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

By James Orion

This paper introduces a fusion of the James Orion Report (JOR) framework with Bayesian posteriors to evaluate UAP cases in a structured and conservative manner. 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 become meaningful to evaluate Non-Human Probability (NHP), ensuring that non-human explanations are considered conditionally on a solid evidentiary foundation.

Bayesian reasoning is then used to update the relative likelihood of competing explanations as new information becomes available, allowing conclusions to shift without prematurely asserting certainty. In combination, SOP, NHP, and Bayesian updating ensure that confidence in a non-human explanation increases 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 methods, an emphasis on sensor-rich cases can leave credible observations from trained witnesses or environmental context underexamined. This evidentiary reality motivates the need for a transparent and conservative framework capable of operating under incomplete and heterogeneous data conditions.

Accordingly, the JOR–Bayesian fusion framework systematically incorporates witness credibility, environmental conditions, and physical or sensor evidence into SOP and NHP scoring. To enforce conservative evidence accumulation under these conditions, a stabilizing constant $K = 0.20$ was assigned, ensuring that high SOP or NHP values emerge only through convergence of multiple independent evidentiary factors rather than from isolated or incomplete observations. The resulting posterior probabilities reflect the full spectrum of available evidence while limiting probability inflation under uncertainty.

To illustrate the method, two UAP cases from James Orion Report V2 are examined: one Tier 1 case and one Tier 2 case. These cases are presented as illustrative examples to demonstrate the interaction between SOP, NHP, and Bayesian posteriors. The reported C, E, and P values reflect application of the published scoring rubrics to the author's compiled dataset and are intended to show how the framework behaves under differing evidentiary conditions, rather than to establish definitive conclusions about the cases themselves.

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**	$P(E \mid NH) =$NHP; $P(E \mid H) = \min(1, 1 -$NHP $+K \cdot$SOP)
5	**Bayesian Priors**	$P(H) = 0.8; P(NH) = 0.2$
6	**Apply Bayes' Theorem**	$P(NH \mid E) = \dfrac{P(E \mid NH) \cdot P(NH)}{P(E \mid NH) \cdot P(NH) + P(E \mid H) \cdot P(H)}$
7	**Posterior Probabilities**	$P(NH \mid E), P(H \mid E) = 1 - P(NH \mid E)$

Tier 1 case - Aguadilla, Puerto Rico 2013

SOP Probability Score

Total C = 0.87

Total E = 0.90

Total P = 0.91

Using the probability formula $\text{SOP} = w_1(C) + w_2(E) + w_3(P)$ the SOP score is 0.90 rounded up by 0.01.

SOP Calculation

$$\text{SOP} = w_1 C + w_2 E + w_3 P$$

Plug in numbers:

$$\text{SOP} = 0.40 \cdot 0.87 + 0.30 \cdot 0.90 + 0.30 \cdot 0.91$$

Step-by-step:

1. $0.40 \cdot 0.87 = 0.348$
2. $0.30 \cdot 0.90 = 0.270$
3. $0.30 \cdot 0.91 = 0.273$

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. $0.40 \cdot 0.87 = 0.348$
2. $0.30 \cdot 0.90 = 0.270$
3. $0.30 \cdot 0.95 = 0.285$

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 = 0.87

Total E = 0.90

Total P = 0.95

Using the probability formula $\text{NHP} = w_1(C) + w_2(E) + w_3(P)$ the NHP score is 0.91 rounded up by 0.01.

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) = 0.2, P (H) = 0.8

This will anchor the Bayesian calculation so we don't inflate NHP artificially. The posterior probability can increase beyond 0.2 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):

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

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

$$\text{Posterior} = \text{Prior updated by evidence}$$

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:

$$P(E \mid NH) = \text{NHP} = 0.91$$

- 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.

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

$$P(E|H)=1-0.91+0.20\times0.90=0.270\approx0.27$$

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

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

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:

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

- Posterior probability of human explanation:

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

.

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 = 0.90 and a NHP = 0.46 (Bayesian Posterior)

Tier 2 case - Socorro, New Mexico 1964

SOP Probability Score

Total C = 0.65

Total E = 0.82

Total P = 0.72

Using the probability formula $\mathrm{SOP} = w_1(C) + w_2(E) + w_3(P)$ the SOP score is 0.73 rounded up by 0.01.

NHP Probability Score

Total C = 0.65

Total E = 0.82

Total P = 0.77

Using the probability formula $\mathrm{NHP} = w_1(C) + w_2(E) + w_3(P)$ the NHP score is 0.74 rounded up by 0.01.

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) = 0.2,   P (H) = 0.8

This will anchor the Bayesian calculation so we don't inflate NHP artificially. The posterior probability can increase beyond 0.2 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:

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

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

$$\text{Posterior} = \text{Prior updated by evidence}$$

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

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

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:

$$P(E \mid NH) = \mathrm{NHP} = 0.74$$

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.

$$P(E \mid H) = \min(1, 1 - \mathrm{NHP} + \mathrm{K} * \mathrm{SOP})$$

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

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

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

Plug in numbers:

1. Multiply likelihoods by priors:

$$0.74 \cdot 0.2 = 0.148$$
$$0.41 \cdot 0.8 = 0.328$$

2. Add to get denominator:

$$0.148 + 0.328 = 0.476$$

3. Divide numerator by denominator:

$$P(NH \mid E) = \frac{0.148}{0.476} \approx 0.31$$

4. Posterior probability of human explanation:

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

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 = 0.73 and a NHP = 0.31 (Bayesian Posterior)

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 × 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 × SOP	0.268	0.406
Prior × Likelihood (NH)	0.182	0.148
Prior × 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.

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	0.81–0.85 (max)	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 (±0.02–0.10)

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 (±0.00–0.05)

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

Flight Behavior Classification	Modifier	Description
Moderate Anomaly	+0.04	Clear hovering, rapid directional change, or acceleration beyond conventional aircraft
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

Limitations and Future Work

Having gone through the factor scoring rubrics and their application, it's important to highlight some limitations and areas for future work.

First, the scores assigned to Witness Credibility (C), Environmental Conditions (E), and Physical or Sensor Evidence (P) are based on structured judgment using the scoring rubrics. While this approach is common in fields like intelligence analysis, risk assessment, and incident investigation, the exact weights and modifiers are ultimately design choices rather than fixed truths. To keep things as objective as possible, all modifiers are bounded, hard caps are enforced, and the full scoring procedure is documented so that others can replicate it or adjust it if needed.

Second, the framework doesn't assume that C, E, and P are fully independent. In reality, these factors can influence one another—for example, poor environmental conditions may make both sensor readings and witness reports less reliable. Conservative weighting and caps help limit this effect, but future versions could tackle it more explicitly with blind scoring, independent analysts, or hierarchical Bayesian models.

Third, the likelihood functions used in the Bayesian update are intentionally simple and conservative. The formulation of the human-explanation likelihood reflects the reality that many confirmed physical objects turn out to be conventional, even when the initial evidence seems unusual. These likelihoods aren't meant to be complete physical models—they're designed to make sure posterior probabilities rise only when the evidence is strong and consistent.

Finally, the prior probabilities are based on contemporary UAP reporting and chosen to be deliberately skeptical. Different priors or weighting schemes could easily be substituted without changing the framework's structure, allowing other researchers to test assumptions and explore sensitivity. Future work could automate the workflow using probabilistic programming tools (e.g., PyMC), apply formal sensitivity analyses, and extend the method to larger and more diverse UAP case sets. While the methodology is robust, the presentation is technical and illustrative; broader application across multiple cases would benefit from automated workflows and summary reporting for accessibility.

Taken together, the JOR–Bayesian fusion framework offers a transparent and conservative way to combine different types of evidence, while keeping the question of whether a real object exists clearly separate from questions about its possible origin.

References

Bayesian Inference / Bayes' Theorem (Core Methodology)

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). Bayesian data analysis (3rd ed.). CRC Press.

UAP Reporting and National Context (Justifying Priors & Explainability)

United States Department of Defense, All-Domain Anomaly Resolution Office. (2024). Fiscal year 2024 consolidated annual report on unidentified anomalous phenomena (unclassified).

Available at: https://media.defense.gov/2024/Nov/14/2003583603/-1/-1/0/FY24-CONSOLIDATED-ANNUAL-REPORT-ON-UAP-508.PDF

Skilling, J. (2004). *Nested Sampling for General Bayesian Computation. Bayesian Analysis, 1(4), 833–859.*