A FREE-ENERGY FORMULATION OF THE TRIADIC VALUE MODEL FOR INNOVATION OF MEANING

ANALYSIS OF THE EFFECT OF PRECISIONS ON VALUE-GENERATION PROCESSES BASED ON A GAUSSIAN MODEL

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ABSTRACT

Triadic Value Model (TVM) describes value generation as a dynamic process among intrinsic value, instrumental value, and meaningful value, formulated as Bayesian inference. Meaning Generation Theory (MGT), on the other hand, provides a practical framework for generating new meanings through contextual shifts, but mainly corresponds to only one process within TVM. This study aims to bridge the research gap between TVM and MGT by formulating all value-generation processes in TVM using the free energy principle. By mapping the processes of meaning assignment, value updating, and value embodiment onto information-theoretic quantities—namely Kullback–Leibler divergence, Bayesian surprise, and expected free energy—we analytically derive design-relevant properties of each process. Using Gaussian approximations, we clarify how the variances of prior beliefs, likelihoods, and action-conditioned beliefs influence these quantities. The results provide desing-relevant guidelines for innovation of meaning, showing how exploration and exploitation can be optimally balanced through the manipulation of precision. This framework extends TVM toward a practical methodology and provides a unified theoretical foundation for innovation of meaning grounded in Bayesian cognition and active inference.

Keywords: *innovation of meaning, triadic value model, free energy principle, active inference*

1 INTRODUCTION

In recent years, innovation of meaning (Verganti, 2009) has become a central topic in design research and practice, based on the recognition that the value of products and services depends not only on their functional performance but also on how they are interpreted by people. While conceptual discussions on innovation of meaning have accumulated, methodological challenges faced by designers remain unresolved. In particular, it is difficult to describe value generation based on meaning in a way that is both theoretically coherent and practically operable. Specifically, it remains challenging to address, within a single continuous framework, how

meanings are reinterpreted and how goals and offerings are subsequently updated and embodied as a result of that reinterpretation (Norman & Verganti, 2014; Kushi & Yanagisawa, 2024).

To address this issue, the Triadic Value Model (TVM) conceptualizes value generation as the interrelationship among intrinsic value (goals), instrumental value (means), and meaningful value (value arising from interpreting the relationship between goals and means), and describes value generation as three dynamic processes (Yanagisawa, 2025). These processes are: (1) the generation of instrumental value through the embodiment of intrinsic value as means, (2) the generation of meaningful value through assigning relationships between instrumental value and intrinsic value (goals), and (3) the generation of intrinsic value through legitimizing meaningful value and updating the goals themselves (legitimization).

Meaning Generation Theory (MGT), on the other hand, provides a practical perspective based on context shifts, whereby the interpretation—and thus the meaning—of the same object changes as its context changes, leading to the generation of new meanings (Kushi, Nakaji & Yanagisawa, 2024). For example, a candle may be interpreted as a source of lighting in one context, while in a context oriented toward relaxation it may be interpreted as a means of self-care. In this way, MGT offers a useful framework for addressing innovation of meaning in design practice.

However, a significant gap remains between TVM and MGT. While TVM provides an integrated account of value generation as a dynamic triadic process, MGT primarily corresponds to only one of the three processes in TVM—namely, the generation of meaningful value through meaning assignment. As a result, (i) the process of generating instrumental value through the embodiment of intrinsic value and (ii) the process of updating intrinsic value (goals) through the legitimization of meaningful value lack sufficiently clear and practically applicable methodologies. Moreover, even the process of meaning assignment itself requires more concrete descriptions that allow it to be treated not merely as an ex-post explanation, but as a set of manipulable variables within design practice.

To bridge this gap, this study formulates the entire set of value-generation processes in TVM based on the Free Energy Principle (FEP) (Friston et al., 2006; Friston, 2010), a unifying principle in cognitive neuroscience. The FEP posits that perception, learning, and action can be described as the minimization of variational free energy, with Bayesian inference emerging as a consequence of this minimization dynamics. By mapping each process in TVM onto this minimization framework, this study aims to represent designers' value-generation operations in forms that are analytically tractable and directly connectable to design guidelines.

Specifically, meaning assignment is conceptualized in terms of Kullback–Leibler divergence (KLD) as a component of free energy reduction, value updating is conceptualized as Bayesian surprise (BS), and value embodiment (the generation of means) is conceptualized as expected free energy within active inference. Furthermore, key parameters such as the variance or precision of prior beliefs, likelihoods, and action-conditioned beliefs are treated as design variables. In a design context, these parameters correspond to the degree of commitment to

existing goals (prior beliefs), the reliability and clarity of perceived cues from artifacts (likelihoods), and the uncertainty associated with anticipated outcomes of design actions such as prototyping (action-conditioned beliefs). By analyzing how these parameters influence each information measure, this study derives design-relevant guidelines concerning the balance between exploration and exploitation in innovation of meaning.

In summary, the contributions of this study are twofold: (1) it reconstructs TVM as a process-complete methodology that addresses all three value-generation processes, and (2) it positions innovation of meaning within a unified framework consistent with free energy principle and active inference, thereby deriving design-relevant guidelines with implications for design practice.

2 METHOD

2.1 Triadic value model

TVM is a theoretical framework that models the dynamic processes of value generation (Yanagisawa, 2025). TVM describes value generation in terms of Bayesian inference. Bayesian inference is a method for probabilistically inferring causal states from observed events. According to the Bayesian brain hypothesis, the brain perceives the world through Bayesian inference (Knill & Pouget, 2004). Bayesian inference can be expressed as follows.

$$p(s|o) = \frac{p(s)p(o|s)}{p(o)} \tag{1}$$

Here, s denotes a state and o denotes an observation. This model infers the state of the environment, which is the cause, from observations. $p(s)$ represents the prior distribution, $p(o|s)$ the likelihood, and $p(s|o)$ the posterior distribution. These correspond to the predicted state, the observed state, and the perceived state, respectively. According to the Bayesian brain hypothesis, the brain does not directly perceive observations; rather, it perceives the product of prediction and observation.

In TVM, the prior distribution represents intrinsic value, the likelihood represents instrumental value, and the posterior distribution represents meaningful value. intrinsic value corresponds to the goal, instrumental value to the means for achieving the goal, and meaningful value to the value of interpreting the means in relation to the goal. In other words, the prior distribution describes the goal, the likelihood describes the means, and the posterior distribution describes interpretation. By taking a goal as a prior belief and observing an instrument as a means, the meaning of the instrument is interpreted as a posterior belief.

To systematically describe value generation across its full cycle, this study employs the free energy principle, which describes perception, learning, and action as the minimization of free energy (Friston et al., 2006; Friston, 2010). By mapping free energy minimization onto the three processes of the Triadic Value Model, this work provides a unified basis for deriving practical design methodologies.

2.2 Free energy principle

The free energy principle explains perception, learning, and action as the optimization of parameters of an internal generative model that represents the external world, such that a quantity known as free energy—an index of prediction error—is minimized (Friston et al., 2006; Friston, 2010). Free energy can be expressed as follows (Yanagisawa, 2021; Yanagisawa & Honda, 2025).

$$\begin{aligned} F &= E_{q(s)}[\ln q(s) - \ln p(s,o)] \\ &= D_{KL}[q(s)\|p(s|o)] + D_{KL}[p(s|o)\|p(s)] + E_{p(s|o)}[-\ln p(o|s)] \end{aligned} \tag{2}$$

Here, $q(s)$ denotes the recognition distribution, and $p(s,o)$ denotes the generative model. Free energy is defined as the expectation, under the recognition distribution, of the difference between the logarithms of the recognition distribution and the generative model. The free energy principle explains perception as the optimization of the recognition distribution so as to minimize free energy. The first term corresponds to the Kullback–Leibler divergence between the recognition distribution and the posterior distribution. When the recognition distribution is optimized to match the posterior distribution, the Kullback–Leibler divergence becomes zero. In other words, the Kullback–Leibler divergence represents the component of free energy that is reduced through perception. Assuming that, prior to perception, the recognition distribution corresponds to the prior distribution, the free energy reduced by perception (KLD) can be expressed as follows.

$$KLD = D_{KL}[p(s)\|p(s|o)] \tag{3}$$

The second term is the Kullback–Leibler divergence of the posterior distribution with respect to the prior distribution, referred to as Bayesian surprise (BS).

$$BS = D_{KL}[p(s|o)\|p(s)] \tag{4}$$

When the prior distribution is updated to the posterior distribution, BS becomes zero. BS represents the component of free energy that is reduced through learning (Bayesian updating). Bayesian updating is a statistical procedure in which the posterior distribution is used as the prior distribution for the next perceptual step and is updated to a new posterior distribution by observing new data.

The third term represents observational uncertainty (U), defined as the expected negative log-likelihood under the posterior distribution. While U can be reduced through action, future observations are unknown prior to action. Accordingly, action is described in terms of minimizing expected free energy, as formalized in active inference (Friston et al., 2016; Parr et al., 2022).

2.3 Active inference

Active inference explains action as the minimization of expected free energy (Friston et al., 2016; Parr et al., 2022). Expected free energy can be expressed as follows.

$$\begin{aligned} G &= E_{p(o|s)}E_{q(s|\pi)}[\ln q(s|\pi) - \ln p(s,o)] \\ &= D_{KL}[q(s|\pi)\|p(s)] - E_{q(o|\pi)}\big[D_{KL}[q(s|o,\pi)\|q(s|\pi)]\big] + E_{q(o|\pi)}[-\ln q(o|\pi)] \end{aligned} \tag{5}$$

Expected free energy is the expectation of free energy with respect to the likelihood, which is a function of observations. Here, π denotes an action. The recognition distribution is the probability distribution over states conditioned on action. Expected free energy can be decomposed into three terms. The first term is the Kullback–Leibler divergence between the recognition distribution and the prior distribution, which represents the discrepancy between the prior distribution predicted under a given action and the actual prior distribution (Risk). The second term is the expected value, with respect to the predicted observation distribution under a given action, of Bayesian surprise (Epistemic Value). The third term is the entropy of the observation probability distribution predicted under a given action.

Minimization of expected free energy is achieved through minimization of Risk, maximization of Epistemic Value, and minimization of entropy. Risk minimization is achieved when the prior distribution predicted under a given action matches the actual prior distribution. In other words, Risk is minimized by selecting actions that fulfill prior beliefs, which corresponds to exploitative behavior. In contrast, maximization of Epistemic Value is achieved by maximizing the Bayesian surprise predicted under a given action and therefore corresponds to exploratory behavior. Entropy minimization is achieved by selecting actions that minimize the uncertainty of predicted observations, corresponding to actions that reduce uncertainty in anticipated outcomes.

2.4 Correspondence between information measures and TVM

The processes described by the free energy principle and active inference are mapped onto the processes of TVM. Specifically, information-theoretic quantities in the free energy principle and active inference are associated with the value-generation processes in TVM.

KLD represents the component of free energy that is reduced through perception. Because it is reduced in the process of generating a posterior distribution from observations, KLD is considered to correspond to the process of generating meaningful value by assigning meaning to instrumental value.

BS represents the component of free energy that is reduced through learning (Bayesian updating). Because it is reduced in the process of updating the prior distribution through the posterior distribution, BS is considered to correspond to the process of updating intrinsic value by legitimizing meaningful value.

Expected free energy is the expectation of free energy with respect to the likelihood, which is a function of observations, and is minimized through action. Because it represents the information quantity minimized in the process of generating observations through action based on a prior distribution, expected free energy is considered to correspond to the process of generating instrumental value through the embodiment of intrinsic value. Minimization of expected free energy is achieved through minimization of Risk, maximization of Epistemic Value, and minimization of entropy. This implies that, in the process of generating instrumental value through the embodiment of intrinsic value, there exist exploitative actions that generate instrumental value to fulfill intrinsic value, exploratory actions that maximize the updating of intrinsic value through the legitimization of meaningful value, and actions that minimize the uncertainty of instrumental value.

2.5 Gaussian approximation

In order to construct practical methodologies corresponding to each process of TVM, the prior distribution, likelihood, and action-conditioned recognition distribution required for computing each information measure are represented using explicit probability distributions. Specifically, Gaussian distributions are adopted.

When the prior distribution, likelihood, and action-conditioned recognition distribution are approximated by Gaussian distributions, they can be expressed as follows.

$$p(s) = N\left(\mu_p, \sigma_p^2\right) \tag{6}$$

$$p(o|s) = N\left(s, \sigma_l^2\right) \tag{7}$$

$$q(s|\pi) = N(\mu_\pi, \sigma_\pi^2) \tag{8}$$

Here, μ_p denotes the mean of the prior distribution, σ_p^2 denotes the variance of the prior distribution, σ_l^2 denotes the variance of the likelihood, μ_π denotes the mean of the action-conditioned recognition distribution, and σ_π^2 denotes the variance of the action-conditioned recognition distribution. By approximating the prior distribution, likelihood, and action-conditioned recognition distribution with Gaussian distributions, the information measures corresponding to each process of TVM can be computed.

3 RESULT

By substituting Eqs. (6) and (7) into Eq. (3), KLD can be expressed as follows.

$$KLD = \frac{1}{2}\left(\frac{\sigma_p^2\left(o-\mu_p\right)^2}{\sigma_l^2\left(\sigma_p^2+\sigma_l^2\right)} - \ln\frac{\sigma_p^2+\sigma_l^2}{\sigma_l^2} + \frac{\sigma_p^2}{\sigma_l^2}\right) \tag{9}$$

By substituting Eqs. (6) and (7) into Eq. (4), BS can be expressed as follows:

$$BS = \frac{1}{2}\left(\frac{\sigma_p^2\left(o-\mu_p\right)^2}{\left(\sigma_p^2+\sigma_l^2\right)^2} + \ln\frac{\sigma_p^2+\sigma_l^2}{\sigma_l^2} - \frac{\sigma_p^2}{\sigma_p^2+\sigma_l^2}\right) \tag{10}$$

Figure 1 shows how the KLD and BS vary as functions of the variance of the prior distribution (σ_p^2) and the variance of the likelihood (σ_l^2). Across all conditions, KLD increases monotonically with increasing σ_p^2. In contrast, increasing σ_l^2 consistently reduces KLD. BS exhibits a similar dependence on σ_l^2, decreasing as the likelihood variance increases. With respect to the variance of the prior distribution, BS varies more gradually than KLD and shows a weaker sensitivity to σ_p^2 within the range visualized in Figure 1. Taken together, Figure 1 indicates that the maximization of both KLD and BS is facilitated by increasing the uncertainty of prior beliefs and improving the precision of observations.

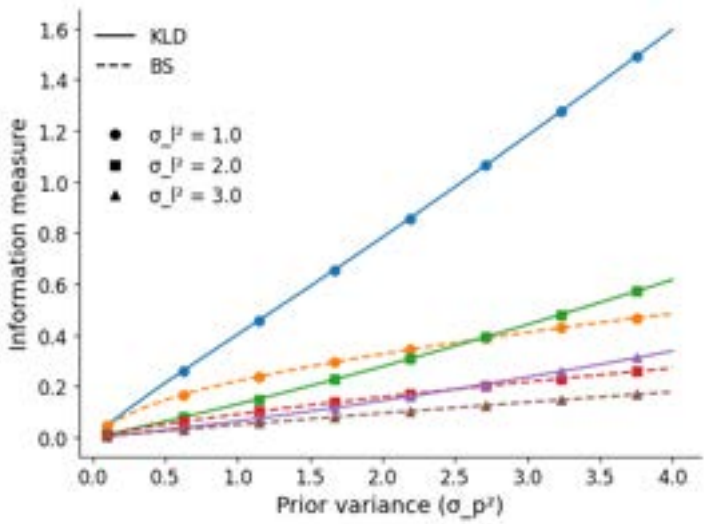


Figure 1. Effects of prior variance (σ_p^2) and likelihood variance (σ_l^2) on Kullback–Leibler divergence (KLD; solid lines) and Bayesian surprise (BS; dashed lines). Marker shapes indicate different values of σ_l^2.

By substituting Eqs. (6), (7), and (8) into Eq. (5), expected free energy can be expressed as follows:

$$G = \frac{1}{2}\left(\frac{\left(\mu_\pi - \mu_p\right)^2}{\sigma_p^2} + \ln\frac{2\pi\sigma_p^2\sigma_l^2}{\sigma_\pi^2} + \frac{\sigma_\pi^2}{\sigma_p^2}\right) \tag{11}$$

Figure 2 illustrates the relationship between expected free energy (G) and the variance of the action-conditioned belief (σ_π^2), with the prior variance held constant. The curve exhibits a clear U-shaped profile, with a minimum occurring when σ_π^2 is equal to σ_p^2. When σ_π^2 is smaller than σ_p^2, expected free energy increases. Conversely, when σ_π^2 exceeds σ_p^2, expected free energy also increases. These results indicate that expected free energy is minimized when the uncertainty of beliefs about outcomes predicted under a given action is comparable to the uncertainty of prior beliefs.

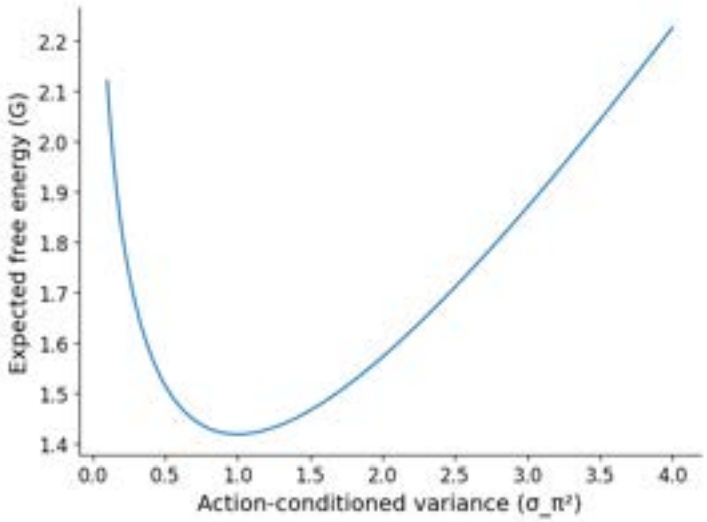


Figure 2. Expected free energy (G) as a function of action-conditioned variance (σ_π^2), showing a minimum when σ_π^2 is comparable to σ_p^2.

4 DISCUSSION

The variance of the prior distribution (σ_p^2) reflects the openness or ambiguity of intrinsic goals. The variance of the likelihood (σ_l^2) corresponds to the clarity or reliability of instrumental value embodied in artifacts. The variance of the action-conditioned belief (σ_π^2) represents the uncertainty of outcomes predicted to result from a given action. In design practice, this corresponds to how widely the consequences of an intervention—such as a prototype or scenario—are expected to vary, rather than the action itself. Framing innovation of meaning as the coordinated manipulation of these three variances allows designers to systematically balance inquiry and realization.

The process of innovation of meaning consists of three stages: identifying new meaningful value from existing instrumental value, updating existing intrinsic value through newly generated meaningful value, and optimizing existing instrumental value according to newly updated intrinsic value. For example, in the case of a candle, a designer identified a new meaning of self-care from the traditional candle, updated the goal from lighting to relaxation based on this meaning, and optimized the candle into an aromatherapy candle to serve the new goal. In the Method section, the process from instrumental value to meaningful value was associated with KLD, the process from meaningful value to intrinsic value with BS, and the process from intrinsic value to instrumental value with expected free energy. Accordingly, the process of innovation of meaning is interpreted as the maximization of KLD, the maximization of BS, and the minimization of expected free energy.

The maximization of KLD and BS corresponds to the epistemic emotions that drive the inquiry cycle proposed by Yanagisawa and Honda (2025). The minimization of expected free energy represents a balance between exploratory and exploitative behavior. Exploratory behavior corresponds to actions that maximize predicted epistemic emotions, whereas exploitative behavior corresponds to the generation of instrumental value that fulfills a given goal. In this sense, the minimization of expected free energy entails both the activation of the inquiry cycle and the achievement of goals.

As shown in Figure 1, the combined magnitude of KLD and BS increases as the variance of the prior distribution (σ_p^2) increases and decreases as the variance of the likelihood (σ_l^2) increases. This visual trend is consistent across the parameter ranges examined and indicates that the joint processes of meaning assignment and value updating are amplified when prior beliefs are less constrained while observational precision is high. From this perspective, Figure 1 suggests that innovation of meaning is facilitated by loosening commitment to existing goals and simultaneously attending to reliable observational cues, allowing newly generated meanings to exert a stronger influence on the updating of intrinsic value.

Figure 2 indicates that expected free energy is minimized when the variance of predicted outcomes conditioned on action (σ_π^2) is comparable to the variance of prior beliefs (σ_p^2). This condition reflects a balance between exploratory and exploitative actions in design. When σ_π^2 is much smaller than σ_p^2, designers favor highly predictable outcomes, resulting in conservative actions that limit exploration. In contrast, when σ_π^2 is much larger than σ_p^2, actions prioritize exploration at the expense of reliably realizing intrinsic value. The condition $\sigma_\pi^2 \approx \sigma_p^2$ therefore represents an optimal balance, in which designers explore new possibilities while still effectively exploiting existing beliefs to generate instrumental value in innovation of meaning.

In summary, the maximization of KLD and BS and the minimization of expected free energy are mapped onto the process of innovation of meaning. The maximization of KLD and BS is driven by weakening prior beliefs and increasing observational precision. The minimization of expected free energy is achieved by generating instrumental value through actions that are predicted to produce outcome variances comparable to those of prior beliefs. These design-relevant guidelines are expected to inform an innovation of meaning process that optimally balances exploration and goal achievement.

The present analysis relies on a Gaussian (Laplace) approximation of distributions, which is valid only in the vicinity of the mode. Consequently, the derived design guidelines characterize value-generation dynamics primarily around expected meanings and do not fully capture tail phenomena such as radical reinterpretations. As discussed by Yanagisawa and Honda (2025), such tail behaviors require the introduction of non-Gaussian components, such as uniform distributions. Therefore, the results of this study should be interpreted as local, expectation-centered guidelines rather than global guarantees for all innovation of meaning processes.

5 CONCLUSION

In this study, the three value-generation processes described by the Triadic Value Model (TVM) were formalized based on the free energy principle and active inference, and were reconstructed as a practical methodology. Specifically, the process of assigning meaning to instrumental value was associated with Kullback–Leibler divergence, the process of updating intrinsic value through the legitimization of meaningful value with Bayesian surprise, and the process of generating instrumental value through the embodiment of intrinsic value with expected free energy.

Through an analysis based on Gaussian approximation, this study clarified how each information measure varies with the variances of the prior distribution, the likelihood, and the action-conditioned recognition distribution. The results demonstrate that innovation of meaning can be understood as the maximization of KLD and BS and the minimization of expected free energy. The maximization of KLD and BS drives the inquiry cycle by weakening prior beliefs while increasing observational precision. In contrast, the minimization of expected free energy provides action guidelines that appropriately balance exploratory and exploitative behaviors, thereby enabling the simultaneous achievement of goals and updating of values.

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