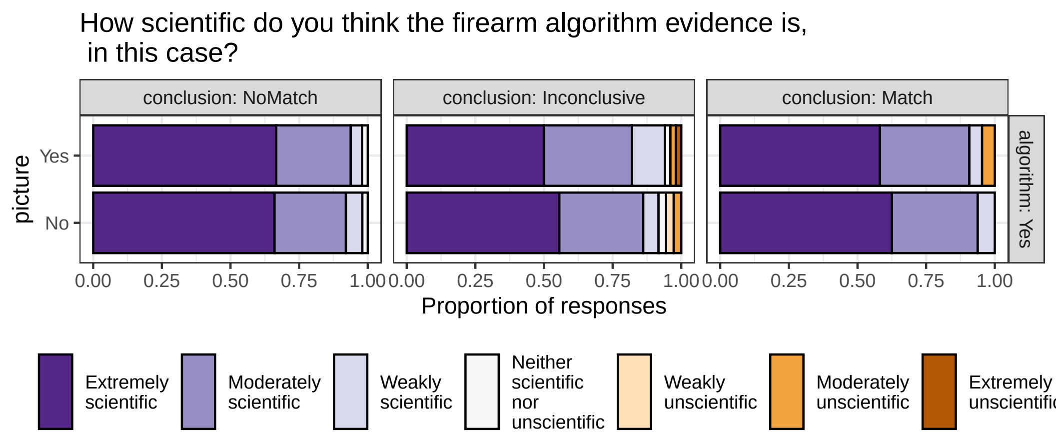

Figure 2.15: Histogram of perceived algorithm scientificity in this case

for those who received the inconclusive condition. Individuals who received the algorithm were more likely to select "Moderately scientific", while those who did not receive the algorithm were more likeley to select "Extremely scientific".

2.3.7 Understanding

Individuals were asked to rate their understanding of both the algorithm and the examiner's personal bullet comparison on a 5-point Likert scale. Most responses ranged from 3 ("I understood about half of the method") to 5 ("I understood everything"), leading to less scale compression than was seen in scales relating to credibility, reliability, and scientificity.

For the firearms examiner's personal comparison, few individuals selected that they understood less than half the method (Figure 2.16). Those who did not receive the algorithm were more likely to select "I understood everything" compared to those who did receive the algorithm, across all conclusions. There was not a discernible difference in responses based on the presence or absence of images.

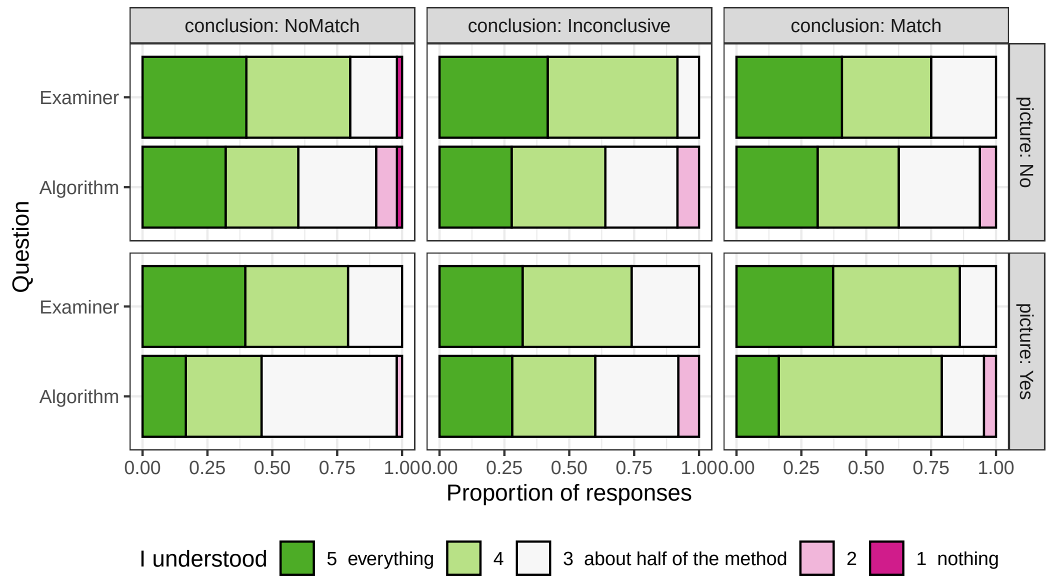

Figure 2.16: Histogram of understanding for the explanation of the firearms examiner

The results for the particpants' understanding of the algorithm description differs based on the presence or absence of images (Figure 2.16). When images are absent, participants selected values from "I understood about half the method" to "I understood everything" with a fairly uniform frequency, with a few participants selecting values in the lower categories. When images were present, however, category selection appeared to relate to conclusion. Those receiving the match condition were more likely to select 4 than other categories, meaning that they felt they understood more than half of the method but didn't understand everything. Those receiving the non-match condition were more likely to select that they understood half of the method compared to other categories. Those with an inconclusive condition had responses fairly evenly distributed across the top three categories, similar to when images were absent. As in the case without images, few individuals indicated that they understood less than half of the method. It is unclear what may have

Table 2.2: Understanding Frequency

	NoMatch	Inconclusive	Match
2.0	1	4	2
3 I understood about half of the method	25	16	7
4.0	14	16	27
5 I understood everything	8	14	7

caused these differences in ratings of understanding.

To investigate this potential relationship further, Table 2.2 was created. Because the counts are so small for the individual cells, the resemblence to a relationship based on conclusion is possibly due to random variation.

2.3.8 Uniqueness

Individuals were asked whether or not they thought that guns left unique markings on discharged bullets and casings after reviewing the testimony. Of the 569 responses, only 16 individuals indicated that they did not think guns left unique markings. These respondents were split across conditions. Thus, respondents in this study overwhelmingly believe in the uniqueness of markings on discharged bullets.

2.3.9 Strength

Individuals were also asked to rate the strength of evidence, both against Richard Cole and against the gun.

When asked about the case against the defendant, shown in Figure 2.17, there was a small difference in terms of the algorithm. When the examiner reached a non-match conclusion, individuals who also received the algorithm were more likely to select the lowest category ("not at all strong") compared

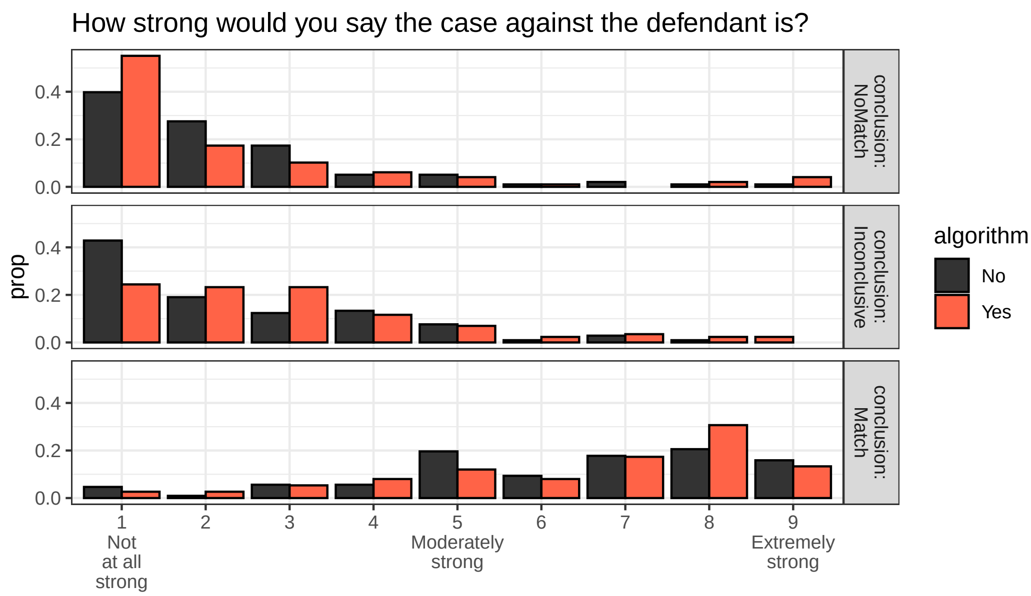

Figure 2.17: Histogram of perceived strength of evidence against the defendant

to those who did not receive the algorithm. Alternatively, in the case of an inconclusive decision, individuals who did not receive the algorithm were more likely to select "not at all strong" compared to those who did receive the algorithm. For the match condition, responses were more widely distributed.

When asked about the strength of evidence against the defendant's gun, there was no real difference between those who received the algorithm and those who did not (2.18). The match condition resulted in a more concentrated distribution at higher strength values than were seen for the strength of evidence against Cole.

In comparing how individuals scored strength of evidence and the probability that they assigned to Cole committing the crime and the gun being present at the crime scene, the results were largely consistent (2.19). In general, the probability assigned increases as the assigned strength of evidence increases, which is to be expected.

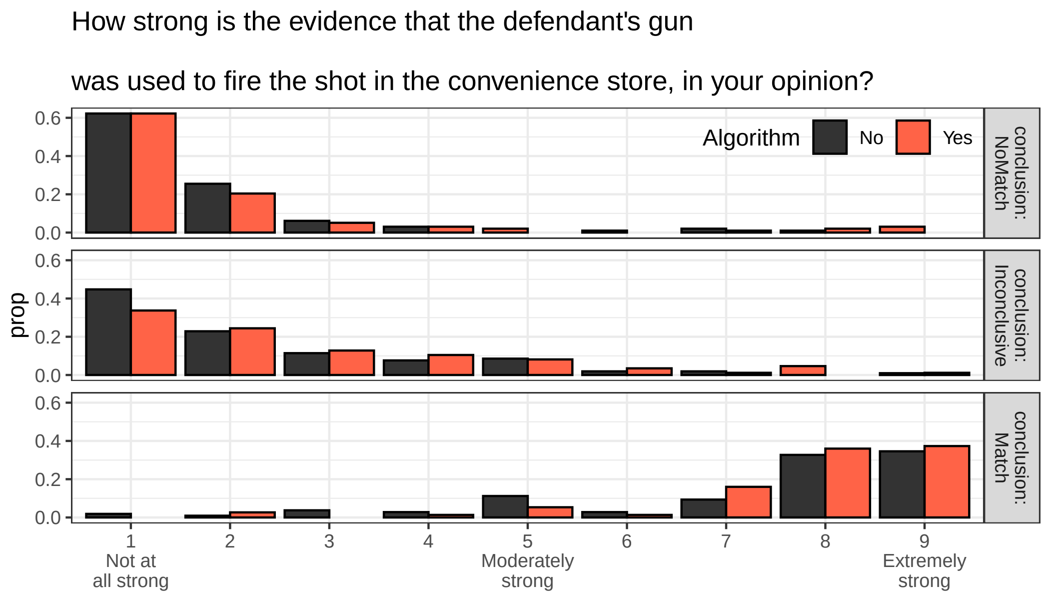

Figure 2.18: Histogram of perceived strength of evidence against the gun

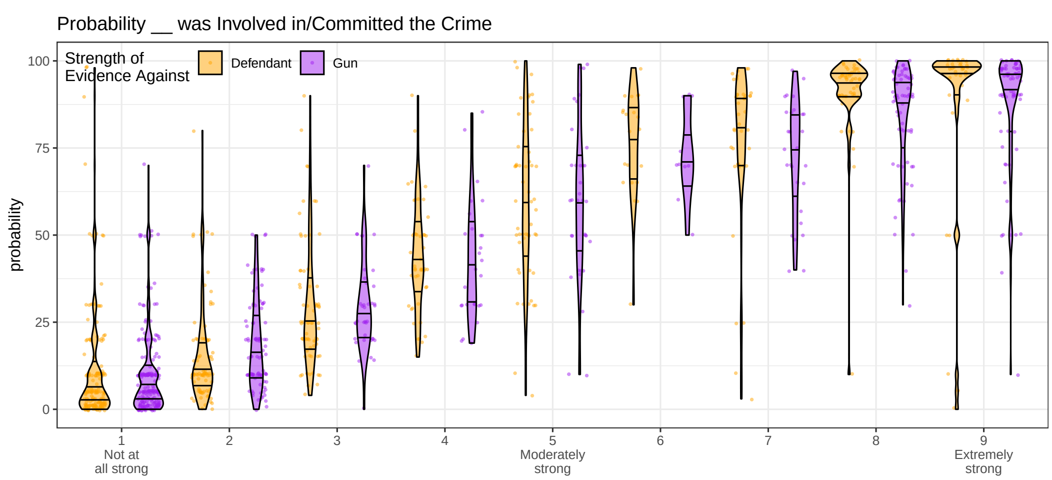

Figure 2.19: Probabilities based on perceived strength of evidence.

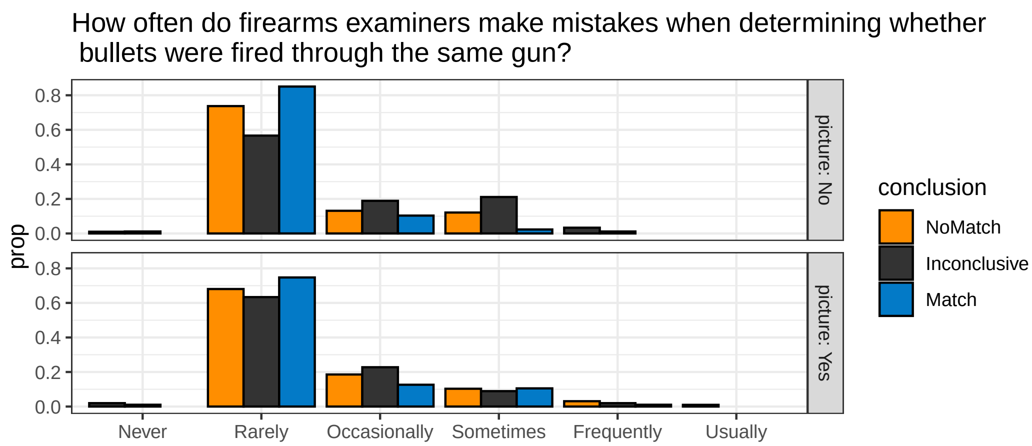

Figure 2.20: Histogram of perceived frequency of mistakes made by firearms examiners

2.3.10 Mistakes

Individuals were asked how often firearms examiners make mistakes when determining whether bullets were fired through the same gun, with a scale from "Never" to "Usually". "Rarely" was by far the most selected category, as shown in Figure 2.20. There does not appear to be a strong relationship between how often individuals felt firearms examiners made mistakes and factors such as conclusion, images, or the algorithm.

2.3.11 Comparing Algorithm Values to Examiner Values

Participants who received the algorithm condition were asked to evaluate their feelings on the reliability, credibility, scientificity, and their understanding of both the algorithm method as well as the traditional bullet analysis method, as discussed in previous sections. Results for both methods were compared on an individual level as well as on a group level. The group level results are represented in histograms, while the individual level results are represented in parallel coordinates plots. Note that these results only reflect the feelings of

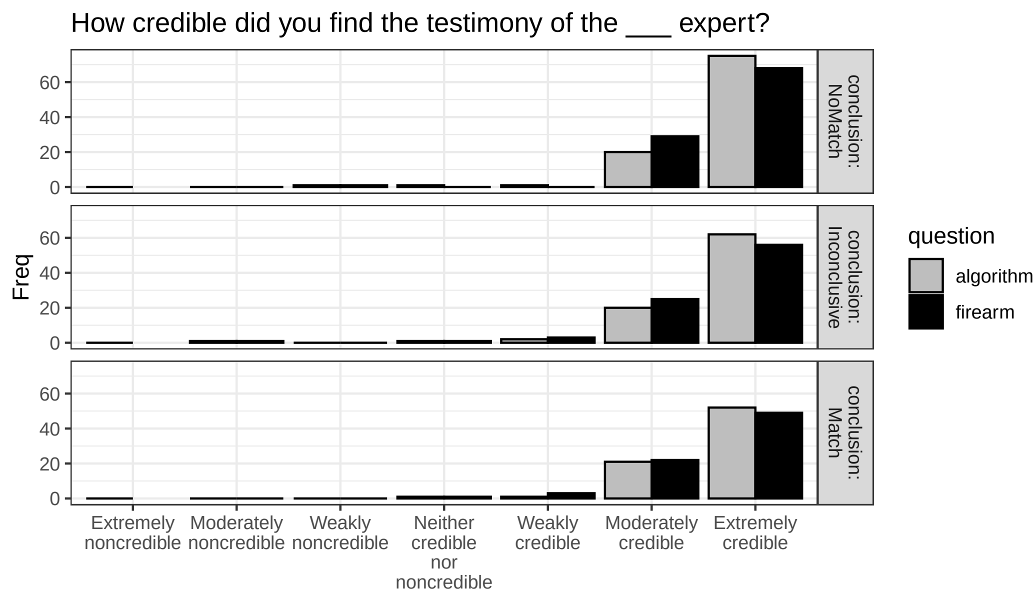

Figure 2.21: Histogram of perceived credibility of experts

individuals who received the algorithm condition.

2.3.11.1 Group Level Results

In terms of credibility, as shown in Figure 2.21, the algorithm and the expert scored fairly similarly, with the algorithm expert resulting in slightly more individuals selecting “Extremely credible” than the firearms expert. As mentioned before, most participants limited their selection to the two highest categories - “Moderately credible” and “Extremely credible”.

For reliability, shown in Figure 2.22, a similar number of individuals selected “Extremely reliable” for both the algorithm evidence and the examiner’s comparison, with a larger proportion of individuals selecting “Extremely reliable” in the match condition when the algorithm is present. There appears to be, however, a difference in the categories of “Moderately reliable” and “Weakly reliable”. Individuals were more likely to select that the algorithm

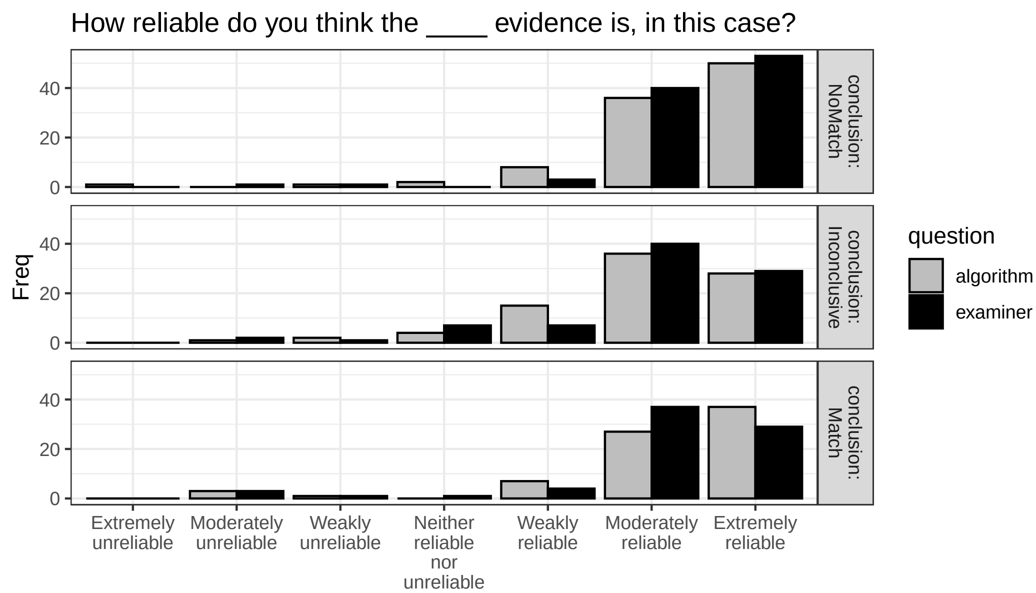

Figure 2.22: Histogram of perceived reliability of evidence

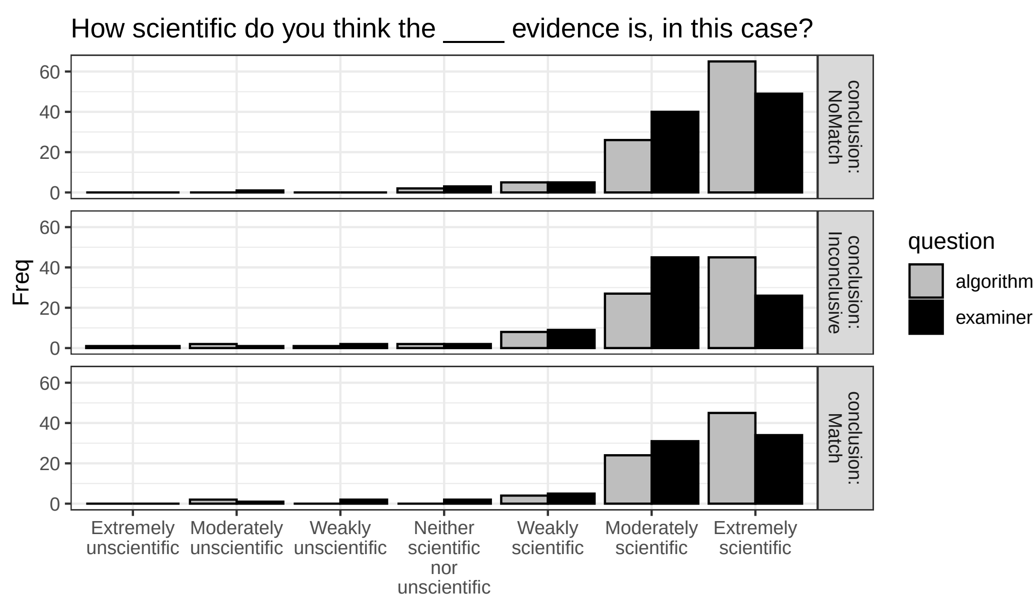

Figure 2.23: Histogram of perceived scientificity of evidence

was "Weakly reliable", while they were less likely to select that the algorithm was "Moderately reliable", compared to the examiner.

Individuals generally saw the algorithm as more scientific than the expert,

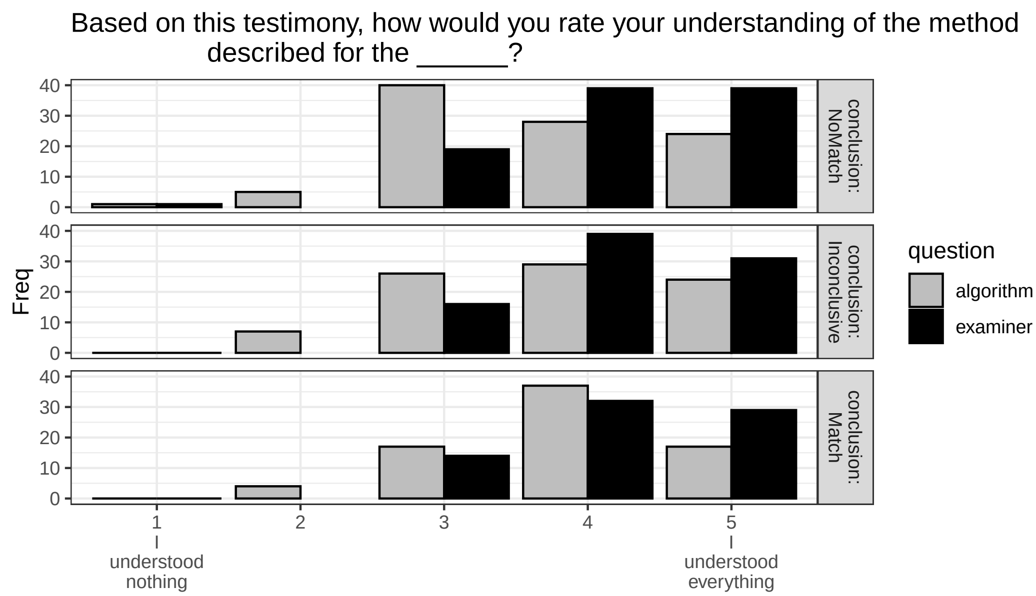

Figure 2.24: Histogram of participants' understanding

as shown in Figure 2.23. They were more likely to select "Extremely scientific" in the case of the algorithm when compared to the expert. Accordingly, they were less likely to select "Moderately scientific" in the case of the algorithm when compared to the examiner. No real difference can be seen in the lower values on the scale, due to few individuals selecting these categories.

Individuals rated their understanding of the examiner's bullet comparison higher than their understanding of the algorithm method, generally speaking (2.24). Participants were more likely to select a 4 or 5 with regards to their understanding of the examiner's comparison, while they were more likely to select a 3 or 4 with regards to their understanding of the algorithm method. While these questions gauge how well participants believe they understand the given concepts, Dunning, Heath, & Suls (2004) indicate that individuals are not unbiased judges of their own understanding.

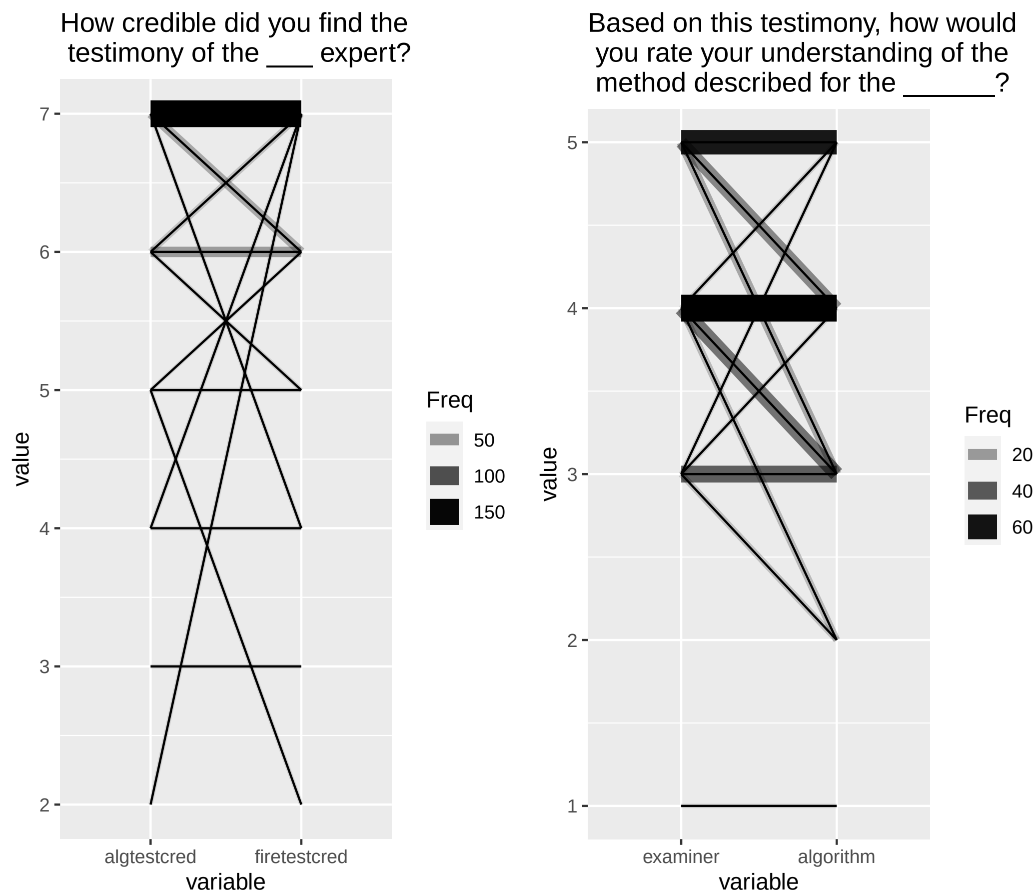

Figure 2.25: Plots of understanding and perceived expert credibility

2.3.11.2 Individual Level Results

Figure 2.25 depicts parallel coordinate plots for participants' ratings of the credibility of the experts, as well as their understanding of the methods described in the testimony. Higher values indicate higher scores in understanding and credibility. These plots map the frequency that individuals selected the shown combination of values for credibility or understanding. In the case of credibility, we can see that most individuals selected the highest category of credibility for both the algorithm and the firearms expert. In the case of understanding, individuals tended to select the two highest categories the most.

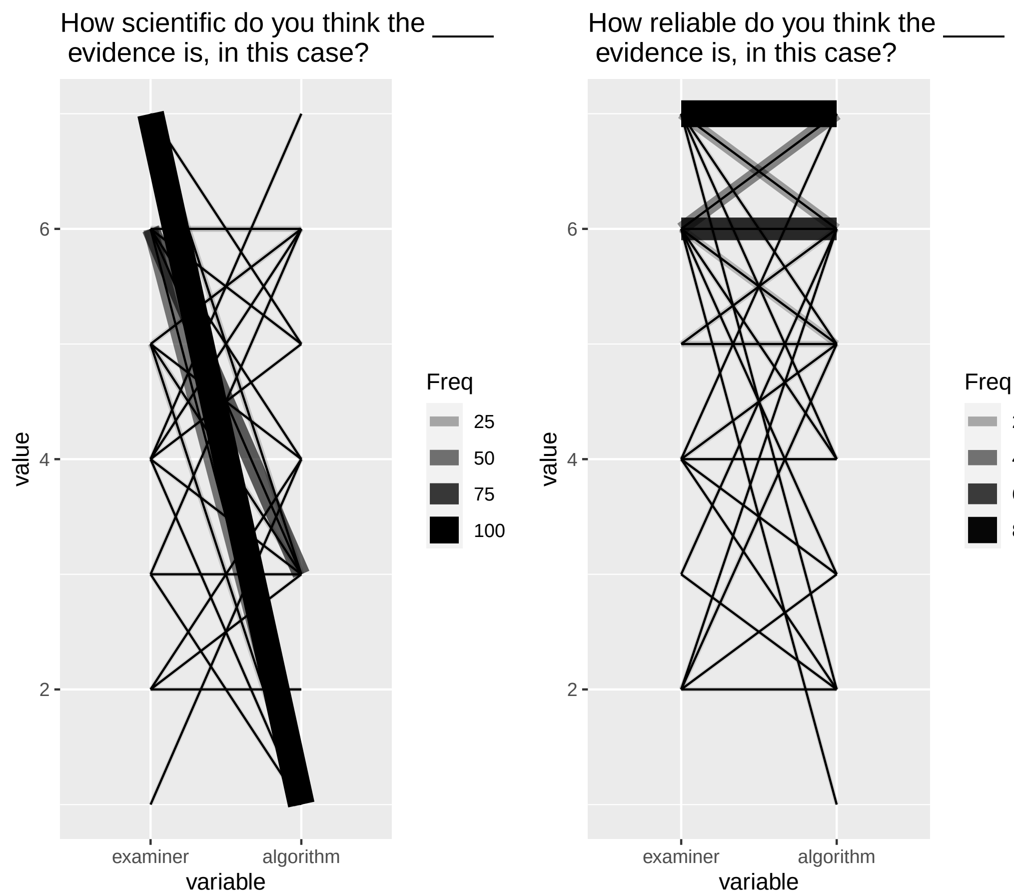

Figure 2.26: Plots of perceived scientificity and reliability of methods

It can also be seen that there is a trend of individuals selecting a category lower for the algorithm compared to what they selected for the examiner by the thicker downward line between categories 4 and 5, as well as between categories 4 and 3. This corresponds to Figure 2.24 in that individuals tend to give higher understanding ratings to the examiner's bullet comparison method than they did for the algorithm.

Figure 2.26 demonstrates the trends for selection for how scientific and reliable individuals felt the evidence was. In terms of how scientific individuals felt the evidence was, it appears that most participants selected the highest category for both the algorithm and the examiner. Some participants selected

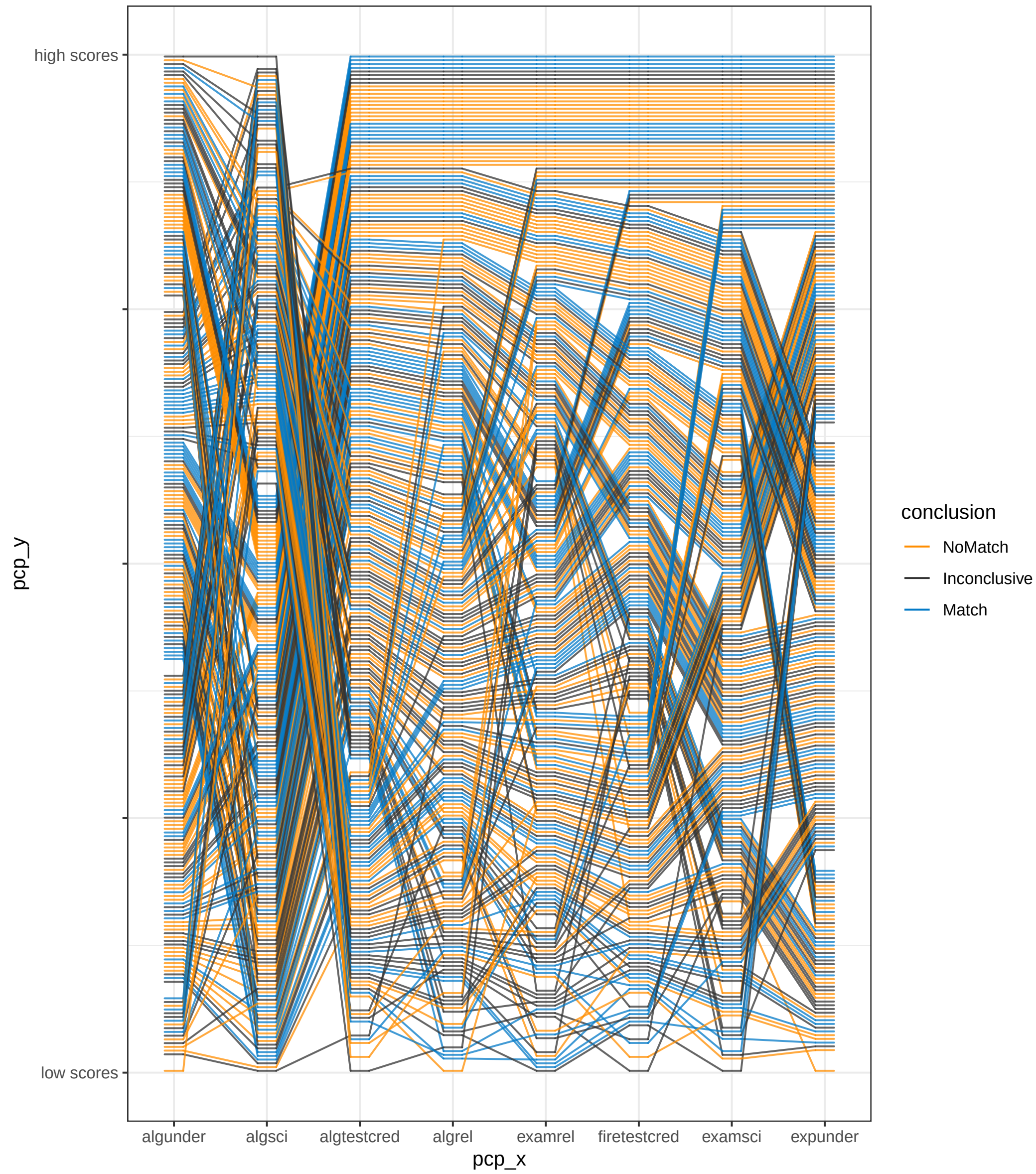

Figure 2.27: Parallel Coordinate Plot for reliability, credibility, scientificity, and understanding

the second highest category for the examiner, and the highest category for the algorithm. Others selected the second highest category in both cases. In terms of reliability, participants tended to choose one of the two highest categories for both the algorithm and the examiner. Some participants switched between the two highest categories for the algorithm or the examiner, in similar numbers.

Figure 2.27 shows individual responses across all of the considered questions. There were some individuals who selected the highest category for responses across the board, while others selected the highest response for all except their understanding of the algorithm. In fact, algorithmic understanding seems to have the least consistent responses, based on the differences in the lines between algorithmic understanding and algorithmic scientificity. These coordinate plots indicate that individuals tended to choose the same categories for the algorithm and the examiner across variables, with most variation between categories resulting from individuals moving up or down a single category. Relatively few individuals changed their response by more than one category, when comparing between the algorithm and the expert. These results generally reflect the trends shown in the histograms in the previous section.

2.4 Discussion

2.4.1 Summary of Results

As can be seen in most graphics, scale compression was an issue with this study. The vast majority of participants selected the two highest categories for questions rating how credible, reliable, and scientific the expert/method was. This corresponds with B. Garrett & Mitchell (2013)'s study of fingerprint match language, where they did not find a significant difference in the participants' feelings of guilt based on various match language. B. Garrett & Mitchell (2013) hypothesized that this may relate to strong feelings reliability for fingerprint evidence, resulting in individuals viewing any match as automatically reliable (without the need for stronger language). In future studies, we will be evaluating different methods of response, aside from Likert scales, to study other formats that may yield less compressed results. People generally seemed to have less faith in inconclusive decisions. They understood the examiner's comparison better than the algorithm comparison, which was expected given the statistical complexity of the algorithm procedure. In general, participants also found the algorithm to be more scientific than the examiner, when presented with both methods. The presence of images did not have a discernible effect in terms of credibility, reliability, or scientificity. Participants' views of the credibility of the experts and the frequency with which firearms examiners make mistakes did not depend on the algorithm, images, or conclusion.

2.4.2 Limitations

Some of the major limitations for this project relate to the format and distribution of the survey material: the pool of participants, the format of the testimony, the limited testimony, and the inability to deliberate. These limitations are also mentioned by B. Garrett et al. (2020).

Participants were limited to those who participate in online survey-taking websites. These participants may not be representative of the US population, due to differences in computer access or use, occupation, or other such factors. These factors may have an effect on study responses. Another issue in representation results from the process of jury selection. Because individuals are not randomly approved for serving on a jury, the jury itself is unlikely to be composed of a representative sample of American citizens. Abramson (2018) argue that selection for jury duty does not result in a representative sample due to some courts' reliance solely on voter registration records for contacting eligible jurors, as well as large non response and non deliverable issues that are more prevalent in African American and Hispanic communities when compared to non-Hispanic White communities.

Testimony was presented in a written format, which is unlike the courtroom setting of spoken testimony, where the jurors can see the experts. However, the use of written testimony allowed for the use of gender-neutral names for the experts (Terry and Adrian), which may be more difficult to achieve in a courtroom or video setting. Potential jurors may also develop views regarding the reliability/credibility of the examiner that are dependent on external factors - such as appearance or speech - rather than based on the testimony itself.

Testimony in this case was limited to only include the firearms evidence. This led to some confusion on the part of the “inconclusive” and “not a match” scenarios, where there did not appear to be relevant evidence for the prosecution. While the goal of this format was to ensure that participants focused on the bullet matching testimony (without the compounding influence of other witnesses or evidence), this would not be representative of courtroom testimony.

In a courtroom setting, jurors are able to deliberate with each other before reaching a conclusion with regards to the case. These deliberations tend to be evidence-driven, as opposed to majority rule (Bornstein & Greene, 2011, p. 65). While the majority decision may be reflected in the final result, some studies suggest that juries tend toward leniency when there is not a definitive majority in a criminal trial (MacCoun & Kerr, 1988). The act of deliberation may result in different evaluations for Likert scale questions of reliability/credibility or strength of evidence than individual thought, even if a difference in guilty verdict rates are not found after deliberation for this simple case style.

There were several typos that were not corrected for approximately the first half of the participants. For all scenarios, the firearms examiner was referred to as Alex Smith in the questions, whereas the name was Terry Smith throughout the testimony. Several participants noted this discrepancy in their feedback on the survey, allowing us to fix the typo before all surveys were completed. There did not appear to be confusion due to the typo on the part of the participants. "Convenience" was also misspelled in one question. For exclusion testimonies, the name "Alex Smith" also occurred in the cross examination. In the case of non-algorithm inconclusive testimonies, the question: "Can you describe the process of obtaining these test fired bullets?" was missing, but the response: "The test-fired bullets came from a test fire of the gun recovered from the traffic stop." remained unchanged. Due to the nature of the online survey, any differences caused by these typos would be confounded with demographics as well as date or time.

2.4.3 Future Research

One of the most notable features of the histograms presented in this research is the overwhelming proportion of respondents that selected the two highest categories, whether it be in terms of reliability, credibility, or scientificity. The concentration of responses in the two highest categories may obscure potential differences in treatments, simply due to the issue of overall trust in the system. It may also effect how well ordered logistic regression models fit the data. This effect may be diminished through the use of jury instruction, and not referring to the firearms examiner or the algorithm witness as experts (as suggested by United States Courts for the Ninth Circuit (2019)).

Efforts are also being made to streamline the testimony into a single document, to prevent confounding typos. Because the written court testimony may be difficult to follow and may give witnesses an air of impartiality, future studies will include images for relevant actors, and color coded speech bubbles to clarify which side the witness is speaking for. We plan to develop a tool that can be used in testing courtroom scenarios, with versatile images for a variety of situations. These proposed changes can be seen in Appendix B.

An additional response to the study that was recorded is participants' note sheets. Many participants copied and pasted portions of the testimony into their note sheets for later reference. We plan to evaluate these note sheets, and develop a method for presenting the written notes alongside the testimony in order to produce a 'heat map' of the text that participants found relevant.

Chapter 3

Text analysis with Transcripts

3.1 Introduction

When conducting studies that rely on participants reading a longer document, researchers may be interested in determining what portions of the document participants find worth noting. This could provide useful information about areas of interest by creating a type of heat map for the document. When the study document consists of multiple pages and notes are recorded sequentially, the problem then becomes twofold: first the participants' notes must be cleaned so that the recorded text corresponds to the current page, then a method must be developed to match the frequency of the participants' notes to the study document.

In order to clean the notes, two different methods are considered and then combined: the First n Character method and the Longest Common Substring method. The First n Character method relies on the concept of edit distance for matching and removing previous notes from sequential study documents. This method was developed specifically for this document comparison. The Longest Common Substring method, on the other hand, searches for common text between two sequential pages to be removed. After the notes are cleaned, sequences of 5 words (collocations) are used to find areas of the testimony that participants focus on. For indirect matches, such as typos, weights are applied to these fuzzy matches to contribute to the total count.

This method was applied to notes taken from a recent study. Dr. Vanderplas and I conducted a study on jury perception, in which participants were asked to read over a testimony transcript and answer some questions related to the scenarios. Participants were supplied with a notepad in order to take notes throughout the testimony. We are interested in comparing this notepad to the given testimony, in order to determine which portions of the testimony the participants found to be worth recording the most. Portions of the testimony that bear the most similarity to the collective notes will be more highlighted than testimony that appears less frequently in the collective notes. The method outlined above resulted in scenario testimonies that indicate where participants copied notes.

3.2 Background

For data cleaning, a previous page's notes are matched to the next page's notes in order to remove duplicate text. This can be thought of as a form of pattern matching. There are plenty of examples of pattern matching in text analysis - such as Baeza-Yates & Gonnet (1992) and Landau & Vishkin (1988). These papers rely on a set pattern to be found in the reference text, with a defined number of differences allowed between the pattern and the text. According th Baeza-Yates & Gonnet (1992), many algorithmic methods have been developed to solve this problem, with allowances for mismatches between the reference text and the pattern. A similar allowance for differences is present in Landau & Vishkin (1988), where differences are defined as either insertions, deletions, or substitutions. This definition of differences is the same definition that is used in computing Levenshtein distance, also known as edit distance (Levenshtein (1966)). Levenshtein considered the issue of insertions, deletions, and substitutions with binary code. This concept has later been extended to include more extensive strings, as demonstrated by Konstantinidis (2005). The edit distance can be used to determine the extent of matching text when comparing two sequential note sheets, in order to identify if a portion of notes should be removed.

One thing that differentiates this problem from other text analysis methods is that there is no set in stone pattern - while the analysis is based on the previous page of notes, individuals do not always keep the previous page of notes the same - some delete parts, and some add new information in the middle. Thus, the goal is to not only find and remove only exact matches of the entire previous note sheet, but to also remove previous notes - whether they be shorter or discontinuous. While evaluating edit distance is useful when finding direct matches, the Longest Common Substring (LCS) method can be used to find pieces of notes that match between pages, so that this repeated text can be removed.

Landau & Vishkin (1988)'s discussion of pattern matching with k differences includes both a dynamic programming approach, as well as the construction of suffix trees. These methods correspond to those proposed for finding the Longest Common Substring between two sequences. This problem has been used to compare biological sequences (Crochemore, Iliopoulos, Langiu,

& Mignosi (2017)). An early solution for finding the longest common substring involves the construction of a suffix tree (Charalampopoulos, Kociumaka, Pissis, & Radoszewski (2021)). The suffix tree method is described by Gusfield (1997); in short, each unique suffix of a string would contribute a new branch to the suffix tree, where leafs consist of the string's terminal character: $ is used avoid recurrence with previous characters in the string. While I have located a package on Github that utilizes the suffix tree for LCS (Lang (2019)), I have been unable to successfully download the package. Another solution implemented by Bielow, Mastrobuoni, & Kempa (2016) in a CRAN R package uses dynamic programming, which involves the construction of a matrix that records the length of a matching string at character i for string 1 (in the ith row), and character j for string 2 (in the jth column). Because the dynamic programming method has an R implementation, it is utilized for this analysis. The comparison between suffix tree and dynamic programming methods will be evaluated in a future analysis.

Once the participants' notes are cleaned, they must be compared to the study transcript. In the realm of non-fixed pattern matching, there are plagiarism recognition methods (such as TurnItIn). In these cases, a portion of a student's text is cross referenced with published or online references, in order to determine if the text was copied. Because this type of correspondence is on a larger level than individual words, collocation analysis is used. While collocations traditionally refer to words that occur more frequently together - such as "white house"(Merriam-Webster (2023)), tools for collocation analysis helpfully provide the frequency of occurrence for strings of a specified length (Schweinberger (2022)). In a reference to algorithmic detection of plagiarism in computer programs, Parker & Hamblen (1989) describe an algorithm that uses the character differences in order to compare how similar programs are. Other algorithms they discuss use code-specific features such as number of operators, lines of comments, and number of various loop statements. Because we are only concerned with the content of the notes, there is little information to be gained from formatting, as there is in plagiarism detection in programs. However, character differences can effectively be used to indicate similarity between participants' notes and the study testimony. This is useful in situation where individuals do not copy the notes directly. In these cases, fuzzy matching can be used to find the testimony collocation that is the most similar to the participants' written notes. This approximate string matching allows for matching strings that do not correspond directly (Gusfield (1997)), which would allow for matching up participants' inexact notes with the closest testimony collocation.

3.3 Methods

3.3.1 Data Cleaning

Table 3.1 is an example of what sequential notes may look like, taken from the second and third pages of a study participant's notes. Because participants are provided with the same continuous notepad throughout the study, the database records each page as a "screenshot" of what is written on their notes when they advance to the next page - this provides cumulative notes.

In order to appropriately clean the notes, the duplicated text ("Richard Cole - has been charted with willfully discharging a firearm in a place of business. This crime is a felony.") needs to be removed from the third page, to

Table 3.1: Participant Note Example

page_count	notes
2	Richard Cole - has been charged with willfully discharging a firearm in a pla
3	Richard Cole - has been charged with willfully discharging a firearm in a pla

leave only notes that correspond to the third page's testimony. The functions used in this data cleaning are included in the `seqstrclean` package (Rogers & VanderPlas, 2024b).

3.3.1.1 First n Character (FNC) Method

In scenarios such as the table above, a straightforward method for note cleaning would be to measure the length of the previous page's notes (n), and compare the previous notes to the first n characters in the current pages notes via edit distance. The edit distance is the number of characters that would need to be changed in order to transform the first string into the second string. This includes insertions, deletions, and substitutions(in the case of the "adist" function from the R Core Team). For example, "Hat" and "Hot" would have an edit distance of 1, because the strings match if the "a" is turned into an "o". Similarly, "Over there" and "there" would have an edit distance of 5, since 5 characters are deleted (the letters in "Over" plus an additional space). If the edit distance is small (indicating a correspondence to the previous page's notes), the first n characters can be removed. If we consider the table is above, it is clear to see how this method can be applied. The page 2 notes perfectly line up with the first two lines in the page 3 notes, resulting in an edit distance of 0 when comparing the first n characters of the third page. Thus, by removing this beginning section, we would be left with the notes that are unique to page 3 - namely, the last two lines.

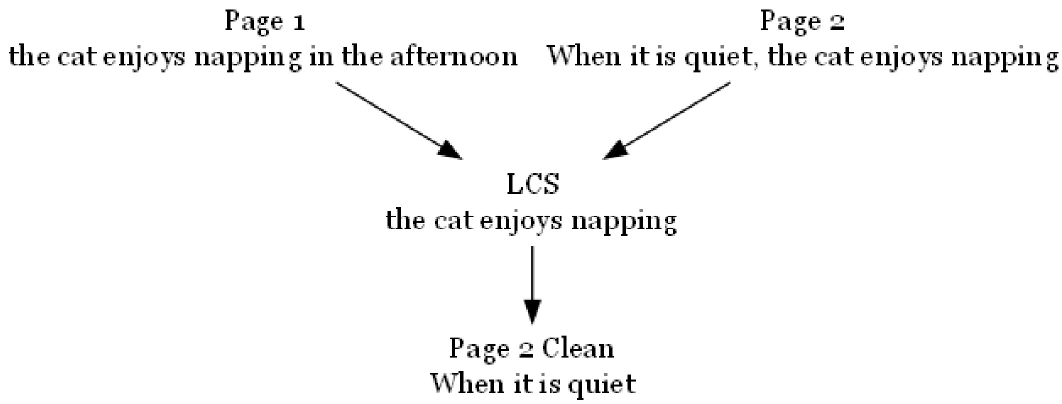

Figure 3.1: Longest Common Substring Diagram

This method works well when participants take notes sequentially. In some instances, however, participants will delete portions of their previous notes, add new notes either before or in the middle of their old notes, or duplicate their old notes. When participants delete a portion of their notes or add new notes before/in the middle of their old notes, the edit distance between the old and new notes could be large. The first n character method would not be able to appropriately clean these notes.

3.3.1.2 Longest Common Substring (LCS) Method

Another method for matching text between two different sets of notes is the Longest Common Substring (LCS). This method searches two strings for the longest sequence of sequential characters that they have in common, which is then returned. For example, in Figure 3.1, the LCS between the two strings is “the cat enjoys napping”. In the process of note cleaning, this would be the string that is removed from the second page of notes, resulting in “When it is quiet” as the cleaned (non-repeated) notes.

The PTXQC package (Bielow et al. (2016)) implements LCS using dynamic programming, as opposed to the suffix tree method (which has not been implemented in CRAN). Their dynamic programming process is described below. This method creates an empty matrix, where the number of rows correspond to the length of the first string, and the number of columns correspond to the length of the second string. Thus, the first cell would correspond to the first character of both strings, and so on. If the characters match and it is the first row or column, then the cell gets a value of 1. If the characters match and it is not the first row or column, the the cell receives the value of the (i-1,j-1) cell plus one. The first string's index for the substring of the longest length is saved. This process is shown in Table 3.2, with two strings: "cabbacced" and "bbacccade". The diagonal of numbers in red indicate the longest substring, beginning with 'b' and ending with 'c' Thus, "bbacc" is identified as the LCS.

Table 3.2: Dynamic Programming for LCS

_	c	a	b	b	a	c	c	e	d
b	0	0	1	1	0	0	0	0	0
b	0	0	1	2	0	0	0	0	0
a	0	1	0	0	3	0	0	0	0
c	1	0	0	0	0	4	1	0	0
c	1	0	0	0	0	1	5	0	0
c	1	0	0	0	0	1	2	0	0
a	0	1	0	0	1	0	0	0	0
d	0	0	0	0	0	0	0	0	1
e	0	0	0	0	0	0	0	0	0

The Longest Common Substring method is able to handle the issues found in the First n Character method, which is demonstrated in Table 3.3. If notes are deleted, the LCS method can identify the substring from the previous notes, despite the large edit distance that would prevent removal in the First n Character method. If new notes are inserted in the middle of previous notes, the First n Character method would compare the Page 1's notes with the red text of the Page 2 notes shown in the second row, resulting in an edit distance that would prevent removal. With the LCS method, the first substring "The cat ran" could be identified and removed, then in a second iteration, the second substring of "up the tree" can also be removed, leaving only the new text. In the case of duplication, the First n Character method would be able to identify the first iteration of text that matches Page 1 and remove it; but it would not be able to identify the second occurrence of the text. As before, the LCS method would be able to identify both instances through two iterations, and remove all Page 1 text.

Table 3.3: LCS Comparison for FNC Issues

Issue	Page 1	Page 2	LCS	Edit Distance
Deletion	The cat ran up the tree	The cat ran	The cat ran	12
Insertion	The cat ran up the tree	The cat ran, chased by a dog, up the tree	(The cat ran)(up the tree)	11

Issue	Page 1	Page 2	LCS	Edit Distance
Duplication	The cat ran up the tree	The cat ran up the tree The cat ran up the tree	(The cat ran up the tree)(The cat ran up the tree)	0

While the LCS method is able to solve the issues related to the First N Character method, it has some issues of its own. If the testimony itself contains duplicate text, such as the text related to swearing in witnesses, the LCS method would remove the new text that corresponds to the later testimony. The other issue with the LCS method is the time required when it is applied to the entire testimony. In the validation study described below, the LCS method took approximately 30 times as long as the FNC method.

3.3.1.3 Hybrid Method

In order to compare the two methods described above, I cleaned a subset of the survey response notes to have a "correct" baseline with which to calculate error rates. This dataset consists of 561 pages of 'notes' (including blanks) with 35 unique participants. 30 participants were randomly selected from the larger dataset, while 5 participants were selected based on demonstrated issues with data cleaning. The 5 selected participants included an individual who deleted almost all of the beginning notes; two individuals who pasted new notes in the middle of old notes; an individual who duplicated notes; and an individual who included the algorithm expert's trial confirmation as well as the forensic scientist's - duplicate text that should be included as the new notes.

For the FNC method, the length of the previous notes is compared to the beginning of the current page's notes. If the edit distance is below a certain threshold, these notes are removed. In this case, I changed the threshold with values of 0 character difference, 5 character difference, and 15 character difference (set as less than 1, less than 6, and less than 16). In the case of LCS, a threshold must be picked for the minimum matching substring length to be considered 'previous notes' and removed. If the threshold is too small, the LCS method can identify words like "the" as matching previous testimony to be removed. If the threshold is too large, the LCS method may be unable to remove substrings when new text is inserted in the middle of the old text. Here, I tried several different character lengths: 40 characters, half the previous note length, a third of the previous note length, and a fourth of the previous note length plus 5 (to compensate for shorter strings).

I also investigated the use of a hybrid method in the hope that the FNC method could be used as a quick way to clean the simplest cases of notes, while the LCS method could be used to clean up the notes that are less clear-cut. In order to determine which observations would need the second cleaning method, I created Figure 3.2.

Here, the yellow circles indicate the FNC method with a 16 character threshold, while the black circles represent the LCS method with a threshold of 1/3 the previous character length. Larger circles indicate a larger amount of error when compared to the hand-cleaned notes. The y axis shows the edit distance computed between the current and previous notes for the FNC method, while the x axis indicates the length of the clean notes. The horizontal

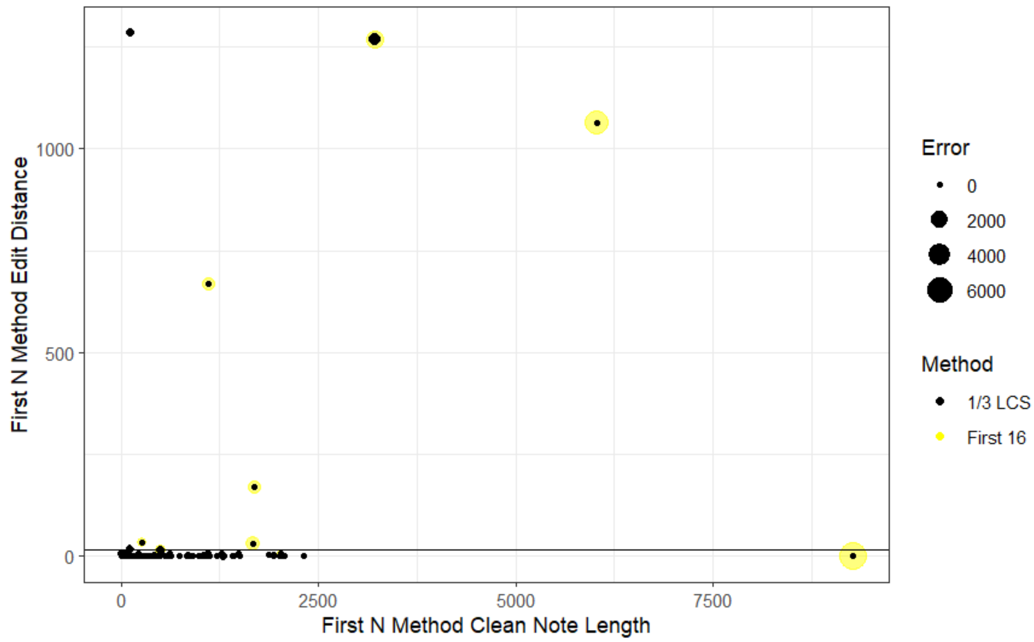

Figure 3.2: Error Comparison

line is the 16 character threshold for the FNC method. As can be seen, most observations are located in the bottom left of the graph, and have relatively small circles. These are notes where the FNC method was effectively applied. In the observations above the threshold, most have a larger error when the FNC method is applied compared to the LCS method, with the exception of one observation in the top left. In that case, the error appeared to be equal for both methods. There is also a larger FNC method error for the observation on the bottom right of the graph. This was a case of duplicate text, resulting in abnormally long notes. This graph appears to show that and edit distance above the threshold of 16 for the FNC method and the length of the cleaned notes can be used as criterion for determining when the LCS method should be applied. I chose to set a threshold of 4 standard deviations above the mean note length for cleaned notes of the current page to constitute "unusually long" notes to apply the LCS method to. I chose 1/3 of the previous notes as the LCS threshold because the mean edit distance to the correct notes was comparable to the 1/4 + 5 character threshold, but it is more conservative for larger notes.

Table 3.4: Comparison of Note Cleaning Methods

Methods	Error	SD	Time (Minutes)
FNC 1 Character	498.965	2769.826	2.4
FNC 6 Character	201.353	1890.009	2.5
FNC 16 Character	36.912	411.252	2.5
LCS 40 Character	6.337	35.497	75.8
LCS 1/2 Previous Notes	7.288	104.692	85.7
LCS 1/3 Previous Notes	3.064	26.769	76.3
LCS 1/4 Previous Notes + 5	2.823	26.137	73.6
Hybrid (FNC 16 and LCS 1/3)	2.135	24.625	3.5

The results of this study are shown in Table 3.4. Notably, the mean edit distance to the correct notes (or the error) is large for the FNC methods, with a high level of variation. However, the computation time is approximately 2.5 minutes. In the case of the LCS method, the error is much lower, but the computation time is above an hour. The hybrid method appears to combine the benefits of both of these methods. The error rate is on par with that of the LCS methods, while the time is only slightly above that of the FNC methods. The hybrid method was therefore implemented for the larger database. The flowchart in Figure 3.3 shows how this hybrid method can be applied.

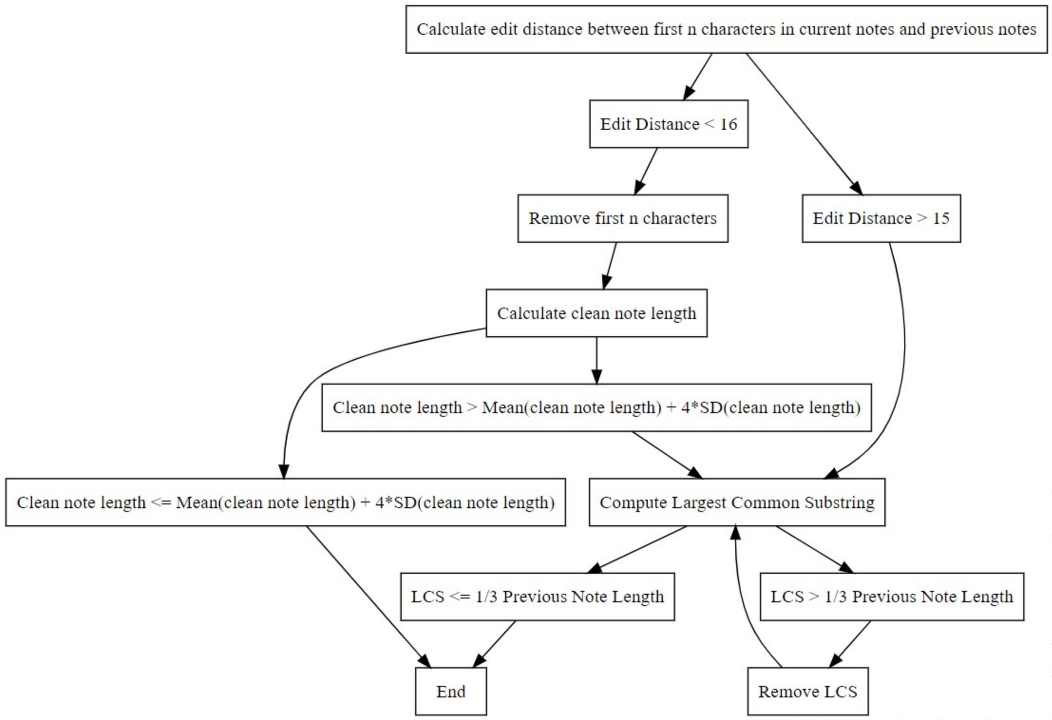

Figure 3.3: Hybrid Flowchart

3.3.2 Note Analysis

3.3.2.1 Collocations

In order to analyze which areas of the text individuals focus on, we must first find a way to compare their notes to the written testimony. One way to do this comparison is through collocation analysis, which uses the frequency of strings of sequentially-appearing words (n-grams) in order to identify words that tend to 'stick together'. For example, in the case of the phrase "The cat ran up the tree", there would be three collocations of length 4: "The cat ran up", "cat ran up the", and "ran up the tree". By matching the collocations that appear in the testimony to a frequency of the collocation from the given notepad, we would be able to get frequency values for all n-grams that occur in the testimony. The functions for creating highlighted text can be found in the package `highlightr` (Rogers & VanderPlas, 2024a).

In setting the size of the collocation, there are two important factors to keep in mind: the frequency with which a phrase appears in the testimony itself, and the number of words in a row that individuals may directly copy from the testimony. If the number of words considered in a collocation is too short, we may run into an issue of phrases occurring multiple times throughout the testimony, without having a way to distinguish which sections are of importance. For example, if we used a collocation of length two, a common phrase in the testimony would be "Richard Cole". Because this phrase occurs so frequently in the testimony, it does not by itself tell us if there are particular portions of the testimony that individuals find important, even if we add weights to calculate the relative frequency. On the other hand, if we use a collocation of length 10, it is unlikely that a large amount of individuals would copy the exact 10-word phrase, which would result in fewer observations. In considering these two issues, we decided on a collocation size of 5. This would be long enough to avoid many common phrases such as "the bullet matching algorithm", but short enough that individuals may copy the phrase down directly. The implementation of collocations used the 'quanteda' package, with guidance from a tutorial by Schweinberger.

N-grams are identified in the testimony, and assigned ordered word numbers (so the first n-gram of length 5 will have words 1-5, the second will have words 2-6, and so on). These are then bound with collocations from the notes based on the sequence of 5 words, in order to assign a frequency to each n-gram. The average is then taken per word out of the possible words that the n-gram could have appeared in (for example, the first word can only appear

collocation <chr>	count <int>
discharging a firearm in a	134
firearm in a place of	133
a firearm in a place	130
in a place of business	129
willfully discharging a firearm in	121
with willfully discharging a firearm	93
charged with willfully discharging a	91
been charged with willfully discharging	76
has been charged with willfully	75
place of business this crime	74

Figure 3.4: Collocation Count for Page 2

in a single n-gram, so its average will be equal to the frequency of the first collocation). When multiple 5-grams appear in the same testimony page, the note frequency is divided by the number of appearances in the testimony in order to account for multiple occurrences. The table below shows the highest frequencies for the second page of the testimony:

"In this case the defendant Richard Cole has been charged with willfully discharging a firearm in a place of business. This crime is a felony. Mr. Cole has pleaded not guilty to the charge. You will now hear a summary of the case. This summary was prepared by an objective court clerk. It describes all of the evidence that was presented at trial."

The highlighted collocations in Figure 3.4 show all of the collocations for the word "willfully" from the testimony above. The frequencies for 'willfully' can be averaged: $\frac{121+93+91+76+75}{5} = 91.2$. This number will correspond to the shading of the word "willfully" in the highlighted testimony of Figure 3.5.

Note that the words have a gradient. This is to ensure a smooth transi-

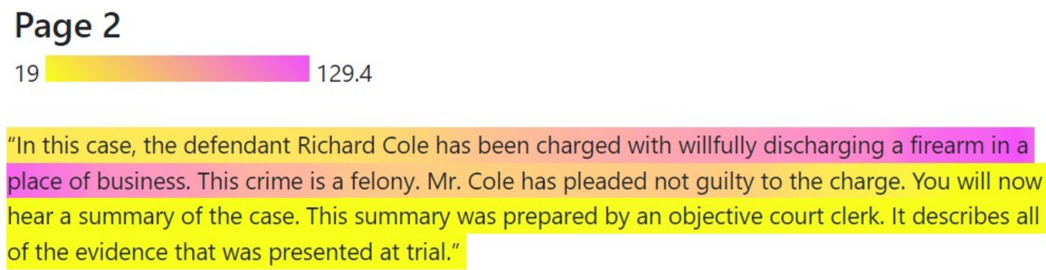

Figure 3.5: Collocation Count for Page 2

tion between words in order to give an overall "highlight" effect, because we are interested in the important phrases in the testimony as opposed to the importance of individual words.

In order to create this effect, we first implemented a graph of the testimony in 'ggplot2'(Wickham (2016)) in order to assign color values to the frequencies. Then we used HTML gradient boxes, where the left color is that of the previous word, while the right color is based on the frequency of the current word. This results in a smooth transition between words.

3.3.2.2 Fuzzy Matching

In order to perform fuzzy matching on the indirect collocations from participants' notes, I used 'stringdist_join' from the 'fuzzyjoin' R package (Robinson (2020)). This function conducts a join with the best matching observations from the second dataset. For example, consider asking young children to spell their birth month. This may result in a dataset like Table 3.5.

Table 3.5: Dataset of misspelled months

Name	Month
Billy	Mach
Jimmy	Apil

Table 3.6: Fuzzy Match by Month

month.x	month.y	name	dist
June	Jun	Benny	1
March	Mach	Billy	1
August	Agust	Bobby	1
May	Mae	Frances	1
February	Febary	Gary	2
August	Agast	Greg	2
April	Apil	Jimmy	1
October	Octobr	Steve	1
February	Febrey	Tammy	3

Name	Month
Frances	Mae
Gary	Febary
Steve	Octobr
Bobby	Agust
Tammy	Febrey
Greg	Agast
Benny	Jun

We may then want to match the children's written months to their correctly spelled counterparts. While 'stringdist_join' will give values for all matches between the two datasets, we can use group_by and slice_min to find the month that is closest to the misspelled value.

In Table 3.6 above, "month.x" is the correctly spelled month, "month.y" is the children's spellings, and "dist" is the edit distance between the two words. This same concept is applied to the notepad dataset. In this case, the transcript of the testimony is considered the "correct" version, and the participants' collocations that do not directly match are considered the misspellings. This method finds the closest transcript collocation to the written collocation, with a maximum edit distance of 99 for collocations to still be considered a match.

Because the intent of the participant is more clear with simple typos (such as a single letter change) than with larger differences (such as the changing of multiple words), the count for these fuzzily matched observations are weighted based on the edit distance. Specifically, a weight of $\frac{1}{dist+0.25}$ is used, where $dist$ represents the edit distance (between 1 and 99). An edit distance of 0 would receive a weight of 1, since fuzzy matching need not be applied. Another factor in the calculation is the number of matches per 'misspelled' collocation. To return to the month example, if an individual were to spell a month "Jur", the edit distance to both "June" and "July" is 2. It is then unclear which month the person was born in, but they most likely meant June or July. Similarly, some collocation notes had the same edit distance for multiple transcript collocations. In these cases, the frequency of the 'misspelled' collocation notes are split evenly between the closest transcript collocations. This results in a total fuzzy frequency per transcript collocation of:

$$\sum_{i=1}^{n} \frac{x_i}{(d_i + 0.25)c_i}$$

where x_i is the count for note collocation i, d_i is the distance between the transcript collocation and the 'misspelled' collocation i, and c_i is the number of transcript collocation matches for note collocation i. This quantity is then added to the count of direct collocation matches calculated in the previous section.

3.3.2.3 Standardization

The testimony analyzed comes from a 2x2x3 factorial design (presence or absence of images, presence or absence of the algorithm, and the conclusion: match, inconclusive, or not a match). Due to this design, the testimony diverges and merges in several places. For clarity, when the testimony corresponds, the frequency for all scenarios are considered together. However, when the testimony diverges, each scenario is considered separately. In order to consistently evaluate the frequencies throughout the testimonies, the final frequency count was standardized by the number of scenarios included. This would result in collocations with a final frequency weight of:

$$(z + \sum_{i=1}^{n} \frac{x_i}{(d_i + 0.25)c_i})\frac{1}{ks}$$

In this case, z is the count of direct matches; $\sum_{i=1}^{n} \frac{x_i}{(d_i+0.25)c_i}$ is the weighted fuzzy match count as defined above; k is the number of times the collocation re-occurs in the transcript page itself; and s is the number of scenarios included in the frequency count.

3.4 Results

3.4.1 The Data

Our study consisted of 559 uniquely recorded participants. Of these 559 participants, 430 recorded something on the notepad. This has resulted in 10,329 pages of notes with at least something recorded. For individuals who clicked through the survey multiple times but submitted a single result, the notes correspond to the closest time less than their submission time for ob-

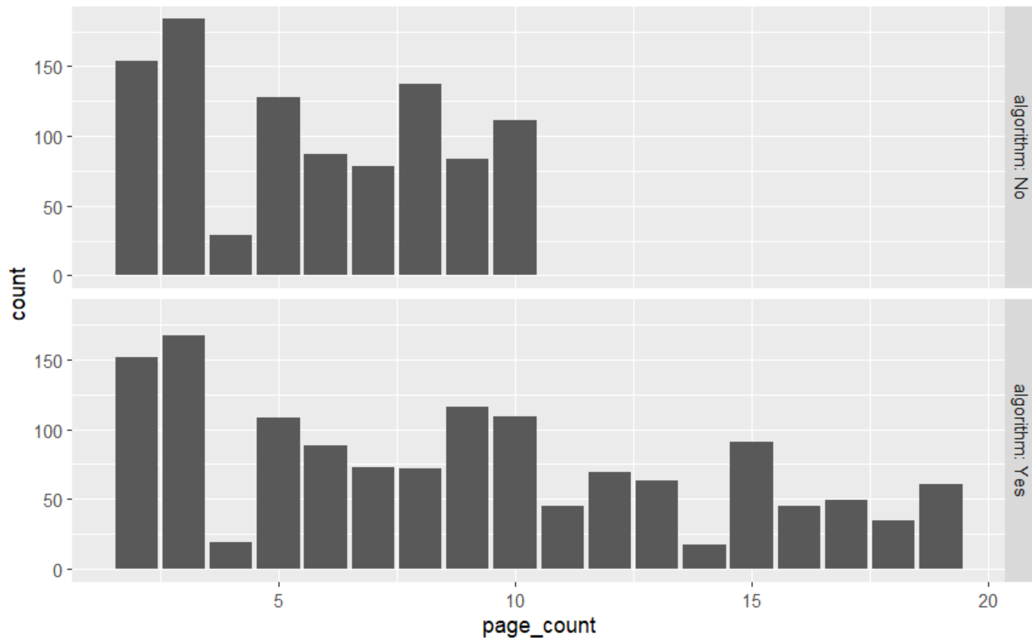

Figure 3.6: Number of Notes Taken Per Page

servation per page number. Note pages that corresponded to the questions (and not the testimony) were removed; this was above page 10 in conditions without the algorithm and page 19 in conditions with the algorithm.

3.4.2 Data Cleaning

On the complete dataset, the hybrid method took a total of 19.33 minutes. This again demonstrates the time benefit of the hybrid method over the Longest Common Substring method - it took less time to clean the complete dataset with the hybrid method than it took to evaluate the reduced dataset with the LCS method. The data cleaning resulted in a total of 2371 note pages with some text recorded. This is much smaller than the uncleaned total of 10,329 note pages, demonstrating a significant reduction in the note size (as is expected when removing the previous page's notes).

Figure 3.6 consists of the number of participants who took notes based on the page number. In both the algorithm and the non-algorithm scenario, more individuals took notes on the first two pages of the testimony compared to the rest of the testimony. However, the plot shows that individuals took notes throughout the testimony.

3.4.3 Final Output

This final note analysis, which includes fuzzy matching, is attached as "Collocation_Comment_Analysis.html". In visually comparing the highlighted transcripts for fuzzy matches to those without fuzzy matching, the results appear to be fairly similar. While the fuzzy matching did increase the frequency number, the overall trends remained the same for the dataset. This can be seen in Table 3.7. The ranking of the collocations remains fairly consistent, aside from differences that can be seen in collocations that had the same non-fuzzy count.

Table 3.7: Table of Collocation Frequencies

collocation	nonfuzzy count	fuzzy count
discharging a firearm in a	134	151.19
firearm in a place of	133	139.43
a firearm in a place	130	137.01
in a place of business	129	136.70
willfully discharging a firearm in	121	136.33
with willfully discharging a firearm	93	107.52
charged with willfully discharging a	91	101.56
been charged with willfully discharging	76	83.24
has been charged with willfully	75	78.75

collocation	nonfuzzy count	fuzzy count
cole has been charged with	74	76.12
a place of business this	74	88.34

The standardized frequency values remain fairly consistent throughout the testimony. Some areas that individuals focused on were the crime and its extent (in terms of injury), the qualifications/process of the firearms examiner, and the results from the analysis. While this type of analysis may allow us to determine the areas that participants copied into their notes, it does not indicate why the participants found this testimony worth copying. This may either indicate areas that participants saw as interesting or confusing, or a mixture of both. The functions for data cleaning and collocation plotting are included in "Comment_Functions.R", and the script for creating the final note analysis is "Collocation Comment Analysis.qmd".

3.5 Discussion

3.5.1 Conclusion

Overall, this process appears to effectively clean and display notes with the desired highlight format. For sequential notes, such as this case, the First N Character method manages to clean the notes in most cases. In the cases where the FNC method is ineffective (when the edit distance is above the threshold or the clean notes are unusually long), the Longest Common Substring method can be applied. This process was demonstrated in a dataset of 35 participants, and showed a significant note reduction on the full dataset.

After the notes are cleaned, collocations can be used to determine what phrases participants decided to copy into their notes. The length of the collocation was chosen to be long enough to avoid commonly repeated phrases, but short enough that participants may directly copy the phrase into their notes. Notes that were not directly copied were included with weights proportional to edit distance through the use of fuzzy matching. The final output qualitatively indicates which portions of testimony participants find relevant to copy.

3.5.2 Future Research

In the future, I also want to find an implementation of suffix trees to more effectively implement the LCS method. Another application of this type of analysis may be used in the evaluation of student note taking.

3.6 Notes

- Participants of the first study were allowed to take notes while reading through the transcripts, which are saved by page number
- We would like to use this to highlight which parts of the testimonies the participants found to be important
- First attempt:
  - ggplot: allows for both a gradient and transparency to be added to words based on their frequency
  - graphing words of the transcript resulted in uneven spacing
  - Relative frequency was computed based on the number of times the word appeared on the page

- Second attempt:
  - Using CSS instead of ggplot: can set gradient through color outputted by ggplot
  - Words can be equally spaced
  - Labels added with gradient scale
  - Change from relative frequency of individual words to average collocation frequency per word (with collocations of length 5) -Include fuzzy matching for indirect matches (typos/skipped words)

Chapter 4

An Investigation of Response Types

4.1 Background

4.1.1 Study 1 and Scale Compression

The results from the initial study found in Chapter 2 call into question the use of Likert response scales when evaluation jury perception of firearms experts, as well as the use of a transcript testimony format.

Responses pertaining to the credibility of the expert, as well as the reliability and scientificity of the evidence, suffered from scale compression when a Likert scale was used - participants indicated overall confidence in credibility, reliability, and scientificity by mainly selecting the two highest categories of each scale. This lack of variation in scale responses makes it difficult to discern potential differences between treatment conditions. Due to this difficulty, we conducted a micro study comparing various response types, in order to determine substitute questions that may be more sensitive to scenario differences. Additional changes include the addition of jury instructions on the part of the judge, instructing members of the jury to treat the firearms examiner as they would any other witness and removing the use of the term “expert”. Additional cross examination testimony with regards to the firearms examiner's inability to specifically tie the defendant to the crime scene is included as well. The transcript for the second study can be found in Appendix B.

In the initial study, some participants were confused about who the witnesses were testifying for. This may be due to the testimony format, which does not clearly identify the speaker with each line, instead using "Q:" and "A:" in most cases, as shown in Appendix B. This lack of visuals for tracking speakers is not representative of the courtroom setting, and may have contributed to the confusion expressed by a participant. The transcript format may also lend an air of impartiality to the witnesses due to the relatively unclear identity of the individual asking the questions. Due to this potential issue, we strove to develop a general tool that can be used in online courtroom studies to provide visual representation of relevant actors, making it easier to track speakers, and with versatility in terms of individual characteristics.

In order to minimize the chance of confounding typos as seen in Study 1, we used one master file with all lines of testimony, labelled by the scenario in which the testimony occurs. Thus, there is no longer multiple files of repeated text. We also use unique identification throughout the database files in the form of Prolific ID's and a random number assigned to the participant instead of relying on unique fingerprints, so the demographics section can more easily be linked to the final results.

4.1.2 Study Visualization

Appendix B shows the characters that have been developed for this study, as well as a screenshot of the study format. These characters were drawn so that the clothes and heads can be interchanged, providing a wide variety of characters for potential scenarios. One difficulty in including drawn figures with realistic skin tones and figures is the influence of perceived race or gender on the participants' judgements. Stanley, Sokol-Hessner, Banaji, & Phelps (2011) found a relationship between implicit racial bias and the perceived trustworthiness of individuals based on images of black and white males. They also found that 80% of participants exhibited pro-white implicit bias. Because of this potential bias introduced by visual figures, we plan to conduct a study in order to determine how these figures are perceived at a later time. For the current study, the same figures are used consistently across all conditions to prevent a confounding effect.

To investigate a which response type may be most informative for this study and to troubleshoot the use of figures and speech bubble format, we conducted a smaller micro study using various response types.

4.2 Methods

4.2.1 Study Format

Participants were presented with the same scenario described in Chapter 2: participants read a trial transcript regarding an attempted convenience store robbery, where the only evidence presented is a bullet comparison between the defendant's gun and a bullet recovered from the scene of the crime (a scenario from B. Garrett et al. (2020)). In this case, however, the only factor that was changed was the conclusion of the firearms examiner: either an indentification or exclusion. In all conditions, the algorithm was absent and there were no images. The testimony largely followed that of Chapter 2, aside from differences in the format and additional testimony described above. In this case, it was also explicitly stated that the testimony did not reflect all evidence presented in the case, because in the exclusion condition there may not be enough evidence to bring the case to trial.

At the end of the testimony, the participants were asked a variety of questions regarding the strength of evidence in the case. Questions of probability, strength of evidence, and decision to convict were repeated from the Chapter 2 study. Participants were asked to evaluate the probability that the defendant committed the crime, both with a visible probability scale (allowing the participants to select the exact probability integer) and with a non-visible scale (only the numbers of 0 and 100 were available on the extremes of the scale). The strength of evidence was a Likert scale with values from "Not at all strong" to "Extremely strong" with nine points. In terms of conviction, participants were reminded of the decision criterion of "beyond a reasonable doubt" when making a decision in a criminal trial, and asked if they would choose to convict.

New questions for this micro study asked individuals to give their opinion of the guilt of the defendant, as well as assessing the chances that the defendant committed the crime, how much they would be willing to bet that the defendant was either innocent or guilty, and their opinion of the defendant. In addition to a question regarding whether or not the participant would choose to convict, we also asked the participants to give their personal opinion on the guilt of the defendant. This provides a second threshold for assessing the strength of evidence, aside from the "beyond a reasonable doubt" standard. Two different questions were asked with regards to the chances that the defendant committed the crime. One was in a multiple choice format, with extreme values of "Impossible to be guilty" and "Certain to be guilty", and intermediate values ranging from "About 1 chance in 10,000" to "About 9,999 chances in 10,000" with denominator values changing by a decimal place for each choice, and a middle value of "1 chance in 2". This format was taken from Thompson & Newman (2015)'s study of DNA, which consisted of larger scaled values in the denominator (up to 1 in 10 million). The second question allowed participants to select both the numerator and denominator: "About _____ chance(s) in _____ that the defendant is (innocent/guilty)", where participants were able to select to express the value as innocence or guilt. In both cases, the numerator had to be less than or equal to the denominator. Individuals who thought that the defendant was guilty were asked how much they were willing to bet that the defendant was guilty, if hypothetically researchers provided them with $50 and they would double their money if they were correct, and vice versa. A final new question was open ended, and asked participants to provide their opinion of the defendant.

We first asked individuals to provide their opinion of the defendant, their conviction decision, and their personal opinion of the guilt of the defendant. All other questions were randomized in a way that guaranteed the two probability questions and the two chance questions were not asked directly following each other.

4.2.2 Prolific

Participants were recruited in a similar manner as Study 1 in terms of the representative sample and self-screened jury requirements through Prolific.

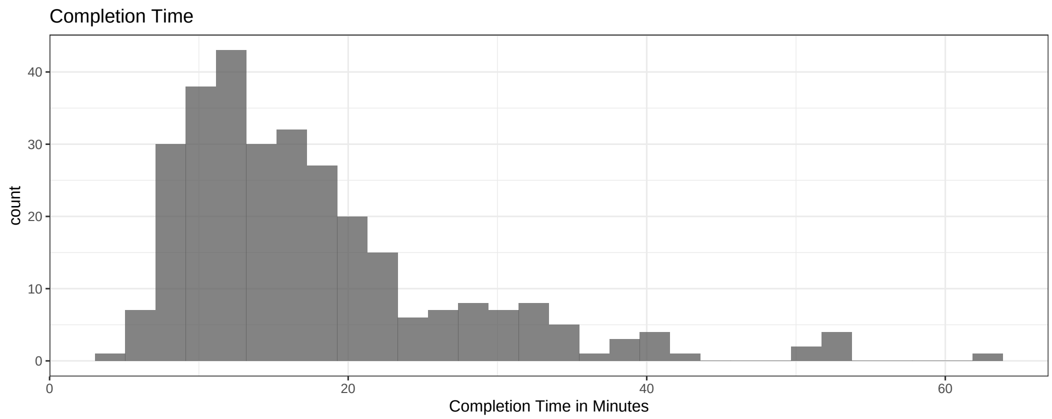

Figure 4.1: Prolific Completion Time

Participants were paid \$4.07 with a median completion time of 15 minutes and 15 seconds according to Prolific, for an average reward of \$16.01 per hour. There were 300 paid participants who completed the survey, 22 individuals who decided to not complete the survey ("returned"), and 8 participants who did not complete the survey before Prolific's cutoff time ("Timed-out"). Figure 4.1 shows the time spent on the survey, according to Prolific. One individual took 3.43 minutes to complete the survey, which is an unusually short amount of time (the next smallest time was 6.02 minutes). While this completion time is within three standard deviations of the mean (mean = 17.67, sd = 9.62) and does not fall within Prolific's criterion for rejection, we do not feel that this participant would have had adequate time to appropriately complete the survey, and have removed them from analysis.

4.3 Results

4.3.1 Participants

Of the 306 completed surveys, 145 participants were men, 156 participants were women, and 5 participants identified as other or non-binary. The median

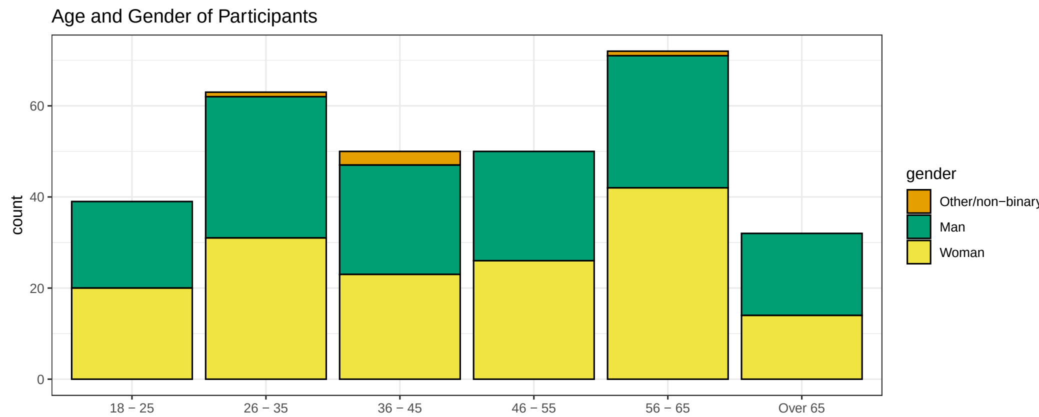

Figure 4.2: Demographic Information

age category was 46 - 55. Age and gender are shown in Figure 4.2. Individuals were asked a single attention check question with regards to the caliber of gun used in the attempted robbery. 298 participants passed the attention check, meaning that only 7 participants failed the attention check, and will not be included in the analysis. There were 147 participants in the identification condition, and 151 participants in the elimination condition who passed the attention check. We adjusted the probability of receiving each condition throughout the survey to ensure categories were relatively equal.

4.3.2 Questions from Study 1

There were some procedural changes made to this study compared to the original study that may influence results; namely, more detailed cross examination and the inclusion of jury instructions. Another significant difference between the two studies is the time frame - notably, in this microstudy, a participant commented that they had recently read an article about the unreliability of firearms evidence. More widespread criticism of firearms examination may lead to lower feelings of reliability.

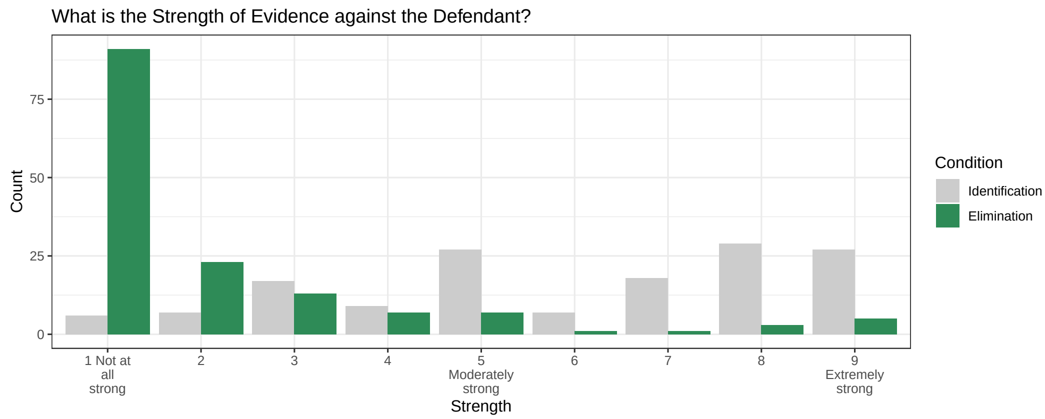

Figure 4.3: Microstudy Strength of Evidence

In both studies, participants are asked if they would choose to convict, given the "beyond a reasonable doubt" threshold. In this study, 54.42% (or 80 out of 147) individuals who received the identification condition chose to convict, while 3.97% (or 6 out of 151) participants who received the elimination condition chose to convict. The conviction percentage for the identification condition in this study is slightly lower than the comparable condition in the original study (without the use of the algorithm and images): 61.82 (or 34 out of 55). However, there is not a significant difference between studies (p-value 0.43). None of the 49 individuals in the original study who received the elimination condition without the use of the algorithm or images chose to convict.

Figure 4.3 shows participant responses to the strength of evidence in this study. As can be seen, those in the elimination category tended to choose the smallest value for the strength of evidence ("Not at all strong"), while in the case of the identification condition, individuals tended to distribute their views of the strength of evidence more evenly. This graph resembles the strength of evidence results from the initial study, shown in Figure 2.17. While not

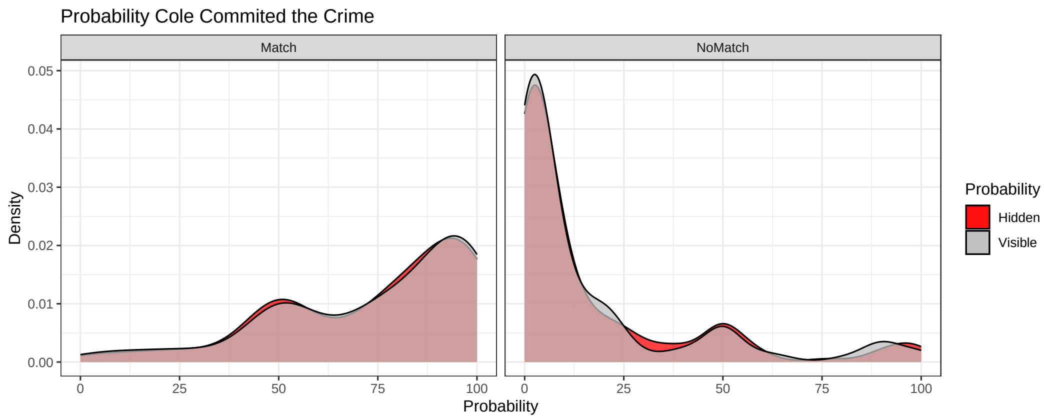

Figure 4.4: Probability Cole Committed Crime

as dramatic as the scale compression for questions of reliability, credibility, and scientificity, the elimination results for strength of evidence do appear to show a scale limitation in the way that individuals tended to select the lowest category.

Figure 4.4 demonstrates the participants' selected probabilities that the defendant committed the crime. As in the case of the strength of evidence, the graph resembles the probability graph found in the initial study (Figure 2.6), where there is a higher peak of extreme values for the elimination conditions than for the identification condition. When using a t-test to compare the mean visible probabilities for the identification and elimination condition to those comparable conditions of the initial study, there is not a significant difference for the identification condition, but is a significant difference in the elimination condition (p-values of 0.15 and 0.01, respectively). The estimated mean is higher in this follow up study (16.57) than the initial study (9.98) in the elimination condition. For the identification condition, the estimated probabilities are 74.52 for the follow-up study and 79.78 for the initial study. In this study, there does not appear to be a difference in the density curves based on the visibility of the probability scale.

4.3.3 New Study Questions

In addition to asking participants if they would choose to convict, participants were also asked about their opinion of the guilt of the defendant. In this case, 74.15% (or 109 out of 147) individuals who received the identification condition thought the defendant was guilty, while 3.97% (or 6 out of 151) participants who received the elimination condition thought the defendant was guilty. Figure 4.5 shows the comparison between the participant's decision to convict and their personal opinion. Approximately half of the participant in the identification condition who chose not to convict thought the defendant was in fact guilty. This indicates that participants have different thresholds for their personal opinion of guilt compared to the "beyond a reasonable doubt" threshold. Of the 80 individuals who chose to convict in the identification condition, 5 participants thought the defendant was in fact innocent. This discrepancy may be due to participants reversing the strength of the thresholds - they feel that the evidence is strong enough to convict, but are not wholly convinced.

Figure 4.6 indicates how much participants said they would be willing to bet that the defendant was either guilty or innocent, if provided with $50. If the participant indicated that they thought the defendant was innocent, they were asked how much they would be willing to bet that the defendant was innocent, and vice versa. This figure indicates that most people who thought Cole was innocent in the elimination condition were willing to bet the full amount (84 out of 141 participants). It also appears that people tended to

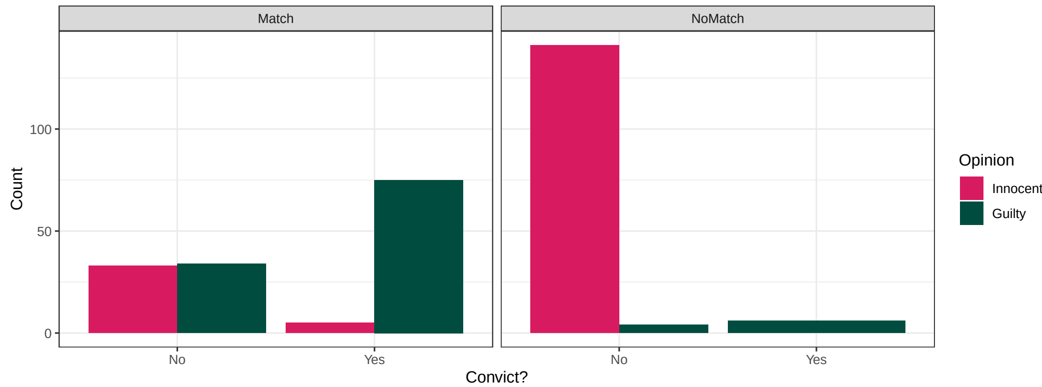

Figure 4.5: Comparison of opinions of guilt and choice to convict

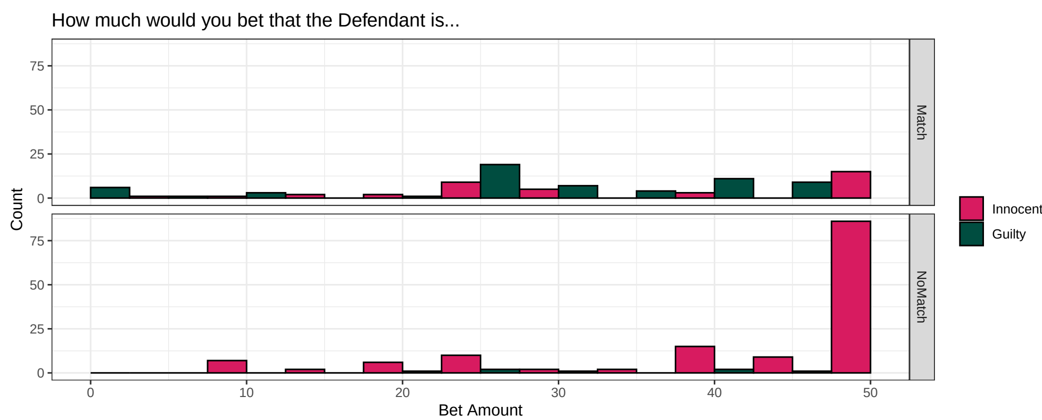

Figure 4.6: If the researchers provided 50 dollars, how much would you be willing to bet?

select values multiples of 5 (283 out of 298, with 8 additional individuals selecting 0). Those in the identification condition selected less extreme values (for both those who thought the defendant was guilty and those who thought the defendant was innocent) than what is seen in those with the elimination condition who thought the defendant was innocent. In this way, the betting response is similar both to the strength of evidence response and the probability of committing the crime response.

The remaining questions relate to the chance that the defendant committed the crime. One question, shown in Figure 4.7, allowed participants to select the chance that the defendant committed the crime from a multiple choice scale. Because the scale includes both extreme values that favor innocence and guilt, this question remained the same regardless of the participant's opinion on the guilt of the defendant. This scale does not provide a linear distance between intervals, but instead changes by multiples of 10 in the denominator (ex. one category is 1 in 10, and the next category is 1 in 100). The exceptions are the endpoints, which are "Impossible to be guilty" and "Certain to be guilty", as well as the midpoint of 1 chance in 2. In this case, the scale in the elimination condition does not encounter the ceiling or floor effect that has been seen in previous scales, as participants did not overwhelmingly select the lowest value. Instead, participants are distributed mainly throughout the lower half of the scale, while those in the match condition tended to be a little closer to the center. In both cases, participants are not crowded into a small number of categories. Thus, the multiple choice chance scale appears to have less scale compression than seen previously in the other response types. This wider distribution may be the result of decompressing the end points - individuals have a variety of values to select that reflect their judgement of a low probability that the defendant committed the crime, or a low strength of evidence.

A final question asks individuals to provide a numerical chance that the defendant is either innocent or guilty, depending on the participants' choice. Their responses were limited so that the numerator was smaller than the denominator, resulting in a range of values from 0 to 1, in most cases. There were 3 responses with values greater than 1 that will not be considered in this

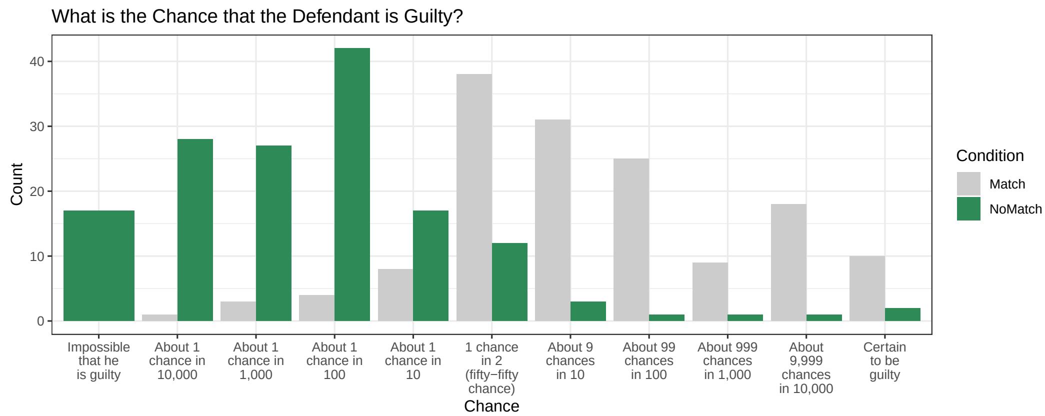

Figure 4.7: Multiple Choice Chance

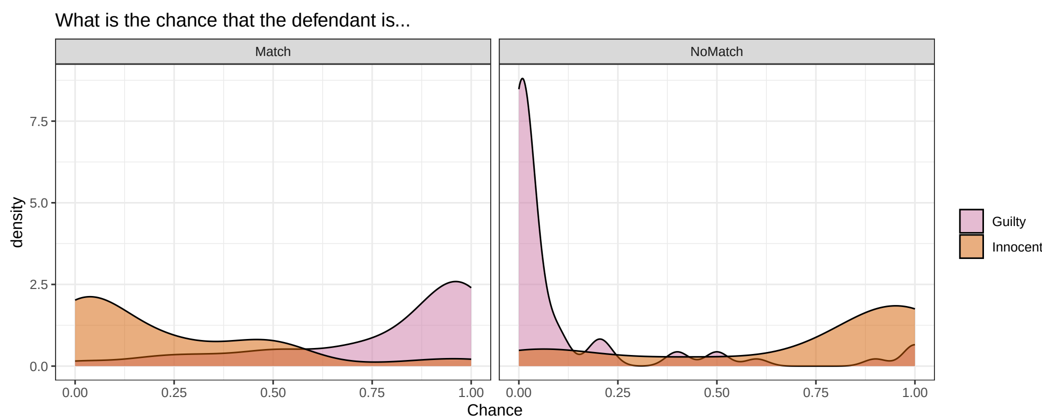

Figure 4.8: Free Response Chance

analysis. These results are shown in Figure 4.8. As seen in previous graphs, in the case of the elimination condition, individuals gave small values for the chance that the defendant had in fact committed the crime, resulting in a sharp peak. Alternatively, individuals were less extreme when they expressed their opinion as the chance that the defendant did not commit the crime. In the case of the identification condition, those who expressed their opinions as either guilt or innocence gave similar results, resulting in symmetry between the two distributions. As shown in Figure 4.9, those who thought the defendant was innocent were more likely to favor inputting chance values in terms of

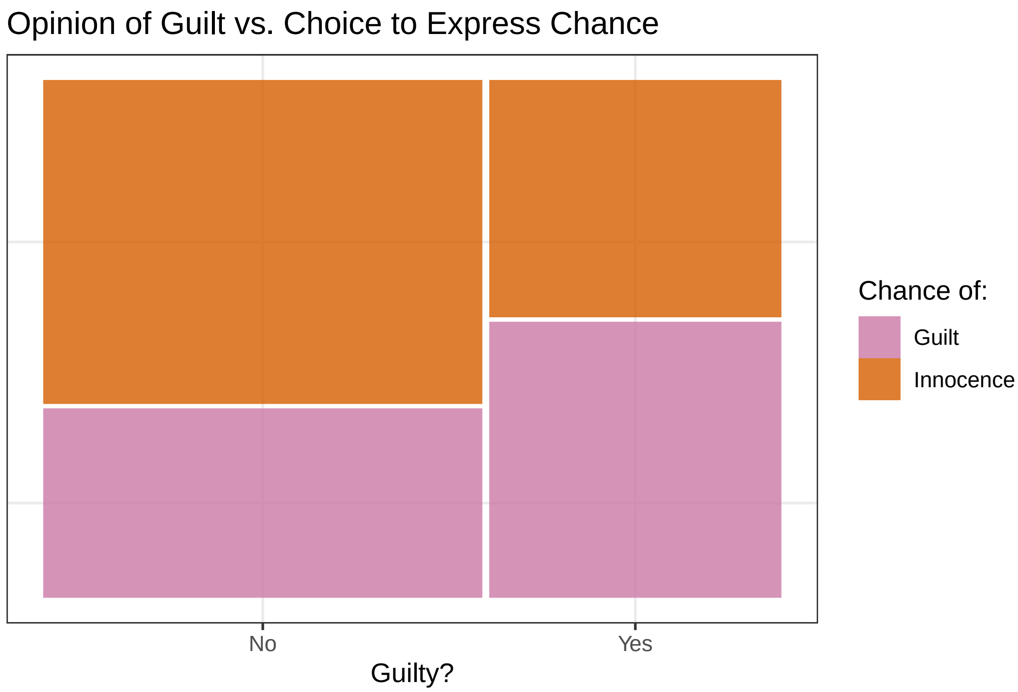

Figure 4.9: Participants who chose to express chance in terms of guilt or innocence, based on their opinion of the guilt of the defendant.

innocence, while those who thought the defendant was guilty showed no clear preference. The default value of the question is “innocent”, with the option of switching to “guilty”.

4.3.4 Scale Comparison

4.3.4.1 Numeric and Multiple Choice Chance Comparison

Consistency across response types is another important aspect of this study. If different question types result in responses that are inconsistent, it would be difficult to tell which questions truly capture the attitudes of the participants, in order to most accurately answer the research questions. As mentioned in the Chapter 1, there have been studies to suggest that individuals may struggle with the interpretation of chance scales. Questions of how

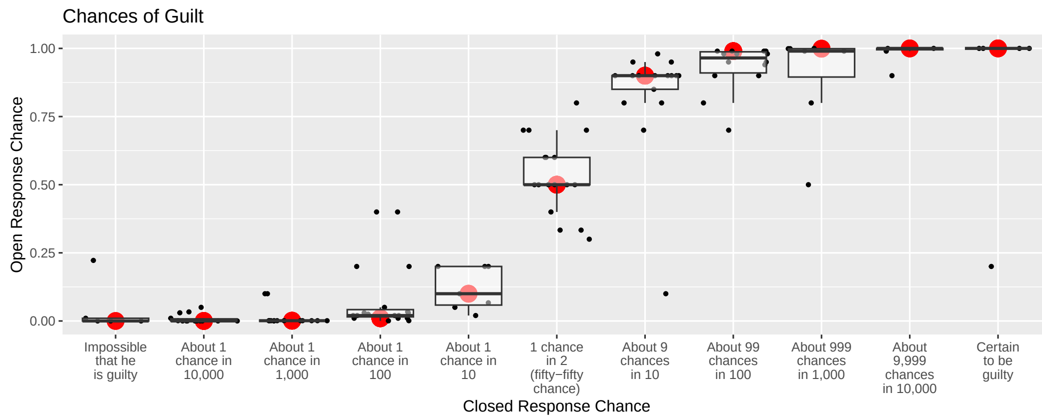

Figure 4.10: Chance of Guilt Comparison

much a participant is willing to bet may also depend on their personal feel for risk, and betting hypothetical money may have different results than betting real money. Because individuals may be influenced by the order of the questions, the order was randomized and recorded.

Figure 4.10 shows the comparison of the multiple choice chance responses to the numeric chance responses, in the case that the participants chose to express the numeric chance in terms of guilt. The red dots represent the actual value corresponding to their selection of the multiple choice chance (for example, the red dot for “About 1 chance in 10” is located at the y-value of 0.10). This allows for comparison on the consistency between the multiple choice and the numeric scales. For values of “1 chance in 2”, “About 1 chance in 10”, and “About 9 chances in 10”, the responses seem fairly consistent - however, it is difficult to tell if these values are consistent for more extreme values, because they are compressed on the linear scale.

Figure 4.11 demonstrates the lower half of the multiple choice scale, when the x axis is transformed by log 10. The lines indicate the numerical equivalent to the multiple choice wording, including a black line for the unpictured

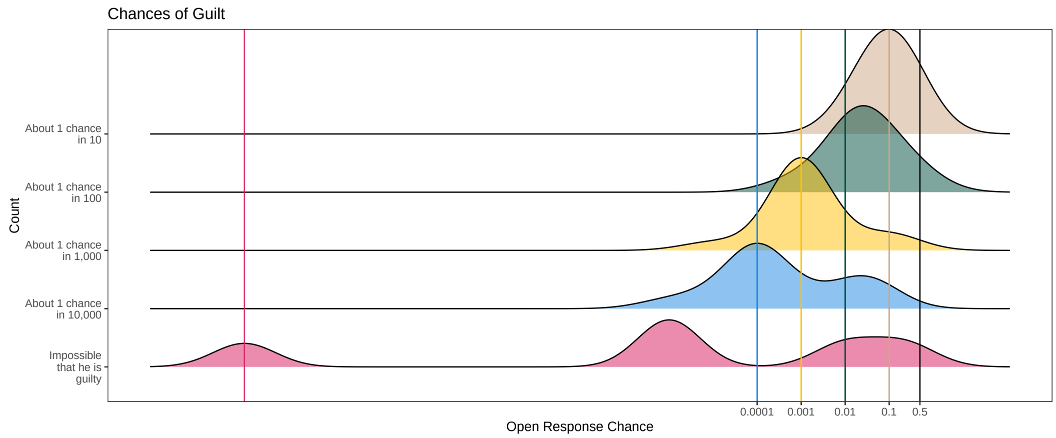

Figure 4.11: Guilt Chance Comparison Log 10 Scale

category of "1 chance in 2 (fifty-fifty chance)". From this transformed scale, there still appears to be some consistency between when participants choose their own chance numerically and when they were offered a multiple choice. This can be seen in the graph when the observations are inside the boundaries that align with its multiple choice category - meaning that it is not beyond the category. However, many individuals did not show consistent choices between scales - particularly in the "About 1 chance in 10,000" condition and the "About 1 chance in 100" condition, where several numerical choices would have better aligned with different selections in the multiple choice section, as demonstrated by the closeness of several observations to other lines.

Figure 4.12 demonstrates the upper half of the multiple choice scale. In order to visualize these compressed values, the numerical chance selected by participants was subtracted from 1 and a log 10 transformation was used on the x axis. Thus, values can be interpreted as the chance that the defendant was innocent, even though participants chose to express their values in terms of guilt. The lines indicate the numerical equivalent to the multiple choice wording, if expressed in terms of innocence. While those selecting "About 9

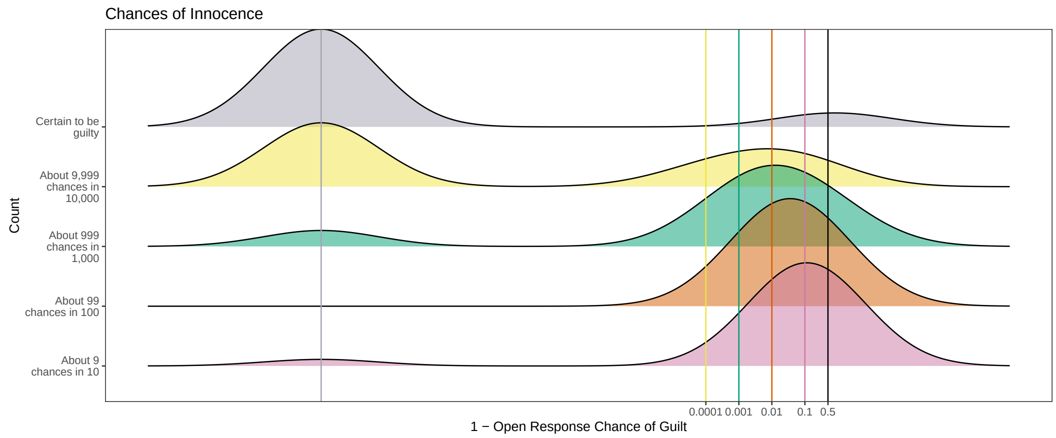

Figure 4.12: Guilt Chance Comparison Log 10 Scale, where values were subtracted from 1

chances in 10" were fairly consistent with the expected value, there is a fair amount of inconsistency between participants' multiple choice selection and their numerical values for all other categories. Those who selected "Certain to be guilty" tended to choose guilt values of 1 (or, alternatively, chance of innocence values of 0).

This same procedure can be repeated for those who thought the defendant was guilty, as shown in Figure 4.13. In this case, because individuals chose to supply the chance that the defendant did not commit the crime, the multiple choice chance indicators were reversed by subtracting the given value from 1. There appears to be some confusion on the question wording in this case. as demonstrated by numerous responses in the "About 1 chance in 1,000" and "About 1 chance in 100" categories that appear as low chance values - indicating that individuals selected a low chance of innocence when given the numerical format, but a high chance of innocence when given the multiple choice. Most median numeric values on the left half of the multiple choice scale do not align with the translated value from the multiple choice scale.

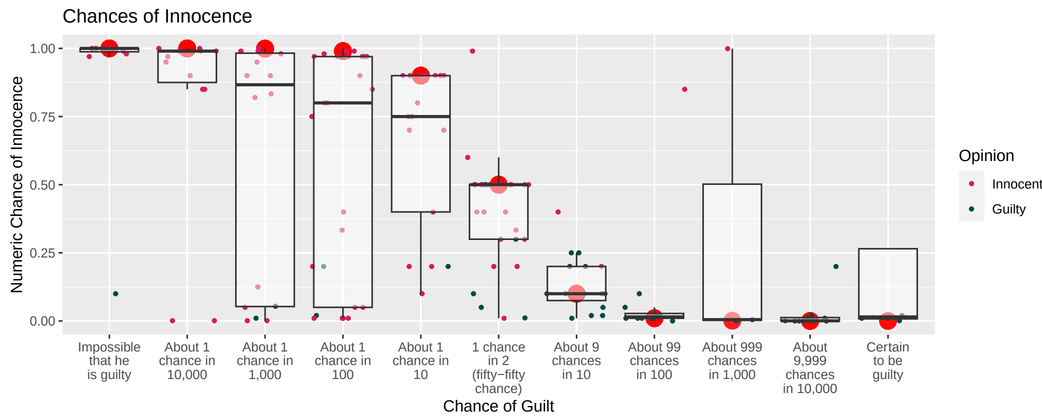

Figure 4.13: Chance of Innocence Comparison

The reduced consistency seen in these graphs may related to the change in the question wording, where the multiple choice question considers the chance of guilt, while their numeric chance considered the chance of innocence. Most individuals who had inconsistent responses between the numeric and multiple choice chance question thought that the defendant was innocent, indicating that the multiple choice scale is more consistent with their beliefs.

This appearance confusion is reinforced in Figure 4.14, displaying the values corresponding to the lower half of the multiple choice scale. As in Figure 4.12, I have reversed the numeric values so a log transformation can be used to better visualize the data. The only multiple choice value that shows some consistency with the numeric counterpoints is "About 1 chance in 10", while for all other multiple choice options participants tended to provide a lower chance of numerical innocence than their multiple choice selection would indicate (shown by values further right on the scale). In two cases, for those who selected "About 1 chance in 100" and "About 1 chance in 1,000" of guilt, the most popular category is above a fifty-fifty chance, indicating confusion on the scale. Those who selected "Impossible that he is guilty" also tended

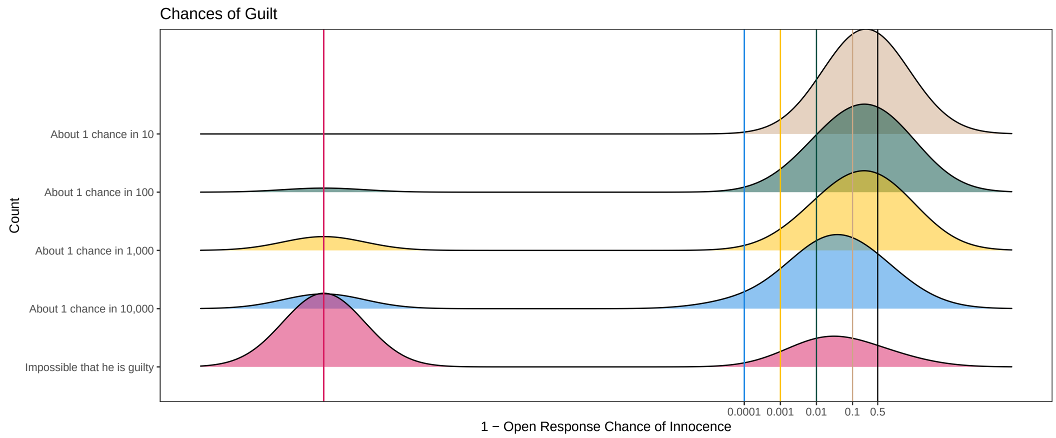

Figure 4.14: Innocence Chance Comparison Log 10 Scale, where values were subtracted from 1

to select chance of guilt values at 0, also demonstrating consistency (although several individuals also chose "Impossible that he is guilty" and assigned higher chances of guilt).

Interestingly, this inconsistency did not hold as strongly for the upper part of the multiple choice chance scale, shown in Figure 4.15. Here, lines indicate the appropriate level chance of innocence corresponding to the multiple choice scale of guilt. In this case, the first two categories ("About 9 out of 10" and "About 99 out of 100") correspond quite well between the multiple choice answer and the numeric counterpart. Although this consistency is not as present in the other categories, they are closer to the ballpark than what is shown in Figure 4.14.

4.3.4.2 Probability and Chance Scale Comparison

The comparison of multiple choice chance and visible probability scales is shown in Figure 4.16. In the case of the probabilities, individuals were only able to select integers between 0 and 100, meaning that this scale would

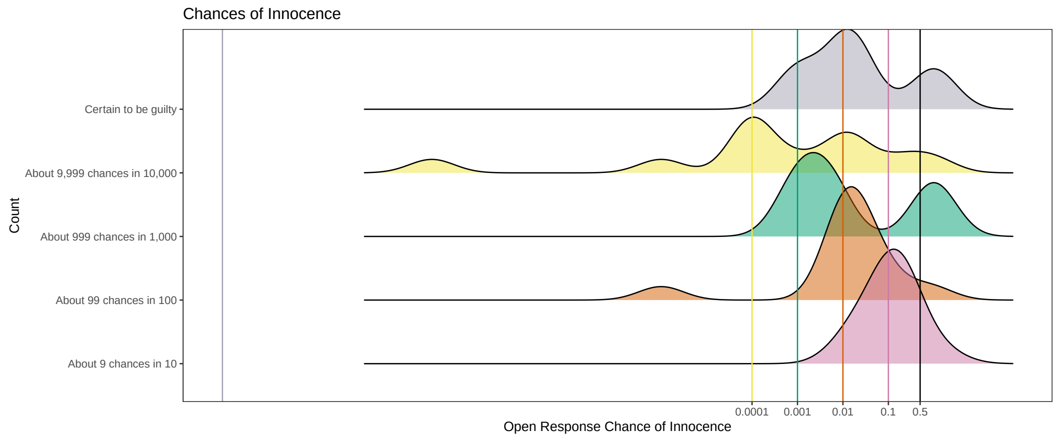

Figure 4.15: Innocence Chance Comparison Log 10 Scale

not translate to the more extreme values of the multiple choice chance scale (outside of the values of “About 1 in 100” and “About 99 in 100”). While there is some discrepancy between choice selection, particularly in participants who selected a lower chance that the defendant is guilty, responses seem to overall be consistent. Probability values tend toward the middle, pulling away from the extreme values on the probability scale that would correspond to their multiple choice chance answers. Those who selected high probability values but low multiple choice chance values expressed that their opinion was that the defendant was guilty. This indicates that their selected probability value is more consistent with their opinion than the multiple choice chance value. In this case, it seems that a few individuals may have found the use of the chance scale to be more confusing than the probability scale.

Figure 4.17 shows the log-transformed comparison of probability values and the participant’s multiple choice chance decision. If participants were consistent in their choices of chance category and visible probability, we would expect that individuals selecting “About 1 chance in 1,000” or lower would exclusively select probability of guilt values of 1% or 0%, because 1% corresponds

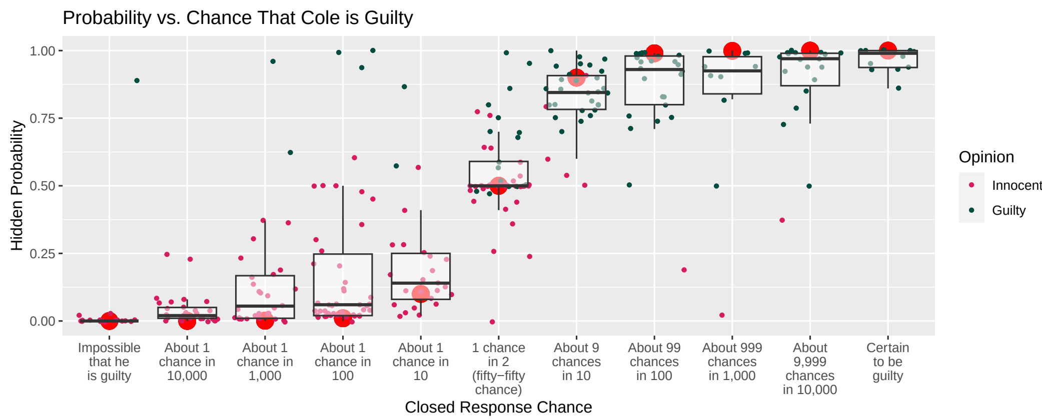

Figure 4.16: Probability and Chance Comparison

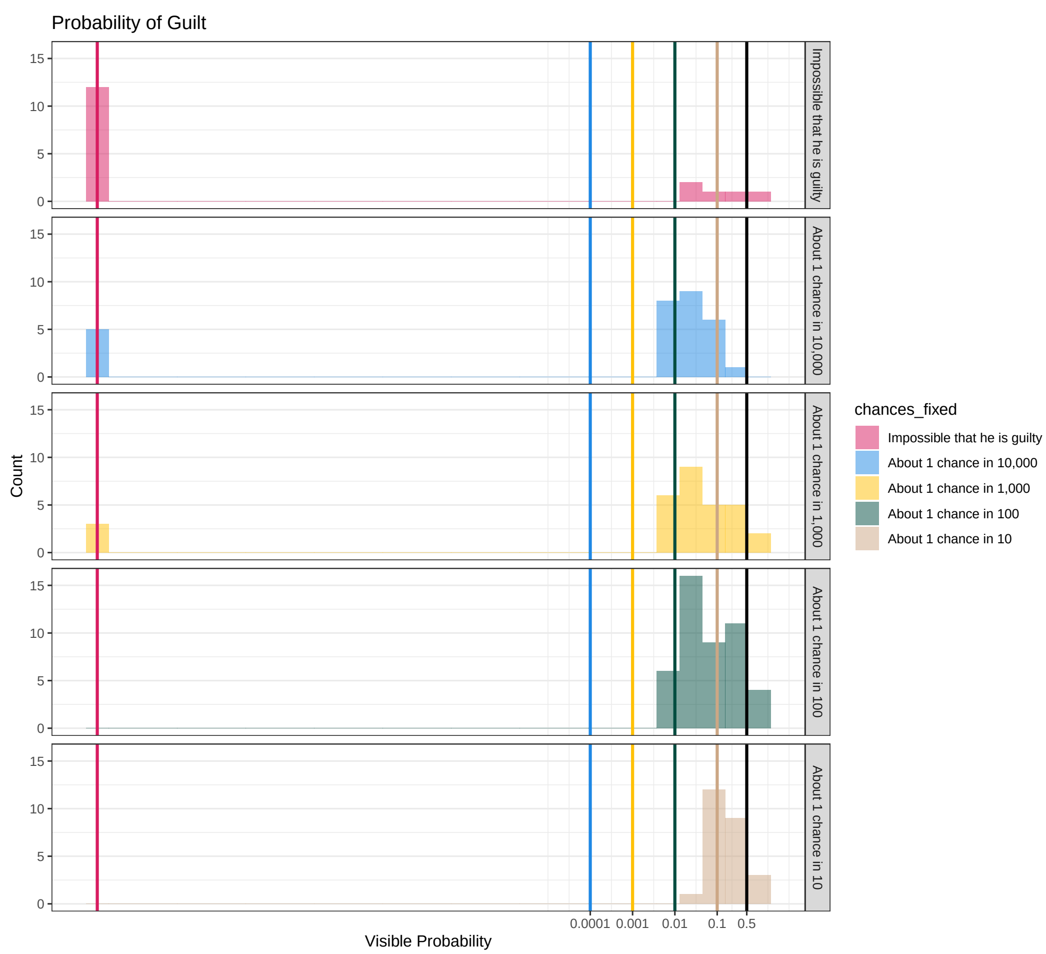

Figure 4.17: Guilt Probability Comparison Log 10 Scale

to "About 1 chance in 100". While most individuals in the "Impossible he is guilty" category did select 0%, this prediction does not hold true for the other categories. In the case of "About 1 chance in 10,000", approximately an equal number of individuals selected values between 1% and 10%, as did those who selected the "About 1 chance in 1,000" and "About 1 chance in 100" categories. While this is expected in "About 1 chance in 100", the estimate appears to be high for "About 1 chance in 1,000" and "About 1 chance in 10,000". Those in the "About 1 chance in 10" category selected relatively expected probabilities, demonstrating that this issue mostly affects the extreme values. While 50% was the most popular (and default) value on the visible probability scale (selected by 33 participants), the next two most popular values are 0% and 1% (both selected by 21 participants).

Figure 4.18 is similar to Figure 4.17 in its less-frequent-than-expected choice of extreme values, and the accurate alignment of the most extreme ("Certain to be guilty") and least extreme ("About 9 chances in 10") categories. Those who selected "About 99 chances in 100" of guilt tended to favor close to a 10% probability of innocence (by selecting a 90% probability of guilt), as opposed to the expected 1% probability of innocence (or 99% probability of guilt); the same can be said for those who selected "About 999 chances in 1,000" that the defendant is guilty. Individuals who selected the "About 9,999 chances in 10,000" favored 99% probability of guilt (or 1% probability of innocence).

Overall, Figures 4.17 and 4.18 demonstrate some inconsistency between selected multiple choice scale and participants' assigned probability. Results in both cases generally indicate consistent beliefs in guilt: By far most individu-

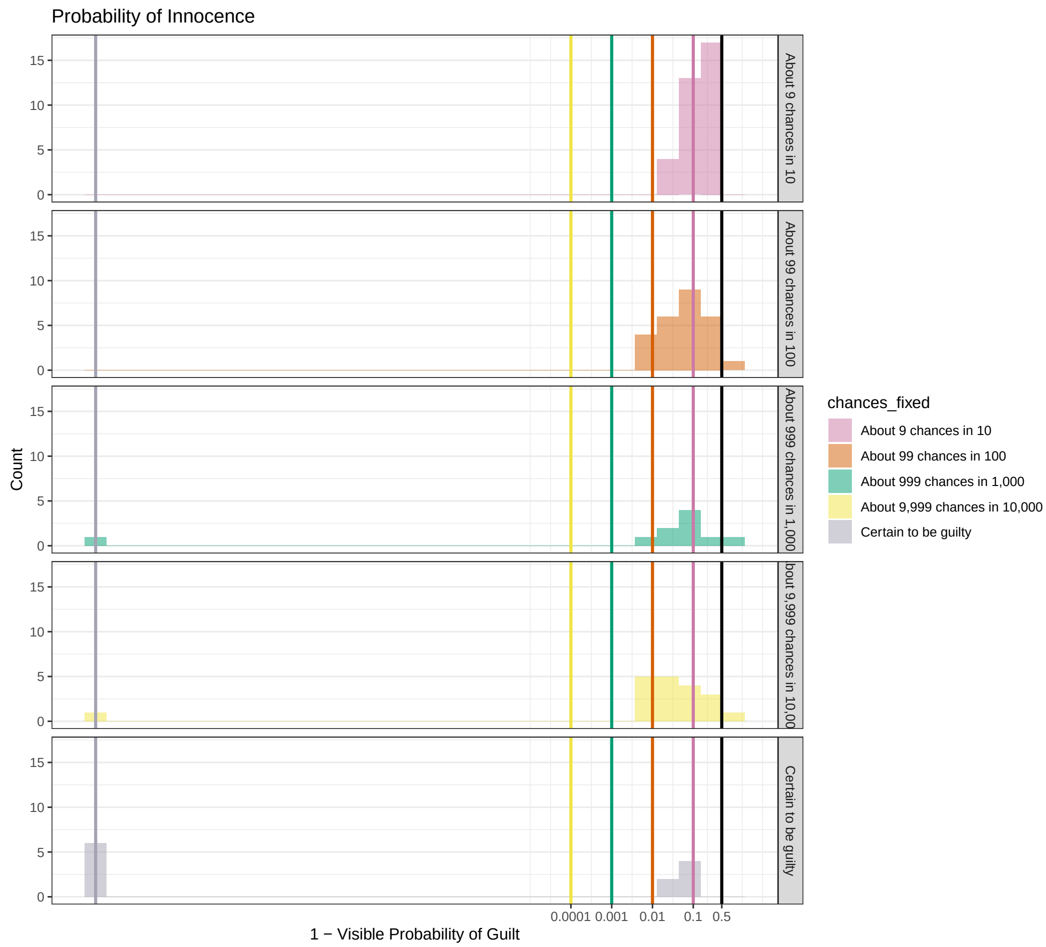

Figure 4.18: Guilt Probability Comparison Log 10 Scale, where probability values were subtracted from 1

als who selected a multiple choice chance value corresponding to the defendant being more likely to be guilty than innocent selected a corresponding probability value in the same range (i.e. less than a 50% probability of being innocent), and vice versa. However, the inconsistency in the scales is present in the form of magnitude: participants tended to select less extreme probability values than was indicated by their multiple choice chance selections.

Figure 4.19 shows a comparison of the perceived probability that the defendant committed the crime compared to the perceived chance that the de-

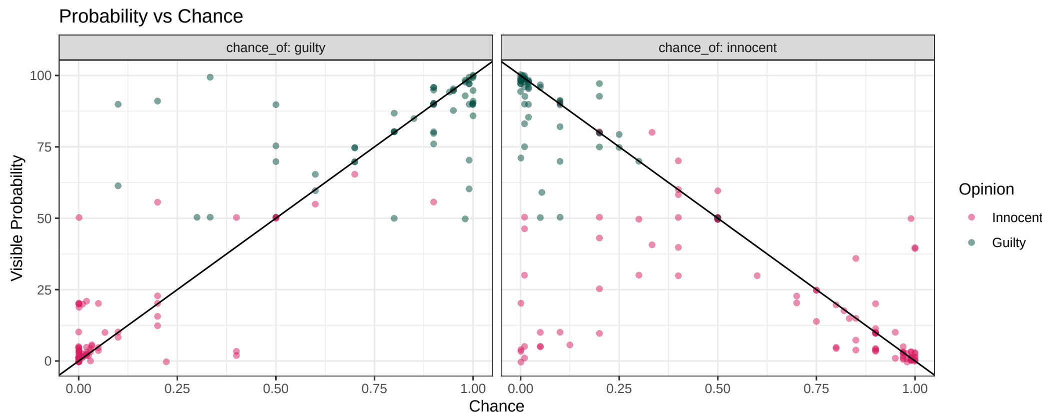

Figure 4.19: Probability and Chance Comparison

fendant is guilty, when expressed on a continuous scale. The plot lines would indicate a direct correspondence between chance value and probability Values are clustered near the corresponding corners of each plot. This may be due to the compression on the probability scale - values of chance that are more extreme than 1 in 100 or 99 in 100 are represented with a single probability value. Most responses that do not follow the line are below it when participants chose to express chance of innocence. The clustering of low chance of innocence and low probability of guilt shown in the bottom left of the plot indicate participants who were confused about the chance scale - their opinion indicated that they thought the defendant was innocent, yet they assigned a low chance of innocence in the numerical scale. The correlation between the probability and the chances of guilt is 0.9, while the correlation between the probability and the chances of innocence is -0.69. While there is a fairly strong correlation in the case of chances of guilt and probability, the correlation between the probability and the chances of innocence is weaker. This may be a result of confusion in the scale reversal of the chance of innocence scale, while the chance of guilt smoothly corresponds with expressing the probability of guilt.

Figure 4.20 shows the relationship between individuals' ratings of the strength of evidence, and the categorical selection of the chance that the defendant committed the crime. While strength of evidence is on a 9-point Likert scale, the multiple choice chance scale has 11 values, giving participants more selection. The left graph is for the identification condition, while the right graph is for the elimination condition. On the y-axis, lower values correspond to weaker strength of evidence and a lower chance of committing the crime, while higher values correspond to stronger strength of evidence and a higher chance of committing the crime. In the case of the identification condition, individuals in the strength condition selected various values for the chance that the defendant committed the crime, indicating that participants do not interpret the chances of committing the crime as the same amount of strength of evidence uniformly. Responses for the identification condition are also spread across many values on the scale, consistent with what we saw in the strength of evidence and multiple choice chance graphs. In the case of the elimination condition, most individuals chose the smallest level for the strength of evidence. However, participant responses diverged in terms of the multiple choice chance that the defendant committed the crime: values corresponding to the lowest strength of evidence span four categories for the multiple choice chance, ranging from "Impossible that he is guilty" to "About 1 chance in 100". The most popular categories corresponding to the weakest level of evidence strength were "About 1 chance in 10,000" and "About 1 chance in 100". Similar to the relationship between probability and numeric chance, this graphical comparison indicates compression on the strength of evidence scale.

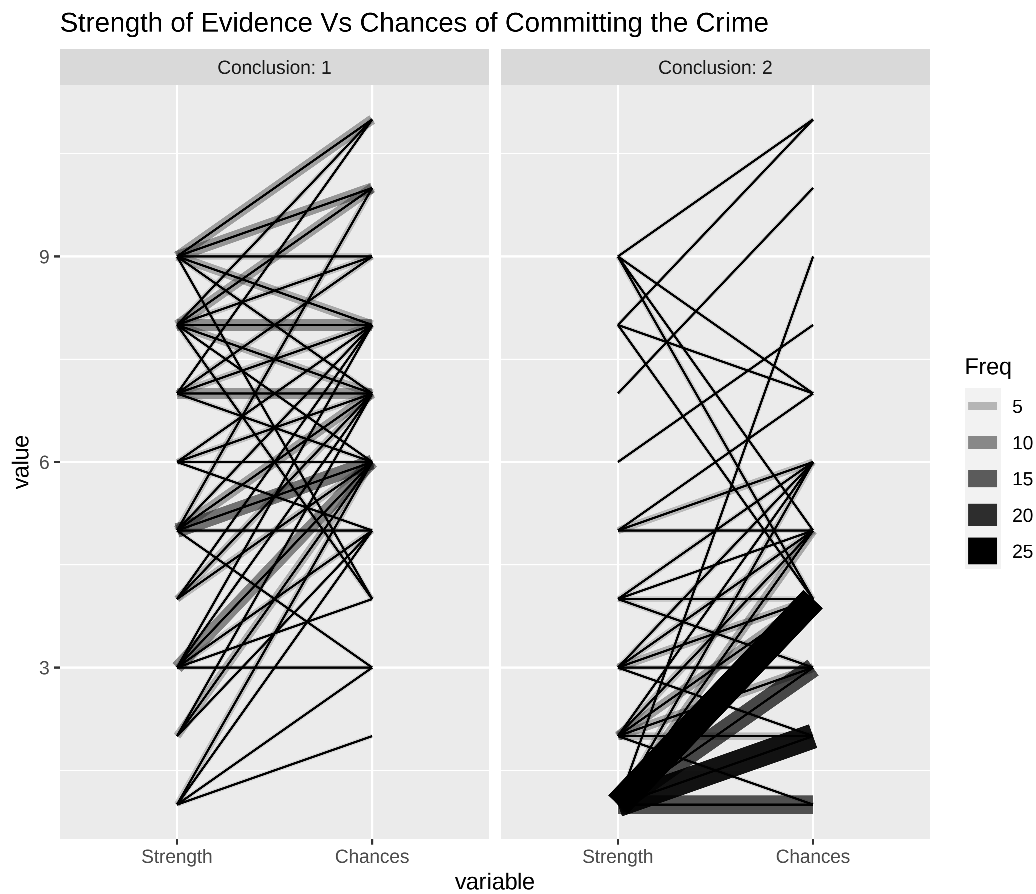

Figure 4.20: Plots of perceived strength of evidence and categorical likelihood

The lowest strength of evidence category can be mapped to several different values for the chance that the defendant committed the crime.

Figure 4.21 depicts the results for our study comparing the chances that the defendant committed a crime to the decision to convict. Participants cross the threshold of being more likely to convict when they select "About 9 chances in 10" in the identification condition, with roughly equal numbers above "About 9 chances in 10" in the elimination condition. This indicates that participants set a threshold of "beyond a reasonable doubt" to be at "About 9 chances in 10". These results are consistent with Thompson et al. (2013), who found a threshold of about 9 chances in 10, where participants

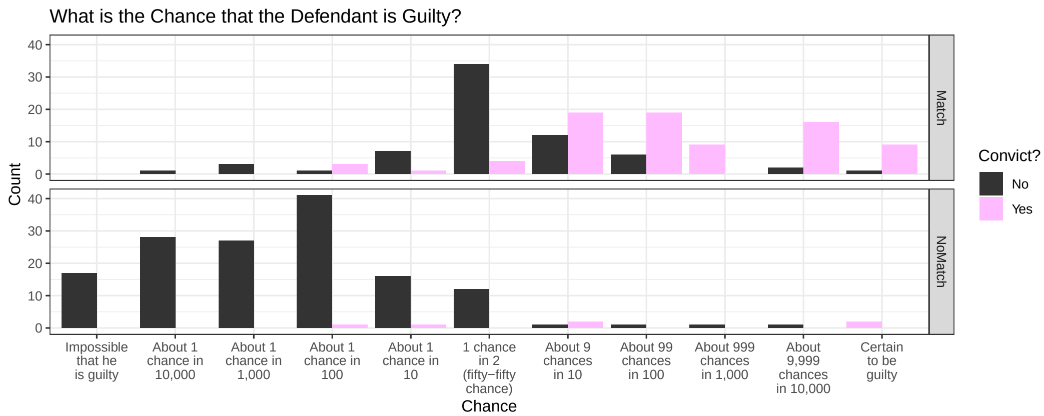

Figure 4.21: Multiple Choice Chance and Conviction Choice

who selected 9 chances in 10 or a higher chance amount were more likely to select a guilty verdict, while those below 9 chances in 10 were more likely to select a not guilty verdict.

Another threshold that we consider in this study is participants' personal feelings of the guilt of the defendant. We would overall expect the threshold for this opinion to be lower than the "beyond a reasonable doubt" threshold used in their conviction decision. Figure 4.22 demonstrates the relationship between the chance scale and the participant's opinion of the guilt of the defendant. In this case, individuals generally thought the defendant committed the crime if they were above the "fifty-fifty chance" value for the identification condition, showing a lower threshold for their opinion of guilt than seen in Figure 4.21, when they were asked for their conviction choice. Individuals who selected the "fifty-fifty chance" appear to be fairly evenly split on their opinion of the guilt of the defendant in the identification condition. This is to be expected when the participant believes that there is an approximately equal chance that the defendant committed the crime, but are asked to make a binary decision.

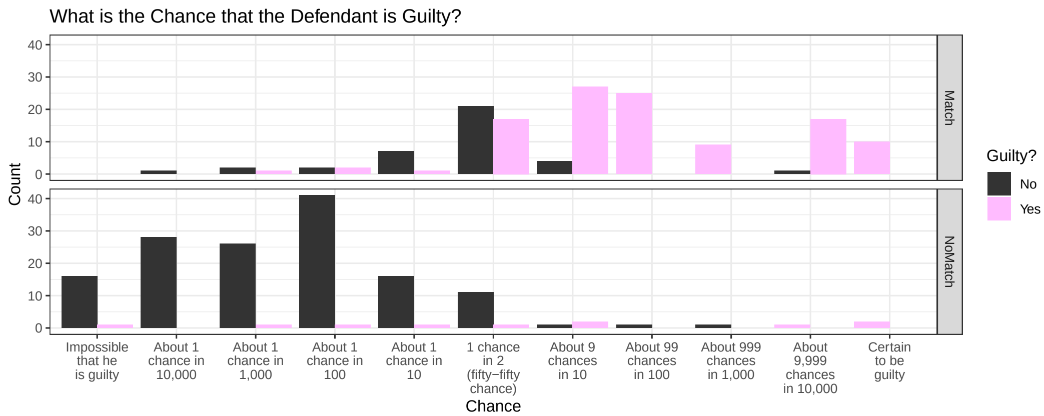

Figure 4.22: Multiple Choice Chance and Opinion of Guilt

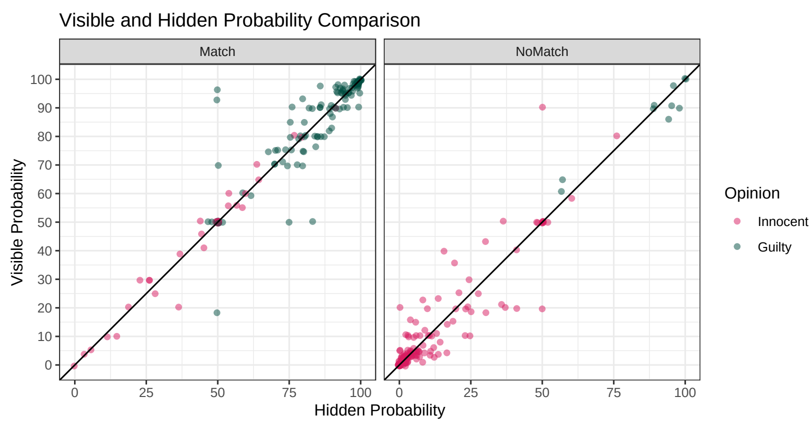

Figure 4.23: Probability and Chance Comparison

4.3.4.3 Probability Comparison

Figure 4.23 shows the correspondence between the visible and hidden probabilities. The values appear to be fairly 1:1. In the visible probability scale, there is a slight trend of values clustering on multiples of 5 that is not present in the hidden probability scale. For the identification condition, those who thought the defendant was guilty tended to select probability values above 50/%. The correlation between the probabilities is 0.98, indicating a strong relationship between the hidden and visible scales.

Figure 4.24 compares the amount that individuals were willing to bet to their hidden probability that the defendant had/had not committed the crime. Whether the participants were betting on the guilt or innocence of the defendant depended on their personal opinion of guilt - those who thought the defendant was guilty bet on the defendant's guilt, while those who thought the defendant was innocence bet on the defendant's innocence. Values are clustered at two points. For those who thought the defendant was innocent, they were willing to bet almost all of the $50 and assigned a low probability to the defendant committing the crime. For those who thought the defendant was guilty, they were also willing to bet almost all of the $50, but assigned a high probability to the defendant committing the crime. There is no clear pattern to individuals who fell outside of these two extreme points. The correlation is 0.58 in the case that the participants were asked to bet on if the defendant committed the crime, and -0.57 when participants were asked to bet on if the defendant did not commit the crime. These correlations are lower than both correlations between numeric chance and probability. Based on the graph, this may indicate that both the probability scale and the betting scale suffer from compression in the most extreme values, with little correspondence on the remainder of the scale.

Mattijssen et al. (2020) compared likelihood and strength of evidence ratings from 10 examiners who regularly used likelihood scales. While this sample size is rather small, they found that examiners tended to give higher verbal degrees of support than they should have, based on their likelihood ratio. A similar effect can be investigated in the potential jurors of this study, when asked to rate the strength of evidence in the case as compared to their perceived probability that the defendant committed the crime.

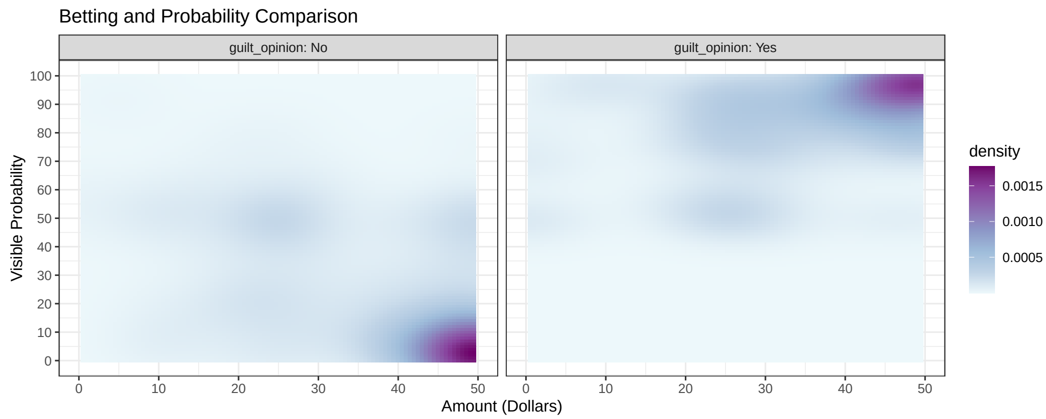

Figure 4.24: Betting and Probability Comparison

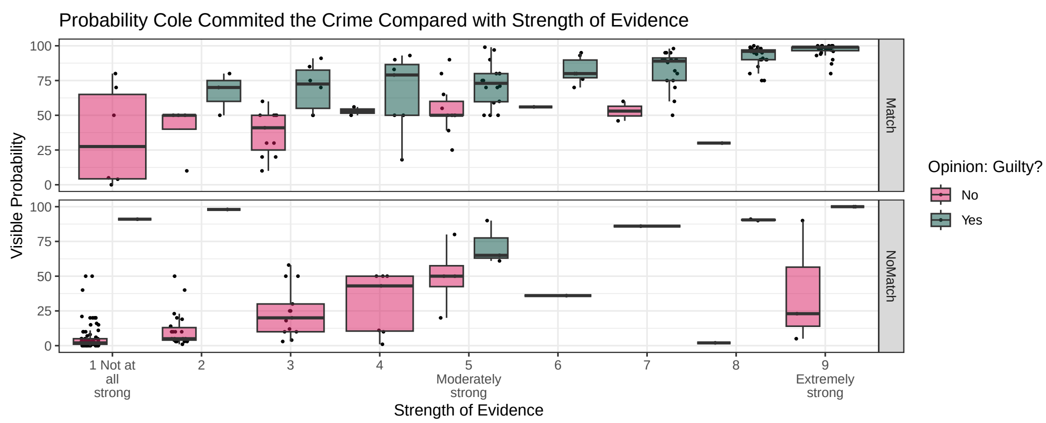

Figure 4.25: Strength of Evidence and Numerical Chance of Committing the Crime

Figure 4.25 shows the relationship between the strength of evidence compared to the probability that the defendant committed the crime. In the identification condition, there is a generally increasing correspondence between the perceived strength of evidence and the participants' predicted probability that the defendant committed the crime. This correspondence is less clear in the elimination condition, perhaps due to scale compression.

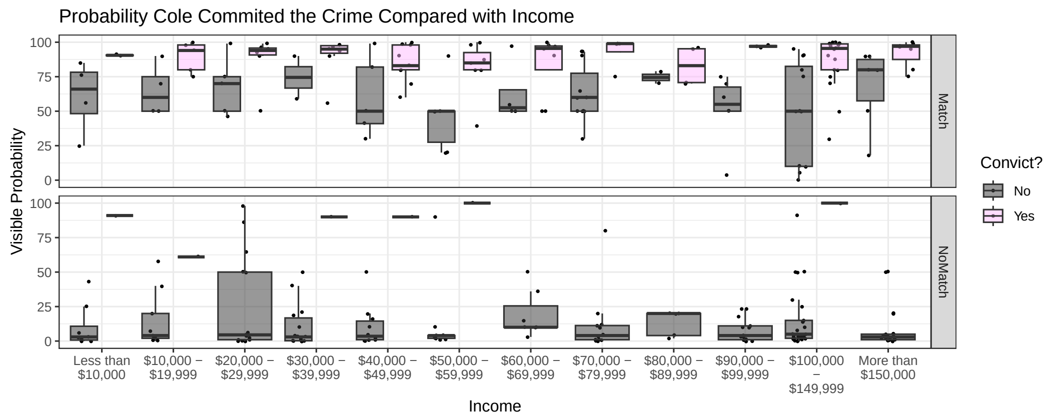

Figure 4.26: Income and Probability Comparison

4.3.5 Demographic Comparison

Demographic information, such as income, race, gender, and education level, was collected on the participants. This demographic information can be compared with the participants' responses.

4.3.5.1 Income

Figure 4.26 explores a potential relationship between income and believed probability that the defendant committed the crime. There does not appear to be a relationship between the two variables.

Bases on Figure 4.27, some individuals in the match condition chose to convict across all income levels. There does not appear to be a clear trend between conviction choice and income. Several income brackets chose to convict over the choice not to convict, but these brackets are spread throughout the scale. In the case of the elimination condition, the individuals who did choose to convict came from different income brackets.

One may expect income to make a difference in how much individuals choose to bet on their opinion in the case, either in the amount of risk an

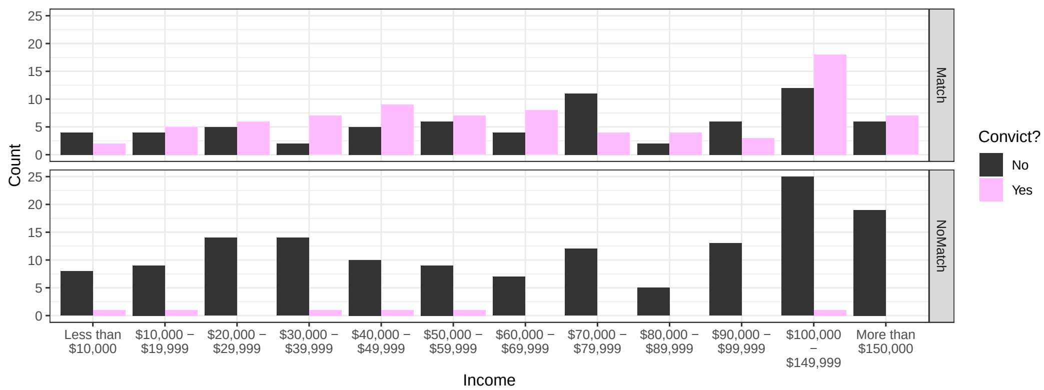

Figure 4.27: Income and Conviction Comparison

Figure 4.28: Income and Betting Comparison

individual is willing to take or in their desire to keep hypothetical money. This does not appear to be the case, however, based on Figure 4.28. As discussed earlier, many participants in the elimination condition were willing to bet the full amount that the defendant was innocent. This is reflected across most income categories as well. In the case of the identification condition, we saw earlier that participants were not as extreme in their bets as is seen in the elimination condition. This trend is also reflected in the boxplots, with a fairly similar distribution of both the innocent and guilty bets across all income categories.

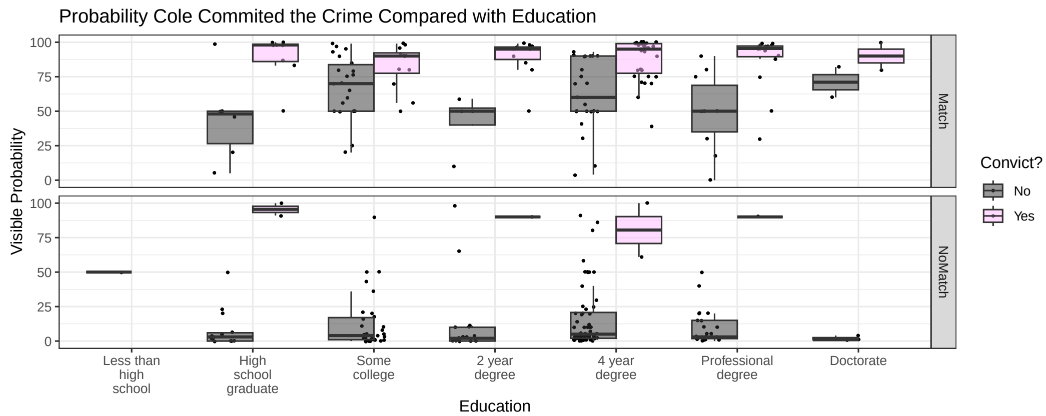

Figure 4.29: Education Level and Probability Comparison

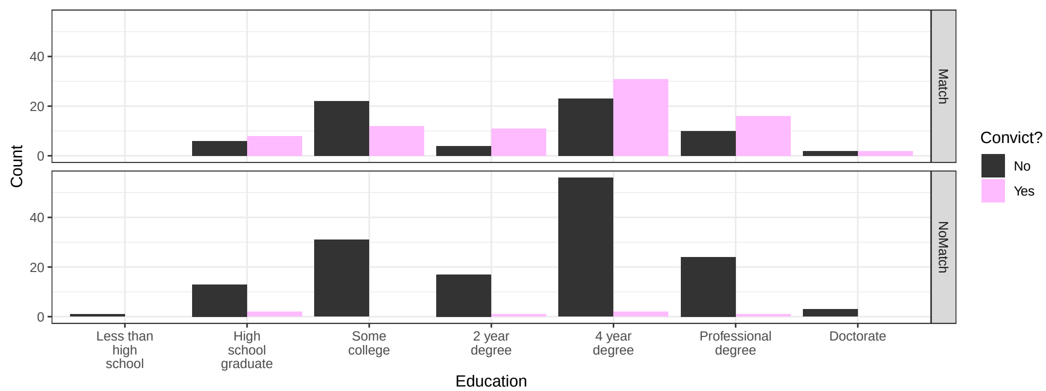

Figure 4.30: Education and Conviction Comparison

4.3.5.2 Education

Figure 4.29 shows the education level along with the participants' probability that the defendant committed the crime. In this case, there does not appear to be a relationship between education level and probability, as the boxplots for probability are similarly distributed across education levels.

Figure 4.30 shows the relationship between the decision to convict and education level. As before, there doesn't appear to be much of a relationship between education level and conviction decision. In the identification condition, individuals chose to convict across all educational categories.

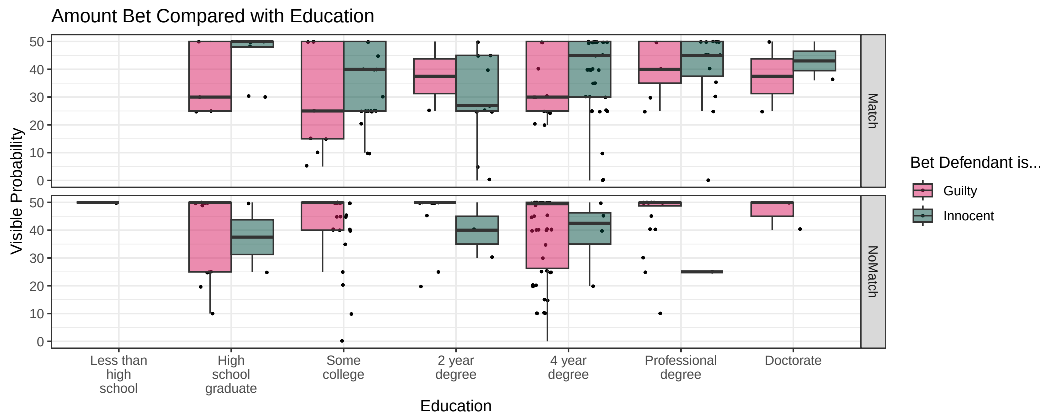

Figure 4.31: Education and Betting Comparison

Figure 4.31 shows the relationship between the betting and the education level. There does not appear to be a trend between the education level and the amount that participants were willing to bet. Based on these graphs, it does not appear that there is a relationship between education level and responses.

4.3.5.3 Gun Comfort

Participants were asked to rate how comfortable they are with guns. Figure 4.32 shows the relationship between choice to convict and comfort with guns. There does not appear to be a big trend in conviction rate. However, it can be seen in the identification condition that those who were extremely uncomfortable with guns were more likely to convict, while those who were extremely comfortable with gones were less likely to convict.

4.3.6 Notepad Analysis

While the notepad analysis for this study still needs to be conducted, analysis of preliminary results indicate that individuals were less likely to directly copy testimony compared to the first study. This may be due to the change

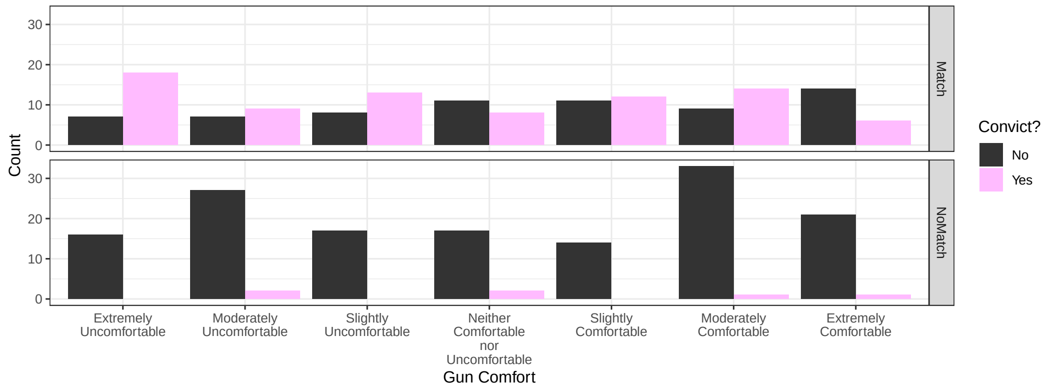

Figure 4.32: Gun Comfort and Conviction Comparison

in format - the use of speech bubbles breaks up the text, which may prevent highlighting the entire page of testimony. Due to this potential change, the potential length of the collocation may need to be shortened.

4.4 Conclusion

Several things can be determined through this exploration of response type. Probability and strength of evidence scales suffer from scale compression in the elimination condition, as can be seen by the proclivity of participants to overwhelmingly select near the most extreme values. The amount that participants were willing to bet was also compressed around the maximum amount, with no clear relationship between probability and betting amount, aside from individuals generally betting near the maximum and selecting extreme values on the probability scale. The chance scales were less compressed, with the best results from the multiple choice scale. Individuals who chose to numerically express chance of innocence as opposed to chance of guilt demonstrated more of a tendency to reverse the scale.

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Chapter 5

Conclusion - Initial Study Revisited

5.1 Introduction

The initial goal of this research was to investigate how a bullet matching algorithm or demonstrative evidence may affect juror perception of the courtroom evidence and procedure. In the course of this investigation, we encountered two issues: confusion based on the transcript-based testimony format and Likert scale compression. In order to address these issues, we redesigned the study format to include cartoons and color-coded speech bubbles for clarity, and conducted a survey investigating response type. We also designed a method for analyzing participant notes that were taken while reading through the testimony, to create a 'heatmap' of areas of text that participants found to be important.

These diverging avenues of investigation have again merged for a final study. The new cartoon study format seemed to alleviate the confusion that came from the initial transcript format, the response type study indicates that phrasing questions in terms of chance (i.e. "1 chance in 10 that…") reduced/eliminated(?) the scale compression seen in Likert scales, and the text analysis provides useful information about what participants found worth copying into their notes. While some scales can be rephrased in terms of chance, others, such as how scientific the approach is, were more difficult to reframe. These questions also suffered from scale compression, which may result from an issue of calibration. While a continuous scale would potentially alleviate the limiting effect of categories, the issue of calibration may still remain: individuals may still choose a cluster of high values on the continuous scale. The process of scale calibration can be seen in the game *Wavelength* (Warsch, Hague, & Vickers, 2019). In this game, one team member tries to get the rest of the team to select values on a continuous scale. Individuals attempt to calibrate their scales to each other through discussion, sometimes setting end points that they reference to. We wish to have a similar process without discussion, by giving participants end points to compare their experience to in terms of scientificity.] In consolidating the information learned from these sub-studies, we returned to the initial study with significant changes designed to assist in elucidating the relationship between the inclusion of an algorithm in courtroom testimony and juror perception.

5.2 Methods

The same initial study scenario is used, as explained in Chapter 2: Richard Cole is accused of attempted robbery, and the only evidence presented to study participants is the bullet comparison between the bullet recovered from the scene and Cole's gun. Independent variables include the examiner's conclusion (match/not a match/inconclusive), the use of demonstrative evidence, such as images (yes/no), and the use of the bullet matching algorithm, with additional testimony from an algorithm expert (yes/no). The study was reformatted to resemble the format of the response type study - including cartoons, speech bubbles, color-coding, and jury instructions. This also involved streamlining the testimony transcript to come from a single document, in order to reduce the chance of confounding typos. Questions with regard to reliability, scientificity, and credibility were re-worded from Likert scale format to chance format.

5.2.1 Study Format

As in Chapter 2, the trial scenario was based on B. Garrett et al. (2020), where a bullet is recovered from an attempted robbery of a convenience store and compared to a gun found in the defendant's vehicle in a routine traffic stop. While the initial study specified that this bullet comparison was the only evidence linking the defendant (Richard Cole) to the crime scene, in this follow up study we instead specified that the transcript provides "select evidence" presented at trial. Because the examiner may reach an inconclusive or non-match decision, the bullet evidence may not carry enough weight to justify a trial if no other evidence is present. However, to stay consistent with the initial study, the scenario description included the fact that the store clerk was unable to make an identification because the robber was wearing a ski mask. As before, participants were asked to use the study notepad to record relevant information, as they would be unable to re-read the testimony. Participants were then provided with mock court testimony complete with cartoon figures and speech bubbles, followed by questions regarding their impression of the witnesses and the evidence presented. While the initial study referred to the firearms examiner and algorithm developer as expert witnesses, this language was removed to coincide with recommendations from United States Courts for the Ninth Circuit (2019). This transcript included witness testimony, cross examination, jury questions in reference to error rates, and jury instructions on witness testimony. The transcript also included additional cross examination on the subjectivity of the firearm examiner's bullet comparison. Additional testimony was also included for the swearing in of the witnesses, in order to more clearly indicate that they were testifying for the prosecution (the initial study started after the witness had been called and sworn in). The witness then testified to their qualifications and the bullet matching process before describing their comparison of the fired evidence to the test fire from the defendant's gun and the subsequent results. In the scenarios that included the algorithm, the firearm examiner would describe the algorithm's match score for the comparison, and an interpretation of how the match score corresponds to their personal bullet comparison. The examiner conclusions are described as follows: the match condition includes correspondence in class and individual characteristics; the inconclusive condition includes correspondence in class characteristics, but not enough correspondence in individual characteristics to declare a match; and the exclusion condition included correspondence in class characteristics, but disagreement in individual characteristics. Demonstrative evidence included images of rifling (baku13, 2005; Gremi-ch, 2009), a bullet comparison, and algorithm images (shown in Chapter 2. Cross examination consists of questions regarding the ability to uniquely identify the source of the bullet, and an increased number of questions regarding the subjectivity of the bullet comparison.

An algorithm developer also testified if the algorithm was used in the testimony. The testimony would begin with their qualifications and relationship with the algortihm, before the developer describes the process of obtaining a match score. As in the initial study, this algorithm description matches that of Hare et al. (2017). They then mention the algorithm's publication history, the open source nature of the code, and if the algorithm can be applied to the type of gun used in this case. In cross examination, they were asked about the relative newness of the algorithm and subjective calibration aspects, as well as limitations in terms of the types of bullets that the algorithm can evaluate. The testimony from the initial study is found in Appendix A, while additional modifications are described in Appendix B

Participants are then asked to consider the testimony and respond to a set of questions. They are asked if they would choose to convict, based on the 'beyond a reasonable doubt' threshold. Unlike the initial study, participants are also asked if they personally believe that the defendant is guilty. As demonstrated in Chapter 4, these two questions can act in conjunction to judge how participants perceive the strength of evidence in the case - those who personally believe the defendant was guilty but choose not to convict are placing the evidential strength somewhere between enough evidence to sway their personal belief, but not enough evidence to say the defendant is guilty 'beyond a reasonable doubt'. Because of the scale compression found in Likert scales in the initial study, the questions regarding the strength of evidence, the credibility of the examiners, the reliability and scientificity of the evidence, and the understanding of the procedures were changed. Instead, questions were formed in terms of chance scales, as described in Chapter 4. Chapter 4 also demonstrates some of the limitations of asking participants to give a probability that the defendant committed the crime - in the match condition, responses are clustered at the end of the scale. Participants were also asked to answer two attention check questions: one regarding the caliber of the recovered bullet to ensure the participant read the testimony, and another asking for the participant to select a specific value to ensure the participant read the question. Participants who received the algorithm were asked additional questions regarding the algorithm evidence, as well as their perception of the the evidence as a whole (considering both the algorithm and the firearm examiner's comparison)

Appendix A

Testimony Transcripts

A.1 Firearm Examiner

Q: Please state your name.

A: John Smith

Q: Who do you work for? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: The local police department

Q: What do you do for the police department? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: I am a firearms examiner (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

Q: How long have you been doing that? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: X amount of years

Q: What is a firearms examiner? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: A firearms examiner is someone who looks at cartridge cases and bullets to determine whether they were fired in a particular firearm.

Q: What training is required to become a firearms examiner with the local police department? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: I received my bachelor's degree in forensic science and in X year I transferred to the crime lab from the crime scene unit. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7) I underwent a two-year training program, which was supervised by experienced firearms examiners (*State of Florida vs. Sheppard Jr.*, 2012, pp. 798–799); I've toured manufacturing facilities and saw how firearms and ammunition were produced; and I've attended several national and regional meetings of firearms examiners.(*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

Q: And during the course of your career, were you tested in proficiency to make sure.. you were still conducting appropriate examinations? (*State of Florida vs. Sheppard Jr.*, 2012, pp. 798–799)

A: Yes. I have undergone annual proficiency examinations.(*State of Florida vs. Sheppard Jr.*, 2012, pp. 798–799)

Q: Is the local police department lab accredited? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: Yes, it is accredited by ASCLID/LAB (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

Q: And in addition to what you just told us, do you have other qualifications? (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p.

2)

A: Yes, I do.(*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 2)

Q: Can you tell us what those are? (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 2)

A: Yes. I received training in the use of a bullet matching algorithm. This is an algorithm that evaluates the characteristics of two fired bullets, in order to produce a score for the similarity of the bullets, where more similar bullets are more likely to have been fired from the same gun. I attended a workshop on the algorithm on [DATE], held by CSAFE – Center for Statistics and Applications in Forensic Evidence. This involved use of the algorithm alongside my personal judgement. I found that my conclusion was reflected in the similarity score produced by the algorithm in all ## cases.

Q: Where does the bullet matching algorithm come from? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 5)

A: It was created by ________. (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 5)

Q: How long has the state police been using the bullet matching algorithm? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 5)

A: They have been using it since ###.

Q: Have you testified in court previously regarding the bullet matching algorithm? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 5)

A: Yes, I have, approximately ## times. (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 5)

Q: Have you, as a firearms examiner, have you testified about opinions, given your opinion about the results of your testing? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 5)

A: Yes, I have. (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 5)

Prosecution: Your Honor, at this time I would ask that XXX be qualified as an expert in the field of firearms identification subject to cross examination. (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 4)

Court: Any cross on their credentials? (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 4)

Defense: No, Your Honor (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 4)

Court: This witness is an expert in the area of firearms identification. They can testify to their opinions as well as facts. Go ahead.(*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 4)

Q: What work did you do on this case? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 8)

A: I was asked to compare a bullet from the crime scene to a test fire from XX gun.(*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 8)

Q: Did you examine how many lands and grooves the bullet had? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 17–18)

A: Yes. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 17–18)

Q: Can you explain for the jury what that means? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 17–18)

A: Yes… In the interior of a barrel there are raised portions called lands and depressed areas called grooves. When a bullet passes down the barrel, a bullet will spin and that gives it stability and accuracy over a distance. Those raised areas are designed by the manufacturer. They're cut into the barrel. And each particular file has a different combination of lands and grooves. But essentially what those lands do will grip a bullet and spin it and as that bullet passes down the barrel, it scratches the random imperfections of that barrel into the bullet.(*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 17–18)

Q: Now, for these bullets, you counted up the lands and grooves and determined the direction of the twist, correct? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 17–18)

A: Yes. This bullet had six lands. And the interior of the barrel, the barrel will either twist right or it will twist left. And this particular case, the barrel twists right. And you can see that by looking at the bullet. If you look at the base of the bullet, either it goes to the left or goes to the right.(*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 17–18)

—Test-fired bullets admitted into evidence—

Q: Can you describe the process of obtaining these test-fired bullets?

A: The test-fired bullets came from a test fire of XX gun.

Q: You mentioned test firings, can you explain what that means? (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 6)

A: In test firing first what I would do is make sure the firearm is safe to actually test fire. Then I would use lab ammunition and I would test fire it, meaning that I'm creating a fired bullet. Typically you do two at a time. That way you have a fired bullet to compare to another fired bullet. (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 6)

Q: Would you then have taken the test firings you created and did you compare those test firings to the fired evidence that you had also received? (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 6)

A: Yes. First what I would do is compare my test shot to test shot. I'm looking for a detailed microscopic pattern. Once I have done that then I would compare it to the fired evidence.(*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 6)

Q: And how about the number of lands and direction of twist for the test fires? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

A: It also had six lands, and twisted to the right (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

Q: Okay. Now, did you compare the test-fired bullets to the fired evidence under the comparison microscope? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

A: Yes, I did. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

Q: What is your conclusion? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

A: I found that there were sufficient individualizing characteristics to conclude that the two bullets were fired from the same barrel.

Q: How were you able to conclude that? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

A: I placed them under the comparison microscope, and I roll the bullet around 'til I can see the agreement in a particular area, unique surface contour that has sufficient agreement. At that point, when I've seen that, I start to rotate the bullets around and I look at all the different lands and grooves, impressions, for that unique detail. When I can see those, that agreement on multiple areas of the bullet, I identify the bullet as having sufficient agreement.(*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

Q: Did you use an algorithm to compare these bullets as well?

A: Yes, I used the algorithm to compare the two test fires to each other. I also used the algorithm to compare the better-marking test fire to the fired evidence that I received.

Q: Could you explain how this algorithm compares bullets?

A: The algorithm uses 3D measurements to make a comparison between the surface contours of each of the lands on each bullet. These comparisons result in a match score between 0 and 1, where 1 indicates a clear match, and 0 indicates that there is not a match. The bullet is aligned based on the maximum agreement between the lands, and the average match score for the lands is computed. This average score gives an overall match score for the entire bullet.

Q: What was the match score between the two test-fired bullets?

A: The match score was 0.9-.

Q: What was the match score between the better-marked test fire bullet and the fired evidence?

A: The match score was 0.XX.

Q: What does this match score indicate about the bullets?

A: The match score indicates that there is substantial similarity between the two bullets, which suggests that they were most likely fired from the same barrel.

Q: Now, how many times have you compared bullets to determine if they were fired from the same gun? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

A: I'd say thousands. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

Q: And do you ever see two bullets that have agreement in every area of the bullet? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

A: No. The firing process of a firearm is dynamic, kind of like a contained explosion. When the firing pin hits the primer, which is basically the initiator, what gets it going, it will explode, bur the gun powder inside the casing, and the bullet will travel down the barrel, picking up the microscopic imperfections of the barrel, and the cartridge case will slam rearward against the support mechanism. During that dynamic process, each time it happens, a bullet will be marked slightly differently from one to the next. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 19–20)

Q: When you reached a conclusion, did you write up a report? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 23)

A: Yes, I did. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 23)

Q: Is it the local police department's protocol to have somebody else who's a firearms tool mark examiner in your lab review that report, review your work, and determine if it's correct? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 23)

A: Yes. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 23)

Q: That's what we call peer review? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 23)

A: Peer review, yes. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 23)

Q: Thank you, no further questions. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 40)

–Cross examination—-

Q: Now, are you telling the jury today that in your opinion there's only one gun in the entire world that could have produced the markings that you saw on these bullets? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 65)

A: I'm saying that the probability that the two markings were made by different sources is so small that it is negligible. (Office of Legal Policy, 2020, p. 2) (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 65)

Q: Exclusive to any other gun? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 65)

A: I obviously haven't tested every other gun, but it is a practical impossibility. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, p. 65)

Q: That's your opinion. And your opinion, by the way, is subjective, right, and it's based on your experience? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 72–73)

A: Based on my training and experience, yes. (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 72–73)

Q: Is there something fixed about the amount of what has to be found to constitute sufficient agreement? (*U.S. Vs. Harris*, 2016, pp. 4459–4460)

A: No, there is not a fixed amount or a numerical value. (*U.S. Vs. Harris*, 2016, pp. 4459–4460)

Q: How long did you say you've been trained in the bullet matching algorithm? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

A: Since XXX (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

Q: Okay. So that's fairly new; is that fair to say? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

A: It is still fairly new, yes. (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

Q: The software uses modeling; is that correct? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

A: Yes, it does. (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

Q: You, personally, don't know the source code; is that correct? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 -

21)

A: That's correct.(*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

Q: And, in fact, you, personally, would not be able to tell us the specific math that goes into this program; is that fair to say? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

A: We did receive training on what the math is doing. (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

The Court: Terry Smith, the jury has asked me to forward this question to you. Answer if you're able. To what percentage is the science accurate is the first question. And then I think the rest of that explanation of that question goes on to say, to determine that the bullets were fired from the same firearm, are you 100 percent sure? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 100–101)

A: My opinion, I am 100 percent sure that these bullets were fired from this firearm. There is a published error rate for firearms examiners. The positive identification is less than two percent. I believe it's about 1.5 to 1.9. That's just a general number that's out there.(*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 100–101) The false negative identification rate is less than three percent. (Chumbley et al., 2021)

A.2 Algorithm Expert

Inspired by *State of Arizona vs. Eduardo Vasquez Celaya* (2007), *The People of the State of Illinois v. Eugene Banks, et. al* (n.d.), *The People* *of the State of Michigan v. Andrew Mack Johnson, Jr.* (2018), *U.S. Vs. Harris* (2016), *State of Florida vs. Sheppard Jr.* (2012), Hare et al. (2017), Vanderplas et al. (2020), and Perlin (2012). Should create citations by line as above.

Q: Please state your name.

A: Adrian/Avery Jones

Q: Who do you work for? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: XXX place

Q: What is your current occupation?

A: XXX

Q: How long have you been doing that? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: X amount of years

Q: What training is required to hold this occupation? (*State of Arizona vs. Eduardo Vasquez Celaya*, 2007, pp. 6–7)

A: I have a Ph.D. in XX, and have spent X time developing the bullet matching algorithm algorithms. I have spent X years collaborating with firearms examiners during the development and rollout of this algorithm.

Q: Are you familiar with the bullet matching algorithm?

A: Yes. I was involved in the development of the algorithm.

Prosecution: Your Honor, at this time I would ask that XXX be qualified as an expert in the bullet matching algorithm subject to cross examination.

Court: Any cross on their credentials? (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 4)

Defense: No, Your Honor (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 4)

Court: This witness is an expert in the area of the bullet matching algorithm. They can testify to their opinions as well as facts. (*The People of the State of Illinois v. Eugene Banks, et. al*, n.d., p. 4)

Q: How many times have you testified regarding this bullet matching algorithm?

A: XX times.

Q: Could you describe how this bullet matching algorithm compares bullets?

A: Yes. For certain types of guns, the barrel will have lands and grooves, known as rifling. This rifling spins the bullet in order to make its trajectory more stable. Due to the manufacturing process, this rifling can produce identifiable markings on the bullet, based on random differences between barrels. Because of these random imperfections, the striation marks left on bullets can be compared in order to determine if it is likely that they were fired from the same gun.

(Description based on Hare et al. (2017)) The first step is to determine where the lands on the bullet are located. These lands will be the sunken area that contains the striation marks between the smoother grooves. 3D scans are then taken for each land, and the 'shoulders', or area transitioning from the land to the groove, is excluded from the analysis.

Next, a stable area of the 3D scan containing the striations is selected, and a cross-section of this area is used to show the striations along with the topology of the region. A smoothing function is applied to remove some of the imaging noise from the 3D scan, leaving the striae intact. A second smooth is subtracted from the striations in order to remove the curvature of the region, leaving only the striae – this is what we call a signature. The signature for the two bullets being compared are aligned such that the best fit between the two signatures is achieved. The striation marks between the two signatures are then compared by evaluating how many of the high points and low points correspond. The algorithm can calculate the number of consecutively matching striations (CMS), or consecutively matching high points and low points – these are features used directly by some examiners to characterize the strength of a match. It also calculates the cross correlation between the two signatures, which is a numerical measure of the similarity between the two lands ranging between –1 and 1.

These traits are combined using what is known as a random forest. Each forest is composed of decision trees, which use a subset of the observed values in order to make a decision about whether or not the bullets constitute a match. The other observations are held out in order to determine an error rate. When the random forest makes a prediction, each decision tree "votes", producing a numerical value between 0 and 1 corresponding to the percentage of trees which evaluate the features as being sufficiently similar to have come from the same source.

Q: Have you tested this algorithm?

A: Yes. This algorithm was tested and validated on a number of different test sets of bullet scans. It was found that, as long as there are sufficient marks on the bullet, the algorithm could successfully distinguish between bullets fired by the same gun and those fired from different guns. Examiners' visual comparisons are also limited by the presence or absence of individualizing marks. Two test sets were using consecutively rifled barrels, which should be the most difficult to assess, and it was shown that the algorithm could distinguish between the bullets fired from two separate guns with complete accuracy. (Vanderplas et al., 2020)

Q: Can this algorithm be used on XX bullets fired from an XX firearm, such as the firearm in question for this case? (Discussion of limitations (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 11))

A: Yes, this algorithm can be used on these types of bullets, given that this type of firearm marks well.

Q: Has this algorithm been published? (Perlin (2012) for importance of publication)

A: Yes. The algorithm and its process has been discussed in peer reviewed journals such as Law, Probability, and Risk, The Annals of Applied Statistics, and Forensic Science International. The algorithm is also open source, which means that the full source code, documentation, and numerical weights are available online for anyone to examine.

–Cross examination—-

Q: How long has the bullet matching algorithm been used in court cases? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

A: Since XXX

Q: Okay. So that's fairly new; is that fair to say? (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

A: It is still fairly new, yes. (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 19 - 21)

Q: This algorithm requires some decision making on the part of the operator, such as how much the signature is smoothed and what part of the bullets are inputted into the system, correct? (subjective aspects (*The People of the State of Michigan v. Andrew Mack Johnson, Jr.*, 2018, p. 21))

A: Yes, there are certain parameters which must be specified, but the system defaults are usually sufficient and have been validated with a number of different firearms and ammunition types. There are also operating protocols for determining which parts of the bullet are scanned, so while this process is manual, there are clear criteria and the associated variability from scanning is well understood, and published in Forensic Science International.

Q: Can this algorithm be applied to all bullets? (gun specific/issues with damaged bullets)

A: No, the algorithm only works on traditionally rifled bullets which are largely undamaged. The algorithm has not been validated to work on seriously damaged or fragmented bullets.

Appendix B

Study 2 Changes

B.1 Cautions Against Expert Witnesses

B.1.1 Jury Instructions

You have heard testimony from Terry Smith and Adrian Jones who have testified to opinions and the reasons for their opinions. This opinion testimony is allowed because of the education or experience of this witness. Such opinion testimony should be judged like any other testimony. You may accept or reject it, and give it as much weight as you think it deserves, considering the witness's education and experience, the reasons given for the opinion, and all the other evidence in the case. (United States Courts for the Ninth Circuit, 2019)

B.1.2 Opinion Witness

United States Courts for the Ninth Circuit (2019) suggests that witnesses should not be qualified as experts, as it may cause the jury to place undue weight in their testimony. Instead, Richey (1994) implements the term "opinion witness" in the place of "expert witness". This practice has been adopted in our revised testimony, when qualifying the witness based on experience and education.

B.1.3 Cross Examination

The strength of evidence ("the probability that the two markings were made by different sources is so small that it is negligible") was moved from the cross examination to the direct examination, since this strength of evidnece should be introduced by the prosecution. Additional testimony regarding subjectivity was added to the cross examination as well, from (*U.S. Vs. Harris*, 2016, p. 54):

Q: You have a criterion in you head, a subjective criterion, of what will constitute an identification. Is that correct?

A: Yes.

Q: All right. If we brought three more people in, would their subjective criterion in their head be identical to yours?

A: They would look for that same sufficient agreement. However, based on their training and experience on difficult comparisons, they may or may not come to the same decision.

Q: Right. But they also could reach the same decision but have a different subjective criterion than you. Is that fair?

A: They may, possibly. I don't know. I can't speak for other examiners.

Additional testimony was also added to address the distinction between evidence that the gun was at the crime scene, and evidence that Cole was at the crime scene (*State of Florida vs. Sheppard Jr.*, 2012, p. 831):

Q: You can't tell us anything about who shot the firearm, correct?

A: That is correct.

B.2 Clarifying Sides

To make sure individuals are clear on who the firearms examiner is testifying for, testimony was added related to the calling and the swearing in of the witness. The testimony below is from *The People of the State of Michigan v. Andrew Mack Johnson, Jr.* (2018).

Court: Your next witness, please.

Prosecution: The People would call John Smith.

Court: Hello.

Smith: Hi

Court: Would you raise your right hand for me? Do you sear the testimony you're about to give will be the truth, the whole truth, nothing but the truth, under penalty of perjury?

Smith: I do.

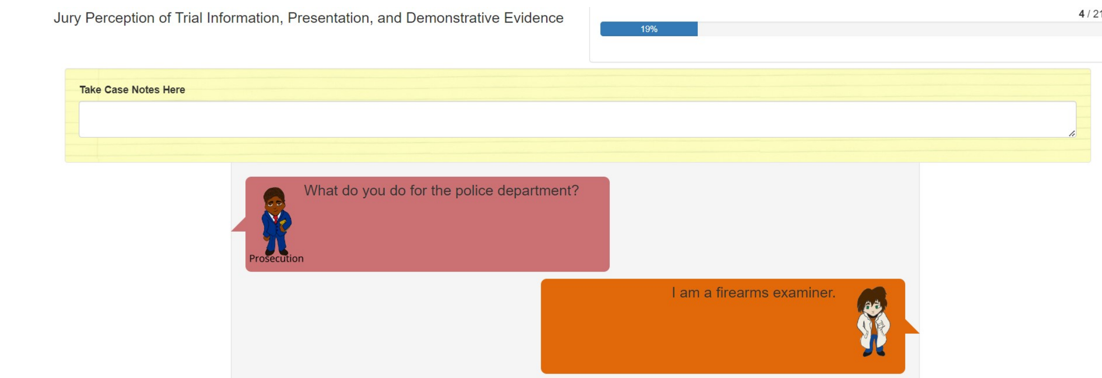
Court: Please be seated. State your full name for the record and spell your last name.

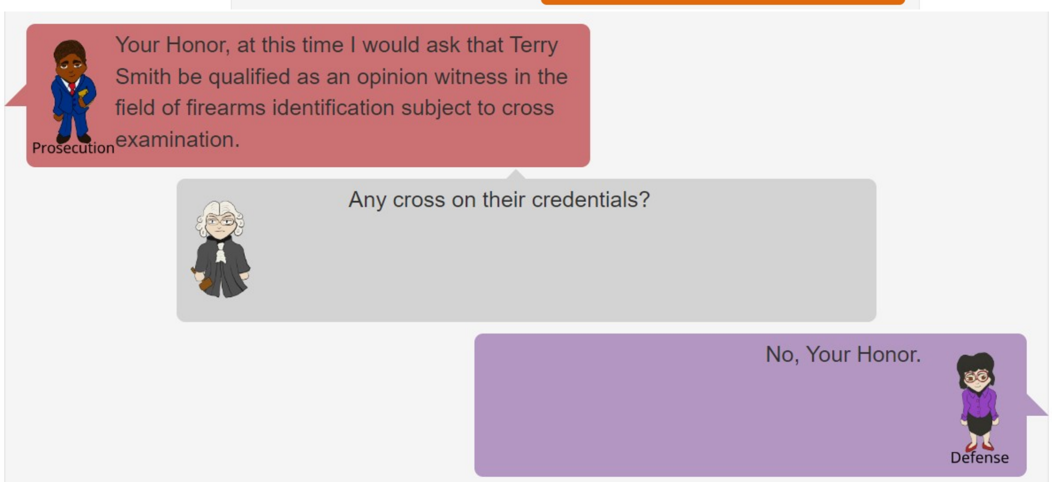
Witness: My name in John Smith, last name S-m-i-t-h

B.3 Images

In order to clarify the speakers in the testimony and create a more engaging environment, we implemented character drawings (by Richy Meleus) to represent various actors that may be present in the courtroom. These characters' faces and clothing are largely exchangeable, allowing for a large combination of clothing and characteristics.

These images were placed in their respective speech bubbles in order to indicate the speaker, with color coding to indicate which side witnesses were testifying for: the prosecution's side had warmer colors, the defense had cooler colors, and the judge was a neutral grey.


Jury Perception of Trial Information, Presentation, and Demonstrative Evidence
4 / 21
19%
Take Case Notes Here
What do you do for the police department?
Prosecution
I am a firearms examiner.


Your Honor, at this time I would ask that Terry Smith be qualified as an opinion witness in the field of firearms identification subject to cross examination.
Prosecution
Any cross on their credentials?
No, Your Honor.
Defense

Colophon

This document is set in EB Garamond, Source Code Pro and Lato. The body text is set at 11pt with *lmr*.

It was written in R Markdown and $\LaTeX$, and rendered into PDF using huskydown and bookdown.

This document was typeset using the XeTeX typesetting system, and the University of Washington Thesis class class created by Jim Fox. Under the hood, the University of Washington Thesis LaTeX template is used to ensure that documents conform precisely to submission standards. Other elements of the document formatting source code have been taken from the Latex, Knitr, and RMarkdown templates for UC Berkeley's graduate thesis, and Dissertate: a LaTeX dissertation template to support the production and typesetting of a PhD dissertation at Harvard, Princeton, and NYU

The source files for this thesis, along with all the data files, have been organised into an R repository, which is available at `https://github.com/rachelesrogers/UNL_Thesis`.

This version of the thesis was generated on 2024-02-14 12:58:21.25027.

The computational environment that was used to generate this version is as follows:

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## - Session info -------------------------------------------
##  setting  value
##  version  R version 4.3.1 (2023-06-16 ucrt)
##  os       Windows 10 x64 (build 18363)
##  system   x86_64, mingw32
##  ui       RTerm
##  language (EN)
##  collate  English_United States.utf8
##  ctype    English_United States.utf8
##  tz       America/Chicago
##  date     2024-02-14
##  pandoc   3.1.1 @ C:/Program Files/RStudio/resources/app/bin/quarto/bin/tools/ (via rma
##
## - Packages -----------------------------------------------
##  ! package           * version date (UTC) lib source
##    assertthat          0.2.1   2019-03-21 [1] CRAN (R 4.3.1)
##    bit                 4.0.5   2022-11-15 [1] CRAN (R 4.3.1)
##    bit64               4.0.5   2020-08-30 [1] CRAN (R 4.3.1)
##    bookdown            0.37    2023-12-01 [1] CRAN (R 4.3.2)
##    cachem              1.0.8   2023-05-01 [1] CRAN (R 4.3.1)
##    callr               3.7.3   2022-11-02 [1] CRAN (R 4.3.1)
##    cli                 3.6.1   2023-03-23 [1] CRAN (R 4.3.1)
##    colorspace          2.1-0   2023-01-23 [1] CRAN (R 4.3.1)
##    crayon              1.5.2   2022-09-29 [1] CRAN (R 4.3.1)
##    data.table          1.14.8  2023-02-17 [1] CRAN (R 4.3.1)
##    devtools          * 2.4.5   2022-10-11 [1] CRAN (R 4.3.1)
##    DiagrammeR        * 1.0.10  2023-05-18 [1] CRAN (R 4.3.1)
##    digest              0.6.33  2023-07-07 [1] CRAN (R 4.3.1)
##    dplyr             * 1.1.3   2023-09-03 [1] CRAN (R 4.3.1)
##    ellipsis            0.3.2   2021-04-29 [1] CRAN (R 4.3.1)
##    evaluate            0.23    2023-11-01 [1] CRAN (R 4.3.2)
```

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##    farver           2.1.1   2022-07-06 [1] CRAN (R 4.3.1)
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##    fuzzyjoin      * 0.1.6   2020-05-15 [1] CRAN (R 4.3.1)
##    generics         0.1.3   2022-07-05 [1] CRAN (R 4.3.1)
##    GGally         * 2.1.2   2021-06-21 [1] CRAN (R 4.3.1)
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##    ggmosaic       * 0.3.3   2021-02-23 [1] CRAN (R 4.3.1)
##    ggpcp          * 0.2.0   2022-11-28 [1] CRAN (R 4.3.1)
##    ggplot2        * 3.4.4   2023-10-12 [1] CRAN (R 4.3.2)
##    ggrepel        * 0.9.3   2023-02-03 [1] CRAN (R 4.3.1)
##    ggridges       * 0.5.6   2024-01-23 [1] CRAN (R 4.3.2)
##    git2r            0.32.0  2023-04-12 [1] CRAN (R 4.3.1)
##    glue             1.6.2   2022-02-24 [1] CRAN (R 4.3.1)
##    gridExtra      * 2.3     2017-09-09 [1] CRAN (R 4.3.1)
##    gtable           0.3.4   2023-08-21 [1] CRAN (R 4.3.1)
##    hms              1.1.3   2023-03-21 [1] CRAN (R 4.3.1)
##    htmltools        0.5.7   2023-11-03 [1] CRAN (R 4.3.2)
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##    httpuv           1.6.11  2023-05-11 [1] CRAN (R 4.3.1)
##    httr             1.4.7   2023-08-15 [1] CRAN (R 4.3.1)
##    huskydown      * 0.0.5   2023-10-04 [1] Github (benmarwick/huskydown@addb48e)
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##    later            1.3.1   2023-05-02 [1] CRAN (R 4.3.1)
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##   stringr          * 1.5.1   2023-11-14 [1] CRAN (R 4.3.2)
##   tibble           * 3.2.1   2023-03-20 [1] CRAN (R 4.3.1)
##   tidyr            * 1.3.0   2023-01-24 [1] CRAN (R 4.3.1)
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##   tidyverse        * 2.0.0   2023-02-22 [1] CRAN (R 4.3.1)
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##   usethis          * 2.2.2   2023-07-06 [1] CRAN (R 4.3.1)
##   utf8               1.2.3   2023-01-31 [1] CRAN (R 4.3.1)
##   vctrs              0.6.3   2023-06-14 [1] CRAN (R 4.3.1)
##   viridisLite        0.4.2   2023-05-02 [1] CRAN (R 4.3.1)
##   visNetwork         2.1.2   2022-09-29 [1] CRAN (R 4.3.1)
##   vroom              1.6.3   2023-04-28 [1] CRAN (R 4.3.1)
##   withr              2.5.1   2023-09-26 [1] CRAN (R 4.3.1)
##   xfun               0.40    2023-08-09 [1] CRAN (R 4.3.1)
##   xtable             1.8-4   2019-04-21 [1] CRAN (R 4.3.1)
```

```
##    yaml                 2.3.7   2023-01-23 [1] CRAN (R 4.3.0)
##
##  [1] C:/Users/rrogers9/AppData/Local/R/win-library/4.3
##  [2] C:/Program Files/R/R-4.3.1/library
##
##  D -- DLL MD5 mismatch, broken installation.
##
## ----------------------------------------------------------
```

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