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Framing: a computable principle of design for systems

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ABSTRACT: Why do all design acts begin by explicating a bounded frame of work? In design ontology, framing is the selection and representation of components and features in a system to guide perception and decision of designers but remains implicit. As a structural abstraction it becomes an explicit principle, formalised by a computational methodology that parameterises bounds and projects elements of a design having weighted attributes, in a relational context. Thus, the cognitive act becomes epistemic to compute for generating and evaluating frames, aligning design reasoning with scientific discourse.

KEYWORDS: computational design methods, design analysis, design synthesis, artificial intelligence (AI), design principles

1. Introduction

Design specifies the intent of constituting any artefact or artificial systems. Simon's (1996) The Sciences of the Artificial defines *design as the transformation of existing situations into preferred ones through bounded reasoning*. Every design act constructs a system that separates an interior of relevance from an exterior of irrelevance. This boundary condition defines not only the limits of an object and its attributes, but also the cognitive scope of *representing the formulation of any wicked problem*. Simon's (1996) concept of *bounded rationality* captures this logic, wherein designers operate under limited *information*, *attention* and *computational capacity*, and therefore *frame* problems, *satisficing* to render them solvable and tractable. *Reasoning*, is contingent upon the scope within which alternatives are *projected* rather than being *unconstrained* or *exhaustive*. Schön (1983) further characterized designing as a reflective conversation with the situation, such that before technical problem-solving can begin, practitioners must first *name* elements of attention and then *frame* the context in which they are attended to. Dorst and Cross (2001) identified that design proceeds through co-evolution of problem and solution spaces, wherein the *'frame'* acts as the stabilizing bridge between them. An expansion of this rational paradigm is the notion of *'frame creation'* (Dorst, 2011), the cognitive process through which designers actively construct the problem space rather than merely search within a predefined one. Dorst (2011) argued that *design reasoning operates by reframing situations*, that is re-defining context, values and *relationships* to generate meaning and innovation under ill-structured conditions. Within this body of work, framing can be understood as an epistemic constraint that renders designing possible by transforming the unbounded complexity of the world into a tractable system through conditional reasoning, thereby turning open possibility progressively into specific form and function. *In this sense, framing is not a prelude to design but an enabling act*. As a cognitive operation, framing operates a priori: any act of design presupposes the *delimitation* of a system, the *projection* that represents a selected viewpoint, the *prioritisation of attributes* of its components, and *contextual relationships* among the constructs. Despite its centrality, framing remains largely *unarticulated* and *implicit* within formal design theory and practice, often treated descriptively rather than prescriptively. This reveals a dual gap: *ontological*, namely the absence of a formal definition of what constitutes a frame and its structural components and their properties; and *epistemological*, namely the absence of systematic, reproducible methods to identify, evaluate, or compare framing decisions beyond subjective judgement, intuition or retrospective interpretation.

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Consequently, widely practiced design principles (Lidwell et al., 2010) maybe interpreted as *lower-order operations* insofar as their applicability, meaning and relevance are *entirely contingent* upon prior framing. Hence, we inceptively address this lacuna by proposing it as a *formal*, *computable abstraction*, a *higher-order design construct*, contributing towards articulating the *structural conditions* required for operably *modelling design-reasoning* in *practice*. Framing makes tacit design mechanisms *evaluable*, enabling systematic synthesis, comparative analysis and empirical validation across contexts.

1.1. Purpose and aim

Design problems are not a priori givens, rather they are constructed through cognitive and structural decision that delimits a field of concern (Cross, 2011). The act of *framing* governs the creative synthesis of possibilities, and the analytical, comparable evaluation of outcomes, regardless of discipline. Lacking a *formal structural abstraction*, this operation remains subjective, relying on intuition, experience, or convention, which inhibits reproducibility and rigorous analysis. The purpose is to transition Framing from an *implicit* to an *explicit* act, i.e. a verifiable, *objective construct*. The aim is to develop a robust formalisation of this fundamental act in design cognition. The computational formulation proposed in this research, however, is an *a posteriori formalisation of this precondition*. It doesn't create framing but *models it for operation* with its *mathematical representations* that can be generalised across disciplines in the formal, natural, applied, and social sciences, as well as humanities. We posit it as a precondition that governs how general design principles abstracted from nature (e.g. balance, order, contrast, variety, repetition, pattern, hierarchy, et al.) manifest in artificial systems which are intended for a purpose.

1.2. Objective and scope

Framing is defined as an *ordered tuple* $F = \langle B, \pi, w \rangle$, where each component denotes an operator acting on a shared universe of discourse. ***Bounds*** B specify which elements are included or excluded from consideration; ***Projection*** π determines how selected elements are represented; ***Weights*** w assign relative salience to attributes describing those elements. Collectively, these operators define structural conditions under which a system is *delimited*, *represented*, and *prioritised*. These parameters bound a set of possible elements in a composition situated within a contextual space, and project a selected subset into representation space based on weights of their attributes. Relationships r are contextual linkages arising from interactions of elements within this space, defining conditions of *intelligibility* for a system rather than its *material instantiation*. This computable formulation captures a universal mechanism by which designers construct meaning, coherence, and tractability in systems composed of interconnected components. An *objective scoring function* $J(F) = (I(F;Y), E(F), S(F))$ evaluates framings through a vector of criteria, where I denotes *informativeness* with respect to an *observer* or *task* Y; E denotes *clarity* as structural order (or *negentropy*), and S denotes *cost* or *instability*. Task-dependent coefficients α, β, γ may be used for trade-offs when scalarisation is required, but evaluation induces a *Pareto front* rather than a single scalar optimum, allowing competing framings to be compared *reproducibly* and *relatively falsified*. It enables two complementary capabilities as well: (1) *Synthetical Creation* allows parameterisation by explicit logic and reasoning for generating framings; (2) *Analytical Evaluation* enables systematic comparison and refinement of framings using objective metrics. In treating framing not as a stylistic device but as a cognitive act of system definition, this research establishes a foundation for computing and modelling design reasoning itself. While presented here in static form for conceptual clarity, the operators may be extended to time-dependent (t) formulations when abstracting dynamic or evolving systems. Thus, it opens pathway toward *objectifying subjective interpretations* in goal-oriented design processes, where structuring of intent, meaning, perception, and decision-making now become *measurable*, *simulative* and *transferable* possibly between *human cognition* and *artificial intelligence*.

1.3. Methodology

This study employs a rigorous and reproducible methodology to standardise *framing* through semantic coherence, systematic literature mapping, computational decomposition and mathematical modelling, following design science research (DSR) methods (Cross, 2001; Hevner, 2004; Blessing & Chakrabarti, 2009) integrated with techniques like machine learning, exploratory data analysis, et al. We therefore aim to derive *falsifiable* mathematical objects apparent in design theory and practice, and *functionalise* them through a *generalizable* computational methodology for abstraction, which is *reproducible* as well.

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1.3.1. Corpus synthesis and abstraction

A corpus (*103977 sentences)* was compiled from open-source internet repositories (*Wikipedia, DBpedia, Wiktionary*) and domain-specific categories covering various disciplines in formal sciences, applied sciences, natural sciences, social sciences, humanities, etc. for *master string* of *'Framing' AND 'Design'*. Text preprocessing used spaCy for *tokenization*, *lemmatization* and *NER-based pruning*. Sentences were embedded via *SentenceTransformers* (*all-MiniLM-L6-v2*) into a *384-dimensional* (384D) semantic space. Dimensionality reduction through *UMAP* and clustering via *K-Means* identified semantic clusters (n=25, silhouette-optimized = 0.0196). Topic Modelling using *BERTopic (zero-shot model)* revealed deeper latent structures (n=5). The *semantic filtering* pipeline removed junk data, excluded scattered and irrelevant terms, using deterministic token cleaning, natural language processing (NLP), large language models (LLM) (*gpt-oss-120b*). Semantic coherence of the *embeddings* and statistical profiling filtered out *1041 top-validated terms* (only *828 were retained,* based on dominance, coherence *>99.95)*.

1.3.2. Semantic scoring and visualization

A composite scoring model weighted term relevance by *Term Frequency-Inverse Document Frequency (TF-IDF)* (50%), cross-cluster prevalence (30%), and latent topic contribution (20%), ensuring no creep bias or concept anchoring. Resulting highest-ranked monogram terms (n=300) were visualised using *WordCloud*. Semantic networks can represent high-dimensional relational structures between top terms, using cosine similarity over averaged sentence embeddings to map inter-term proximities as a weighted graph. To reveal deep semantic coherence between terms, *Truncated Singular Value Decomposition (TSVD)* was applied for *Latent Semantic Analysis (LSA)*. It identified principal semantic components (n=52) explaining over *4.6% of cumulative variance*. Each component revealed dominant academic n-grams such as boundaries, constraints, attention, relationships, salience, context, et al. and their cross-dimensional relevance was partially verified through *correlation matrices of latent embeddings*. Inter-cluster semantics were discovered via *centroid similarity (cosine > 0.65)*, revealing conceptual overlaps.

1.3.3. Algorithm for literature mapping

Top-ranked semantic terms (Figure 1) were transformed into structured search queries for *Scopus* and *Web of Science*. Retrieved literature was manually mapped onto the semantic clusters to trace theoretical precedents for the operators that are essential for theory formation of Framing across engineering design, systems science, architecture, computing, et al. grounding each operator with domain agnostic evidence.



Figure 1. Word Cloud created by semantic mapping through natural language processing; the gradient key shows the relevance of monograms, while font size represents *TF-IDF* scores in corpus

1.3.4. Modelling and verification

The implemented computational framework enables semantic modelling of any concept by extracting its features and latent patterns over public literature with machine learning techniques. Afterwards they must be empirically validated via deduction or induction via experimentation. Based on the scope of this conceptual paper, we have provided cross-domain case studies, demonstrating how constructs of an abstraction can be parameterised, computed, and evaluated across practical and theoretical contexts. This approach is grounded in (1) epistemic consistency derived from cross-domain literature,

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(2) computational transparency via semantic clustering pipelines, and (3) empirical verifiability through quantitative metrics and repeatable procedures. Limitations include corpus selection bias, semantic drift in embeddings, and the non-deterministic nature of key pipeline components (e.g. UMAP, K-Means, LLM, et al.), which may cause minor variations across runs. Despite these constraints, it provides a systematic, data-driven approach to externalise design cognition, formalising Framing for computation.

2. Literature review

2.1. Design ontology and systems science

A major contribution in design theory is the *Function-Behaviour-Structure (FBS) ontology* (Gero & Kannengiesser, 2004). FBS formalizes design as transformations between abstract functions (what the design is for), behaviours (how it works), and structures (what it consists of). These transformations depend critically on framing of representations, as the designer must decide which functions to include, which behaviours to simulate, which structures to consider, and relations to prioritise. Thus, it implicitly models the framing process by defining the subset of conceptual and physical elements that constitute the system of design reasoning. Similarly, studies (Cross, 2001; Goel & Pirolli, 1992) show that experts alternate between *divergent* and *convergent* framing i.e. redefining problem spaces to generate solutions. In *Design-by-Analogy* (Linsey et al., 2012), framing controls distant or close analogical mappings drawn that influence creativity and novelty, and mediate cognitive transitions between concept abstraction and concrete representation in design reasoning and knowledge. *General Systems Theory* (Von Bertalanffy, 1968) formalized the idea that any system is constituted by the relations among its elements and the boundary that distinguishes it from its environment. *Without a boundary, there is no system identity, and hence no analysis, control, feedback, or adaptation* (Ashby, 1957). Mirroring this principle, framing defines what is internal, what is external, and how the two interact through interfacial relationships. This recurs in control theory, cybernetics and ecology, regulating flows of matter, energy, and information.

2.2. Theoretical foundation of 'framing' synthesis

2.2.1. Bounds: systemic limits

The concept of bounds B generalises the notion of system boundary from systems theory to cognitive and perceptual domains. In engineering design, boundary definition corresponds to *problem structuring* (Pahl & Beitz, 1996) and *domain decomposition* in modelling. Boundaries in technical systems serve as the operational constraints defining the extent of the problem space and permissible transformations (Hubka & Eder, 1988). In differential equations, boundary conditions establish system interaction with external environments. In thermodynamics, they *delineate open, closed or isolated systems*, specifying permissible energy exchanges. In decision sciences, boundary setting parallels problem structuring as a means of *constraining attention to relevant features*. Formally, let the universe of discourse be a finite set $\mathcal{U} = \{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n\}$, representing spatial, temporal, conceptual, or parametric possibilities. Each element $\varepsilon_i$is described by an attribute vector $\mathbf{a}_i \in \mathbb{R}^k$. The operator is defined as a subset $B \subseteq \mathcal{U}$, which selects the elements admissible for consideration. The bounded element set is therefore $\mathcal{E}_B = \{\varepsilon_i \in \mathcal{U} \mid \varepsilon_i \in B\}$. This operation performs a domain restriction $\mathcal{U} \to \mathcal{E}_B$. Defining the tractable design space within which reasoning and synthesis occur (Goel & Pirolli, 1992). This *domain restriction* does not eliminate contextual influence but determines what is explicitly considered within the frame, thereby transforming unbounded complexity into manageable, computable structures. Thus, no representation, comparison, or evaluation is possible prior to *delimiting* what exists in a designer's mental model.

2.2.2. Projections: structural mapping

Projection π denotes the organisation and mapping of bounded elements into a representation space. Formally, projection is defined as a mapping $\pi : \mathcal{E}_B \to \mathcal{R}$, where $\mathcal{R}$ is a representation space that may be *visual*, *geometric*, *symbolic*, *numerical*, *topological*, or *semantic*. The projected configuration is given by $\mathcal{E}_\pi = \pi(\mathcal{E}_B)$. Projection determines how elements are seen, related, or computed. It establishes the representational logic through which bounded elements become intelligible, operable. It may preserve, distort, or abstract invariants depending on representational intent. In art, it corresponds to composition perspective, historically codified in Renaissance geometry and later formalised through Gestalt grouping principles (Arnheim, 1954). In design cognition, it mirrors *representational transformations between problem and solution spaces* (Oxman, 1997). In engineering design, it corresponds to mappings between

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functional and physical domains, such as the design structure matrix (Eppinger & Browning, 2012). In computational geometry, projection operators transform 3D structures into 2D visualisations (orthographic, axonometric, etc.) formalising how perception emerges from abstraction within bounds.

2.2.3. Weights: relative salience

Weight operator w represents the relative importance assigned to each attribute of an element within the projected frame. Let $\mathbf{a}_i \in \mathbb{R}^k$ for each $\varepsilon_i \in \mathcal{E}_\pi$ then the operator is defined as $w : \mathbb{R}^k \to \mathbb{R}^k$, producing weighted attribute vectors $\tilde{\mathbf{a}}_i = w(\mathbf{a}_i)$. This operation encodes salience or emphasis across finitely many behavioural and structural attributes of projected elements, thereby inducing *hierarchy*, *dominance*, and *relevance* within a framed system. In perceptual psychology, visual weighting corresponds to saliency maps that guide attentional focus (Itti, Koch & Niebur, 1998). In engineering design, weighting schemes are fundamental to multi-criteria decision-making encoding trade-offs among competing objectives such as performance, cost, aesthetics, and manufacturability (Keeney & Raiffa, 1976). In machine learning, weights appear as *tensors* or *attention coefficients* that modulate the contribution of features or attributes (Vaswani et al., 2017). Lexical embeddings (Mikolov et al., 2013) similarly encode *relative importance* across *semantic dimensions*. Thus, w can be interpreted as an allocation of salience over attribute space, shaping perceptual emphasis and decision-making without altering the underlying set of elements.

2.2.4. Relationships: contextual linkages

Contextual relationships r arise from the interaction of projected elements $\mathcal{E}_\pi$ having weighted attributes $\tilde{\mathbf{a}}_i$ within a *shared contextual space*. These relationships encode interdependencies among elements and between elements and their environment. Formally, relationships are represented as a relation $r \subseteq \mathcal{E}_B \times \mathcal{E}_B$, which induces a weighted graph $C = (\mathcal{E}_B, r)$. Edge weights are domain-dependent quantities such as interaction strength, similarity, distance, cost, probability, information flow, *based on scientific principles and laws rather than abstract preferences*. The contextual space is within which all projected frames interrelatedly operate. Relationships are implicit or explicit properties of the contextual space shaped by the interaction of *internal and external factors in universe* $\mathcal{U}$. In semiotics, meaning emerges from relations rather than isolated units. *Artificial neural networks* define mechanisms for representing *interconnectivity* and *interdependency* among discrete components through weighted relational structures, binding all *neural units into coherent systems*. (Hinton et al., 2006). Network theory provides a mathematical representation for relationships using directed and weighted edges to connect nodes (Newman, 2010) such as in *knowledge graphs for relational databases*. Gero & Kannengiesser (2004) argue about underlying interrelationships among constructs of functions, behaviours, and structures.

2.3. Theoretical foundation of 'framing' analysis

2.3.1. Clarity: order or entropy

Clarity $E(F)$ measures the internal structural regularity of a framed configuration. It is defined through structural entropy computed over a distribution derived from the *projected* and *weighted structures*. Let $\{p_i\}$ denote a *probability distribution* over structural states induced by the frame, such as spatial partitions, topological categories, attribute groupings, or other representational bins derived from $\pi(\mathcal{E}_B)$. Structural entropy is defined as: $H_s(F) = -\sum_i p_i \log_2 p_i$. Hence, $E(F) = 1 - \frac{H_s(F)}{H_{s,\max}}$ such that higher clarity corresponds to lower structural entropy and greater regularity, uniformity, and internal coherence. This notion of clarity concerns internal dispersion only. It does not measure *usefulness or task relevance*. A configuration may be highly ordered yet trivial. Conversely, excessive dispersion increases ambiguity and reduces intelligibility. In engineering design, reduced structural ambiguity increases the probability of satisfying functional requirements, consistent with *Axiom of Information*, which defines information content in terms of probability of success (Suh, 2001). In visual perception, structural order relates to readability and legibility describing ease of *communicating* meaning (Arnheim, 1954). In computational aesthetics, *entropy quantifies cohesion and symmetry measures for differentiation* (Rigau et al., 2008).

2.3.2. Cost: signal or noise

Cost $S(F)$ represents degradation of coherence through imbalance, inefficiency, or noise. In multi-objective optimisation, *cost functions* capture penalties associated with resource constraints, instability or

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excessive complexity (Deb, 2011). Analogously, in design, loss corresponds to imbalance of attention or instability of form, such that loss quantifies the extent to which perceived signals are obscured by noise in any context. Thus, minimising *cost functions* improve *interpretability*, *efficiency* and *usability* by reducing irrelevant variation, drawing parallel to reducing cognitive load as in ergonomics. In signal processing, instability and inefficiency are commonly expressed through signal-to-noise SNR relations, (Oppenheim & Schafer, 1999). In this abstraction, noise represents variability that does not contribute to task-relevant discrimination, while signal represents variation aligned with functional or perceptual intent of the structure. Cost therefore measures *instability* or *inefficiency* of representation relative to meaningful structure, such that: $S(F) = \frac{P_{\text{noise}}}{P_{\text{signal}}}$ or equivalently, $\text{SNR}(F) = 10\log_{10}\left(\frac{P_{\text{signal}}}{P_{\text{noise}}}\right)$.

2.3.3. Informativeness: utility or impracticality

Informativeness I(F; Y) measures how effectively a framed configuration reduces uncertainty with respect to an *observer*, *task*, or *environmental response* Y communicated for its utilitarian coherence. Information Theory (Shannon, 1948), grounds quantifying reduction of uncertainty while maintaining relevance, and is formally defined as *mutual information*: $I(F;Y) = \sum_{i,j} p(F_i, Y_j)\ \log\frac{p(F_i,Y_j)}{p(F_i)\,p(Y_j)}$, which measures the reduction in uncertainty about Y provided by observing the framed configuration F. It also captures *structural–functional* coherence mediated by *behaviours*, rather than internal order. In design evaluation, informativeness relates to utility functions in *decision and game theory* (Von Neumann & Morgenstern, 1944), where higher utility corresponds to clearer, more purposeful organization of elements. From a systems perspective, it parallels Ashby's Law of Requisite Variety (1957) that is a system must encode *sufficient information* to respond to *environmental complexity without redundancy*. That, we can extract informativeness from systemic distributions of elements' complexity consistently. However, informativeness I(F; Y) is distinct from clarity $E(F)$. Clarity measures internal structural regularity through structural entropy H(F), whereas informativeness measures conditional predictability of task outcomes given the frame. That is, a configuration may be internally ordered yet uninformative, or structurally complex yet highly task-relevant. *Higher informativeness* I(F; Y) therefore indicates *stronger functional coupling*, not merely *higher structural order or clarity* $E(F)$ *of projected elements*.

2.3.4. Factors: subjectivity or objectivity

The factors α, β, γ regulate the *relative influence of each evaluative dimension as coefficients* of informativeness, clarity, and cost within objective function J(F). In statistical modelling, it corresponds to weighting parameters analogous to regression coefficients in linear models or factor loadings in factor analysis (Harman, 1976) and empirically estimated through human or system feedback, experimental measurement, or comparative sensitivity analysis of model outputs. In fuzzy decision systems (Zadeh, 1975; Dubois & Prade, 1980), such coefficients encode *degrees of preference or confidence*, *enabling objective measurement of subjective judgement*. Design-specific implementations include preference aggregation and multi-attribute utility theory (Keeney & Raiffa, 1976). A human-in-the-loop calibration mechanism (Amershi et al., 2014) can iteratively adjust α, β, γ through user feedback or task-specific evaluation, ensuring that simulated assessments align with contextual performance criteria. Thus, α, β, γ function as trade-off coefficients that calibrate evaluative priorities from an observer's point-of-view, into *quantifiable assessments for explicit, reproducible comparison of computed alternative framings*.

3. Computational modelling

Framing is abstracted as a structured state defined by the finite ordered tuple $F = \langle B, \pi, w \rangle$, where each operator captures a distinct dimension of system definition within a contextual space Cover a universe of discourse. This formulation defines a space of possible framings rather than a single instantiated model, and provides an explicit and computable criterion for assessing whether a framing is structurally adequate for a given purpose, rather than relying solely on tacit judgement. Framing is treated as a universal prerequisite for design cognition: any act of *synthesis*, *analysis*, *perception*, or *decision* requires the delimitation of a system through B, the selection of a representation through π, and the prioritisation of attributes through w, all operating under contextual relationships structured within C. The formulation supports both *generative uses*, F enabling the *synthesis* of artefact configurations within a *defined design space*, and *evaluative uses*, $J(F)$ enabling *analytical* comparison through an *objective vector function* for scoring, rather than treating framing as a metaphorical or purely interpretive construct. It therefore

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constitutes a domain-agnostic computational abstraction analogous to an operator identification or state-space description, while leaving domain-specific instantiation, parameterisation, and empirical calibration to future work. While all design activity necessarily involves framing, not all framing decisions are fully reducible to formal computation such as semantic, affective, cultural, ethical dimensions may only be approximated through measurable proxies or partially encoded selections within B, π, and w. The model is therefore *universal as a structural abstraction of the cognitive act of framing, not as a complete encoding of meaning, value, or intention,* but as a computable representation that renders design reasoning observable, analysable, and systematically comparable across domains.

3.1. Synthesising frames using parameterisation

Framing in this paper is treated as a *parametric state* defined by *ordered tuple* $\mathrm{F} = \langle \mathrm{B}, \pi, \mathrm{w} \rangle$, operating over a shared universe of discourse $\mathcal{U}$ within a contextual space C. Bounds $B \subseteq \mathcal{U}$ determine admissible element membership; projection $\pi : \mathcal{E}_B \to \mathcal{R}$ maps bounded elements into structural, spatial, symbolic, or conceptual configurations; and weights $w : \mathbb{R}^k \to \mathbb{R}^k$ allocate salience across attribute dimensions. Relationships r arise from interactions among bounded, projected, and weighted elements and are formalised as properties of the contextual space $C = (\mathcal{E}_B, r)$, rather than as independent parameters of the framing tuple. Under this formulation, Framing operates as a *generative constraint data structure governing system constitution algorithm.* Operators interact in a complementary manner: *B constrains admissible existence*, *π specifies mediation of representation*, and *w modulates attribute salience*, while contextual relations structure their interdependencies. Framing is therefore not a *stylistic overlay*, but a formal mechanism that conditions admissibility, representation, and priority within design reasoning. Although presented statically for conceptual clarity, the operators admit *time-indexed extensions for modelling evolving systems*. Such extensions form the kernel that controls iteration, feedback, and refinement intrinsic to engineering design processes carried out by designers, abstracted as intelligent agents, for creating designs in *any tangible or virtual environment without altering the core abstraction.*

3.2. Analysing frames using multicriteria optimisation

Framing quality is evaluated through the vector-valued objective function $\mathrm{J(F)} = (\mathrm{I(F; Y)}, \mathrm{E(F)}, \mathrm{S(F)})$, where informativeness measures task-relevant coherence, clarity measures structural order, and cost measures instability or inefficiency. Rather than collapsing evaluation into a single scalar, assessment proceeds via Pareto dominance $\mathrm{J(F)} \in \mathrm{ParetoFront(I, E, S)}$. This reflects real design practice, where improvements in one dimension may incur trade-offs in another. Scalarisation $\mathrm{J}_\alpha\mathrm{(F)} = \alpha\mathrm{I} + \beta\mathrm{E} - \gamma\mathrm{S}$ is optional and task-dependent, used only when operational requirements demand ranking. This formulation supports: *generative tuning during synthesis*, *analytical comparison of alternative framings*, and *human-in-the-loop calibration of evaluative priorities*. A framing is considered adequate not by absolute optimality, but by robust performance across relevant objectives under variation of observer, scale, or representation. It enables comparison of frames with different trade-offs, mirroring real design practice where *structural feasibility* may trade-off against *functional density*. For instance, a high-informativeness frame with moderate-clarity and low-cost may be optimal for engineering precision. Thus, a *fuzzified threshold* satisfies solution-space, constituting as *'good'* or *'bad' enough* framing.

3.3. Procedural realization

Computing a framing can be expressed as a parametric procedural sequence composed of four operators, each with explicit computational responsibility. This sequence defines an execution logic rather than a fixed algorithm, and is implementable across domains and simulation environments. *Boundary Definition (B)* establishes the system's domain by restricting the universe of discourse to a finite, tractable and computable subset. Implementations include geometric bounding regions, domain masks, constraint filters, index selection, memory scopes, or conceptual inclusion rules. This step reduces unbounded possibility to tractable structure. *Projection Mapping* (π) transforms bounded elements into a representation space. Implementations include spatial coordinate transforms, graph-based topology construction, symbolic encodings, dimensionality reduction, or representational remapping. Projection converts raw elements into structured configurations with explicit adjacency, order, or hierarchy. *Salience Assignment* (w) allocates emphasis across attribute dimensions via weighting functions or tensor fields. Weights may derive from functional importance, constraint severity, probabilistic relevance, saliency models, or learned attention coefficients. This operator governs internal priority structure within

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the frame. *Contextual Structuring* ($r \in C$) where relationships emerge as weighted interactions among framed elements, forming a contextual network. These relations encode dependency, similarity, flow, or influence and are represented using graphs, matrices, or tensors, enabling multimodal *relational modelling*. Together, these operators yield a complete computed frame, and because they are modality-agnostic, the same procedure applies to examples like: physical artefacts, digitised assemblies, visual compositions, abstract models, neural representations, engineering simulations, urban plans

3.3.1. Algorithmic implementation

The model admits an iterative workflow (Figure 2) suitable for computation ensuring that it is not merely conceptual but procedurally executable within simulation, optimisation, or generative environments:

1. *Intent specification:* define elements, universal constraints, and contextual requirements.
2. *Parametric synthesis:* generate candidate framings using $F = \langle B, \pi, w \rangle$.
3. *System realisation:* render or simulate the framed configurations (spatial or temporal).
4. *Analytical evaluation:* compute objective score using the vector function J(F).
5. *Search optimal solution:* explore framing space using suitable algorithmic strategies.
6. *Selection:* identify Pareto-optimal framings based on task priorities, adjusting α-β-γ.
7. *Iterative refinement:* adjust operators and mappings based on feedback (Pahl & Beitz, 1996).

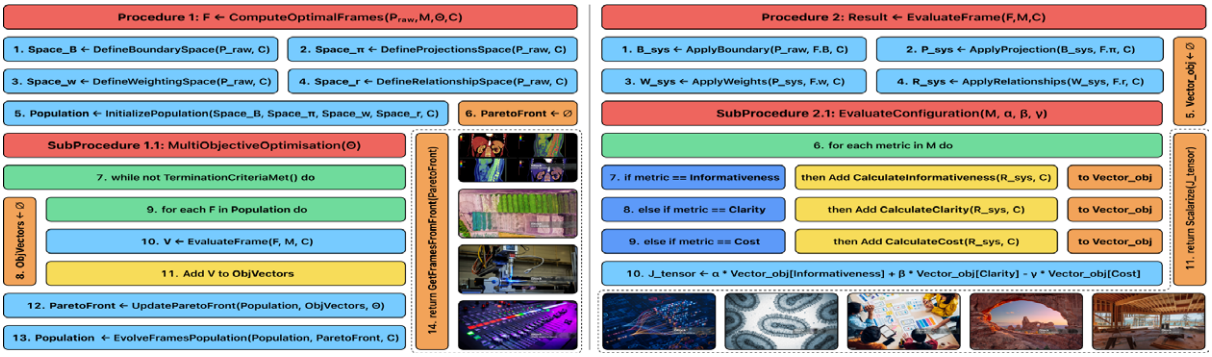


Figure 2. Block diagram with pseudocode for synthesis (P1) and analysis (P2); image credit: *iStock*; examples of *framing* illustrated; sequences, selections and iterations are organised in hierarchy

3.3.2. Universal 'higher-order' nature of framing

Framing *precedes* and *conditions* compositional principles, *unifying* them as *expected behaviours* within a structural abstraction. Balance emerges from weighting distribution in projection plane; hierarchy from differential weighting; unity from relational connectivity; contrast from representational differentiation; proportion from bounding ratios; pattern from repeated weighting; emphasis from concentrated salience (Lidwell et al., 2010). These *implicit design rules for elements* arise from *a priori framing conditions* in compositional formations, manifesting as *emergent properties* in a system i.e. whole is greater than sum of its parts, as observed in swarm intelligence. *Without explicit framing, they lack contextual meaning*.

3.4. Examples, applications and implications

Framing generalises across disciplines insofar as heterogeneous domains can be formally described through same operators. Although medium and scales differ widely, an underlying structural mechanism remains invariant: a system is rendered intelligible by bounding what is considered, projecting it into a representation, weighting it by attribute salience, and situating it within contextual relations. Revealing framing as domain-agnostic and not a stylistic intuition, but a general cognitive and computational operation underlying scientific modelling, engineering analysis, image processing, computational aesthetics, artificial intelligence, and more related fields. It provides a principled basis for interpretable generative design (Singh & Gu, 2011), systematic evaluation of machine outputs like *explainable artificial intelligence,* and even reflective design pedagogy in which tacit reasoning becomes observable, measurable, and teachable. Hence, any intuition of composing any artificial system is expressed via explicit, tuneable parameters, enabling inspection and manipulation of design reasoning via compute. To demonstrate this generality, focused examples are presented, each illustrating framing as a *pervasive cognitive act* governing *system definition prior to optimisation, inference, or decision*.

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3.4.1. Example 1. Computer vision and perceptual systems

In computer vision, Framing is explicit and computationally enforced. *Bounds B* are instantiated as a *region of interest*, commonly a *bounding box* or *segmentation mask*, that restricts analysis to a subset of the visual field. This restriction is essential and without it, the combinatorial complexity of pixel-level interpretation renders perception intractable. *Projection* π is implemented through the imaging and feature-extraction pipeline, including *camera models*, *convolutional filters*, and *embedding spaces*. These projections transform raw pixel intensities into structured representations such as feature maps or latent vectors, determining which invariants (edges, textures, shapes) become perceptually available. *Weights w* operate over attributes of these representations, typically via confidence scores, attention maps, or class probabilities. They assign salience to features or regions, governing detection priority and decision thresholds. Contextual relationships arise from spatial adjacency, overlap or co-occurrence, forming implicit relational graphs over detected entities. Even so, misaligned framings lead to *overfitting* or *underfitting*, causing systemic failures of trained models. Hence, system performance, interpretability and robustness depend less on the classifier alone than on how a visual scene is framed prior to inference.

3.4.2. Example 2. Engineering design and structural analysis

In engineering analysis, Framing governs both modelling fidelity and computational feasibility. Bounds *B selects subsystem or assembly under consideration*, excluding irrelevant components while preserving necessary interfaces, defining the *scope of analysis* and directly influences solution validity. Projection π is realised through modelling abstractions such as *meshing*, *coordinate transformations, or reduced-order models*. These projections convert physical geometry into numerical representations suitable for simulation, determining resolution, approximation error, and solvable degrees of freedom. Weights *w* are applied to attributes such as *stress*, *strain*, *displacement*, or *safety margins*. They highlight critical regions or failure modes, often through scalar fields or thresholds, thus establishing systemic hierarchy, distinguishing structurally dominant effects from negligible ones. Relationships encode load paths, constraints, and conditions, forming a contextual network of dependencies. Engineering insight emerges not merely from numerical results, but from how the system has been framed prior to computation. Different framings of the same artefact can yield divergent conclusions about performance or safety.

4. Present limitations, future work and conclusion

Any computational model entails inherent limitations. *Boundary ambiguity arises* when determining where a system ends, particularly in biological or socio-technical systems with porous or fuzzy edges. *Projection may oversimplify* by omitting critical information, as when aggregated models obscure local extremes. *Weighting bias is unavoidable* when subjective priorities are encoded; miscalibration can distort perceived importance. Qualitative, affective, or socio-cultural nuances are only partially representable through numerical parameters, limiting fidelity. *Frame-of-reference dependence implies that distinct observers may produce equally valid but incompatible frames*. Algorithmic overconfidence is an epistemic risk, as formalisation may convey unwarranted objectivity when assumptions are embedded in parameter choices. These limitations define clear directions for future work, like *empirical validation* is required through designer studies, behavioural experiments, and cross-domain applications. Further research will *refine semantic grounding*, calibrate constructs via *experimental procedures*, and possibly compare computational assessments with *expert judgement* (e.g. Delphi methods). Extensions may incorporate dynamic cognition, multimodal parameterisation, and adaptive algorithms that update *design state transitions* upon feedback from simulations, improving robustness and generalisability. By operationalising it as a computable construct that conditions system definition, *this research models a foundational design cognitive act as a testable and reproducible framework without claiming to capture meaning or intention in full*, but providing an explicit structural basis for investigating design reasoning.

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