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Coherence of probability judgments from uncertain evidence: Does ACH help?

Christopher W. Karvetski* David R. Mandel†

Abstract

Although the Analysis of Competing Hypotheses method (ACH) is a structured analytic technique promoted in several intelligence communities for improving the quality of probabilistic hypothesis testing, it has received little empirical testing. Whereas previous evaluations have used numerical evidence assumed to be perfectly accurate, in the present experiment we tested the effectiveness of ACH using a judgment task that presented participants with uncertain evidence varying in source reliability and information credibility. Participants (N = 227) assigned probabilities to two alternative hypotheses across six cases that systematically varied case features. Across multiple tests of coherence, the ACH group showed no advantage over a no-technique control group. Both groups showed evidence of subadditivity, unreliability, and overly conservative non-Bayesian judgments. The ACH group also showed pseudo-diagnostic weighting of evidence. The findings do not support the claim that ACH is effective at improving probabilistic judgment.

Keywords: probability judgment, Analysis of Competing Hypotheses, coherence, uncertainty, evidence

1 Introduction

Criminal investigators, intelligence analysts and other experts routinely judge the probability of competing hypotheses using evidence of varying quality and type. For example, human intelligence from informants can provide valuable insight but also must be carefully evaluated in terms of the source's reliability and the credibility of the information provided, a step formally know as *information evaluation* within the intelligence cycle (Irwin & Mandel, 2019; Samet, 1975). The failure to correctly evaluate these characteristics can lead to serious intelligence errors. For instance, significant evidence that motivated the US-led 2003 invasion of Iraq was based on fabricated claims of the informant code-named *Curveball*, who described working as a chemical engineer in support of Iraq's biological weapons program (Drogin & Goetz, 2005).

To improve the quality of intelligence assessments, the US intelligence community advises analysts to use structured analytic techniques (SATs) (e.g., Office of the Director of National Intelligence, 2015; US Government, 2009). A prominent SAT designed to aid analysts in evaluating multiple hypotheses on the basis of evidence of varying quality is the Analysis of Competing Hypotheses (ACH), formulated by Central Intelligence Agency (CIA) analyst Richards Heuer (Heuer, 1999; Heuer & Pherson, 2014).

ACH starts with generating a set of mutually exclusive and collectively exhaustive hypotheses that are listed in columns of a matrix, whereas items of evidence are listed in rows. The analyst evaluates the quality of each item of evidence in terms of its (a) credibility and reliability and (b) relevance, and then moves along each row and assesses the pairwise consistency of each item of evidence with each hypothesis. The analyst then aggregates the assessments into final inconsistency scores, which are intended to enable the analyst to evaluate the relative likelihood of the hypotheses, at least on an ordinal scale. Whether used independently or by a group of analysts, ACH is typically implemented in a software tool called PARC (Palo Alto Research Center, 2006), in which all inputs are selected from standardized lists (e.g., "high", "medium", "low" for credibility/reliability and relevance; "very inconsistent", "inconsistent", "neutral/not applicable", "consistent", "very inconsistent" for hypothesis-evidence consistency). PARC matches the selected ratings to numeric values and uses these to calculate an inconsistency score for each alternative hypothesis.

The attitude of the intelligence community towards SATs (and ACH, in particular) has been that, although they may not be perfect aides to the analyst's unaccompanied reasoning processes, they are almost certain not to do harm and probably do good (Heuer, 2005). However, as others have noted (Dhami, Mandel, Mellers & Tetlock, 2015; Karvetski, Olson, Gantz & Cross, 2013; Mandel & Tetlock, 2018), this conclusion may be premature. SATs usually involve multiple steps that are of questionable reliability and validity, and this

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*KaDSci LLC. Email: ckarvetski@gmail.com.

†Defence Research and Development Canada

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is true of ACH (Chang, Berdini, Mandel & Tetlock, 2018; Mandel, 2020). For instance, ACH does not give analysts guidance on how to parse or chunk evidence, or how to treat evidence that is not independent. For instance, Karvetski, Mandel and Irwin (2020) found that ACH users tended to rate two perfectly correlated cue values as if they were fully independent sources of evidence. Increasing the salience of the information redundancy made the tendency to treat the evidence as independent even stronger. This suggests that ACH encourages the use of a simple "copy repeating patterns" heuristic that fully ignores correlational structure in evidence. Similarly, ACH does not define what consistency means or how it should be assessed. Some analysts might interpret it as the probability of the evidence given the hypothesis, while others might interpret it as the inverse probability. Others still might regard it as a call for an intuitive judgment of how well the evidence and hypothesis seem to match one another—namely, as a call for the application of the representativeness heuristic, which has been implicated in several cognitive biases (Kahneman & Tversky, 1972). This imprecision of input terms may foster inter-analyst inconsistency or the same analyst might exhibit inconsistency over time or even within a specific case.

While ACH is promoted to mitigate confirmation bias — the search for (or use of) evidence to support a preferred hypothesis (Nickerson, 1998) — the technique may be susceptible to other biases that are present within evidential evaluation processes. For example, the enhancement effect implies that an increased perception of the degree to which the evidence is compatible with three or more mutually exclusive and exhaustive hypotheses can result in all hypotheses being judged as more likely than possible (Rottenstreich & Tversky, 1997; Tversky & Koehler, 1994). This implies the assigned hypothesis probabilities sum to more than one. Given that ACH provides no check on additivity violations and does not even make the probabilities of hypotheses explicit, it is unlikely to mitigate this bias in evidence assessment.

Recent research on the effectiveness of ACH calls into question the effectiveness of this method for mitigating biases and improving judgment accuracy. Whitesmith (2019) found that ACH did not mitigate either confirmation bias or serial-position effects on the interpretation of evidence in reasoning about an intelligence analysis scenario (also see Lehner, Adelman, Cheikes & Brown, 2008). Mandel, Karvetski and Dhami (2018) found that intelligence analysts who were instructed to use ACH on a probabilistic hypothesis-testing task were *less* coherent and marginally less accurate in assigning probabilities to the hypotheses than analysts in a control group who were not instructed to use any SAT. Moreover, a subsequent examination of analysts' information use from the same experiment showed that analysts in the ACH condition were *less* likely to use relevant base-rate information than analysts in the control condition (Dhami, Belton & Mandel, 2019). In another experiment, Karvetski et al. (2020) found that mock analysts who judged the probabilities of alternative hypotheses before and after using ACH were less coherent (i.e., violating complementarity and additivity constraints on probabilities) and they did not significantly differ from the control group in terms of accuracy. In fact, aggregated judgments were more accurate before using ACH than after using it, and the benefit of *not* using ACH increased with the size of the aggregate. As intelligence communities in the US and elsewhere invest in research to leverage the wisdom of crowds through mechanisms such as prediction markets (e.g., see Stastny & Lehner, 2018; cf. Mandel, 2019), the relative cost of using ACH versus other methods may be amplified.

The preceding research not only casts doubt on the efficacy of ACH, it also challenges the claim that SATs, at worst, do not help. The studies by Mandel et al. (2018), Dhami et al. (2019), and Karvetski et al. (2020) show that use of ACH can make analysts' probability judgments about alternative hypotheses worse than if ACH were not used. However, skeptics might counter that the aforementioned studies not only lack mundane realism, they also differ from real-life analysis in ways that undermine the external validity of the research. For instance, participants in Mandel et al. (2018) and Karvetski et al. (2020) received statistical evidence that was described as being perfectly accurate and precise and that was communicated using numeric probabilities, much as in earlier experiments on probabilistic hypothesis testing (e.g., Slowiaczek, Klayman, Sherman & Skov, 1992; Villejoubert & Mandel 2002). These features enabled unambiguous scoring of accuracy using probabilistic truth criteria, but they sacrifice mundane realism and perhaps external validity as well. Therefore, such studies should be complemented by research that represents evidence more closely to how it often appears in real-life investigations.

1.1 The Present Research

The aim of the present research was to provide a more externally valid test of ACH. As in prior studies on ACH (e.g., Mandel et al., 2018; Karvetski, 2020), participants were asked to assign probabilities to alternative hypotheses. However, to improve the external validity of tests of ACH, we presented evidence (based on a hypothetical suspect's criminal record) with probabilities that were imprecisely communicated using linguistic terms such as *likely*, much as an analyst would encounter in the everyday intelligence practice (Barnes, 2016; Ho, Budescu, Dhami, & Mandel, 2015; Mandel, 2015a). In each of six cases, we also presented evidence from two human sources claiming to know the suspect. This evidence was coded in terms of the source's reliability and the credibility of the information, following the Admiralty coding system widely used in the evaluation step of the analysis stage within the intelligence cycle (Irwin & Mandel, 2019; Samet, 1975). Prior to re-

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ceiving case-specific information, participants were asked to translate the verbal probabilities and alphanumeric source reliability/information credibility values used in the cases into their own probabilistic interpretation of the evidence.

Although we have foregone the ability to directly assess ACH's effectiveness on correspondence criteria (i.e., accuracy) in this research, using the participants' own probabilistic interpretation of the evidence allows us to assess the effect of ACH on multiple coherence criteria. Coherence criteria gauge the extent to which judges agree with normative constraints on judgment or decisions or are otherwise internally consistent (Hammond, 2000). As such, coherence criteria are fundamental to sound reasoning, which the intelligence community views as a pillar of analytic integrity (Office of the Director of National Intelligence, 2015). Coherence metrics have been shown to covary with correspondence metrics such as accuracy in forecasting (Mellers, Baker, Chen, Mandel & Tetlock, 2017). Several studies also show that judgment accuracy can be improved by exploiting individual differences in coherence (Fan, Budescu, Mandel & Himmelstein, 2019; Karvetski, Olson, Mandel & Twardy, 2013; Mandel et al., 2018; Wang, Kulkarni & Poor, 2011). Therefore, performance on coherence criteria can provide at least indirect evidence of how likely a method such as ACH is to improve accuracy.

As in some earlier research (Dhami et al., 2019; Mandel et al., 2018), the present research compared the performance of individuals using ACH to a control condition in which participants judged probabilities without instruction to use any SAT. The present experiment explored a fuller set of coherence metrics than in previous studies. A first test of coherence examined the consistency between posterior probability judgments and choice. Mandel (2015b) found that when intelligence analysts were asked to judge the posterior probabilities of binary complements and subsequently asked to make a binary choice regarding which hypothesis was correct, only 53% chose the alternative with the higher probability across all eight problems. This proportion substantially increased to 83% after brief training in Bayesian reasoning using natural sampling trees similar to protocols used in other studies (e.g., Sedlmeier & Gigerenzer, 2001). Dhami et al. (2019) further found that analysts who used ACH were less likely than control analysts to show consistency between their final conclusions and the penultimate judgments. However, that analysis was based on a small sample. In the present research, which used a much larger sample of participants, we also studied the consistency between probabilities assigned to binary complements and whether participants selected the alternative with the higher probability in their binary choices. If ACH improves the quality of reasoning, then we might expect greater consistency between judgment and choice in the ACH condition than in the control group.

As a second test of coherence, we examined how reliable participants were in their probability judgments across cases that had isomorphic evidence configurations. In the present research, the six cases we used were comprised of three isomorphic pairs of cases (i.e., surface characteristics were switched but the cases had the same structure). If ACH is effective at mitigating unreliability due to so-called "unstructured reasoning," we should observe greater reliability (i.e., within-pair consistency) among participants using ACH than among those in the control group.

Several studies show that people violate the additivity constraint in probability judgment, for example by providing subadditive judgments of probabilities among mutually exclusive and exhaustive hypotheses that sum to more than unity (Ayton, 1997; Mandel, 2005, 2008; Tversky & Koehler, 1994). In an exercise that involved having analysts assess the likelihood of four competing hypotheses in a single case using diagnostic cues of various levels of support, Mandel et al. (2018) found that compared to a control condition, ACH led to greater subadditivity (i.e., the sum of four mutually exclusive and exhaustive hypotheses exceeded 1). Karvetski et al. (2020) further confirmed that ACH increased within-subject incoherence using a task that involved judging the probabilities of three mutually exclusive and collectively exhaustive hypotheses within a single case. In the present research, we tested the effect of ACH on additivity violations from the complementarity rule, which requires that $P(x) + P(\neg x) = 1$. This provided a third test of coherence.

Some studies evaluating adherence to the complementarity rule have found additivity (Tversky & Fox, 1995; Tversky & Koehler, 1994; Wallsten, Budescu & Zwick, 1993), while others have found superadditivity (Macchi, Osherson & Krantz, 1999, Mandel, 2005, 2015b), or a varying pattern of either superadditivity and subadditivity (Idson, Krantz, Osherson & Bonini, 2001; Villejoubert & Mandel, 2002) or additivity and subadditivity (Dhami & Mandel, 2013). It appears that the direction of complementarity violations is influenced by the totality of evidential support for the hypotheses. For instance, Idson et al. (2001) found that if participants had little knowledge to draw upon, judgments were superadditive, whereas if participants had greater knowledge, judgments were subadditive. In a related vein, Villejoubert and Mandel attributed the direction of bias from complementarity to the inverse fallacy, the tendency to confuse posterior probabilities with their inverse, diagnostic probabilities. They found that when the sum of the diagnostic probabilities was less than unity, $P(\text{D}|\text{H1}) + P(\text{D}|\text{H2}) < 1$, posterior probabilities were superadditive, $P(\text{H1}|\text{D}) + P(\text{H2}|\text{D}) < 1$. However, when the sum of the diagnostic probabilities was greater than unity, $P(\text{D}|\text{H1}) + P(\text{D}|\text{H2}) > 1$, posterior probabilities were subadditive, $P(\text{H1}|\text{D}) + P(\text{H2}|\text{D}) > 1$. The present research includes multiple case scenarios that varied the level of total evidential support, thus allowing further tests of whether complementarity violations can be

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explained by characteristics of evidence. We hypothesized that as total evidential support increases, the total probability assigned to complementary hypotheses will also increase, inducing subadditivity of probability estimates.

As noted earlier, we elicit for every participant a probabilistic interpretation of each uncertainty term. We calculated participant-specific Bayesian posterior probabilities using these estimates. This allowed us to analyze the coherence in a fourth manner: namely, as agreement in the most likely hypothesis and the absolute deviation between the participant's elicited posterior probabilities and those computed using Bayes theorem from their preceding translation estimates. In addition to testing whether ACH improved consistency, we tested whether there was evidence of conservatism (Edwards, 1968; Phillips & Edwards, 1966)—namely, insufficient belief revision in light of the evidence.

Finally, as a fifth test of coherence, we examined how participants in the ACH condition weighed evidence. Lehner et al. (2008) found that non-diagnostic evidence was often assigned non-neutral consistency scores, indicating a form of pseudo-diagnosticity in consistency judgments, which the authors called *projection error*. The proportion of such errors did not differ between participants trained in and using ACH and those who were neither trained in nor asked to use ACH. Lehner et al.'s study, however, was statistically underpowered, having only 24 participants assigned to four conditions. Therefore, their findings, both those found to be significant and those found to be nonsignificant, are of questionable replicability and must be interpreted cautiously. In the present research, we examined a related issue; namely, whether non-diagnostic evidence equally favoring two alternative hypotheses would be accordingly rated with an equal degree of consistency in ACH or, alternatively, whether such non-diagnostic evidence would be rated in a manner favoring one hypothesis over the other. Specifically, we tested the hypothesis that participants using ACH will assign more positive consistency ratings to the hypothesis suggested to be true by the evidential claim if the probability of truth were disregarded. For example, assuming x and $\neg x$ as binary complements, for an evidence claim that there is a 50% chance that x is true, it would be appropriate for x and $\neg x$ to be assigned equal consistency ratings in ACH. A strict normative constraint might go even further, requiring that analysts assign both hypotheses a *neutral* rating. However, on the basis of research on framing effects, which shows that what is explicated in a statement has more impact on judgment than what is logically implied (Mandel, 2008; Tombu & Mandel, 2015), we expected that the hypothesis explicitly matched to truth in the claim would receive a more positive rating.

2 Method

2.1 Participants

Participants ($N = 227$) were recruited using the online crowdsourcing service Qualtrics Panels and were required to (a) be at least 18 years of age, (b) be fluent in English, (c) be a Canadian citizen, (d) possess a Bachelor's or higher degree, and (e) complete the experiment on a computer (i.e., smartphones were prohibited). The mean age was 40.7 years (*SD* = 11.9) and 26.4% were male.

2.2 Experimental design

The experiment used a one-factor (Method) between-subjects design in which participants were randomly assigned to the ACH condition or to the control condition. In the ACH condition, participants used the ACH method as implemented in the PARC tool (PARC, 2006), whereas in the control condition, participants were not required to use a SAT.

2.3 Procedure

The data were collected as part of a larger online survey. Participants first read the consent form and provided they consented, they were first asked to answer ten general knowledge questions for an unrelated study. The next task was the primary one relevant to the present research, which is described in detail below[1]. Following this task, participants completed other tasks that were not related to the aims of the present research, following which demographic information was collected and participants were debriefed.

In the primary task, participants were asked to imagine that they were hired as an analyst for a "Federal Law Enforcement Agency" whose mission was to help local law enforcement agencies crack down on gang activity within their respective locales. In particular, participants were told they would be investigating multiple graffiti crime cases, each of which concerned a single suspect, and that investigated activity within each standalone case could be "either gang-related or else the act of a street artist with no gang affiliation", and that their task was "sorting through each scenario provided by the local law enforcement centres, [with the objective of providing] a probabilistic assessment concerning whether the graffiti activity is gang-related or the work of a street artist." Both statements implied these two outcomes of gang member (*GM*) or street artist (*SA*) as mutually exclusive and collectively exhaustive hypotheses.

Prior to encountering any of the cases, participants provided an initial set of five judgments that addressed the ques-

[1] A full transcript of the primary task with all supporting screenshots, as well as data and R code, are available from the Open Science Foundation at https://osf.io/prvkm/.

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Table 1: Prompts for probability equivalents (P_e) for uncertainty terms.

Elicited Judgment	Assessed Question
P_{HL}	Assume a background check reveals that it is *highly likely* that a suspect belongs to a certain category (e.g., gang member or street artist). What is the probability that the suspect is in fact a member of the described category?
P_L	Assume a background check reveals that it is *likely* that a suspect belongs to a certain category (e.g., gang member or street artist). What is the probability that the suspect is in fact a member of the described category?
P_{A1}	Let's say an informant's reliability is assigned an A (completely reliable) and the credibility of the informant's information is assigned a 1 (completely credible). If this informant were to make a claim about a suspect on the basis of the information he or she provided, what is the probability that the claim is accurate?
P_{C3}	Let's say an informant's reliability is assigned a C (fairly reliable) and the credibility of the informant's information is assigned a 3 (possibly true). If this informant were to make a claim about a suspect on the basis of the information he or she provided, what is the probability that the claim is accurate?
P_{F3}	Let's say an informant's reliability is assigned an F (reliability cannot be judged) and the credibility of the informant's information is assigned a 3 (possibly true). If this informant were to make a claim about a suspect on the basis of the information he or she provided, what is the probability that the claim is accurate?

tions shown in Table 1, where participants entered probabilities using a slider-bar that ranged from 0 to 1 with increments of 0.01. We denote each judgment generically as P_e with $e \in E = \{HL, L, A1, C3, F3\}$. These judgments established participant-specific probability equivalents for the verbal uncertainty terms that described evidence in the subsequent cases. The first two questions elicited judgments P_{HL} and P_L, respectively, and addressed the two verbal uncertainty terms of *highly likely* and *likely*. These questions were presented first in randomized order. The remaining three questions elicited judgments for three source reliability and information credibility combinations (P_{A1}, P_{C3}, and P_{F3}) that were taken from the rating system used in NATO's Allied Intelligence Doctrine (NATO, 2015; see also Irwin & Mandel, 2019; Samet, 1975). These questions were also presented in randomized order, and the full rating scale (see bottom of Figure 1) was presented above these questions for reference.

2.3.1 Control condition

After providing inputs for the questions in Table 1, participants in the control condition saw an overview slide describing the format of each case, but they received no additional instruction on how to analyze the cases before encountering the six cases (which are described in the next section). Case order was randomized per participant. Each case featured a case description including a local (generic) gang name with which the individual of the case was suspected of being affiliated, along with three items of evidence. Figure 1 displays an example case presented to participants. The first item of evidence within each case was a background check conducted on the suspect that described which of the two hypotheses was more likely from the findings (*street artist* in the example of Figure 1), as well as a description of law enforcement's subjective probability of that hypothesis being true (*likely* in the example). The other two items of evidence within each case corresponded to the testimony and assessment of two independent informants, where each informant's testimony and assessment showed three components of information: (a) the informant's claim, (b) a rating of the informant's source reliability, and (c) a rating of the credibility of the information. For the case in Figure 1, Informant 1 is rated *F3* and describes the suspect as a street artist. Informant 2, on the other hand, is rated *A1* and describes the suspect as a gang member. Also, participants (in both conditions) were told to "Assume that the informants cannot access the background check information and the informants have had no communication with one another. More generally, assume the three items of evidence are independent of one another. Further, assume that the cases are independent of one another."

For each case, participants in the control condition answered the following two questions:

- What is the probability that the suspect in the case below is a gang member?
- What is the probability that the suspect in the case below is a street artist?

The two elicited questions appeared on separate pages, with ordering counterbalanced, and with the value entered using a slider that ranged from 0 to 1, with increments of 0.01. The full case image (e.g., Figure 1) was displayed below each question, and there was no requirement for the two probabilities to sum to 1, nor a reference made to the

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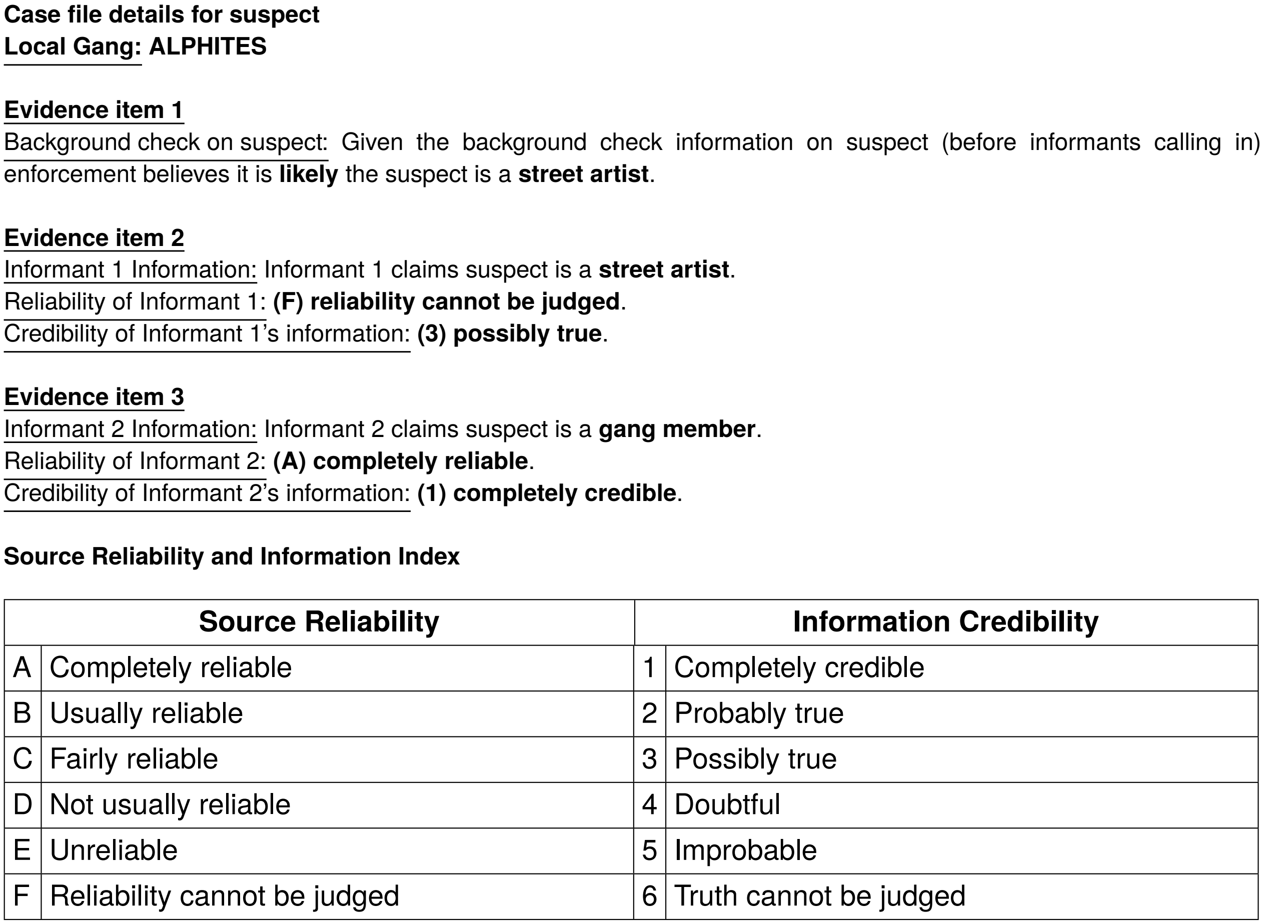

Case file details for suspect
Local Gang: ALPHITES

Evidence item 1

Background check on suspect: Given the background check information on suspect (before informants calling in) law enforcement believes it is **likely** the suspect is a **street artist**.

Evidence item 2

Informant 1 Information: Informant 1 claims suspect is a **street artist**.
Reliability of Informant 1: **(F) reliability cannot be judged**.
Credibility of Informant 1's information: **(3) possibly true**.

Evidence item 3

Informant 2 Information: Informant 2 claims suspect is a **gang member**.
Reliability of Informant 2: **(A) completely reliable**.
Credibility of Informant 2's information: **(1) completely credible**.

Source Reliability and Information Index

Source Reliability		Information Credibility	
A	Completely reliable	1	Completely credible
B	Usually reliable	2	Probably true
C	Fairly reliable	3	Possibly true
D	Not usually reliable	4	Doubtful
E	Unreliable	5	Improbable
F	Reliability cannot be judged	6	Truth cannot be judged

Figure 1: Example case from the judgment task.

relevance of the complementarity constraint.[2] Participants in the control condition were then asked, "Given all the information presented in this case, what will you recommend to your supervisor as the classification for this suspect?" The participants submitted their final recommendation that the suspect be classified as either a street artist or a gang member by clicking on one of two selection buttons labelled "GANG MEMBER" or "STREET ARTIST". The buttons for the final recommendation appeared on the same-screen with counter-balanced placement of which button was first, and again the entire case file image was presented below the buttons. After submitting the discrete recommendation for a suspect in a case, participants in the control condition would then move the next case and repeat the same assessment, until all six cases were completed.

2.3.2 ACH condition

After providing inputs for the questions in Table 1, participants in the ACH condition were presented with an overview slide describing the format of each case (as in the control condition). In contrast to the control condition, participants were also given a one-slide overview on the ACH procedure and were told they would be required to use the method in evaluating the cases, with further instructions embedded within the exercise. The ACH participants then encountered the same six cases presented to the control participants, once again with case order randomized per participant. For each case, the ACH participants went through an ACH assessment procedure within Qualtrics that emulated ACH as implemented in the PARC tool. For each case, participants completed the following ACH assessment procedure:

1. Provide assessments of the *source reliability and information credibility* as high (H), medium (M), or low (L) from a dropdown menu for each of the three items of evidence.
2. Provide assessments of the *relevance* as high (H), medium (M), or low (L) from a dropdown menu for

[2] Two additional probability questions that followed the posterior probability questions were, in hindsight, too ambiguous to use in the present analyses. However, they are listed in the supplementary materials.

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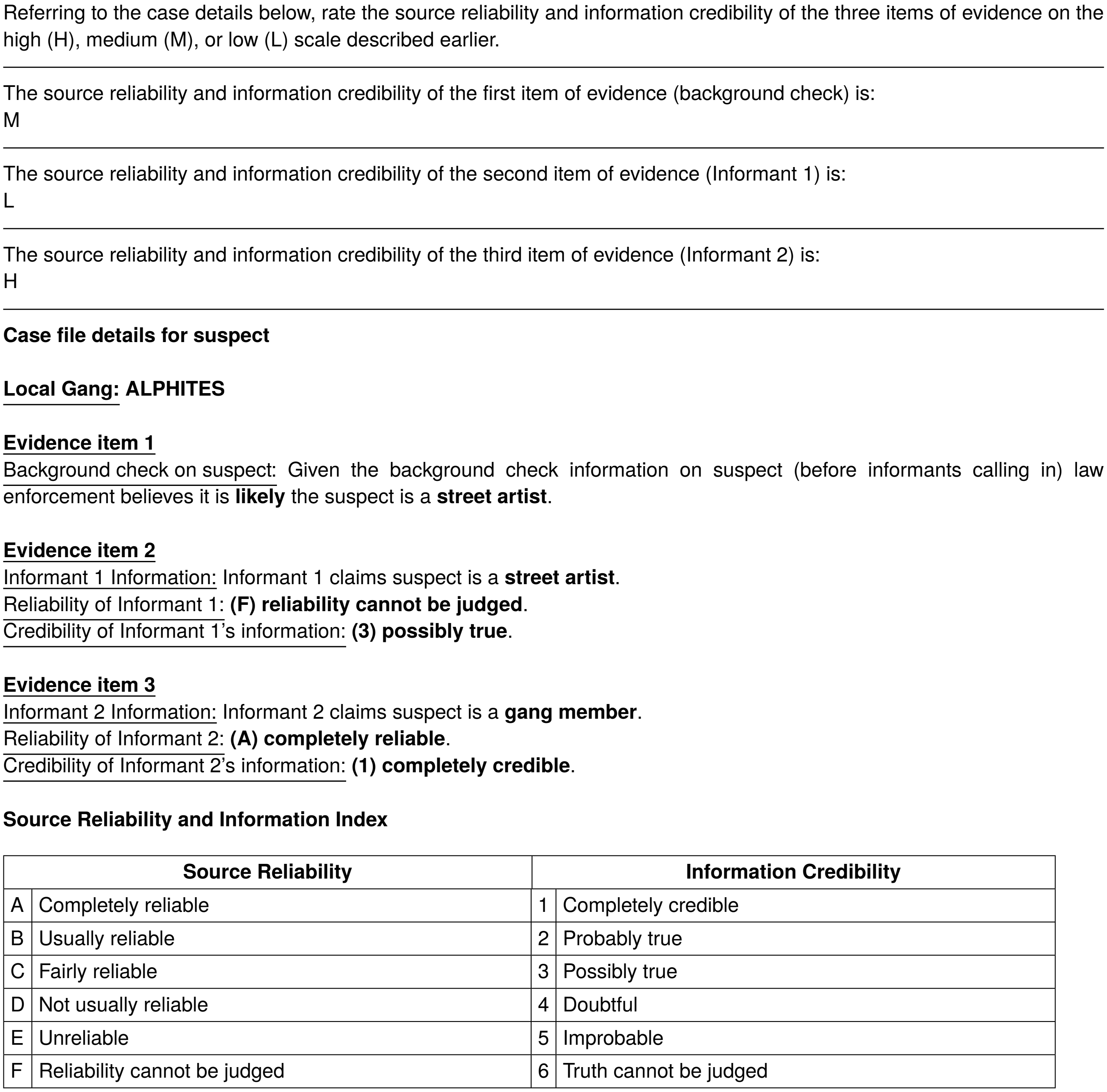

Referring to the case details below, rate the source reliability and information credibility of the three items of evidence on the high (H), medium (M), or low (L) scale described earlier.

The source reliability and information credibility of the first item of evidence (background check) is:
M

The source reliability and information credibility of the second item of evidence (Informant 1) is:
L

The source reliability and information credibility of the third item of evidence (Informant 2) is:
H

Case file details for suspect

Local Gang: **ALPHITES**

Evidence item 1

Background check on suspect: Given the background check information on suspect (before informants calling in) law enforcement believes it is **likely** the suspect is a **street artist**.

Evidence item 2

Informant 1 Information: Informant 1 claims suspect is a **street artist**.
Reliability of Informant 1: **(F) reliability cannot be judged**.
Credibility of Informant 1's information: **(3) possibly true**.

Evidence item 3

Informant 2 Information: Informant 2 claims suspect is a **gang member**.
Reliability of Informant 2: **(A) completely reliable**.
Credibility of Informant 2's information: **(1) completely credible**.

Source Reliability and Information Index

Source Reliability		**Information Credibility**	
A	Completely reliable	1	Completely credible
B	Usually reliable	2	Probably true
C	Fairly reliable	3	Possibly true
D	Not usually reliable	4	Doubtful
E	Unreliable	5	Improbable
F	Reliability cannot be judged	6	Truth cannot be judged

Figure 2: Example of Step 1 in the ACH process as implemented in the experiment.

each of the three items of evidence.

3. Populate matrix cells (6 inputs total) with ratings of the consistency between each item of evidence and each hypothesis, which ranged from very inconsistent (II), inconsistent (I), neutral/not applicable (N), consistent (C), or very consistent (CC). The qualitative ratings had accompanying inconsistency scores.
4. Sum the inconsistency scores for each of the two hypotheses, and select the summation value from a drop-down menu in order to generate a final inconsistency score for each hypothesis.
5. Use the final inconsistency scores and provide probabilities that the suspect in each case is a gang member or a street artist. Then provide a final recommendation that the suspect be classified as either a street artist or a gang member.

Figure 2 shows an example of Step 1 for the example case in Figure 1 (Step 2 used an almost identical process, except with "relevance" substituted for "source reliability and information credibility" within the text). Figure 3 shows

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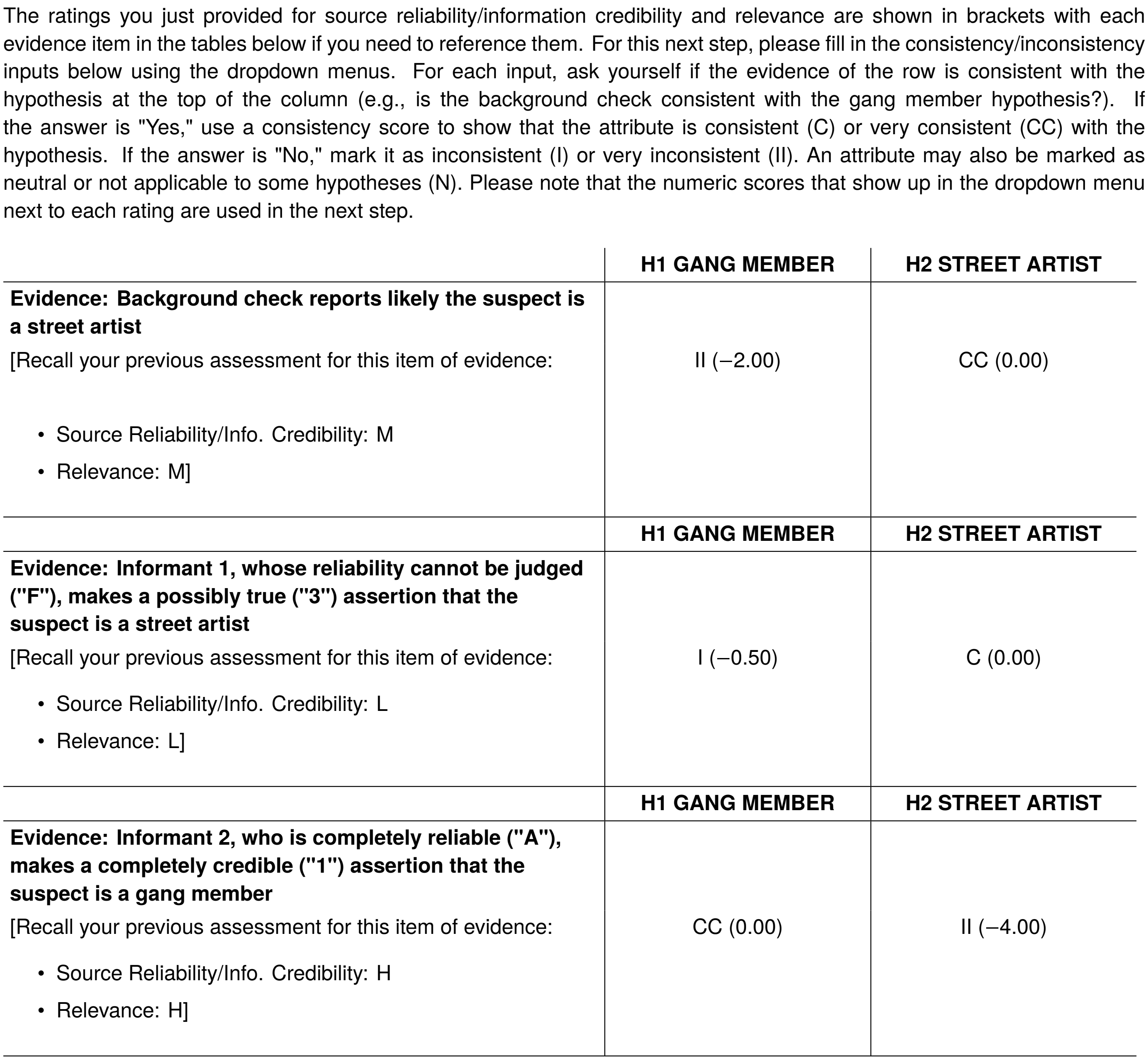

The ratings you just provided for source reliability/information credibility and relevance are shown in brackets with each evidence item in the tables below if you need to reference them. For this next step, please fill in the consistency/inconsistency inputs below using the dropdown menus. For each input, ask yourself if the evidence of the row is consistent with the hypothesis at the top of the column (e.g., is the background check consistent with the gang member hypothesis?). If the answer is "Yes," use a consistency score to show that the attribute is consistent (C) or very consistent (CC) with the hypothesis. If the answer is "No," mark it as inconsistent (I) or very inconsistent (II). An attribute may also be marked as neutral or not applicable to some hypotheses (N). Please note that the numeric scores that show up in the dropdown menu next to each rating are used in the next step.

	H1 GANG MEMBER	**H2 STREET ARTIST**
Evidence: Background check reports likely the suspect is a street artist [Recall your previous assessment for this item of evidence: • Source Reliability/Info. Credibility: M • Relevance: M]	II (−2.00)	CC (0.00)

	H1 GANG MEMBER	**H2 STREET ARTIST**
Evidence: Informant 1, whose reliability cannot be judged ("F"), makes a possibly true ("3") assertion that the suspect is a street artist [Recall your previous assessment for this item of evidence: • Source Reliability/Info. Credibility: L • Relevance: L]	I (−0.50)	C (0.00)

	H1 GANG MEMBER	**H2 STREET ARTIST**
Evidence: Informant 2, who is completely reliable ("A"), makes a completely credible ("1") assertion that the suspect is a gang member [Recall your previous assessment for this item of evidence: • Source Reliability/Info. Credibility: H • Relevance: H]	CC (0.00)	II (−4.00)

Figure 3: Example of Step 3 in the ACH process as implemented in the experiment.

an example of Step 3, where the consistency inputs displayed scores in parentheses (e.g., "II (-4)"). The scores were automatically calculated and were a function of their previously provided reliability/credibility and relevance inputs from Steps 1 and 2. Table 2 shows the scoring rubric used within the experiment to populate the displayed scores, which was selected in order to represent the actual scoring method used in the PARC tool (PARC, 2006). Note that only "inconsistent" and "very inconsistent" ratings are assigned non-zero scores, which is based on Heuer's (1999) "falsificationist" interpretation that the evidence can disprove but cannot confirm hypotheses (see Mandel, 2020, for discussion of the problems associated with this information integration method).

Figure 4 shows the summation process described in Step 4, where the values in the dropdown ranged from 0 to −12 in increments of −0.25. After Step 4, participants were reminded: "According to the technique, the hypothesis that has the LEAST negative score is the MOST probable one, while the one that has the MOST negative score is the LEAST probable hypothesis. For example, if one hypothesis has a final inconsistency score of -4 and a second hypothesis has a final inconsistency score of -1, the technique is suggesting the second hypothesis is more probable. If the scores are tied, then the technique is suggesting that those hypotheses are about equally probable." For Step 5, the probability questions

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Table 2: ACH consistency scoring logic used in the experiment for very inconsistent (II), inconsistent (I), neutral/not applicable (N), consistent (C), and very inconsistent (CC).

Reliability/ Credibility	Relevance	II	I	N	C	CC
High	High	−4	−2	0	0	0
Medium	High	−3	−1.5	0	0	0
Low	High	−2	−1	0	0	0
High	Medium	−3	−1.5	0	0	0
Medium	Medium	−2	−1	0	0	0
Low	Medium	−1.5	−0.75	0	0	0
High	Low	−2	−1	0	0	0
Medium	Low	−1.5	−0.75	0	0	0
Low	Low	−1	−0.5	0	0	0

were presented on separate pages, again with no requirement of (nor reference to) complementarity, and with full visibility of the entire ACH matrix. The questions were phrased as follows:

- Given the final inconsistency scores, what is the probability that the suspect is a street artist?
- Given the final inconsistency scores, what is the probability that the suspect is a gang member?

Participants provided their discrete final recommendation “to their supervisor” by clicking on a button of “GANG MEMBER” or “STREET ARTIST” in the same way as in the control condition. Participants then moved on to the next cased and used the same ACH until all six cases were completed.

2.3.3 Case design

Table 3 describes the six cases used within the experiment (again, Case 1 is presented in Figure 1), each of which can be summarized by the three different pieces of evidence (Background check, Informant 1, and Informant 2). The five distinct uncertainty terms and cases were selected and designed with four goals in mind: (a) to be non-trivial (e.g., not all items of evidence point to one hypothesis), (b) to permit measurement of reliability, (c) to vary evidential support, both for the individual items of evidence, but also in aggregate within a case, and (d) to permit comparison between a participant’s posterior probability judgments and a normative benchmark based on a naïve Bayes model of the participant.

2.3.4 Coherence measures

Reliability With respect to reliability, the cases in Table 3 were paired such that the claims of the first case in the pair were switched for the second case in the pair. For example, in Table 3, the first case background check describes it as “likely” the suspect is a street artist while the second case describes it as “likely” the suspect is a gang member. The first two cases also feature an *A1* informant and an *F3* informant, but the claims are again switched across the cases. Therefore, the probability of street artist (gang member) for the first case is the same as the probability of gang member (street artist) in the second case (and vice versa). For example, if for a given pair of cases a participant provided a probability of gang member of .7 and probability of street artist of .4 for the first case in the pair, and then probability of gang member of .45 and probability of street artists of .6 for the second case in the pair, this participant would have a reliability score measured by mean absolute deviation (MAD) as follows:

$$MAD = \frac{|.7 - .6| + |.4 - .45|}{2} = .075. \quad (1)$$

Perfect reliability within a pair of cases is therefore expressed as $MAD = 0$.

2.3.5 Evidential support

With respect to differing levels of evidential support, we assumed that the five uncertainty terms spanned a large range of evidential support as follows:

$$(1 \approx)P_{A1} > P_{HL} > P_L > P_{C3} > P_{F3}(\approx 0.5). \quad (2)$$

These assumptions are supported by Mosteller and Youtz (1990), who found that the mean probability equivalent for “very likely” as .82 versus .69 for “likely”, and unpublished research of Mandel and Dhami (2018), who found a mean of .93 for *A1* (“completely reliable”, with a “completely credible” claim) , .61 for *C3* (“fairly reliable”, with a “possibly true” claim), and .53 for *F3* (“reliability cannot be judged”, with a “possibly true” claim) among 82 subjects, all of whom were intelligence experts. Having a wide range of evidential support allowed us to test, for example, that the individual consistency scores for participants in the ACH condition correlate with these ratings, and that, in particular, the inconsistency scores of an item of evidence where the corresponding uncertainty term is near 50/50 (i.e., $P_e \approx .5$) supports both hypotheses equally.

Also, given that the three items of evidence within each case were described as pairwise independent, we assumed the total evidential support s_{Pi} for cases within Pair i ($i = 1, 2, 3$) could be measured by adding the evidential support of the individual items of evidence. For the cases in the respective pairs, this implies

$$s_{P1} = s_L + s_{F3} + s_{A1}, \quad (3)$$

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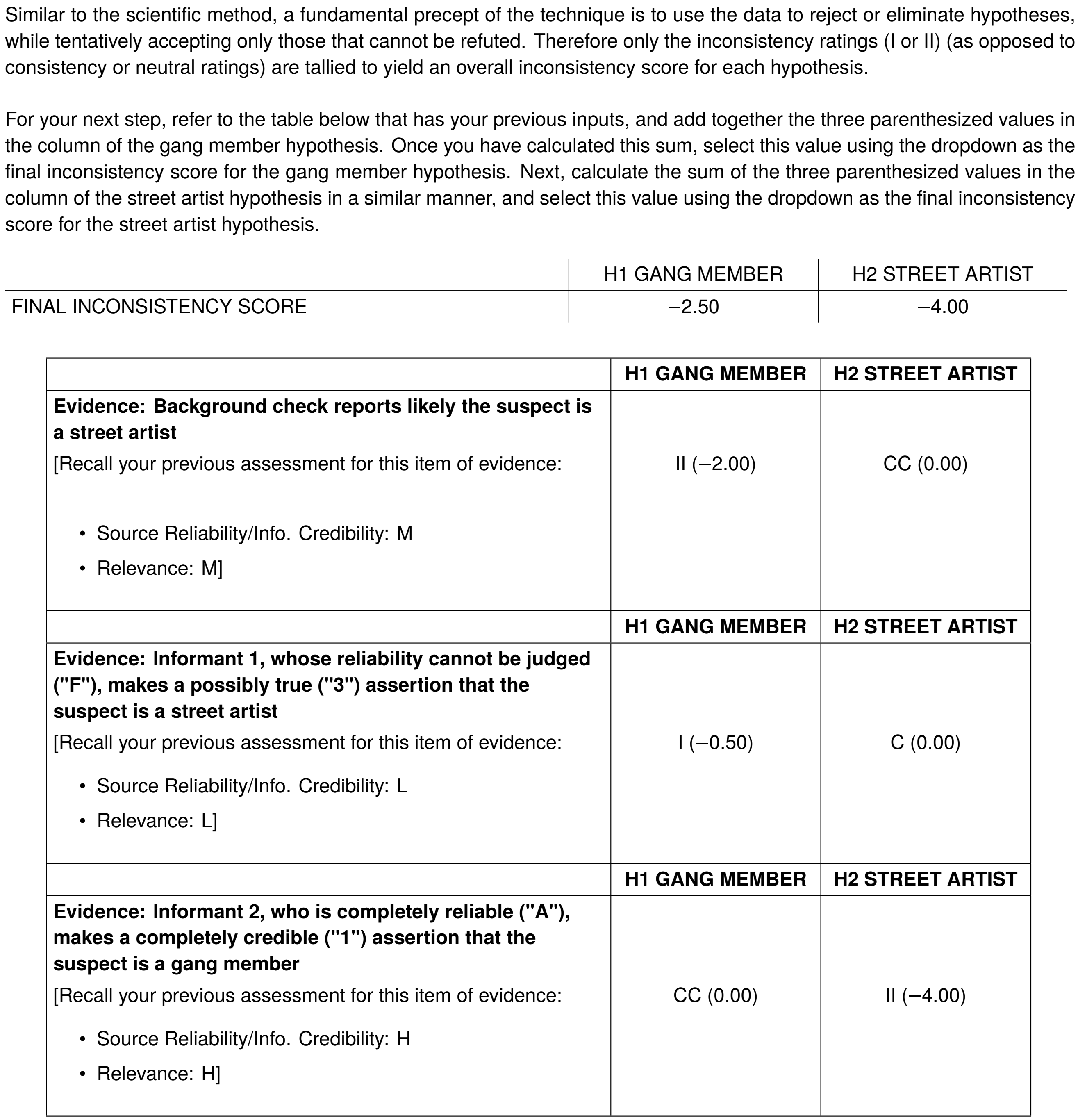

Similar to the scientific method, a fundamental precept of the technique is to use the data to reject or eliminate hypotheses, while tentatively accepting only those that cannot be refuted. Therefore only the inconsistency ratings (I or II) (as opposed to consistency or neutral ratings) are tallied to yield an overall inconsistency score for each hypothesis.

For your next step, refer to the table below that has your previous inputs, and add together the three parenthesized values in the column of the gang member hypothesis. Once you have calculated this sum, select this value using the dropdown as the final inconsistency score for the gang member hypothesis. Next, calculate the sum of the three parenthesized values in the column of the street artist hypothesis in a similar manner, and select this value using the dropdown as the final inconsistency score for the street artist hypothesis.

	H1 GANG MEMBER	H2 STREET ARTIST
FINAL INCONSISTENCY SCORE	–2.50	–4.00

	H1 GANG MEMBER	**H2 STREET ARTIST**
Evidence: Background check reports likely the suspect is a street artist [Recall your previous assessment for this item of evidence: • Source Reliability/Info. Credibility: M • Relevance: M]	II (–2.00)	CC (0.00)
	H1 GANG MEMBER	**H2 STREET ARTIST**
Evidence: Informant 1, whose reliability cannot be judged ("F"), makes a possibly true ("3") assertion that the suspect is a street artist [Recall your previous assessment for this item of evidence: • Source Reliability/Info. Credibility: L • Relevance: L]	I (–0.50)	C (0.00)
	H1 GANG MEMBER	**H2 STREET ARTIST**
Evidence: Informant 2, who is completely reliable ("A"), makes a completely credible ("1") assertion that the suspect is a gang member [Recall your previous assessment for this item of evidence: • Source Reliability/Info. Credibility: H • Relevance: H]	CC (0.00)	II (–4.00)

Figure 4: Example of Step 4 in the ACH process as implemented in the experiment.

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Table 3: Description of six cases used within the experiment. An A1 informant is one that is deemed "completely reliable" and makes a claim that is "completely credible". A C3 informant is one that is deemed "fairly reliable", and makes a claim that is judged "possibly true". A F3 informant is rated as "reliability cannot be judged", and makes a claim denoted as "possibly true".

		Background check		Informant 1		Informant 2	
Case	Pair	Indication	Uncertainty Term	Indication	Uncertainty Term	Indication	Uncertainty Term
1	1	Street artist	Likely	Street artist	F3	Gang member	A1
2	1	Gang member	Likely	Street artist	A1	Gang member	F3
3	2	Street artist	Highly likely	Gang member	A1	Street artist	C3
4	2	Gang member	Highly likely	Gang member	C3	Street artist	A1
5	3	Street artist	Highly likely	Gang member	C3	Gang member	F3
6	3	Gang member	Highly likely	Street artist	C3	Street artist	F3

$$s_{P2} = s_{HL} + s_{A1} + s_{C3}, \tag{4}$$

$$s_{P3} = s_{HL} + s_{C3} + s_{F3}. \tag{5}$$

One assumption is that $s_e = P_e$ for $e \in E = \{HL, L, A1, C3, F3\}$. In other words,

$$s_{P1} = P_L + P_{F3} + P_{A1}, \tag{6}$$

$$s_{P2} = P_{HL} + P_{A1} + P_{C3}, \tag{7}$$

$$s_{P3} = P_{HL} + P_{C3} + P_{F3}. \tag{8}$$

However, this stronger assumption is not needed in order to rank order s_{P1}, s_{P2}, and s_{P3}. To do so, in addition to the additivity assumptions expressed in equations (3)–(5) and the inequality statement in equation (2), we need only to assume $s_e = f(P_e)$ for $e \in E$, with f being a strictly increasing function in P_e.

By comparing the cases of Pair 1 to Pair 2, one can observe that (a) both sets of cases feature an *A1* informant (which cancels out), yet (b) the cases within Pair 2 feature a *highly likely* background check descriptor rather than *likely* and therefore (by assumption) $s_{HL} > s_L$, and (c) the cases in Pair 2 feature a *C3* informant rather than an *F3* informant, and thus (by assumption) $s_{C3} > s_{F3}$. With equations (3) and (4), this implies $s_{P1} < s_{P2}$.

Next, in comparing the cases of Pair 1 with those within Pair 3, the *F3* informant is common to both and cancels out. The inequality statement in equation (2) and the assumption $s_e = f(P_e)$ with f being a strictly increasing function then yields

$$s_{A1} - s_{C3} > s_{HL} - s_L. \tag{9}$$

With equations (3) and (5), this implies

$$s_{P3} < s_{P1} < s_{P2}. \tag{10}$$

This respective rank ordering of s_{Pi} for the three pairs from equation (10) can then be compared with bias from complementarity, defined for case j ($j = 1, \ldots, 6$) within pair i as

$$\Delta_{i,j} = EP_{i,j}(GM) + EP_{i,j}(SA) - 1, \tag{11}$$

where $EP_{i,j}(GM)$ and $EP_{i,j}(SA)$ represent the respective elicited probabilities for the two hypotheses within case j. If there were an enhancement effect, where more evidential support among the hypotheses implied a greater bias from complementarity, we would expect:

$$\Delta_{3,j} < \Delta_{1,j} < \Delta_{2,j}. \tag{12}$$

2.3.6 Bayesian posterior probabilities

In addition to using the elicited judgments from Table 1 for calculating total support as expressed by s_{Pi}, the P_e values are used to calculate a Bayesian posterior distribution for the two hypotheses. First, we assumed that a background check uncertainty equivalent (P_{HL} or P_L) set a participant's base rate for a case. For example, in Case 1 (i.e., Figure 1), the participant's base rate for street artist is P_L and by complementarity the base rate for gang member is $1 - P_L$.

Second, we assumed the P_e values regarding the informants (P_{A1}, P_{C3}, P_{F3}) were measures of information reliability. In other words, given a suspect is truly of a certain state (i.e., gang member or street artist), it was assumed an *A1* informant would report this state in their testimony with probability P_{A1} (and consequently report the opposite state with probability $1 - P_{A1}$). Translating these into conditional probabilities implies that

$$\begin{aligned} &P(\text{A1 reports GM}|\text{suspect is GM}) = \\ &P(\text{A1 reports SA}|\text{suspect is SA}) = P_{A1}, \end{aligned} \tag{13}$$

with similar interpretations for P_{C3} and P_{F3}.

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These translations of the elicited uncertainty judgments along with the independence assumptions of the three items of evidence allow us to calculate participant-specific naive Bayesian posterior probabilities $BP_{i,j}(GM)$ and $BP_{i,j}(SA)$. These two values can be compared to $EP_{i,j}(GM)$ and $EP_{i,j}(SA)$ and the *normalized elicited probabilities* that transform the raw probabilities in order to respect complementarity:

$$NEP_{i,j}(GM) = \frac{EP_{i,j}(GM)}{EP_{i,j}(GM) + EP_{i,j}(SA)} \tag{14}$$

and

$$NEP_{i,j}(SA) = \frac{EP_{i,j}(SA)}{EP_{i,j}(GM) + EP_{i,j}(SA)}. \tag{15}$$

As an example of calculating the Bayesian posterior values and the comparisons with the elicited probabilities, assume a participant provided $P_L = .75$, $P_{F3} = .55$, and $P_{A1} = .95$ and then for Case 1 provided $EP_{1,1}(GM) = .7$ and $EP_{1,1}(SA) = .4$. Normalizing thus yields $NEP_{1,1}(GM) = .636$ and $NEP_{1,1}(SA) = .364$. To derive $BP_{1,1}(GM)$ and $BP_{1,1}(SA)$, Bayes' theorem is used in two steps. First, accounting for the background check and the *F3* informant within Bayes' theorem yields an intermediate probability of street artist as

$$\frac{(.55)(.75)}{(.55)(.75) + (.45)(.25)} = .786, \tag{16}$$

and intermediate probability of gang member of .214. Then updating with the *A1* informant yields a final posterior probability for street artist as

$$BP_{1,1}(SA) = \frac{(.05)(.786)}{(.05)(.786) + (.95)(.214)} = .162, \tag{17}$$

and by the complementarity rule, $BP_{1,1}(GM) = .838$. With this derivation, the Bayesian posterior probabilities are symmetric in that the posterior values in first case within a pair are flipped when compared to the Bayesian posterior probabilities in the second case within the pair.

Having participant-specific Bayesian posterior values permits tests of method effects for multiple forms of coherence between the elicited probabilities and the corresponding Bayesian posterior probabilities, including (a) the frequency that the participants' elicited posterior probabilities agree with the Bayesian posterior probabilities in terms of which hypothesis is most likely, (b) the mean absolute deviation between the two sets of probabilities (regardless of agreement of most likely hypothesis), and (c) the presence of conservatism.

Continuing with the example, the participant's elicited probabilities (raw or normalized) agree with the Bayesian posterior probabilities that gang member is most likely of the two hypotheses in this one case. Furthermore, the mean absolute deviation between the elicited probabilities and Bayesian posterior probabilities for the case in the example is

Table 4: ANOVA results for uncertainty terms. Term denotes *likely, highly likely, A1, C3,* or *F3*.

Factor	F	p
Method	0.002	.85
Term	75.6	< .001
Method × Term	0.50	.74

$$MAD = \frac{|.7 - .838| + |.4 - .162|}{2} = .188. \tag{18}$$

A similar calculation reveals the mean absolute deviation between the Bayesian posterior probabilities and the normalized elicited probabilities as $MAD = .202$. Finally, by comparing the normalized elicited probabilities to the Bayesian posterior probabilities, bias from complementarity is removed and conservatism is measured as distance from 50/50. In this case, the average distance from 0.5 for the normalized elicited probabilities is .136, whereas the average distance for the Bayesian posterior probabilities is .338.

3 Results

3.1 Assumption check

We first tested whether participants were sensitive to the variation of the five qualitative uncertainty terms (i.e., *likely, highly likely, A1, C3,* and *F3*) used in the experiment and that there was no effect of method on the interpretation of these terms. The latter was not expected since the judgments were elicited prior to any method-specific interventions. Using a mixed analysis of variance (ANOVA), with method condition (ACH vs. control) as the between-subject factor, and the five P_e uncertainty terms as a repeated measure, the results are presented in Table 4. We found that method was not significant, whereas the levels of the terms significantly differed as expected. The interaction effect was not significant.

Figure 5 shows additional distributional information in violin plots. Visually, among the source reliability/information credibility indicators, P_{A1} has the tightest distribution, with the median probability above .90, whereas P_{F3} had the largest deviance among participants. In terms of the two linguistic probabilities, as one might expect, *highly likely* had less deviance among participants than *likely*. This is consistent with use of these terms in some lexicons wherein *very likely* represents a subset of *likely* (e.g., Mastrandrea, Mach, Plattner & Matschoss, 2011) and in studies that have compared the variability of interpretations of these terms (e.g., Ho et al., 2015; Wintle, Fraser, Willis, Nicholson & Fidler, 2019).

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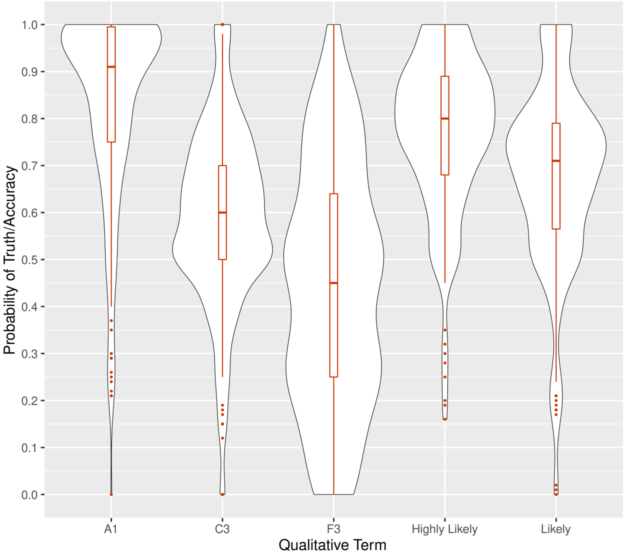

Figure 5: Violin plots of probability equivalents (P_e) of qualitative uncertainty terms. An A1 is informant one that is deemed “completely reliable” and makes a claim that is “completely credible”. A C3 informant is one that is deemed “fairly reliable”, and makes a claim that is judged “possibly true”. A F3 informant is rated as “reliability cannot be judged”, and makes a claim denoted as “possibly true”.

Table 5: Mean probability equivalents (P_e) of qualitative uncertainty terms.. M is the mean value whereas LB and UB are 95% confidence interval lower and upper bounds. An A1 informant is one that is deemed “completely reliable” and makes a claim that is “completely credible”. A C3 informant is one that is deemed “fairly reliable”, and makes a claim that is judged “possibly true”. A F3 informant is rated as “reliability cannot be judged”, and makes a claim denoted as “possibly true”.

P_e	M	LB	UB
P_{HL}	.77	.75	.79
P_L	.68	.65	.70
P_{A1}	.83	.81	.86
P_{C3}	.59	.57	.62
P_{F3}	.44	.41	.47

Table 6: Mean total evidential support by pair. M is the mean value whereas LB and UB are 95% confidence interval lower and upper bounds.

Pair	Level	M	LB	UB
1	Medium	1.95	1.92	1.98
2	High	2.19	2.16	2.23
3	Low	1.80	1.76	1.84

Table 5 shows mean values for each with 95% confidence intervals, which confirms, on average, the inequality in equation (2), and provides justification for our ordering of total evidential support in equation (10).

Assuming $s_e = P_e$ (e.g., equations (6)–(8)), Table 6 displays the mean values of total evidential support for each pair, again with similar ordering as equation (10). In subsequent analyses, we re-order the pairs according to total evidential support with Pairs 3, 1, and 2 representing low, medium and high total evidential support, respectively.

3.2 Coherence of binary choice

As a first coherence test, we investigated the proportion of participants’ consistent responses between judgment and binary choice measures. Each participant had a proportion score that ranged from 0 (0/6 matches) to 1 (6/6 matches). A response was marked as consistent if the choice corresponded to the hypothesis to which a higher probability was assigned. If $EP_{i,j}(GM) = EP_{i,j}(SA)$, either choice was deemed to be consistent. This was viewed as the easiest form of coherence, since the binary choice was made immediately after providing probability judgments for the two hypotheses. If ACH improves the quality of reasoning, then we might expect greater consistency between probability judgment and choice in the ACH condition than in the control group. However, we found no significant effect of method on the mean match rates using either a parametric analysis ($t[218] = 1.14$, $p = .25$, $d = 0.15$) or Fisher’s Exact Test, $p = .79$. The overall match rate across all participants had a mean of .74 with a 95% confidence interval of [.70, .77] (hereafter square brackets are used to signify 95% confidence intervals).

3.3 Reliability

On the one hand, if ACH improves the consistency of reasoning due to its algorithmic steps, we might expect greater reliability of hypothesis probabilities in the ACH condition than in the control group across isomorphic cases. On the other hand, if the ACH inputs introduce noise into the assessment process, we might expect less reliability in the ACH condition than in the control condition across isomorphic cases. While we did not expect total evidential support to influence reliability, we tested the effect of method and total evidential support levels (low, medium, and high) on reliability as measured by mean absolute deviation (MAD) in equation (1) using a two-way mixed ANOVA. The results are shown in Table 7. Indicating an overall significant level of unreliability, the intercept was significant. The main effect of total evidential support and its interaction with method

Table 7: ANOVA results for mean absolute deviation (*MAD*) measuring reliability between isomorphic case pairs. Total evidential support consists of the three levels of support (high, medium, low).

Factor	F	p
Intercept	226.59	< .001
Method	3.86	.05
Total evidential support	0.42	.66
Method × Total evidential support	0.52	.60

were not significant. However, the main effect of method approached significance (p = .051). Unreliability was greater in the ACH condition (MAD = .22 [.19, .24]) than in the control condition (MAD = .18 [.16, .20]), with Cohen's d = 0.20 indicating a small effect size.

3.4 Bias from complementarity

With bias from complementarity described in equation (11), negative values indicate superadditivity, positive values indicate subadditivity and zero indicates additivity, we expected bias from complementarity to generally increase with total evidential support. If the results are consistent with other studies featuring more than two hypotheses (Karvetski et al., 2020; Mandel et al., 2018), where the control group featured subadditivity, we would expect ACH to lead to larger degrees of subadditivity. We tested the effect of method and total evidential support on bias from complementarity (i.e., $\Delta_{i,j}$) using a two-way mixed ANOVA. Each of the three levels of total evidential support (low, medium, and high) had two measures corresponding to the two cases comprising the relevant level. The results are shown in Table 8. The intercept term implies subadditivity was observed in all cases. The effect of method was not significant, nor did method significantly interact with total evidential support. However, the main effect of total evidential support was significant. These results are consistent with an enhancement effect leading to subadditivity, which was not mitigated nor exacerbated by ACH.

Collapsing across method and further investigating within the three discrete levels of total evidential support, Fisher's Least Significant Difference tests showed that mean bias from complementarity was significantly lower (at the α = .01 level) in the low pairs (M = .13 [.10, .17]) than in the medium pairs (M = .18 [.14, .22]) or high pairs (M = .21 [.18, .25]), whereas the difference between medium and high pairs was marginally significant (p = .06).

Finally, granted the continuous definition of total evidential support as defined in equations (6)–(8), we find the overall correlation between bias from complementarity and total evidential support as r(225) = .29, a medium effect. Using a more granular analysis, we also find evidence of the enhancement effect within the discrete pairs. The correlations between bias from complementarity and total evidential support (as measured by equations (6)–(8)) within the three pairs (from low to high) are as follows: r(225) = .39 [.26, .49], .31 [.18, .44], and .29 [.15, .42],

Table 8: ANOVA results for bias from complementarity. Total evidential support consists of the three levels of support (high, medium, low).

Factor	F	p
Intercept	65.97	<.001
Method	1.52	.22
Total evidential support	5.04	<.001
Method × Total evidential support	1.99	.10

3.5 Bayesian coherence

As a third form of judgment coherence, we investigated the multiple degrees to which participants' elicited probabilities corresponded with the corresponding Bayesian posterior probabilities. ACH is not a normative model and exact correspondence with a Bayesian model is not expected. Nevertheless, ACH is promoted as a method of improving analysts' evidential evaluation and updating. Therefore, ACH might be expected to yield judgments that correspond more closely with a Bayesian model than the unstructured judgments of participants in the control group. The results in this subsection address that comparison.

For 10.1% of the sample, the elicited probabilities to the questions in Table 1 resulted in at least one set of Bayesian posterior probabilities that was undefined since there was a zero in the denominator of the equation for Bayes' theorem. In order to ensure the Bayesian posterior values were properly defined for each participant, and to respect Cromwell's rule stating that prior probabilities of 0 and 1 should be avoided unless these values can be logically assumed (Lindley, 1991), for each participant we set elicited uncertainty equivalents of 1 to .9999, and elicited uncertainty equivalents of 0 to .0001 in order to ensure Bayesian posterior probabilities were calculable. This resulted in 31.7% of participants having at least one elicited uncertainty equivalent set accordingly.

As an initial test of the effect of method on Bayesian coherence, we calculated ϕ as the proportion of times the participants' elicited probabilities agreed with the Bayesian posterior values in terms of the most likely hypothesis (with ϕ ranging from 0/6 to 6/6). Within this calculation, the case where $EP_{i,j}(GM) = EP_{i,j}(SA)$ was considered agreement. As shown in Table 9, we did not find a significant effect across methods for proportion of agreement.

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Table 9: Comparisons of the elicited probabilities (both raw and normalized) with Bayesian posterior probabilities in terms of agreement percentage (ϕ) and mean absolute deviation (*MAD*). *M* is the mean value whereas *LB* and *UB* are 95% confidence interval lower and upper bounds.

Measure	*M*	*LB*	*UB*	*t*	*P*	*d*
ϕ	.65	.62	.67	0.46	.65	0.06
MAD (raw elicited)	.31	.30	.32	1.01	.31	0.13
MAD (normalized elicited)	.33	.31	.34	0.86	.39	0.11

We also calculated the mean absolute deviation (*MAD*) between the Bayesian posterior probabilities and the elicited probabilities (both raw and normalized), and averaged the mean absolute deviations across the six cases for each participant. As Table 9 again shows, there was no significant effect of method for either test. That is, participants were no more or less coherent in the ACH condition than they were in the control condition.

The averaged respective probabilities across methods are shown in Table 10, and we see that the means values of the Bayesian posterior values and the elicited normalized values agree in terms of the most likely hypothesis in all cases (note that the elicited normalized values in Case 3 support both hypotheses equally). However, demonstrating conservatism, the elicited normalized probabilities are also closer to 50/50 than the corresponding Bayesian estimates in all cases. Moreover, after removing bias from complementarity by normalizing participants' posterior probability estimates, participants still do not update sufficiently to match the Bayesian posterior probabilities derived from their equivalence ratings. As an initial test of conservatism, we calculated the mean absolute deviation (*MAD*) between the Bayesian probabilities and normalized elicited probabilities with 50/50, and then averaged each mean absolute deviation within participants. Using a paired *t*-test, the average of the Bayesian *MAD* with 50/50 (*M* = .33 [.31, .35]) was significantly greater than that of the normalized elicited *MAD* (*M* = .13 [.11, .14]), $t(226) = 23.20$, $p < .001$, $d = 1.54$. The effect size measure shows that the degree of conservatism exhibited in this experiment was very large.

3.6 Coherence of ACH ratings

Focusing only on participants in the ACH condition, we examined whether consistency ratings of non-diagnostic evidence had a nil impact on posterior probability judgments, as is normatively required. For example, if one item of case evidence is that an *F3* informant whose "reliability cannot be judged" makes a claim denoted as "possibly true" that the suspect is a street artist, and the participant has assessed $P_{F3} = .5$, then one should assume the complementary claim (the suspect is a gang member) should have the same probability of being true (i.e., .5). In the ACH matrix, therefore, the two hypotheses within the row should each receive the same consistency rating, and if a stricter constraint is applied, these values should correspond to a *neutral* rating. Accordingly, the evidence would have no impact on influencing the overall probability of the hypotheses.

Table 10: Average Bayesian, elicited and normalized elicited probability judgments by case. Hyp. = hypothesis, *M* is the mean value, and *LB* and *UB* are 95% confidence interval lower and upper bounds.

		Bayesian (BP)			Elicited (EP)			Normalized elicited (NEP)		
Case	Hyp.	*M*	*LB*	*UB*	*M*	*LB*	*UB*	*M*	*LB*	*UB*
1	GM	.71	.67	.75	.67	.64	.70	.58	.56	.60
1	SA	.29	.25	.34	.51	.47	.54	.42	.40	.44
2	GM	.29	.25	.34	.52	.48	.55	.43	.41	.46
2	SA	.71	.67	.75	.67	.63	.70	.57	.55	.59
3	GM	.41	.37	.45	.59	.56	.63	.50	.48	.53
3	SA	.59	.55	.63	.60	.56	.63	.50	.47	.52
4	GM	.59	.55	.63	.65	.62	.68	.53	.51	.56
4	SA	.41	.37	.45	.59	.55	.62	.47	.44	.49
5	GM	.68	.64	.72	.59	.56	.62	.52	.49	.54
5	SA	.32	.28	.36	.56	.52	.59	.48	.46	.51
6	GM	.32	.28	.36	.53	.50	.56	.46	.44	.49
6	SA	.68	.64	.72	.59	.56	.62	.54	.52	.56

To examine this, for each item of evidence across the six cases, we computed a differential consistency score, δ_C, by comparing the inconsistencies scores within each row of the ACH matrix. Consider the completed ACH matrix in Figure 4, with the first item of evidence claiming it as *likely* the suspect is a street artist, which is the hypothesis *favored* by the evidence. Allowing C_F to refer to the consistency score assigned to the hypothesis *favored* by the evidence (e.g., $C_F = 0$ in Figure 4) and letting C_A refer to the consistency score assigned to the *alternative* hypothesis (e.g., $C_A = -2$), we can define our differential consistency score as $\delta_C = C_F - C_A$ (e.g., $\delta_C = 2$, the net impact on the hypothesis *favored* by the evidence).

In order to test the effect of a non-diagnostic rating, we scaled each P_e around .5 as

$$P_{e,\text{SCALED}} = (P_e - .5) \times 2. \qquad (19)$$

Such scaling implies non-diagnostic ratings (i.e., $P_e = .5$) are centered at 0, and perfectly diagnostic ratings for a focal hypothesis (i.e., $P_e = 1$) are set to 1.

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Using linear mixed regression analysis, we regressed δ_C on the full set of scaled uncertainty terms across all participants, and found the intercept was significant, $B = 0.233$, $SE = 0.074$, Wald = 9.92, $p = .002$, as was the slope term, $B = 0.502$, $SE = 0.082$, Wald = 37.48, $p < .001$; model $R^2 = .055$. Given the scaling, the positive intercept shows that evidence linked to non-diagnostic ratings had a positive mean impact on ACH consistency scores, whereas perfectly diagnostic ratings for a hypothesis favoured by the evidence corresponds to a mean $\delta_C = 0.735$ (0.502 + 0.233). This implies that the impact of evidence associated with non-diagnostic ratings is roughly 32% of the impact of evidence associated with perfectly diagnostic ratings.

To rule out the possibility that participants may have treated consistent information as representing positive values rather than zero (which again is the typical ACH convention, and the one used within the experiment), we replaced the consistency scores used in the preceding analyses with scores that assigned positive values to consistent evidence (e.g., C = 1 and CC = 2 rather than either equaling 0) and repeated the regression analysis. Once again, we found significant effects for the intercept, $B = 0.522$, $SE = 0.152$, Wald = 11.34, $p = .001$, and the slope term, $B = 1.20$, $SE = 0.165$, Wald = 52.89, $p < .001$, with $R^2 = 0.072$. As in the preceding analysis, there is a mean positive impact for evidence associated with a non-diagnostic ratings corresponding to roughly 30% of the impact of evidence associated with a perfectly diagnostic rating for a favored hypothesis.

4 Discussion

The present research sheds additional light on the effectiveness of ACH, one of the intelligence community's most highly promoted structured analytic techniques for helping intelligence analysts sift through uncertain evidence in order to assess the relative likelihood of competing hypotheses. Consistent with recent research (Dhami et al., 2019; Karvetski et al., 2020; Mandel et al., 2018; Whitesmith, 2019), we found no benefit conferred by ACH when compared to a no-SAT control. Participants who used ACH prior to judging posterior probabilities from uncertain evidence were no more additive, coherent in a Bayesian sense, consistent with their binary choices, or able to avoid conservatism than participants who did not use the technique. Participants who used ACH were less reliable across isomorphic cases than control participants who were not asked to use any particular technique, although the effect was small. Moreover, participants who used ACH showed evidence of pseudo-diagnostic evaluation of evidential support for competing hypotheses.

These findings add to the previous literature on the evaluation of ACH in improving facets of judgment quality in at least two respects. First, the range of coherence-related measures of judgment quality that were examined was extended. To the best of our knowledge, intra-individual reliability of judgments, conservatism in belief updating, and consistency with binary choice have not been previously investigated in relation to ACH. Second, the present research used a task that involved reasoning from qualitatively described, uncertain evidence, which, compared to other recent studies (e.g., Karvetski et al., 2020; Mandel et al., 2018) better approximates conditions in which intelligence analysts and criminal investigators encounter evidence. That is, unlike the aforementioned studies, the present research used verbal probabilities to convey likelihood, which—for better or worse—is the communication method currently favored by most intelligence organizations (Dhami & Mandel, 2020; Mandel & Irwin, 2020). As well, the prior studies asked subjects to assume that information presented was perfectly accurate, whereas in the present research, uncertainty about source reliability and information credibility was conveyed as it often is in raw human intelligence reports (Irwin & Mandel, 2019; Samet, 1975). Therefore, the present research not only coheres with the findings of recent studies of ACH, it also improves the external validity of the body of evidence bearing on the method.

The finding that ACH did not improve reliability (and in fact lowers reliability slightly) contradicts the widely held, but largely untested, assumption in intelligence communities that structured analytic methods will be more reliable than an ad hoc "intuitive" analytic judgments (Chang et al., 2018; Mandel, 2020). A potential reason ACH might decrease reliability is that the technique may make the judgment process more cumbersome or susceptible to various degrees of interpretation. For instance, as noted earlier, fundamental concepts such as the meaning of "consistency" are left undefined in documentation describing ACH (Heuer & Pherson, 2014). Chang et al. (2018) used the term *noise neglect* to refer to the intelligence community's failure to attend to this potential downside of SATs. SATs like ACH also shift the analyst's attention from the substantive topic of analysis to the implementation of the technique's many steps. Refocusing on the proper implementation of a purportedly judgment-enhancing technique could, in principle, steer attention away from deliberative reasoning directed towards the substantive reasoning challenges that would motivate the use of such techniques in the first place. The cost of misdirected attention is, of course, a function of the analysts' potential for sound reasoning. An implication of this perspective is that ACH may incur the greatest costs among the best analysts while perhaps offering some ameliorative benefit to the worst performers. This hypothesis could be tested in future research.

In our experiment, we observed a clear violation of the complementarity axiom across the two hypotheses. Although ACH did not exacerbate this bias as in previous studies (Mandel et al., 2018; Karvetski et al., 2020), it did not mitigate the bias either. Also, since adherence to the com-

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plementarity axiom for binary complements is axiomatic in support theory (Rottenstreich & Tversky, 1997; Tversky & Koehler, 1994), the present findings contradict the theory in that regard. Rather, our data support the hypothesis that additivity violations with binary complements are predictable on the basis of total evidential support summed across hypotheses and sources. This particular finding is comparable with the general findings of Idson et al. (2001) and Villejoubert and Mandel (2002). Whereas we observed subadditivity exclusively in our study, and Idson et al. (2001) and Villejoubert and Mandel (2002) observed a combination of subadditivity and superadditivity, the present findings, in fact, are consistent with those studies. This is because all cases in the present experiment had total evidential support exceeding unity, whereas total support was manipulated to be either high or low in the aforementioned studies. Although our finding of subadditivity is inconsistent with the formal binary complementarity axiom of support theory, the notion that subadditivity will increase with support is in fact central to support theory and referred to as the *enhancement effect* (Koehler, Brenner, & Tversky, 1997).

In the present research, we were able to compare two sets of posterior probabilities, those explicitly elicited from participants in response to the specific case materials and those derived from their initial probability estimates in which they provided numeric probability equivalents for the terms they would subsequently encounter in the cases. Using these substitutes in conjunction with Bayes' theorem, we measured the extent to which the implicit (Bayesian) and explicit estimates differed in absolute terms. There was substantial difference that was unaffected by whether or not ACH was used, and this difference persisted even when deviations due to complementarity violations were subtracted. There are multiple reasons for such disagreement. One possibility is that the initial estimates are unreliable and that even moments later, the quantitative equivalencies were inaccessible and new estimates constructed on the fly or "online" were produced that varied with the original values (e.g., see Hastie & Park, 1986). A second possibility is that the initial estimates were adjusted in light of the context in which they appeared in some systematic manner. Brun and Teigen (1988) found that, depending on the study they examined, participants either assigned higher or lower numeric probability equivalents to verbal probabilities when they were presented in context compared to when they were presented out of context. In future research, one could elicit in-context numeric equivalents either instead of the pre-case estimates taken in the present experiment or else in addition to them. Of course, another possibility is that the deviations result from a failure to correctly integrate the evidence, which would be robust in other designs and which is simply not improved by use of ACH.

The findings also showed that within the ACH condition, evidence that corresponded to a non-diagnostic truth/accuracy rating still had a positive contribution or impact towards the hypothesis favored at face value by the evidence. Not only was the net impact of non-diagnostic evidence significantly differing from zero, it had about 30% of the impact of evidence with a truth/accuracy rating that was completely diagnostic for a focal hypothesis. This is potentially detrimental for it indicates that ACH users reasoning about a case with one diagnostic A1 informant claiming Hypothesis 1 and three potentially non-diagnostic F3 informants claiming Hypothesis 2 may judge the alternatives to be equiprobable. We cannot rule out that a similar bias might have been present in the control condition because we did not measure ratings of evidential consistency with the alternative hypotheses. However, future research could, for example, elicit such ratings after posterior probability judgments were made, and could also expand the variety of evidential inputs used within the format of the exercise. For instance, future studies could systematically vary source reliability levels independently of information credibility levels to understand if one is deemed more influential in weighing evidence.

Overall, our findings highlight the importance of directly testing the effectiveness of methods used in practice to improve judgment and decision-making, and these findings underscore the appropriateness of recent calls for better methodological evaluation in intelligence communities (Chang et al., 2018; Dhami et al., 2015; Mandel, 2020; Mandel & Tetlock, 2018). The method we tested in this research—ACH—is not merely one of dozens of methods advocated for use by several allied intelligence communities, it is one of most widely taught and promoted methods. Given the resources spent to train and encourage analysts to use ACH, one might expect to see some positive effects on judgment. In this research and in other recent studies (e.g., Dhami et al., 2019; Karvetski et al., 2020; Mandel et al., 2018; Whitesmith, 2019), however, ACH had either no benefit on measures of judgment quality or produced a decrease in performance. Nevertheless, we do not wish to overstate our claims. Notwithstanding the present experiment's more realistic features, such as imprecise, qualitative evidence including information about source reliability and information credibility, which were presented using alphanumeric codes commonly used in the defense and intelligence communities (Irwin & Mandel, 2019; Samet, 1975), the experimental cases invariably featured three items of evidence and two hypotheses. Future research might examine tasks that include larger troves of evidence and perhaps more alternative hypotheses, and with real analysts. Note, however, that the task used by Mandel et al. (2018) included twelve probabilistic cues and four hypotheses having variable prior probabilities. Real intelligence analysts in that experiment nevertheless performed more poorly using ACH than their counterparts who were left to their unaided reasoning. The mounting evidence from multiple experiments with differ-

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ent samples, tasks, and experimental designs in recent years indicates that ACH does not benefit judgment and, in fact, might impair judgment. Although more research on the topic is warranted, intelligence communities that rely on ACH as a structured analytic method to support intelligence analysis should also take seriously the implications of the current body of evidence and consider alternative methods for improving judgment quality.

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