# The Intent Resolution Engine (IRE): A Neurocognitive Model of Volitional Arbitration

Jason Brisart

Independent Researcher

jason@brisartresearcharchive.com

www.brisartresearcharchive.com

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## 1.0 Introduction

How do we choose between equally compelling options? Why do some intentions persist while others fade? And what underlying neurocognitive mechanisms govern our ability to commit to a goal in the face of distraction or internal conflict?

The Intent Resolution Engine (IRE) is introduced as a unifying theoretical framework that addresses these foundational questions of volitional behavior. It seeks to explain how competing internal goals are dynamically prioritized, filtered, and enacted within the human mind.

At its core, IRE conceptualizes intentions as multidimensional vectors composed of cognitive relevance, emotional intensity, contextual fit, expected reward, and urgency. These vectors compete for expression within a recursive arbitration loop and are continuously compared against a dynamic resolution threshold—a fluctuating internal filter shaped by factors such as fatigue, motivation, environmental complexity, and risk salience.

Volitional action, in this model, emerges when an intention vector surpasses this adaptive threshold, initiating behavioral commitment and motor execution. The arbitration process is shaped by neural circuitry spanning the dorsolateral prefrontal cortex, anterior cingulate cortex, basal ganglia, and associated inhibitory systems.

IRE is not a metaphor but a mechanistically precise, empirically grounded proposal designed for experimental validation. It offers a cohesive lens through which to examine decision conflict, procrastination, multitasking, intention switching, and the illusion of free will—bridging insights from neuroscience, computational modeling, and the psychology of volition.

### 2.0 Core Mechanism

The Intent Resolution Engine (IRE) proposes a vector-based arbitration system for internal goal selection, grounded in recursive neural processing. At the heart of this system is the concept of intention vectors—multidimensional representations of active goals—each parameterized by five interrelated factors:

- Cognitive Relevance (C) – the mental importance or salience of the goal
- Affective Charge (A) – the emotional intensity tied to the goal

- Contextual Fit (X) – how well the goal aligns with the current environment
- Reward Expectancy (R) – anticipated benefit or positive outcome
- Urgency (U) – time sensitivity or pressure associated with delay

Each intention is modeled as a composite vector:

$V = f(C, A, X, R, U)$

These vectors compete within a recursive arbitration loop, a closed-cycle evaluative process that continuously updates and re-evaluates goal representations. At every cycle, each vector's strength is assessed against a resolution threshold (T)—a dynamic limit influenced by system fatigue, stress, attention resources, and motivational calibration. If $V > T$, the intention is committed to and translated into action.

The arbitration loop unfolds over rapid temporal windows (e.g., 100–300 ms), during which dominant vectors are reinforced, subthreshold ones decay or are suppressed, and previously inactive vectors may reenter due to emotional salience or contextual change. This loop is mediated by the dorsolateral prefrontal cortex (vector maintenance), anterior cingulate cortex (conflict monitoring), and basal ganglia (action gating).

A critical feature of IRE is its adaptive threshold modulation, where the resolution threshold itself is plastic—lowered during cognitive fatigue or high urgency, and raised in high-conflict or overstimulated environments. This creates a dynamic decision landscape where both internal states and external conditions shape volitional arbitration.

Through this mechanism, IRE reframes decision-making as the emergent result of recursive vector competition, resolution threshold calibration, and inhibitory control—yielding a tractable and testable model for internal action selection.

## 3.0 Internal Processing Dynamics

The Intent Resolution Engine (IRE) operates through a cyclical, stage-based arbitration architecture that unfolds across five interlinked processing phases. These phases define the temporal and functional flow of volitional decision-making and allow the model to explain transitions from intention formation to behavioral execution:

### 3.1 Intention Initialization

Internal and external stimuli generate a pool of candidate intention vectors. These vectors emerge from motivational signals (e.g., hunger, ambition), memory retrieval (e.g., episodic cues), and environmental affordances (e.g., threats, tasks, opportunities). Each is instantiated with context-specific parameters along the five-dimensional vector space: cognitive relevance (C), affective charge (A), contextual fit (X), reward expectancy (R), and urgency (U).

### 3.2 Evaluation Loop

Once instantiated, vectors enter a rapid recursive evaluation loop, typically operating in subsecond intervals. Stronger vectors—those with high composite scores—are reinforced through top-down attention, while weaker vectors degrade unless bolstered by new input or emotional salience. The dorsolateral prefrontal cortex (DLPFC) sustains these representations, while the anterior cingulate cortex (ACC) detects conflict between vectors and modulates loop intensity.

### 3.3 Threshold Calibration

A core dynamical feature of IRE is the continuous adjustment of the resolution threshold (T). This threshold shifts based on internal state variables such as cognitive fatigue, attentional load, urgency, or stress. The subthalamic nucleus (STN) and orbitofrontal cortex (OFC) contribute to this calibration by increasing caution under risk or lowering thresholds under time pressure. This stage determines whether any vector is strong enough to warrant commitment.

### 3.4 Suppression and Rebound

Vectors that fail to exceed the threshold are either temporarily inhibited or passively decay. Inhibitory structures like the right inferior frontal gyrus (rIFG) suppress irrelevant or impulsive vectors. However, unresolved vectors—particularly those with strong affective or reward signatures—may rebound into the loop, leading to intrusive thoughts, procrastination, or obsessional cycling. These rebound effects explain persistent intentions that linger despite conscious dismissal.

### 3.5 Commitment and Execution

When a vector exceeds the threshold, the system locks the arbitration loop and routes control to execution systems. Premotor and supplementary motor areas initiate motor plans. Competing vectors are globally suppressed to prevent interference. Execution proceeds unless strong error signals or environmental disruptions trigger arbitration reset.

This dynamic flow enables the IRE framework to account for adaptive control under shifting contexts, recursive deliberation, inhibitory failures, intention resurfacing, and resolution bottlenecks. Each stage is time-sensitive and modifiable, making IRE an experimentally testable model of decision-making under cognitive pressure.

## 4.0 Applications and Predictions

The Intent Resolution Engine (IRE) provides a unified explanatory model for volitional behavior, enabling testable predictions across cognitive science, neuroscience, and behavioral psychology. The framework's internal arbitration dynamics support direct experimental validation in both clinical and normative settings.

### 4.1 Decision Conflict and Cognitive Bottlenecks

Interpretation: When two or more intention vectors possess similar strength, arbitration slows and neural conflict increases.

Prediction: In high-conflict trials (e.g., equal-choice tasks), IRE predicts longer decision times and increased anterior cingulate cortex (ACC) activation. EEG recordings should reveal elevated mid-frontal theta activity (4–7 Hz) just prior to resolution.

Illustrative Case: In a forced-choice paradigm between two similarly valued rewards, response latency will increase proportionally with subjective indecision, correlating with ACC amplitude spikes.

### 4.2 Procrastination and Vector Undercoding

Interpretation: Tasks with low affective charge or insufficient reward expectancy result in weak intention vectors that repeatedly fail to exceed threshold.

Prediction: Individuals with chronic procrastination will exhibit reduced activity in the ventral striatum (reward coding) and lower DLPFC engagement during intention formation. Task cues fail to produce sufficient activation to drive action.

Illustrative Case: EEG and fMRI during a study session show reduced frontal activation when participants report "not feeling like" starting a task, despite intention presence.

### 4.3 Habit Formation and Arbitration Bypass

Interpretation: Repetition of the same vector over time leads to basal ganglia-based reinforcement, allowing execution to proceed without full arbitration.

Prediction: In habitual action tasks, IRE predicts decreased DLPFC activity and increased dorsolateral striatal engagement over repeated trials.

Illustrative Case: In a sequence learning task, early trials engage arbitration circuitry, but over time, the arbitration loop is bypassed, showing a neural shift from cognitive to automatic control systems.

### 4.4 Intrusive Thoughts and Affective Vector Rebound

Interpretation: Vectors with unresolved emotional charge are likely to rebound into the arbitration loop even when suppression occurs.

Prediction: Individuals with anxiety or obsessive-compulsive traits will show persistent loop cycling, elevated rIFG and ACC activation, and frequent return of emotionally salient intention vectors.

Illustrative Case: In a cognitive task involving emotionally charged distractions, such vectors will disproportionately return to working memory, even after suppression.

### 4.5 The Illusion of Free Will

Interpretation: Conscious awareness of intention arises only after commitment processes have begun.

Prediction: Libet-style experiments will show readiness potentials (RP) in SMA and motor cortex occurring hundreds of milliseconds before subjective awareness of intention, consistent with loop locking dynamics.

Illustrative Case: Participants in self-initiated movement tasks report awareness of intention after neural activation indicating commitment has already occurred.

These five domains demonstrate IRE's predictive strength, offering direct experimental paradigms for confirmation or falsification. Its structured design allows labs to explore volition through the lens of measurable vector dynamics, advancing both theory and empirical inquiry.

## 5.0 Limitations and Future Work

The Intent Resolution Engine (IRE) represents a foundational attempt to mechanistically model volitional arbitration using vector-based computation and recursive neural dynamics. While the model is conceptually rich and empirically grounded, several limitations should be acknowledged.

### 5.1 Absence of Formal Simulation

IRE currently lacks a complete mathematical or computational simulation to quantify the specific interactions among vector parameters, resolution thresholds, and neural gating mechanisms. While the model provides symbolic structure (e.g., $V = f(C, A, X, R, U)$), future work should formalize these equations using real-world cognitive modeling frameworks or agent-based simulations.

### 5.2 Experimental Grounding Still Preliminary

Although IRE aligns with established neuroscience literature and predicts a wide range of cognitive phenomena, the framework has not yet undergone targeted empirical validation. Experimental designs to isolate arbitration dynamics, threshold fluctuations, and vector suppression are necessary to establish reliability and reproducibility.

### 5.3 Overlap with Prior Models

Several components of IRE—goal competition, reward expectancy, inhibitory control—overlap with existing theories in cognitive control and decision-making. Differentiating IRE's unique contribution lies in its integration of these processes into a recursive arbitration loop governed by dynamically shifting thresholds. Comparative studies are needed to demonstrate superiority or complementarity.

### 5.4 Consciousness Interface Remains Underspecified

While IRE addresses the illusion of free will, the framework does not offer a detailed account of how volitional arbitration integrates with subjective consciousness. Bridging this gap may require integration with broader models of awareness, attentional binding, or internal narrative generation.

### 5.5 Individual Differences and Clinical Applications

Current IRE formulations do not yet account for variability in volitional capacity across individuals or clinical populations. Future work could explore how threshold calibration, vector persistence, and suppression dynamics vary across psychiatric conditions such as ADHD, OCD, depression, or PTSD.

## 6.0 Final Synthesis

The Intent Resolution Engine (IRE) provides a neurocognitive framework for understanding volitional arbitration as an emergent property of recursive vector dynamics and adaptive threshold modulation. By treating intentions as structured, multidimensional vectors—and positioning them within a cyclical, evaluative arbitration loop—IRE offers a formal account of how the mind selects and commits to internal goals.

This model reframes decision-making not as a singular, conscious act, but as the real-time output of competitive vector processing across cognitive, affective, and contextual dimensions. It bridges neural systems involved in attention, motivation, inhibition, and motor planning, and offers falsifiable predictions across a range of behaviors—from procrastination and multitasking to intrusive thoughts and the illusion of free will.

Though still early in its empirical development, IRE lays the foundation for a unified theory of internal goal selection and volitional behavior. Its structural clarity, symbolic formalism, and neuroanatomical mapping provide an actionable platform for future simulation, experimental validation, and clinical application.

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