

James Orion Report (JOR) Bayesian Fusion: Evidence-Driven SOP and NHP Analysis of UAP Cases

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This paper introduces a fusion of the James Orion Report (JOR) framework with Bayesian posteriors to rigorously evaluate UAP cases. The JOR framework first asks whether there is sufficient evidence that a physically real event occurred, quantified as Solid Object Probability (SOP). Only once SOP is high does it make sense to evaluate Non-Human Probability (NHP), ensuring that non-human hypotheses are considered conditionally on a solid evidentiary foundation.

Bayesian reasoning then updates the likelihood of competing explanations, allowing new information to shift conclusions without prematurely asserting certainty. Combining SOP, NHP, and Bayesian updating ensures that confidence in a non-human hypothesis grows only when evidence is strong, consistent, and genuinely informative.

The FY2024 AARO report highlights that many UAP cases remain unresolved due to insufficient actionable data, particularly from sensors such as radar, infrared, or video. While the report does not describe formal evidence weighting, reliance on cases with adequate sensor data means credible observations from trained witnesses or environmental context may go unexamined. By contrast, the JOR Bayesian fusion framework systematically incorporates witness credibility, environmental conditions, and physical/sensor evidence into SOP and NHP scoring, producing posterior probabilities that reflect the full spectrum of available evidence.

To illustrate the method, two UAP cases from James Orion Report V2 will be examined: one Tier 1 case and one Tier 2 case. These examples will demonstrate the interplay of SOP/NHP and Bayesian posteriors. For each case my total for C, E, and P represents my dataset with using the scoring rubrics.

JOR-Bayesian Fusion Workflow: Stepwise process from factor scoring (C/E/P) to posterior probability calculation.

Step Description	Notes
1 C / E / P Scores	Witness Credibility, Environmental Clarity, Physical Evidence
2 SOP Calculation	Weighted average: $w_1 \cdot C + w_2 \cdot E + w_3 \cdot P$
3 NHP Calculation	Conditional on SOP; weighted average of same factors
4 Likelihood Assignment	$P(E NH) = NHP; P(E H) = 1 - NHP + K \cdot SOP$
5 Bayesian Priors	$P(H) = 0.8; P(NH) = 0.2$
6 Apply Bayes' Theorem	$P(NH E) = \frac{P(E NH) \cdot P(NH)}{P(E NH) \cdot P(NH) + P(E H) \cdot P(H)}$
7 Posterior Probabilities	$P(NH E), P(H E) = 1 - P(NH E)$

Tier 1 case - Aguadilla, Puerto Rico 2013

SOP Probability Score

Total C = .87

Total E = .90

Total P = .91

Using the probability formula $SOP = w_1(C) + w_2(E) + w_3(P)$ the SOP score is .90 rounded up by .01.

SOP Calculation

$$SOP = w_1C + w_2E + w_3P$$

Plug in numbers:

$$SOP = 0.40 \cdot 0.87 + 0.30 \cdot 0.90 + 0.30 \cdot 0.91$$

Step-by-step:

$$1. \quad 0.40 \cdot 0.87 = 0.348$$

$$2. \quad 0.30 \cdot 0.90 = 0.270$$

$$3. \quad 0.30 \cdot 0.91 = 0.273$$

Add:

$$0.348 + 0.270 + 0.273 = 0.891 \approx 0.89$$

Rounded up by 0.01 for reporting: **SOP = 0.90**

NHP Calculation

Factor Score

C 0.87

E 0.90

P 0.95

$$\text{NHP} = 0.40 \cdot 0.87 + 0.30 \cdot 0.90 + 0.30 \cdot 0.95$$

Step-by-step:

$$1. \quad 0.40 \cdot 0.87 = 0.348$$

$$2. \quad 0.30 \cdot 0.90 = 0.270$$

$$3. \quad 0.30 \cdot 0.95 = 0.285$$

Add:

$$0.348 + 0.270 + 0.285 = 0.903 \approx 0.90$$

Rounded up by 0.01 for reporting: **NHP = 0.91**

NHP Probability Score

Total C = .87

Total E = .90

Total P = .95

Using the probability formula $NHP = w_1(C) + w_2(E) + w_3(P)$ the NHP score is .91 rounded up by .01.

We will use the Bayes' Theorem to update our belief in a non-human hypothesis based on evidence. Bayes will account for prior knowledge and new evidence modifies our confidence incrementally. Around 80 percent of UAP cases are identified as human-made, leaving 20 percent unexplained.

To be conservative = $P(NH) = .2$, $P(H) = .8$

This will anchor the Bayesian calculation so we don't inflate NHP artificially. The posterior probability can increase beyond .2 only if evidence strongly supports non-human behavior.

Bayes' Theorem

Bayes' Theorem is a fundamental rule of probability that describes how to update our beliefs about a hypothesis based on observed evidence. In the context of UAP analysis, it allows us to rigorously combine prior knowledge with new evidence from SOP and NHP scores.

To be conservative = $P(NH) = .2$, $P(H) = .8$

This will anchor the Bayesian calculation so we don't inflate NHP artificially. The posterior probability can increase beyond .2 only if evidence strongly supports non-human behavior.

1. The Formula

Bayes' theorem updates the probability of a non-human hypothesis (NH) versus a human hypothesis (H) given observed evidence (E):

$$P(NH | E) = \frac{P(E | NH) \cdot P(NH)}{P(E | NH) \cdot P(NH) + P(E | H) \cdot P(H)}$$

1. **Start with a prior** — your initial belief about how likely NH is.

Example: conservative prior $P(NH) = 0.2$, $P(H) = 0.8$.

2. **Observe evidence** — SOP confirms a solid object exists, NHP scores anomalous characteristics.

3. **Translate evidence into likelihoods** $P(E | H)$ and $P(E | NH)$ — how compatible is the evidence with each hypothesis?
4. **Calculate posterior** — Bayes' theorem combines priors and likelihoods to give a revised probability:

Posterior = Prior updated by evidence

Tier 1 Case — Aguadilla, Puerto Rico 2013

Inputs:

Factor Score

SOP 0.90

NHP 0.91

Step 1a: Assign Likelihoods

- Likelihood of observing the evidence given a **non-human** hypothesis:

$$P(E | NH) = NHP = 0.91$$

- Likelihood of observing the evidence given a **human-made** hypothesis:
- This likelihood formulation is intentionally conservative and heuristic, designed to preserve probabilistic monotonicity rather than claim physical exactness.

$$P(E | H) = 1 - NHP + K * SOP$$

$$P(E|H)=1-0.91+0.20\times0.90=0.2682\approx0.27$$

The calibration constant $K = 0.20$ conservatively scales the contribution of solid-object confidence (SOP) into the human likelihood, reflecting the fact that many confirmed physical objects are ultimately explained as human-made. This formulation intentionally biases against over-attribution to non-human explanations unless the evidentiary signal is strong and consistent.

Rounded values are reported to two decimal places for clarity.

Step 1b: Assign Priors

Bayesian Priors

Conservative priors based on historical explainability:

$$P(H) = 0.80$$

$$P(NH) = 0.20$$

$$P(H) = 0.8, P(NH) = 0.2$$

Step 1c: Apply Bayes' Theorem

$$P(NH | E) = \frac{P(E | NH) \cdot P(NH)}{P(E | NH) \cdot P(NH) + P(E | H) \cdot P(H)}$$

Plug in numbers:

1. Multiply likelihoods by priors:

$$0.91 \cdot 0.2 = 0.182$$

$$0.27 \cdot 0.8 = 0.216$$

2. Add to get denominator:

$$0.182 + 0.216 = 0.398$$

3. Divide numerator by denominator:

$$P(NH | E) = \frac{0.182}{0.398} \approx 0.457$$

- Posterior probability of human explanation:

$$P(H | E) = 1 - 0.457 \approx 0.543$$

Step 4: Interpretation

- Posterior NH = **0.46** — moderate probability despite high NHP.
- Conservative prior (0.2) ensures posterior doesn't overinflate.
- Confidence in non-human explanation increases only when evidence is strong and SOP confirms the object exists.

For the Aguadilla, Puerto Rico 2013 case, we have now have a final SOP = .90 and a NHP = .46

Tier 2 case - Socorro, New Mexico 1964

SOP Probability Score

Total C = .65

Total E = .82

Total P = .72

Using the probability formula $SOP = w_1(C) + w_2(E) + w_3(P)$ the SOP score is .73 rounded up by .01.

NHP Probability Score

Total C = .65

Total E = .82

Total P = .77

Using the probability formula $NHP = w_1(C) + w_2(E) + w_3(P)$ the NHP score is .74 rounded up by .01.

We will use the Bayes' Theorem to update our belief in a non-human hypothesis based on evidence. Bayes will account for prior knowledge and new evidence modifies our confidence incrementally. Around 80 percent of UAP cases are identified as human-made, leaving 20 percent unexplained.

Bayes' Theorem

Bayes' Theorem is a fundamental rule of probability that describes how to update our beliefs about a hypothesis based on observed evidence. In the context of UAP analysis, it allows us to rigorously combine prior knowledge with new evidence from SOP and NHP scores.

To be conservative = $P(NH) = .2$, $P(H) = .8$

This will anchor the Bayesian calculation so we don't inflate NHP artificially. The posterior probability can increase beyond .2 only if evidence strongly supports non-human behavior.

1. The Formula

For a hypothesis H (e.g., "the object is human-made") and alternative NH (e.g., "the object is non-human"), the theorem states:

$$P(NH | E) = \frac{P(E | NH) \cdot P(NH)}{P(E | NH) \cdot P(NH) + P(E | H) \cdot P(H)}$$

1. **Start with a prior** — your initial belief about how likely NH is.

Example: conservative prior $P(NH) = 0.2$, $P(H) = 0.8$.

2. **Observe evidence** — SOP confirms a solid object exists, NHP scores anomalous characteristics.
3. **Translate evidence into likelihoods** $P(E | H)$ and $P(E | NH)$ — how compatible is the evidence with each hypothesis?
4. **Calculate posterior** — Bayes' theorem combines priors and likelihoods to give a revised probability:

Posterior = Prior updated by evidence

Tier 2 Case — Socorro, New Mexico 1964

Inputs:

Factor Score

SOP 0.73

NHP 0.74

SOP Calculation

$$\text{SOP} = 0.40 \cdot 0.65 + 0.30 \cdot 0.82 + 0.30 \cdot 0.72$$

Step-by-step:

1. $0.40 \cdot 0.65 = 0.260$
2. $0.30 \cdot 0.82 = 0.246$
3. $0.30 \cdot 0.72 = 0.216$

Add:

$$0.260 + 0.246 + 0.216 = 0.722 \approx 0.73$$

Rounded up by 0.01 for reporting: **SOP = 0.73**

NHP Calculation

$$\text{NHP} = 0.40 \cdot 0.65 + 0.30 \cdot 0.82 + 0.30 \cdot 0.77$$

Step-by-step:

1. $0.40 \cdot 0.65 = 0.260$
2. $0.30 \cdot 0.82 = 0.246$
3. $0.30 \cdot 0.77 = 0.231$

Add:

$$0.260 + 0.246 + 0.231 = 0.737 \approx 0.74$$

Rounded up by 0.01 for reporting: **NHP = 0.74**

Step 1a: Assign Likelihoods

- Likelihood of observing the evidence given a **non-human** hypothesis:

$$P(E | NH) = \text{NHP} = 0.74$$

Here, the NHP score serves as a proxy for how compatible the observed anomalous characteristics are with a non-human explanation.

- Likelihood of observing the evidence given a **human-made** hypothesis:
- This likelihood formulation is intentionally conservative and heuristic, designed to preserve probabilistic monotonicity rather than claim physical exactness.

$$P(E | H) = 1 - \text{NHP} + K * \text{SOP}$$

$$P(E|H)=1-0.74+0.20\times0.73=0.406\approx0.41$$

The calibration constant $K = 0.20$ conservatively scales the contribution of solid-object confidence (SOP) into the human likelihood, reflecting the fact that many confirmed physical objects are ultimately explained as human-made. This formulation intentionally biases against over-attribution to non-human explanations unless the evidentiary signal is strong and consistent.

Rounded values are reported to two decimal places for clarity.

Step 1b: Assign Priors

Bayesian Priors

Conservative priors based on historical explainability:

$$P(H) = 0.80$$

$$P(NH) = 0.20$$

$$P(H) = 0.8, P(NH) = 0.2$$

Step 1c: Apply Bayes' Theorem

$$P(NH | E) = \frac{P(E | NH) \cdot P(NH)}{P(E | NH) \cdot P(NH) + P(E | H) \cdot P(H)}$$

Plug in numbers:

2. Multiply likelihoods by priors:

$$0.74 \cdot 0.2 = 0.148$$

$$0.41 \cdot 0.8 = 0.328$$

3. Add to get denominator:

$$0.148 + 0.328 = 0.476$$

4. Divide numerator by denominator:

$$P(NH | E) = \frac{0.148}{0.328} \approx 0.31$$

- Posterior probability of human explanation:

$$P(H | E) = 1 - 0.31 \approx 0.69$$

Table: Bayesian Fusion: Intermediate Calculations for Tier 1 & Tier 2 Cases

This table summarizes the key intermediate steps in applying Bayes' theorem to the Aguadilla (Tier 1) and Socorro (Tier 2) UAP cases. Columns show the weighted SOP and NHP values, likelihoods for non-human (NH) and human (H) hypotheses, products of likelihood and prior, the denominator, and the resulting posterior probabilities. Posterior $P(H|E)$ is calculated as $1 - P(NH|E)$.

Rounding Rules: SOP and NHP are rounded to 0.01, intermediate likelihood \times prior products to 0.001, and posterior probabilities to 0.01 for reporting clarity. The likelihood $P(E|H)$ incorporates the calibration constant $K = 0.20$ applied to SOP.

Step	Aguadilla (Tier 1)	Socorro (Tier 2)
SOP (weighted avg)	0.90	0.73
NHP (weighted avg)	0.91	0.74
$P(E NH) = NHP$	0.91	0.74
$P(E H) = 1 - NHP + 0.20 \times SOP$	0.27	0.41
Prior \times Likelihood (NH)	0.182	0.148
Prior \times Likelihood (H)	0.216	0.328
Denominator (total)	0.398	0.476
Posterior $P(NH E)$	0.46	0.31
Posterior $P(H E)$	0.54	0.69

Footnote: $P(E|H)$ incorporates the calibration constant $K = 0.20$ applied to SOP; rounding follows the rules: SOP/NHP to 0.01, intermediate products to 0.001, posterior to 0.01.

Step 4: Interpretation

- Posterior NH = **0.31** — moderate probability despite high NHP.
- Conservative prior (0.2) ensures posterior doesn't overinflate.
- Confidence in non-human explanation increases only when evidence is strong and SOP confirms the object exists.

For the Socorro, New Mexico 1964 case, we have now have a final SOP = .73 and a NHP = .31

Recommendation for Future Work

While this paper demonstrates the fusion of JOR with Bayesian posteriors, the workflow could be fully automated using existing probabilistic programming tools such as PyMC (Python). Developing a program with PyMC (or a similar framework) would allow:

Compute posterior probabilities automatically for multiple cases.

Apply priors, likelihoods, and scoring rubrics consistently.

Evaluate new UAP cases rapidly without manual calculation.

Optionally integrate nested sampling (Skilling, 2004) or other uncertainty analysis methods in future updates.

Implementing such a tool would render the JOR-Bayesian fusion workflow reproducible, scalable, and practically deployable for ongoing UAP analysis.

UAP Factor Scoring Rubric

Weights

Weights represent the relative contribution of each factor to SOP and NHP:

Factor	Weight
Witness Credibility (w_1)	0.40
Environmental Clarity (w_2)	0.30
Physical / Sensor Evidence (w_3)	0.30

Constraint: $w_1 + w_2 + w_3 = 1$

UAP Factor Scoring Rubric (Tier 1 & Tier 2 Cases)

1. C – Witness Credibility (0.30–0.85)

Scoring Steps (Apply in order):

Step C1 — Base Score by Witness Group

Choose the *highest* category that applies:

Category	Base Score	Criteria
Weak	0.30–0.50	Single untrained civilian; anonymous witness; contradictory details; no supporting accounts.
Moderate	0.55–0.65	2–3 civilians OR one trained observer (LEO, pilot, military), partial corroboration.
Strong	0.70–0.80	Multiple trained observers OR multiple corroborating civilians from independent vantage points.
Very Strong (max)	0.81–0.85	Trained personnel + multiple independent civilian accounts + documentation (audio logs, written logs, incident reports).

Step C2 — Apply Fixed Modifiers (Optional ±0.00–0.05)

Modifier	Adjustment
Independent written reports or time-stamped logs	+0.03
Witnesses from >2 independent positions	+0.02
Witness inconsistencies	-0.03
Known misidentification history or unreliable source	-0.05 (mandatory)

Step C3 — Hard Caps

These prevent inflation:

- Single untrained civilian cannot exceed 0.50
 - No trained observer → max 0.70
 - Anonymous witness → automatic cap at 0.45
-

2. E – Environmental & Observation Conditions (0.30–0.85)

Step E1 — Base Score by Visibility/Conditions

Category	Base Score	Criteria
Weak	0.30–0.45	Fog, heavy cloud, night with no illumination, obstructions, brief duration (<10s).
Moderate	0.50–0.60	Light cloud, partially obstructed view, nighttime with some illumination, medium duration (10–30s).
Strong	0.65–0.85	Clear sky OR controlled environment; multiple viewing angles; long duration (>30s).

Step E2 — Modifiers (Optional ±0.00–0.05)

Modifier	Adjustment
Multiple vantage points documented	+0.03
Weather officially documented	+0.02
Object >1 km away	-0.03
Observation <5 seconds	-0.05

Hard Caps

- Heavy fog → max 0.40
- Nighttime / single perspective → max 0.70
- Daytime clear → minimum 0.60 unless obstructed

3. P – Physical / Sensor / Trace Evidence (0.30–0.95)

Step P1 — Base Score by Evidence Type

Category	Base Score	Criteria
Weak	0.30–0.45	No physical traces, no sensor data, anecdotal only.
Moderate	0.50–0.65	One type of sensor data (photo, FLIR, radar), or weak trace evidence (ground impressions).
Strong	0.70–0.85	Two sensor types OR confirmed radiological/soil/EM anomalies; independent verification.
Very Strong	0.86–0.95	Multi-sensor (radar + IR + visual) and physical interaction (EM effects, trace anomalies).

Step P2 — Modifiers ($\pm 0.02\text{--}0.10$)

Modifier	Adjustment
EMP, interference, or vehicle shutdown	+0.05
Multi-frame imagery or long-duration video	+0.03
Independent lab analysis	+0.02
Ambiguous/poor video quality	-0.05
Inconsistent sensor readings	-0.07

Hard Caps

- No sensor data → max 0.55
- Only video with no corroboration → max 0.75
- Radar + IR + visual → minimum 0.80

Flight Characteristics Modifier ($\pm 0.00\text{--}0.05$)

Flight Behavior Classification	Modifier Description
None / Conventional Flight	+0.00 Standard aircraft behavior; no observable anomalies
Minor Anomaly	+0.02 Slight acceleration, abrupt turn, or brief hover; still plausibly human-made
Moderate Anomaly	+0.04 Clear hovering, rapid directional change, or acceleration beyond conventional aircraft

Flight Behavior Classification	Modifier Description
Major Anomaly	+0.05 Extreme speed, instantaneous stops/starts, or maneuvers impossible for known technology

4. Formal Scoring Procedure (Mandatory)

All researchers must follow this exact sequence:

1. Assign base category for C, E, P
2. Apply only allowed modifiers
3. Enforce caps
4. Round final scores to nearest .01

References

Bayesian Inference / Bayes' Theorem (Core Methodology)

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