Probability in Recursive Survival Geometry:

Survival Normalisation, Representation Measure, and Analogue Readout

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Abstract

This paper gives a standalone account of probability in Recursive Survival Geometry. The central point is that probability is not introduced as primitive randomness. The formal chain is instead generated histories, accumulated exposed loss, exposure-gate transmission, and normalised survival-representation probability. A history $\gamma_i = (\sigma_{i,0}, \sigma_{i,1}, \sigma_{i,2}, \ldots)$ acquires accumulated loss $A_i(t) = \int_0^t \Gamma(\sigma_i(\tau))W(\varphi_i(\tau))\,\mathrm{d}\tau$, gate transmission $G_i(t) = \mathrm{e}^{-A_i(t)}$, and, after preparation weights q_i are included, represented fraction $p_i(t) = q_i G_i(t)/\sum_j q_j G_j(t)$. The common expression $p_i = S_i/\sum_j S_j$ is therefore only the equal-preparation case with $S_i = G_i$.

The result is formal but not empty. It yields a log-ratio test, $\log(p_i/p_j) = \log(q_i/q_j) - A_i + A_j$, so a locked analogue experiment can compare measured output fractions with independently computed accumulated-loss differences. It also defines survival entropy, effective represented histories, and representation concentration without asserting that probability is primitive chance, matter density, metric curvature, or quantum measurement. The information-filter reading is likewise conditional: p_i says which histories remain represented, while recoverable information requires a support, channel, detector, or measure readout. Null transport and metric terminology are treated as bridge statements, not consequences of probability alone. The paper therefore frames RSG probability as survival-weighted representation, with explicit failure conditions for post-hoc fitting and for any attempted physical over-reading.

Keywords: Recursive Survival Geometry; Probability; Survival Weighting; Representation Measure; Information Filter; Analogue Readout; Entropy; Attenuation.

Short title: Probability in RSG.

IPI release label. Track: formal framework and analogue-protocol note. Strict core: generated histories, exposed loss, exposure gates, normalised survival-representation, log-ratio testing, and non-circularity conditions. Bridge material on information recovery, null transport, matter, metric behaviour, or quantum measurement is not part of the evidential core.

Claim lock. This paper does not derive the Born rule, quantum measurement, matter formation, gravitational curvature, or physical density from p_i. In the strict formalism, p_i is a represented history weight after survival filtering. Stronger readings require additional bridge laws and independent falsifiers.

Reader route. Sections 1 to 4 introduce the representation probability map. Sections 5 to 8 make the empirical analogue content precise. Sections 9 and 10 explain why null transport and information recovery are bridge uses rather than consequences of probability alone. Sections 11 to 13 give a numerical example, failure modes, and the conclusion.

1 Introduction and Claim Status

Probability in Recursive Survival Geometry enters late, not early. This note is a standalone companion to the v1.2 RSG formulation, where survival-normalised output fractions are introduced as the operational probability map for locked analogue tests [9]. The model does not begin by declaring that a random choice occurs. It begins with a family of generated recursive histories, assigns accumulated exposed loss to each history, converts that loss into an exposure-gate transmission, and only then normalises the surviving weights into a probability-like representation measure. The central chain is

$$\begin{aligned}\text{generated histories} &\longrightarrow \text{accumulated exposed loss} \\ &\longrightarrow \text{gate transmissions} \longrightarrow \text{normalised representation probability.}\end{aligned} \tag{1}$$

The word "probability" is therefore used with care. Formally, the quantities p_i are probabilities because they are non-negative and sum to one over the declared represented family. Interpretively, the safer phrase is normalised survival-representation weight. Operationally, p_i is the normalised output after a prepared history has passed through an exposure gate. The TikZ figures use the geometric-probability architecture document as a visual reference for probability as measure, spread, and concentration rather than as a source of additional physics [13].

This distinction governs the whole paper. If p_i is mistaken for primitive randomness, the survival construction looks like an unusual restatement of ordinary probability. If p_i is read as matter density, metric curvature, or physical existence, the formalism overclaims. The careful reading is narrower: p_i is the normalised share of represented history i after a declared loss process and output map have acted.

The compact reading is therefore as follows. A history γ_i is not a single isolated event, but one possible recursive path through structured states. The model then asks how much of that history remains represented after loss has acted along it. The resulting p_i is formally probabilistic, but it is treated here as represented share rather than as a primitive random choice, an actualisation rule, or a physical density term.

Table 1: Claim-status table for probability in RSG.

Claim	**Status**	**Failure condition**
Histories γ_i are generated before probability is assigned.	Definition of the modelling order.	The paper fails as a description of RSG if probability is used before the history family is declared.
Accumulated loss is $A_i = \int \Gamma W \, \mathrm{d}t$.	Internal survival-weighting definition.	It becomes empirical only when Γ, W, paths, and units are fixed before output measurement.
$G_i = S_i = \mathrm{e}^{-A_i}$.	Exposure-gate transmission, equal to the survival multiplier.	Not falsifiable by itself, since it defines the gate score used here.
$p_i = q_i G_i / \sum_j q_j G_j$.	Operational representation probability.	Becomes predictive only with fixed q_i, fixed gates, and a fixed output map.

Table 1: Claim-status table for probability in RSG, continued.

Claim	Status	Failure condition
$\log(p_i/p_j) = \log(q_i/q_j) - A_i + A_j$.	Algebraic consequence of the count map.	Empirical failure occurs if measured log-ratios miss predeclared tolerance.
p_i is not primitive chance.	Interpretation of the formalism.	Fails if the manuscript later treats p_i as an unexplained random selection.
p_i is not matter density or metric curvature.	Guardrail.	Fails if later sections identify representation weight with mass, stress-energy, or geometry without a declared bridge law.

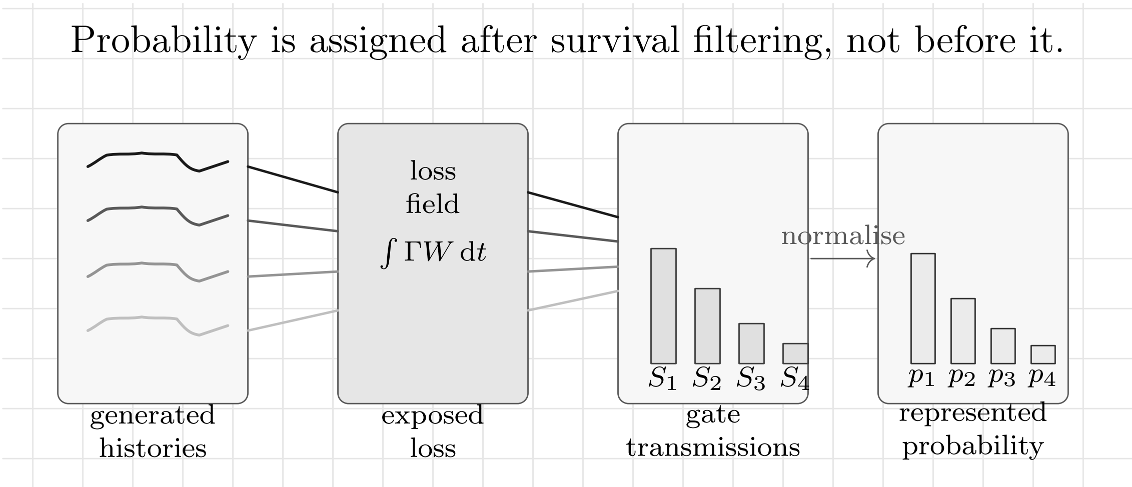


Figure 1: The probability architecture used in this paper. Histories are drawn first, filtered by exposed loss, passed through exposure-gate transmissions, and only then normalised.

2 Probability Is Not Primitive Randomness

The strict RSG construction begins with histories, not dice. A history is a possible recursive path through structured states:

$$\gamma_i = (\sigma_{i,0}, \sigma_{i,1}, \sigma_{i,2}, \ldots). \tag{2}$$

The index i labels one candidate history. The index n labels recursive depth or step number. The notation does not require that every history is physically realised as an object. It records the family over which survival filtering and representation normalisation will later be defined.

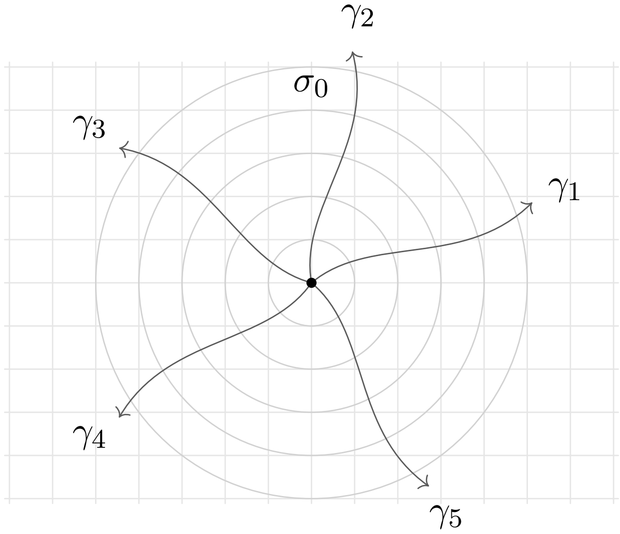
The generated family may be finite, countable, or described by a history measure. The finite case is the safest and is the main case in this paper. Once the histories are declared, the model may assign preparation weights q_i, with $q_i \geq 0$. These preparation weights are not survival probabilities. They describe how much of the initial count, intensity, or represented measure is assigned to each history class before survival filtering.

Thus the strict ordering is

$$\{\gamma_i\}_{i\in I},\ q_i \quad \text{first, then} \quad A_i,\ G_i,\ S_i,\ p_i. \tag{3}$$

The formula is probability-like because it satisfies Kolmogorov-style normalisation over the declared finite family [1]. The interpretation, however, is survival-weighted representation rather than primitive chance. This is close in algebraic form to exponential weighting in statistical mechanics, survival analysis, and evidence normalisation [3, 4, 5]. The proposed RSG distinction is the separation between generated histories and survival selection, together with the exposure factor W inside the loss rate.

In the geometric-probability framing, the generated history family $\mathcal{H}$ plays the role of the sample space, while a cluster $\mathcal{C} \subset \mathcal{H}$ plays the role of an event or represented subset [13]. A finite history family carries probability mass on individual histories. A continuous or branching family requires a density or measure over histories. RSG adds one further layer to this ordinary architecture: the measure is not assigned directly as chance, but is obtained by preparing histories, applying survival loss, and normalising the represented residue.



Generated paths are declared before probability is assigned.

Figure 2: A generated history family. Probability is not the rule that creates the paths in this presentation; it is the normalised representation assigned after exposed loss has been accumulated.

3 Generated Histories and Exposed Survival Loss

Each history accumulates survival loss through an exposed loss rate. In the continuous notation used for compactness,

$$A_i(t) = \int_0^t \Gamma(\sigma_i(\tau))W(\varphi_i(\tau))\,\mathrm{d}\tau. \tag{4}$$

Here Γ is the available dissipation, attenuation, or loss coefficient along the history. The factor W is exposure to that loss. The projected state $\varphi_i(\tau)$ may be a reduced phase variable, a support coordinate, or another declared diagnostic of how history i is exposed to the relevant loss channel.

The effective survival-loss rate is

$$\Lambda_{\mathrm{surv},i}(\tau) = \Gamma(\sigma_i(\tau))W(\varphi_i(\tau)). \tag{5}$$

This expression is the main formal difference between the RSG survival map and ordinary attenuation. Ordinary attenuation would use a path integral of Γ alone. RSG tests whether the exposed-loss product ΓW better predicts output fractions in a declared positive-control regime. In this reading, two histories may pass through the same lossy environment and still lose representation differently because their exposure factors W differ. The claim is therefore not that dissipation alone chooses a history, but that exposed dissipation determines the represented survival score within the declared model.

After loss has accumulated, history i receives the survival multiplier

$$S_i(t) = \mathrm{e}^{-A_i(t)}. \tag{6}$$

For operational readout it is useful to give the same multiplier a gate name:

$$G_i(t) := S_i(t) = \mathrm{e}^{-A_i(t)}. \tag{7}$$

Here G_i is the exposure-gate transmission for history i. If A_i is small, the gate is nearly open and G_i remains large. If A_i is large, the gate is strongly restrictive and G_i becomes small. This is not an additional force or a new physical postulate. It is the concrete multiplicative transmission factor that converts prepared representation into surviving represented output. The exponential form is not novel by itself. It is standard in attenuation, survival, and hazard formalisms. The formal novelty claimed here is the place of this gate inside a recursive-history architecture, not the mere use of e^{-A}.

The term stochastic gate is only appropriate if the model explicitly introduces random gate variables. In the strict probability layer developed here, the gate is an exposure gate: once Γ, W, and the history are fixed, G_i is computed deterministically before normalisation.

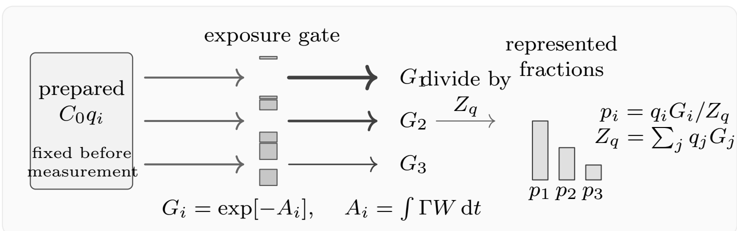


Figure 3: Exposure-gate schematic. The prepared amount $C_{i,0} = C_0 q_i$ passes through a gate with transmission $G_i = \exp[-A_i]$, and only the transmitted amounts are normalised into represented fractions.

4 Operational Probability from Counts

The most operational route to p_i is through counts, intensities, or represented amounts. Let $C_{i,0}$ be the prepared count initially assigned to history class i. If the total prepared

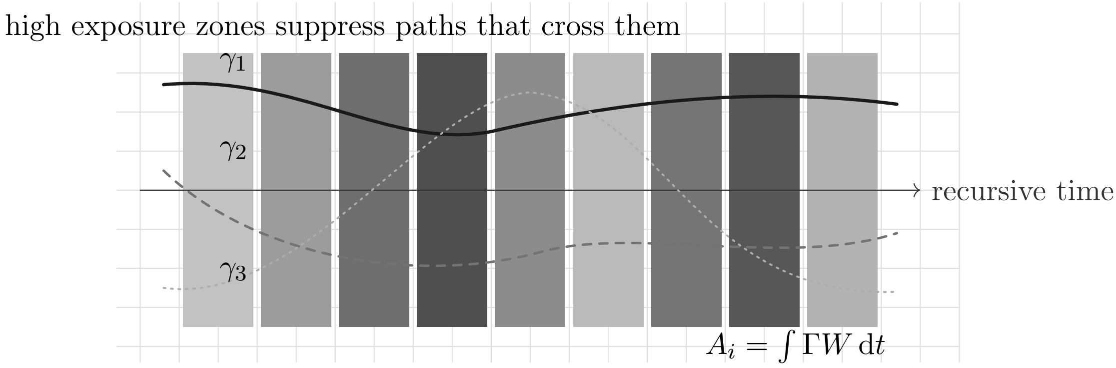


Figure 4: A history bundle crossing an exposure landscape. The loss field is not merely a background medium; the path's exposure to it determines the accumulated loss.

count is C_0 and the preparation weight is q_i, then

$$C_{i,0} = C_0 q_i. \tag{8}$$

For a discrete locked survival process, each step updates the count by a gate transmission factor,

$$C_{i,k+1} = C_{i,k} \exp[-\Gamma_{i,k} W_{i,k} \Delta t_k]. \tag{9}$$

After N steps, the gate transmission is

$$G_i = \exp\left[-\sum_{k=0}^{N-1} \Gamma_{i,k} W_{i,k} \Delta t_k\right] = \mathrm{e}^{-A_i}. \tag{10}$$

The transmitted count is therefore

$$\begin{aligned} C_{i,N} &= C_0 q_i G_i \\ &= C_0 q_i \mathrm{e}^{-A_i}. \end{aligned} \tag{11}$$

The represented output fraction is

$$p_i = \frac{C_{i,N}}{\sum_j C_{j,N}} = \frac{q_i G_i}{\sum_j q_j G_j} = \frac{q_i \mathrm{e}^{-A_i}}{\sum_j q_j \mathrm{e}^{-A_j}}. \tag{12}$$

This is the general finite-family formula. The equal-preparation shorthand is obtained only when all represented histories are prepared equally:

$$q_i = q_j \text{ for all represented } i, j, \qquad p_i = \frac{\mathrm{e}^{-A_i}}{\sum_j \mathrm{e}^{-A_j}} = \frac{S_i}{\sum_j S_j}. \tag{13}$$

The measured output fraction in a finite experiment is

$$\widehat{p}_i = \frac{\widehat{C}_i}{\sum_j \widehat{C}_j}. \tag{14}$$

The empirical claim is not that (12) is new algebra. The empirical claim is that, in a locked analogue medium, independently fixed q_i, A_i, and output maps can predict $\widehat{p}_i$ within stated uncertainty.

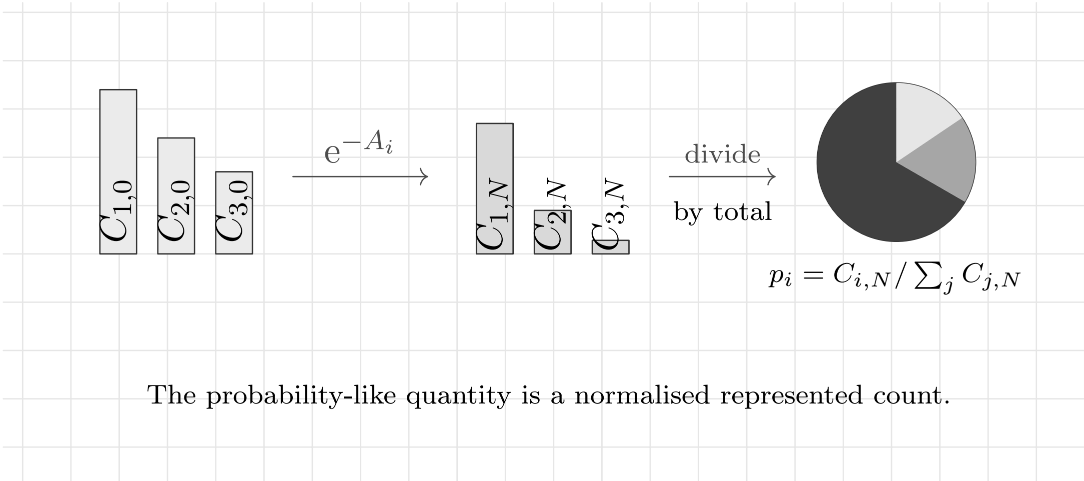


Figure 5: Operational probability from counts. Preparation weights q_i enter before survival filtering; the equal-preparation expression is only a special case.

5 Log-Ratio Geometry and Analogue Readout

The log-ratio form is the most direct way to test the probability map because the common normaliser cancels. From (12),

$$\frac{p_i}{p_j} = \frac{q_i}{q_j} e^{-A_i + A_j}. \tag{15}$$

Taking logarithms gives

$$\log \frac{p_i}{p_j} = \log \frac{q_i}{q_j} - A_i + A_j. \tag{16}$$

For equal preparation,

$$\log \frac{p_i}{p_j} = -A_i + A_j. \tag{17}$$

For equal preparation, the phrase "lower accumulated loss wins representation" is mathematically accurate in the following limited sense:

$$A_i < A_j \quad \Longrightarrow \quad p_i > p_j \qquad \text{when } q_i = q_j. \tag{18}$$

With unequal preparation weights, lower accumulated loss may be outweighed by a smaller initial q_i. The empirical protocol must therefore lock both q_i and A_i before comparison. This handles the distinction between preparation bias and survival filtering: q_i says how the history was initially supplied, while A_i says how much represented weight it lost.

A measured analogue readout supplies

$$\log \frac{\widehat{p}_i}{\widehat{p}_j}, \tag{19}$$

which is compared against (16). This is the preferred test because total intensity calibration errors often cancel in ratios, while path-relative survival remains visible. A complete analogue report should include both objects: the raw measured output vector $\widehat{\mathbf{p}}$ and the log-ratio comparison. The raw vector checks the full output distribution, while the log-ratio display isolates the relative survival claim and removes the shared normalisation.

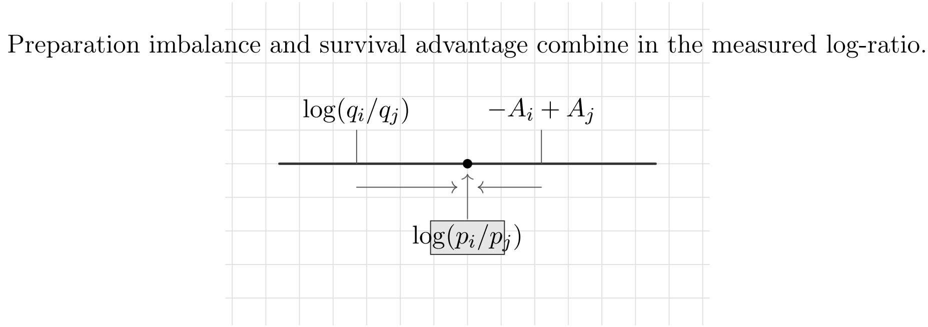


Figure 6: Log-ratio geometry. The represented ratio receives one contribution from preparation and one from differential accumulated loss.

6 History Measures, Normalisability, and Finite Families

For a finite family of histories $\mathcal{H} = \{\gamma_i\}_{i=1}^{N}$, the denominator

$$Z_q(t) = \sum_{j=1}^{N} q_j \mathrm{e}^{-A_j(t)} \tag{20}$$

is the weighted survival normaliser. If at least one $q_j > 0$ and all $A_j(t)$ are finite, then

$$0 < Z_q(t) < \infty. \tag{21}$$

This guarantees that the represented fractions p_i are well defined over the declared finite family.

For a continuous or branching history family, the paper must also declare a base history measure $\mathrm{d}\mu(\gamma)$. The representation measure then becomes

$$\mathrm{d}P(\gamma) = \frac{q(\gamma)\mathrm{e}^{-A[\gamma]}}{Z_q}\,\mathrm{d}\mu(\gamma), \qquad Z_q = \int_{\mathcal{H}} q(\gamma)\mathrm{e}^{-A[\gamma]}\,\mathrm{d}\mu(\gamma). \tag{22}$$

This expression is meaningful only if

$$0 < Z_q < \infty. \tag{23}$$

If the normaliser diverges, vanishes, or depends on a history measure chosen after seeing the result, the probability construction is not operational. The base family, the preparation density, the loss functional, and the detector or output map must be part of the model before the comparison is made.

Table 2: Notation for probability in the RSG representation map.

Symbol	**Meaning**	**Status**
$\sigma_{i,n}$	Structured state of history i at recursive step n.	Generated-state notation.
γ_i	History $(\sigma_{i,0}, \sigma_{i,1}, \ldots)$.	Declared history.
$\mathcal{H}$	History family.	Must be fixed before probability is assigned.
q_i	Preparation weight for history i.	Measured, imposed, or declared before survival filtering.
$C_{i,0}$	Initial count, intensity unit, or represented amount.	Operational input.
$C_{i,N}$	Surviving represented count after N steps.	Operational output before normalisation.
Γ	Available loss, attenuation, or dissipation coefficient.	Must be calibrated independently for empirical use.
W	Exposure of the history to the loss channel.	Model component. RSG-specific tests ask whether it improves on Γ alone.
Λ_{surv}	Effective survival-loss rate ΓW.	Internal survival definition. Not the cosmological constant.
A_i	Accumulated loss along history i.	Path integral of Λ_{surv}.
S_i	Survival weight e^{-A_i}.	Exponential survival score.
G_i	Exposure-gate transmission.	$G_i = S_i = \mathrm{e}^{-A_i}$; multiplicative gate applied to prepared amount before normalisation.
Z_q	Weighted normaliser $\sum_j q_j \mathrm{e}^{-A_j}$.	Must be positive and finite.
p_i	Normalised represented history fraction.	Probability-like representation weight.
$\widehat{p}_i$	Measured output fraction.	Empirical readout.
H_{surv}	Survival entropy over represented histories.	Derived from the p_i.
N_{eff}	Effective number of represented histories.	$N_{\text{eff}} = \mathrm{e}^{H_{\text{surv}}}$.
$\mathrm{d}P(\gamma)$	Continuous represented history measure.	Requires declared base measure and normalisability.
$\mathcal{I}_{\text{rec}}$	Recovered information from represented histories.	Bridge quantity, not implied by high p_i alone.

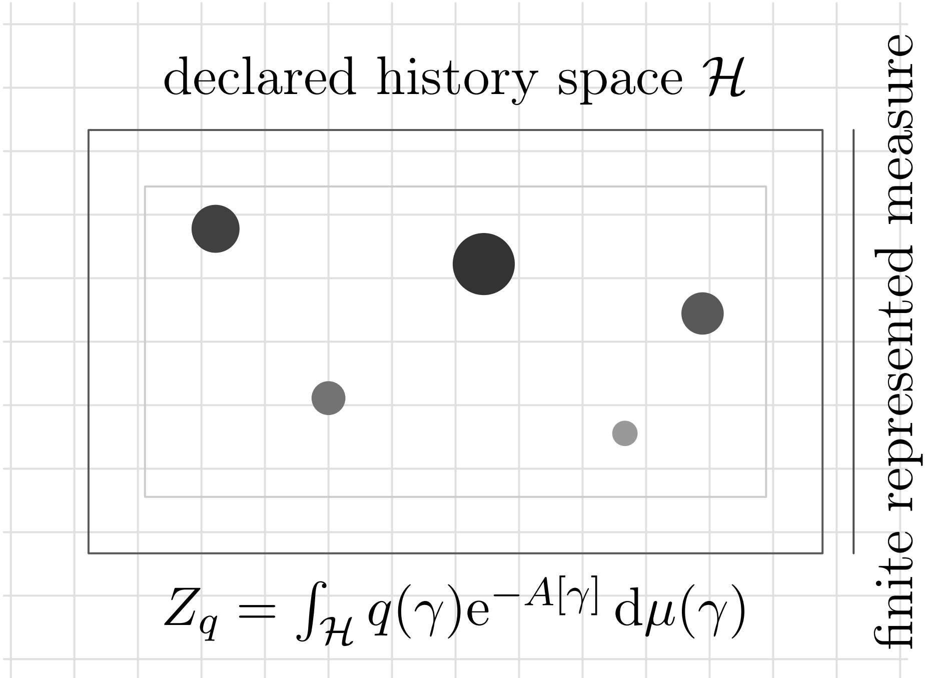


Figure 7: History measure and normalisability. A continuous history family requires a declared base measure and a positive finite normaliser before representation probabilities are meaningful.

7 Survival Entropy and Representation Concentration

Once the represented weights p_i are defined, the survival entropy is

$$H_{\mathrm{surv}} = -\sum_i p_i \log p_i. \tag{24}$$

In the equal-preparation case, $p_i = \mathrm{e}^{-A_i}/Z$, where

$$Z = \sum_j \mathrm{e}^{-A_j}. \tag{25}$$

Substitution gives

$$H_{\mathrm{surv}} = \sum_i p_i A_i + \log Z = \langle A \rangle_p + \log Z. \tag{26}$$

The effective number of represented histories is

$$N_{\mathrm{eff}} = \mathrm{e}^{H_{\mathrm{surv}}}. \tag{27}$$

High survival entropy means many histories remain similarly represented. Low survival entropy means the survival filter has concentrated representation into a smaller set of histories. This is a Shannon readout of the normalised survival measure, not a new thermodynamic law. A thermodynamic interpretation would require an additional bridge from represented histories to physical macrostates, heat, work, or an experimentally defined entropy production.

Let $\mathcal{C} \subset \mathcal{H}$ be a cluster of histories. Its represented share is

$$P(\mathcal{C}) = \sum_{i \in \mathcal{C}} p_i. \tag{28}$$

If histories inside $\mathcal{C}$ have much lower accumulated loss than histories outside it, and if preparation does not overwhelm this advantage, then $P(\mathcal{C})$ approaches one. This is representation concentration. It is not yet matter clumping, mass density, or gravitational attraction. Those readings require a later bridge from represented histories to support-bearing stress-energy or another physical measure.

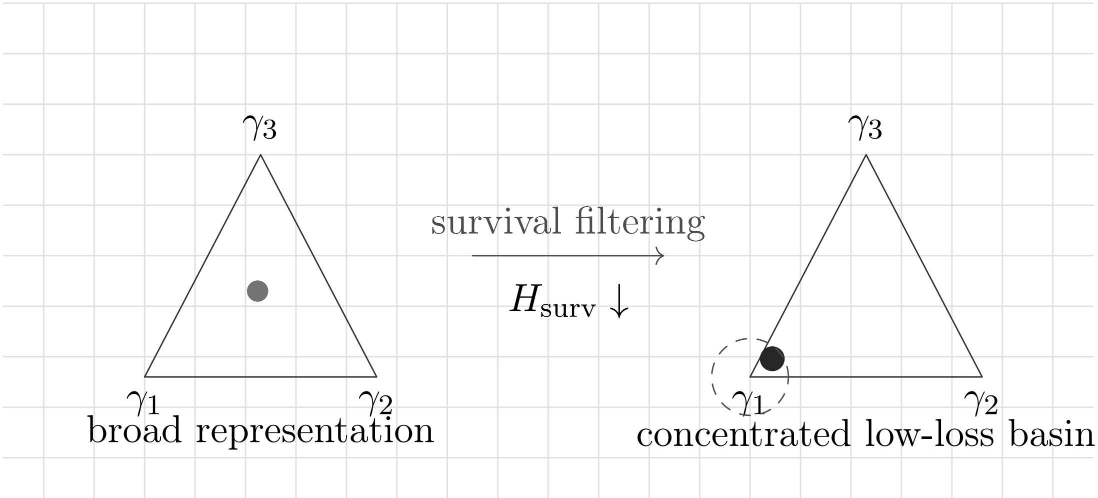


Figure 8: Representation concentration in a probability simplex. Lower survival entropy means the represented measure has concentrated into a narrower basin.

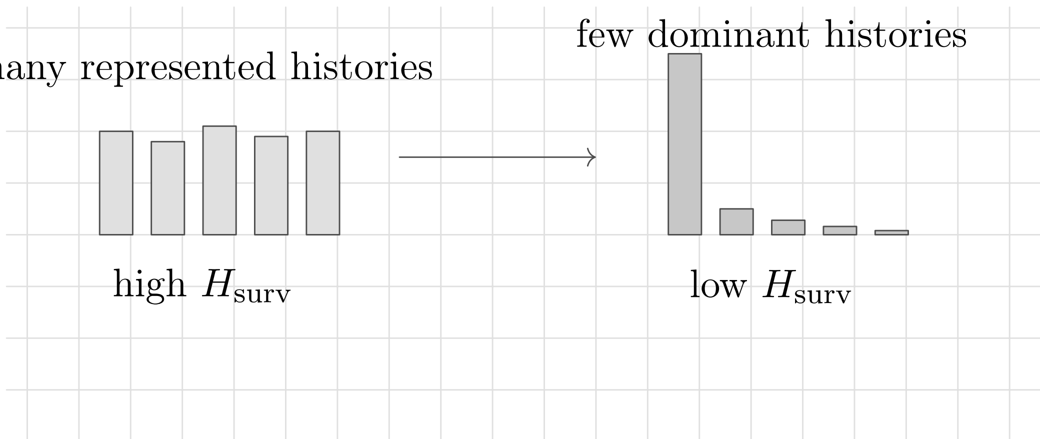


Figure 9: Entropy as spread of representation. Survival entropy is a property of the normalised representation weights, not a new thermodynamic law by itself.

8 Ordinary Attenuation as the Control Model

The RSG probability map is empirically interesting only if it can be distinguished from ordinary attenuation. The control model is

$$A_i^{\mathrm{std}} = \int_{\gamma_i} \Gamma(\sigma_i(t))\, \mathrm{d}t. \tag{29}$$

The RSG model is

$$A_i^{\mathrm{RSG}} = \int_{\gamma_i} \Gamma(\sigma_i(t)) W(\varphi_i(t))\, \mathrm{d}t. \tag{30}$$

The positive-control question is not whether loss occurs. It is whether exposure-weighted loss predicts output fractions or log-ratios better than the ordinary attenuation control. In a locked test, one computes

$$p_i^{\mathrm{std}} = \frac{q_i \mathrm{e}^{-A_i^{\mathrm{std}}}}{\sum_j q_j \mathrm{e}^{-A_j^{\mathrm{std}}}}, \qquad p_i^{\mathrm{RSG}} = \frac{q_i \mathrm{e}^{-A_i^{\mathrm{RSG}}}}{\sum_j q_j \mathrm{e}^{-A_j^{\mathrm{RSG}}}}, \tag{31}$$

then compares both predictions with the measured output vector $\widehat{\mathbf{p}}$. If the W factor does not improve prediction in the declared positive-control regime, the RSG-specific empirical content collapses back to ordinary attenuation for that test.

This is the central non-circularity discipline. The update rule, phase-flow coefficient, calibration scale, histories, preparation weights, loss coefficients, exposure map, detector convention, output map, and thresholds must be fixed before measurement. Otherwise the formula becomes a post-hoc description. Layered optical media supply one natural class of analogue systems in which transfer paths, attenuation, and output intensities can be independently specified [15].

Compare predictions against measured output, not against intuition.

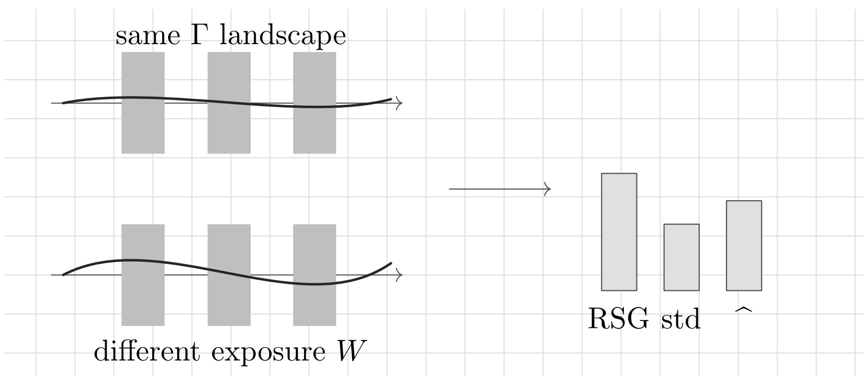


Figure 10: Ordinary attenuation versus exposure-weighted attenuation. A valid RSG-specific test asks whether ΓW improves prediction over Γ alone.

9 Null Transport and the Lossless Clockless Limit

The probability map can describe a lossless class, but it does not derive spacetime geometry by itself. In the survival formalism, a null-like transport candidate is first represented as a class with vanishing effective survival loss:

$$\Gamma W \longrightarrow 0. \tag{32}$$

Then

$$A_i \longrightarrow 0, \qquad S_i \longrightarrow 1. \tag{33}$$

This says that the history does not decay under the survival filter. It does not yet say that the history is a photon, a light ray, or a null geodesic.

The additional RSG bridge condition is that the transport class carries no recurrent internal clock:

$$\mathrm{d}\tau_R = 0. \tag{34}$$

Only after a Lorentzian bridge has been imported may one represent this class by the usual null interval

$$\mathrm{d}s^2 = 0. \tag{35}$$

Thus light-like transport is the lossless, clockless limit only after the metric bridge has been declared. The probability formula alone does not derive the speed of light, electromagnetic propagation, or a metric cone.

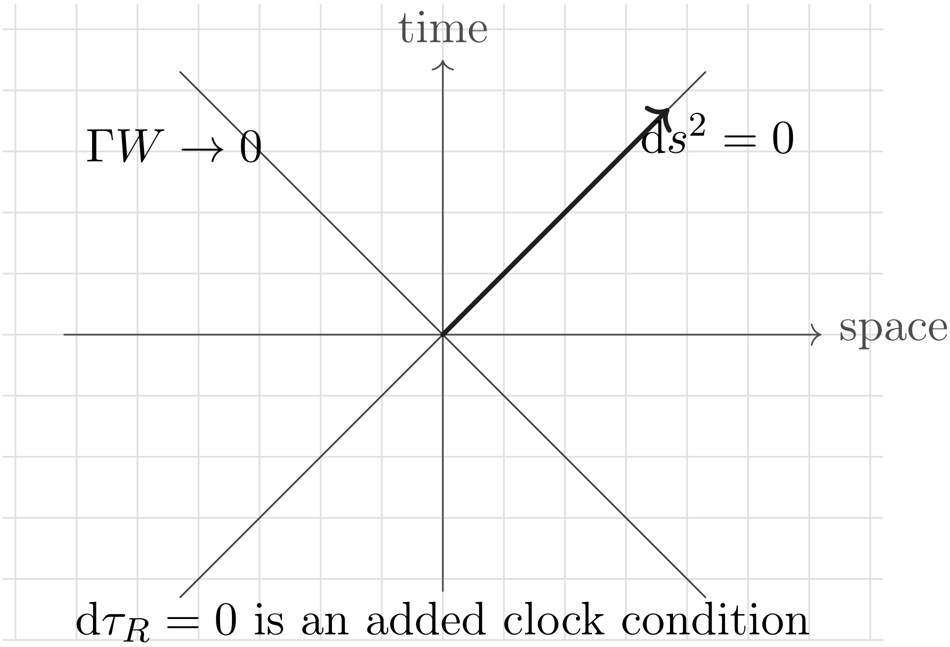


Figure 11: Null transport as a bridge reading. Vanishing survival loss gives $S_i \to 1$; the null cone requires the additional recursive-clock and Lorentzian bridge assumptions.

10 Information Filtering and Recoverable Measure

The information-filter question is different from the probability question. The probability weight p_i asks which histories remain represented. Recovered information asks what can be read from those histories. A high-p_i history is strongly represented, but it is not automatically informative. It becomes informative only if there is a recovery channel, support, detector, or measure readout.

Let $\mathcal{R}$ be a recovery map from represented histories into recorded distinctions. One may write schematically

$$\mathcal{I}_{\text{rec}} = \mathcal{R}(\{p_i, \gamma_i, \mu_i\}_{i \in I}), \tag{36}$$

where μ_i denotes the measure package attached to history i, if such a package has been declared. The formula is intentionally schematic. It prevents a common error: probability weight is not the same thing as recoverable information. The recovery channel is an additional structure.

This placement also clarifies the relationship to information-physics proposals. Shannon information requires a declared probability space over messages [2]. Jaynes' information-theoretic mechanics requires specified constraints and a probability assignment [3]. Landauer's principle concerns the thermodynamic cost of logically irreversible operations, not the automatic physical status of every represented distinction [6]. Vopson's information-mass and infodynamics claims require defined information-bearing states and a physical interpretation of their information content [7, 8]. The present RSG note adopts a weaker claim: survival weighting generates represented history weights. Physical information transport requires an extra carrier-and-recovery bridge, such as the one developed in Austin's information-recovery note [11].

Figure 12: Information filtering. Probability weights say which histories survive representation; a recovery channel says what can be read.

11 Worked Numerical Examples

Consider three equally prepared histories with accumulated losses

$$A_1 = 0, \qquad A_2 = 1, \qquad A_3 = 2. \tag{37}$$

Their survival weights, equivalently their gate transmissions, are

$$S_1 = 1, \qquad S_2 = \mathrm{e}^{-1}, \qquad S_3 = \mathrm{e}^{-2}. \tag{38}$$

The normaliser is

$$Z = 1 + \mathrm{e}^{-1} + \mathrm{e}^{-2}. \tag{39}$$

The represented probabilities are

$$p_1 = \frac{1}{Z}, \qquad p_2 = \frac{\mathrm{e}^{-1}}{Z}, \qquad p_3 = \frac{\mathrm{e}^{-2}}{Z}. \tag{40}$$

Numerically,

$$p_1 \approx 0.665, \qquad p_2 \approx 0.245, \qquad p_3 \approx 0.090. \tag{41}$$

The lowest-loss history has the most open gate and dominates the represented measure. If preparation weights are unequal, the calculation must be repeated with

$$p_i = \frac{q_i \mathrm{e}^{-A_i}}{\sum_j q_j \mathrm{e}^{-A_j}}. \tag{42}$$

This final expression is the correct general formula. The numerical example uses equal preparation only to make the gate effect transparent.

The v1.4 rejected manuscript also used a more physical laser-layer exposure example and a small FFT/windowing toy [10]. These examples are useful here because they show why W must be defined before the probability map is used. In that construction the reduced phase state is $\varphi = (\Theta, \Pi)$, with phase-support norm

$$J(\varphi) = \Theta^2 + \ell^2 \Pi^2. \tag{43}$$

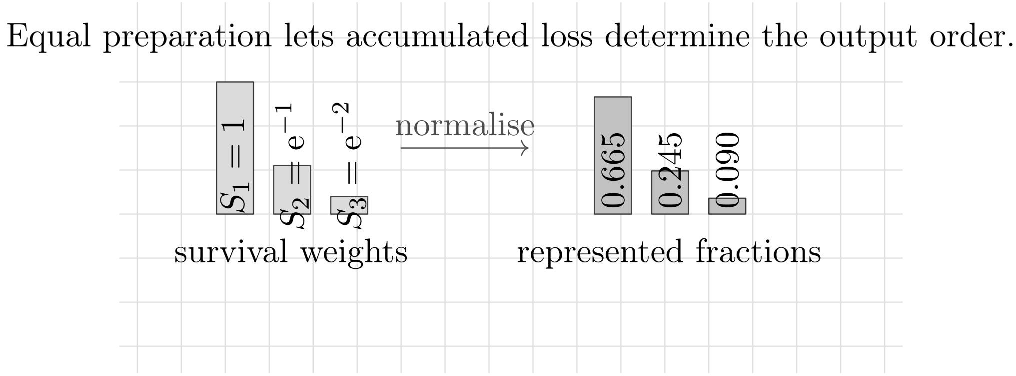


Figure 13: Three-history numerical example. The example illustrates normalisation after survival filtering, not primitive chance.

The exposure factor is then

$$W(\varphi) = \frac{\Theta^2}{J(\varphi)} = \frac{\Theta^2}{\Theta^2 + \ell^2\Pi^2}. \tag{44}$$

For $J > 0$, this gives $0 \le W \le 1$. The status of this formula is important. It is not a universal law of nature and it is not a fitted weight chosen after the result. It is the predeclared fractional exposure of total reduced phase support to a position-like loss channel. A different loss channel would require a different exposure law, declared as a different model before comparison.

In the laser-layer example, a weak selective layer has calibrated loss $\eta = 0.20$. If five prepared field states have measured exposed-support fractions

$$\mathbf{W} = (1.00,\ 0.75,\ 0.50,\ 0.25,\ 0.00), \tag{45}$$

then the exposure-weighted output rule is

$$I_{\rm RSG}(W) = \exp(-0.20W), \tag{46}$$

which is the laser-layer gate transmission $G(W)$. The gate vector is

$$\mathbf{G}_{\rm laser} = \exp[-0.20\,\mathbf{W}] \approx (0.819,\ 0.861,\ 0.905,\ 0.951,\ 1.000). \tag{47}$$

whereas ordinary attenuation predicts the same output for every state,

$$I_{\rm std} = \exp(-0.20) \approx 0.819. \tag{48}$$

With equal prepared amounts, the exposure-gated surviving amounts are therefore

$$\mathbf{C}_1^{\rm RSG} \approx (0.819,\ 0.861,\ 0.905,\ 0.951,\ 1.000). \tag{49}$$

Their normaliser is

$$Z_{\rm laser} \approx 4.536, \tag{50}$$

so the represented laser output fractions are

$$\mathbf{p}_{\rm laser}^{\rm RSG} \approx (0.181,\ 0.190,\ 0.199,\ 0.210,\ 0.221). \tag{51}$$

By contrast, ordinary attenuation gives equal surviving amounts and hence the equal vector

$$\mathbf{p}^{\mathrm{std}}_{\mathrm{laser}} = (0.200,\ 0.200,\ 0.200,\ 0.200,\ 0.200). \tag{52}$$

The point is not that RSG rediscovers polarisation or selective absorption. The point is narrower: in a known component-selective case, W can be read as the measured fraction of support coupled to the loss channel, while ordinary path attenuation is too coarse whenever only part of the support is exposed.

The FFT example in the same rejected manuscript is likewise a locked held-out windowing toy, not a replacement for the Fourier transform. The ordinary discrete transform supplies raw bin weights. A survival layer is then tested only after those bins, exposure values, losses, and the held-out convention have been fixed [16]. With raw FFT preparation weights

$$\mathbf{q} = (0.60,\ 0.25,\ 0.15), \tag{53}$$

predeclared leakage exposures

$$\mathbf{W} = (0.05,\ 0.70,\ 0.95), \tag{54}$$

and common $\Gamma = 1.20$, the accumulated losses are

$$\mathbf{A} = \Gamma\mathbf{W} = (0.060,\ 0.840,\ 1.140). \tag{55}$$

The survival multipliers, now read as gate transmissions, are

$$\mathbf{G} = \exp[-\mathbf{A}] \approx (0.942,\ 0.432,\ 0.320), \tag{56}$$

and the gated surviving bin masses are

$$\mathbf{C}_1 = \mathbf{q} \odot \exp[-\mathbf{A}] \approx (0.565,\ 0.108,\ 0.048), \tag{57}$$

where $\odot$ denotes componentwise multiplication. With

$$Z_{\mathrm{FFT}} \approx 0.721, \tag{58}$$

the survival-ranked output is

$$\mathbf{p}^{\mathrm{surv}} \approx (0.784,\ 0.150,\ 0.067). \tag{59}$$

For the held-out repeated-window reveal

$$\widehat{\mathbf{p}} = (0.781,\ 0.142,\ 0.077), \tag{60}$$

the total absolute errors are

$$\sum_m |\widehat{p}_m - q_m| = 0.362, \qquad \sum_m |\widehat{p}_m - p^{\mathrm{surv}}_m| = 0.021. \tag{61}$$

Total absolute error is the primary diagnostic here because it is transparent and does not add a likelihood model. A scale-normalised companion metric gives the same ordering:

$$\mathrm{RMSE}(\widehat{\mathbf{p}}, \mathbf{q}) \approx 0.129, \qquad \mathrm{RMSE}(\widehat{\mathbf{p}}, \mathbf{p}^{\mathrm{surv}}) \approx 0.0076. \tag{62}$$

The log-ratio residuals also favour the survival-ranked vector. Summing absolute residuals over the three bin pairs gives

$$\sum_{i<j}\left|\log\frac{\widehat{p}_i}{\widehat{p}_j}-\log\frac{q_i}{q_j}\right|\approx 1.861,\qquad \sum_{i<j}\left|\log\frac{\widehat{p}_i}{\widehat{p}_j}-\log\frac{p_i^{\rm surv}}{p_j^{\rm surv}}\right|\approx 0.388. \tag{63}$$

This is the numerical example in which the survival-ranked output retrieves a lower error score than the raw FFT weights. It is still a toy comparison. The correct claim is not that RSG defeats the FFT or proves a new physical law, but that a locked survival-ranking layer can be tested against an unweighted preparation-vector control, and in this declared case it fits the held-out output more closely.

12 Non-Circularity and Failure Modes

The main danger is fitting after the fact. If Γ, W, the history family, preparation weights, output map, detector convention, or thresholds are chosen after the output is known, the formula becomes descriptive curve-fitting. A valid analogue test must fix

$$R,\ \Omega^2,\ \ell,\ \Gamma,\ W,\ \mathcal{H},\ q_i,\ \mathcal{D},\ \mathcal{O},\ \varepsilon \tag{64}$$

before measurement. Here R is the recursive or transfer update, Ω^2 is any declared phase-flow coefficient, ℓ is a calibration scale, $\mathcal{D}$ is the detector convention, $\mathcal{O}$ is the output map, and ε is the acceptance tolerance.

The first failure mode is ordinary-control collapse. If

$$\mathbf{p}_{\rm RSG}\quad\text{does not improve on}\quad\mathbf{p}_{\rm std} \tag{65}$$

in a declared positive-control regime, then the W factor has not earned empirical use in that setting.

The second failure mode is normalisation failure:

$$Z_q\le 0\quad\text{or}\quad Z_q=\infty. \tag{66}$$

In that case the represented probability measure is not defined.

The third failure mode is bridge inflation. A statement about p_i becomes invalid if it is used to claim matter formation, stress-energy, gravitational curvature, or quantum measurement without an added physical law. Support and measure bridges are discussed elsewhere through Surtea-style support and Austin's vacuum-energy reconstruction, but those structures are not supplied by the probability formula itself [14, 12]. In the strict paper,

$$p_i\neq\rho_{\rm matter},\qquad p_i\neq T^{\mu\nu},\qquad p_i\neq g_{\mu\nu}. \tag{67}$$

Those quantities may be related in future models only after a support, measure, conservation, and recovery law has been supplied.

13 Conclusion

Probability in RSG is the normalised representation of generated histories after survival filtering. Its strict formula is

$$A_i=\int\Gamma W\,\mathrm{d}t,\qquad G_i=S_i=\mathrm{e}^{-A_i},\qquad p_i=\frac{q_iG_i}{\sum_j q_jG_j}=\frac{q_i\mathrm{e}^{-A_i}}{\sum_j q_j\mathrm{e}^{-A_j}}. \tag{68}$$

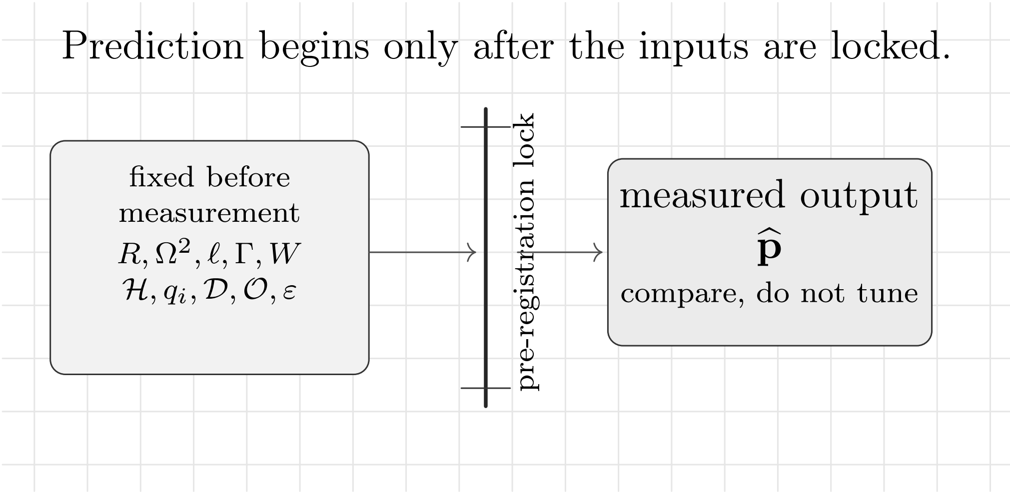


Figure 14: Non-circularity lock. The model is predictive only when histories, losses, exposure, preparation, and output rules are fixed before measurement.

This construction is formally probability-like because $p_i \geq 0$ and $\sum_i p_i = 1$. Its interpretation is not primitive random chance. It is the normalised output of prepared histories after exposure-gate transmission.

The main relevance is that it gives the RSG paper a disciplined bridge between recursive generation and observable output. Generated histories are not automatically equally present. Histories that accumulate less exposed loss have more open gates under equal preparation, while the general formula keeps preparation bias and gate transmission separate. The log-ratio form makes this comparison directly testable in a locked analogue setting, and both raw output fractions and log-ratio plots should be reported. Survival entropy then measures how broad or concentrated the represented family remains.

The guardrails are just as important as the formula. A high p_i history is not automatically matter, information, gravity, or a quantum outcome. It is a strongly represented history. Physical readings require additional support, recovery, measure, conservation, or metric bridges. Used with those limits, probability in RSG is not randomness first; it is representation after survival filtering.

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