The Active Inference Notation Decoder

A Quick Reference Guide for Reading Across the Literature

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The Rosetta Stone: Active Inference Notation Across Authors

Why the same concept looks different in every paper

Concept	Namjoshi (2026)	Beal (2003)	Friston (Pre-2016)	Friston (2017 +)	Blei et al. (2016)
Observed / Observable	y	y	$\tilde{s}, \tilde{a}$ (Markov blanket)	o or y	x
Hidden / Latent	x	x	$\tilde{\Psi}$ (External states)	η (External states)	z
Internal / Representational	-	-	$\tilde{r}$	-	-
Approx. Posterior	$q(x)$	$q(x)$	$q(\tilde{\Psi} \mid \tilde{r})$	$q(\eta \mid \mu)$	$q(z \mid x)$
Generative Model	$p(y \mid x)$	$p(y \mid x, \theta)$	$p(\tilde{\Psi}, \tilde{s}, \tilde{a}, \tilde{r} \mid m)$	$p(o, \eta \mid m)$	$p(x \mid z)$
"x" means ...	hidden	hidden	"Ψ" hidden "$\tilde{s}, \tilde{a}$" observed	"η" hidden "o" observed	observed

Why This Guide Exists

Active inference and variational inference are a single family of mathematical ideas — but reading across the literature feels like navigating without a map. The same concept appears under completely different symbols depending on which paper you are reading. A variable that means 'hidden state' in one paper means 'observed variable' in another. This is not a sign that you are confused. It is a sign that the field developed across multiple communities — statistical learning, theoretical neuroscience, and machine learning — each with its own notational conventions.

This guide is a Rosetta Stone: a single reference that maps the same concepts across five key sources. It accompanies the Themesis YouTube video *Surviving the Notational Nightmare: Active Inference and Generative AI Notation*.

Key Definitions

Observed / Observable (y, o, x, s■, ã): The variables that the agent can directly measure or sense. In neuroscience terms: sensory input. In machine learning terms: the data.

Hidden / Latent (x, Ψ■, η, z): The variables that the agent cannot directly observe but must infer. These are the hidden causes of observations. In Friston's framework, these are the external states of the world.

Internal / Representational (r■, μ): Internal states of the agent that encode its beliefs. In Friston (pre-2016), r■ represents the internal representational states. In Friston (2017+), μ (mu) represents the sufficient statistics of those

internal states — the compressed summary of the agent's beliefs.

Approximate Posterior q(·|·): The agent's best tractable approximation to the true posterior over hidden states. Because the true posterior p(hidden|observed) is computationally intractable, variational inference finds the closest approximation within a tractable family of distributions.

Generative Model p(·,·|·): The agent's model of how the world generates observations from hidden states. This encodes the agent's assumptions about the structure of reality. In pymdp, the A matrix encodes this likelihood mapping.

The Critical Insight: What 'x' Means

In standard algebra and most of mathematics education, *x* is the observed or independent variable — the thing you measure, the input to a function. *y* depends on *x*.

In Namjoshi (2026) and Beal (2003), this is **reversed**: *x* is the **hidden** variable and *y* is what is **observed**. In Blei et al. (2016), *x* is observed and *z* is hidden — closer to the algebra convention but still different. In Friston's papers, *x* largely disappears as a primary variable after 2016.

This single collision between algebra intuition and active inference notation has derailed more serious readers than any other source of confusion in the literature.

Primary References

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