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From Predictive Coding to EBPM: A Novel DIME Integrative Model for Recognition and Cognition

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Featured Application

The DIME model can be applied to the development of adaptive robotic systems that combine ultra-rapid recognition of familiar objects with the ability to operate in unfamiliar or ambiguous environments, thereby optimizing both reaction speed and behavioral robustness.

Abstract

Predictive Coding (PC) frameworks claim to model recognition via prediction–error loops, but they often lack explicit biological implementation of fast familiar recognition and impose latency that limits real-time robotic control. We begin with *Experience-Based Pattern Matching (EBPM)*, a biologically grounded mechanism inspired by neural engram reactivation, enabling near-instantaneous recognition of familiar stimuli without iterative inference. Building upon this, we propose *Dynamic Integrative Matching and Encoding (DIME)*, a hybrid system that relies on EBPM under familiar and low-uncertainty conditions and dynamically engages PC when confronted with novelty or high uncertainty. We evaluate EBPM, PC, and DIME across multiple image datasets (MNIST, Fashion-MNIST, CIFAR-10) and on a robotic obstacle-course simulation. Results from multi-seed experiments with ablation and complexity analyses show that EBPM achieves minimal latency (e.g., ~0.03 ms/ex in MNIST, ~0.026 ms/step in robotics) but poor performance in novel or noisy cases; PC exhibits robustness at a high cost; DIME delivers strong trade-offs—boosted accuracy in familiar clean situations (+4–5% over EBPM on CIFAR-10), while cutting PC invocations by ~50% relative to pure PC. Our contributions: (i) formalizing EBPM as a neurocomputational algorithm built from biologically plausible principles, (ii) developing DIME as a dynamic EBPM–PC integrator, (iii) providing ablation and complexity analyses illuminating component roles, and (iv) offering empirical validation in both perceptual and embodied robotic scenarios—paving the way for low-latency recognition systems.

Keywords: Experience-Based Pattern Matching (EBPM); Predictive Coding (PC); Dynamic Integrative Matching And Encoding (DIME); engram reactivation; cognitive architectures; biologically inspired AI; real-time robotics



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1. Introduction

Over the past three decades, the Predictive Coding (PC) paradigm has become one of the most influential theoretical frameworks in cognitive neuroscience. It posits that perception arises from a hierarchical process of top-down prediction generation, which is continuously compared with incoming sensory data, with discrepancies propagated as prediction errors [1,2]. The PC model has successfully accounted for phenomena such as directed attention, multimodal integration, and the adaptive flexibility of the cortex, being closely linked to Bayesian mathematical principles and the “free energy principle” hypothesis [3].

Nevertheless, this framework presents both conceptual and practical limitations. First, PC entails a high computational and energetic cost, as it requires the continuous generation of internal predictions even in familiar contexts. Second, it assumes that perception is essentially a hypothesis-testing process, which does not accurately capture the rapid and reflexive responses observed at both neuronal and behavioral levels. Third, a substantial body of neurophysiological evidence suggests that recognition in familiar situations occurs through the direct reactivation of stored engrams, without an intermediate stage of generative simulation [4,5].

To address these limitations, we propose a new model—Experience-Based Pattern Matching (EBPM)—developed in this study (Figure 1). EBPM conceptualizes perception and action as the result of the direct activation of multimodal engrams (visual, auditory, motor, emotional), previously formed through experience. Each engram consists of elementary engram units, such as visual edges, motion fragments, or interoceptive cues, which can be reused and combined into complex networks. In this framework, novel stimuli initially activate these units, which may trigger a full familiar engram or partially activate several engrams. If none surpasses an activation threshold, attentional processes are engaged, and new connections are formed—a process equivalent to biological supervised learning.

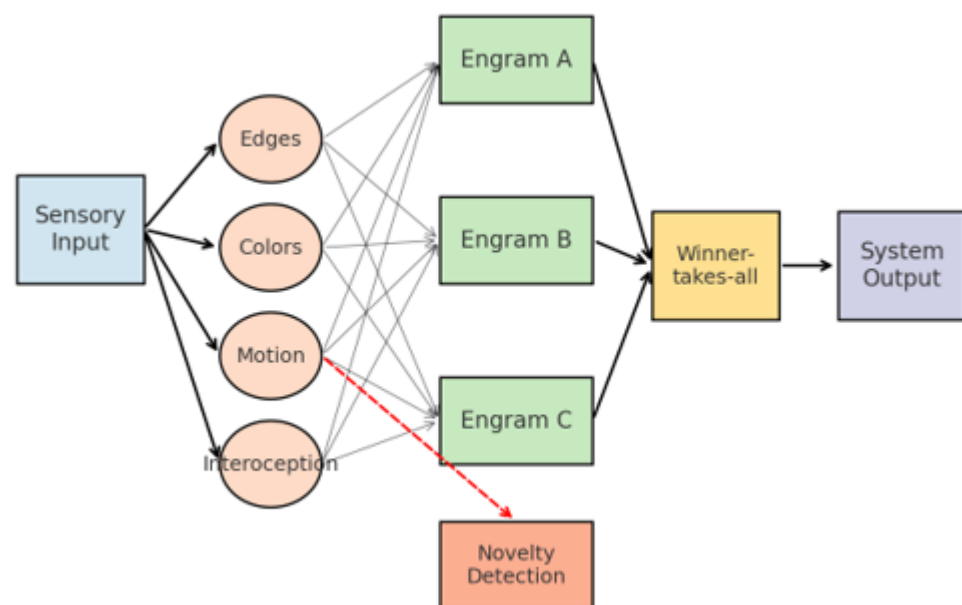


Figure 1. Schematic representation of the EBPM framework.

The EBPM model presents significant advantages over PC (Figure 2) in familiar contexts: faster recognition, reduced energetic cost, and a natural alignment with neurophysiological data (Hebbian plasticity, lateral inhibition, direct memory reactivation). However, like PC, EBPM also has limitations: low robustness to noisy data and reduced flexibility when confronted with entirely novel stimuli.

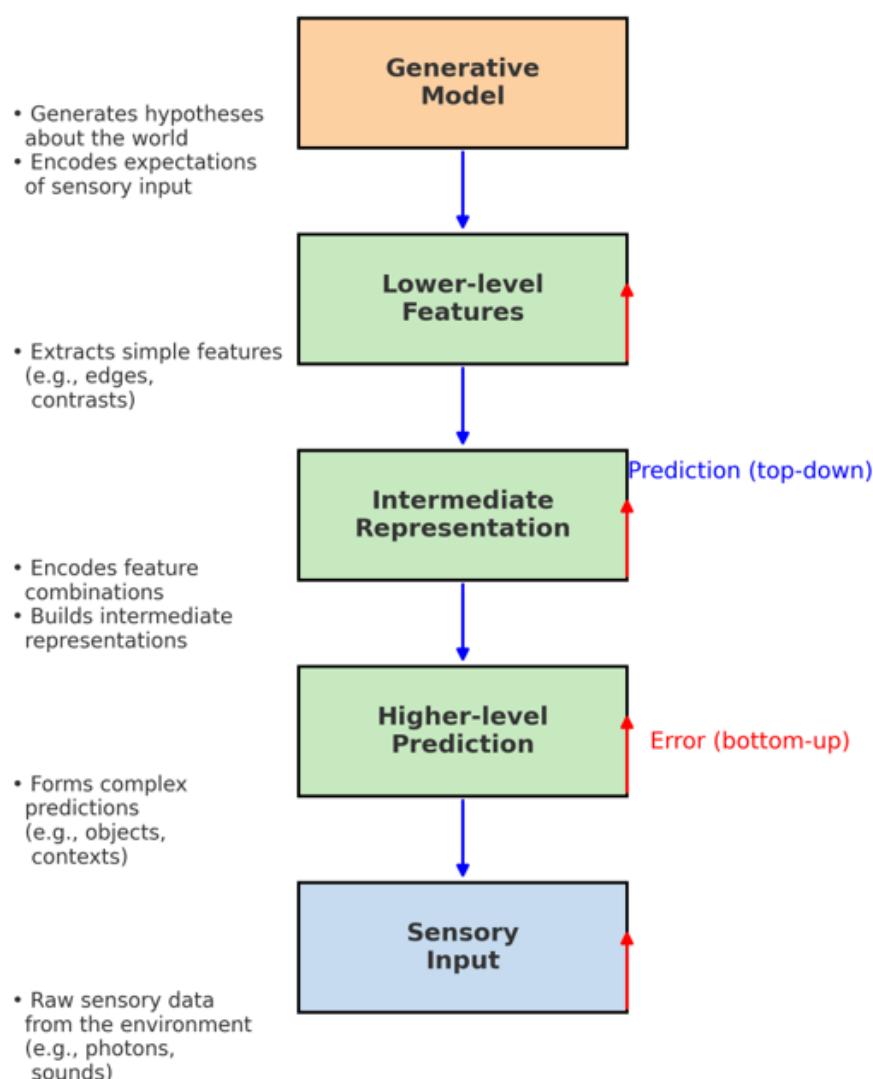


Figure 2. Predictive Coding (PC) architecture.

Building on the observation that neither PC nor EBPM can fully account for all cognitive phenomena, this paper proposes a novel hybrid model—Dynamic Integrative Matching and Encoding (DIME). DIME integrates the two paradigms: it employs EBPM’s direct matching in familiar and rapid situations but can recruit PC’s generative mechanisms when the context is ambiguous or incomplete. A dynamic control mechanism determines which pathway is dominant, ensuring both speed and efficiency, as well as flexibility and robustness. The general architecture of the DIME model is illustrated in Figure 3, which depicts the integration of EBPM and PC processing streams through a central control module.

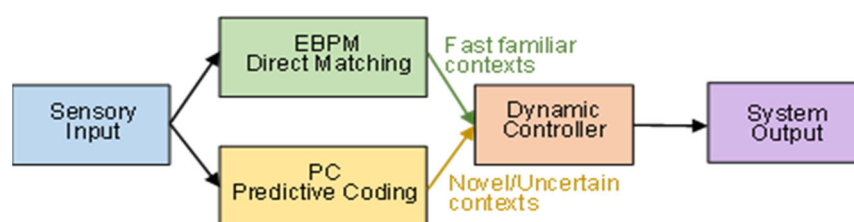


Figure 3. DIME (Dynamic Integrative Matching and Encoding) model.

The aim of this study is twofold: (i) to present the original EBPM model, together with its neurophysiological and algorithmic foundations and (ii) to define the DIME architecture

as an integrative solution between EBPM and PC. This work has an interdisciplinary character, with implications in cognitive neuroscience, artificial intelligence, and robotics. In addition, it proposes a methodological framework for validation through neuroimaging (fMRI, EEG/MEG), artificial neural network simulations, and robotic experiments, thereby providing both theoretical and applied relevance.

Other recognition systems incorporate pattern-matching expert frameworks [6] or hybrid architectures [7] but lack biologically grounded engram reactivation as in EBPM.

In addition to Predictive Coding, alternative frameworks have been proposed to explain recognition and cognition. Prior work on attractor-based memory models and Predictive Coding has argued for complementary roles of fast pattern completion and iterative inference. We build on this view by integrating both into a single decision process. However, these models typically focus either on abstract pattern completion without multimodality or on purely Bayesian formulations without explicit engram reactivation. EBPM therefore differs in scope: it formalizes multimodal engrams and introduces a novelty-driven supervised-like learning process, providing a distinct alternative to both attractor and predictive theories.

See Section 2.3.6 for a method-by-method comparison between EBPM and attractor models, CLS, HTM, SDM, memory-augmented NNs, episodic control, metric-learning, and PC/Active Inference.

While modern deep architectures such as convolutional networks and Transformers achieve state-of-the-art accuracy on benchmarks like CIFAR-10, their objectives differ from ours. EBPM/DIME is not designed to compete with high-capacity deep nets in terms of maximum accuracy but rather to provide a biologically grounded framework that explicitly balances recognition latency and robustness. In this sense, our approach is complementary rather than competitive, emphasizing interpretability and real-time feasibility.

Notation: Throughout this manuscript, we adopt the following notation. Input data are denoted by x , with C classes in total. The embedding produced by EBPM is $z = f_\theta(x)$, and class prototypes are $P_c \in \mathbb{R}^d$. Prototype similarity is $s_c(x) = \cos(z, P_c)$. The scalars T_E and T_P are temperature parameters for EBPM and PC, respectively. In PC, K denotes the number of iterative inference steps. Familiarity is denoted as $\hat{F} \in [0, 1]$, and uncertainty is denoted as $U \in [0, 1]$. The gain parameter of the controller is γ . τ_F denotes a time constant for the temporal integration of familiarity, while Λ is a threshold shift used for calibration. Finally, $\alpha \in [0, 1]$ is the dynamic weighting factor combining EBPM and PC in the DIME model.

2. Materials and Methods

2.1. The Theoretical Framework of the EBPM Model

Similarity, logits, and softmax for EBPM

$$s_c(x) = \frac{z \cdot P_c}{\|z\| \|P_c\|}, \ell_c^{EBPM}(x) = T_E \cdot s_c(x), p^{EBPM}(x) = \text{softmax}(\ell^{EBPM}(x)) \quad (1)$$

where $z = f_\theta(x)$ is the embedding of input, x , $P_c \in \mathbb{R}^d$ is the prototype of class c , T_E is a temperature scaling factor, and $p^{EBPM}(x)$ denotes the class probability distribution estimated by EBPM.

Familiarity EBPM

$$F_{raw}(x) = \max_{c \in \text{Familiar}} s_c(x), \hat{F}(x) = \text{clip}\left(\frac{F_{raw}(x) - \Lambda + 1}{2}, 0, 1\right) \quad (2)$$

where $F_{raw}(x)$ is the maximum prototype similarity among familiar classes, Λ is a calibration shift parameter, and $\hat{F}(x) \in [0, 1]$ is the normalized familiarity estimate used later by the DIME controller.

The Experience-Based Pattern Matching (EBPM) model, proposed in this paper, describes perception and action as the result of the direct activation of multimodal engrams. Each engram integrates the following:

- Sensory components (e.g., visual edges and colors, auditory timbres, tactile cues);
- Motor components (articular configurations, force vectors);
- Interoceptive and emotional components (visceral state, affective value);
- Cognitive components (associations, abstract rules).
- These engrams are constructed through experience and consolidated by Hebbian plasticity and spike-timing-dependent plasticity (STDP) mechanisms [4,8]. They are composed of elementary sub-engrams (feature primitives), such as edge orientations or elementary movements, which can be reused in multiple combinations.

The EBPM Processing Stream:

1. Stimulus activation—sensory input activates *elementary engram units* (sub-engrams) such as edges, textures, tones, and motor or interoceptive signals.
2. Engram co-activation—shared sub-engrams may partially activate multiple parent engrams in parallel.
3. Scoring and aggregation—each parent engram accumulates an activation score based on the convergence of its sub-engrams.
4. Winner selection—if a single engram surpasses the recognition threshold, it is fully activated and determines the output; if several engrams are partially active, the strongest one prevails through lateral inhibition.
5. Novelty detection—if all activation scores remain below the threshold, the system enters a novelty state: no complete engram is recognized.
6. Attention engagement—attention is mobilized to increase neuronal gain and plasticity, strengthening the binding of co-active sub-engrams into a proto-engram.
7. Consolidation vs. fading—if the stimulus/event is repeated or behaviorally relevant, the proto-engram is consolidated into a stable engram; if not, the weak connections gradually fade.

Formally, an engram unit (EU) can be defined as a feature vector $EU_i = [s_i, m, e_i, c_i]$, where s_i denotes sensory primitives (edges, colors, timbres), m_i denotes motor fragments (joint configurations, force vectors), e_i captures interoceptive or affective values, and c_i encodes cognitive associations or rules. A full engram is a sparse set $\{EU_i, \dots, EU_n\}$, stabilized by Hebbian and spike-timing-dependent plasticity (STDP). This formalization differentiates EBPM from generic episodic traces or attractor states by explicitly integrating multimodal dimensions.

Thus, EBPM accounts for rapid recognition in familiar contexts and provides a robust architecture for the storage of multimodal experiences.

This process is illustrated in Figure 1 and is consistent with the principles of Hebbian learning and sparse distributed coding [4,5]. It shows how sensory input activates atomic sub-engrams, which can either fully trigger a stored engram or partially activate multiple candidates. The winner-takes-all mechanism determines the output, while novelty detection engages supervised-like learning.

It is important to emphasize that in EBPM, even novel or weakly familiar stimuli always activate sub-engrams (e.g., edges, textures, tones, and tactile or interoceptive states). These activations may remain below the recognition threshold, being unable to complete any stable engram. In such cases, attention is mobilized, not only to enhance further

sensory sampling but also to increase neuronal gain and plasticity, creating temporary proto-engrams by binding co-active sub-engrams according to the Hebbian rule (‘fire together, wire together’). If the stimulus or event is repeated or behaviorally relevant, these proto-engrams undergo consolidation into stable engrams; if the event does not recur, the weak connections gradually fade. Thus, attention serves a dual role: intensifying the analysis of unfamiliar input while simultaneously facilitating the structural formation of new memory programs for future recognition.

2.2. The Theoretical Framework of Predictive Coding (PC)

Iterative update in PC

$$z^{(k+1)} = z^{(k)} + \eta(x - \hat{x}^{(k)}) \cdot W \quad (3)$$

where $z^{(k)}$ is the latent state at inference step k , $\hat{x}^{(k)}$ is the top-down prediction at that step, x is the input, W are the synaptic weights, and η is a learning rate parameter. The number of inference steps is denoted by K .

Final probabilities in PC

$$p^{PC}(x) = \text{softmax}(\ell^{(K)}(x)) \quad (4)$$

where $\ell^{(K)}$ are the logits after K inference steps, and $p^{PC}(x)$ denotes the final class probability distribution estimated by the PC model.

Predictive Coding (PC) is an established framework according to which the cortex continuously generates top-down predictions, compares them with actual sensory data, and propagates the discrepancies as prediction errors [1,2]. PC has three fundamental elements:

- Internal generative models (hierarchical representations of the environment);
- Prediction errors (differences between input and predictions);
- Adaptive updating (learning through error minimization).

PC provides a good account of the brain’s flexibility in novel environments, its robustness to noise, and its capacity for cross-modal integration. However, its high energetic cost and long latencies make it less suitable for rapid responses.

This architecture is schematically represented in Figure 2, where predictions are transmitted top-down, while errors propagate bottom-up for adjustment. It illustrates the generative top-down predictions, the comparison with incoming sensory data, and the propagation of prediction errors upwards in the cortical hierarchy [1,3].

2.3. Comparison of EBPM and PC

2.3.1. Theoretical Foundation

Over the past two decades, Predictive Coding (PC) has become the dominant framework for explaining perception and cognition. PC posits that the nervous system constructs hierarchical generative models that continuously predict sensory input and update these models through the minimization of prediction errors.

In contrast, the EBPM model proposed here argues that perception and action rely on the direct activation of pre-existing multimodal engrams, without requiring the active generation of predictions. EBPM is grounded in the principle that recognition is determined by the similarity between input and stored patterns; only when the input is insufficient to activate an existing engram do attentional processes and supervised learning come into play.

Thus, the fundamental difference is that PC operates through predictive reconstruction, whereas EBPM operates through direct matching (Table 1).

Table 1. Extended comparison between Predictive Coding (PC) and Experience-Based Pattern Matching (EBPM), with explicit treatment of novelty, attention, and new engram formation.

Aspect	Predictive Coding (PC)	Engram-Based Program Model (EBPM)
Basic principle	Predictions compared with input; error is propagated.	Recognition through engrams composed of reusable sub-engrams; full activation only for familiar stimuli.
Partial activation	-	Partial/similar stimuli → shared sub-engrams are activated; multiple engrams become partially active.
Selection	-	Lateral inhibition: the engram with the most complete activation prevails.
Novelty/unfamiliarity	Unclear how new representations are detected and formed.	If all engrams remain below the threshold: sub-engrams are active, but no parent engram is completed → novelty state. Attention is engaged.
Formation of new engrams (role of attention)	Does not specify a concrete biological mechanism.	Automatic (“fire together, wire together”): in the novelty state, attention increases neuronal gain and plasticity; co-active sub-engrams are bound into a proto-engram. Without repetition, the linkage fades/does not finalize. With repetition, it consolidates into a stable engram.
Signaling absence	Postulates “omission error” (biologically problematic).	No “negative spike.” Silence at the parent-engram level + fragmentary activation of sub-engrams defines novelty; attention manages exploration and learning.
Neuronal logic	Requires an internal comparator/explicit error signals.	Pure spike/silence + lateral inhibition + co-activation-dependent plasticity; attention sets the learning threshold.

2.3.2. Processing Dynamics in the Two Models

Predictive Coding (PC)

1. The brain generates hierarchical top-down predictions.
2. Sensory input is compared with predictions.
3. Prediction errors are transmitted upward and correct the internal model.
4. Perception arises as the result of minimizing the difference between prediction and input.

EBPM

1. The input activates elementary engram units.
2. The elementary engram units simultaneously activate multiple engrams.
3. Through lateral inhibition, the most active engram prevails.
4. If no winner exceeds the threshold, attention is triggered, and a new engram is formed.
5. Perception is the complete reactivation of a pre-existing network, not a reconstruction process.

In EBPM, novelty does not mean absence of activation, but rather fragmentary activation: elementary sub-engrams (edges, textures, sounds, interoceptive states, etc.) respond, yet no parent engram reaches the recognition threshold. This state triggers attention mechanisms, which increase neuronal gain and synaptic plasticity in the relevant circuits. According to the principle, ‘fire together, wire together’, co-active sub-engrams are linked into a proto-engram. If the stimulus/event is repeated (or remains behaviorally relevant), these linkages are consolidated into a stable engram; if not, they remain weak and fade. Thus, attention not only collects additional data but also guides and accelerates the very process of inscribing new engrams.

2.3.3. Comparative Advantages and Limitations

The Predictive Coding (PC) framework describes perception as an iterative process of error minimization between sensory inputs and top-down expectations. In this context, the network dynamically adjusts its internal generative model to predict sensory outcomes, while error units signal mismatches between the predicted and received stimuli. The hierarchical feedback mechanism allows the system to progressively refine its estimates, achieving perceptual stability and adaptive generalization. Table 2 summarizes the structural and computational characteristics of the PC model, highlighting the functional correspondence

between biological prediction–error loops and their artificial implementation within the proposed comparative framework.

Table 2. (a) Conceptual differences between EBPM and PC. (b) Conceptual differences extended with related models.

(a)			
Domain	EBPM	PC Prediction	
Central Mechanism	Direct activation of multimodal engrams	Continuous generation and updating of predictions	
The Role of Prediction	Non-existent; only goal-driven sensitization	Fundamental for processing	
Recognition Speed	Instantaneous for familiar stimuli	Slower, requires iterative computation	
Energy Efficiency	High (without generative simulation)	Lower (increased metabolic cost)	
Attention Control	Goal-driven (sensitization of relevant networks)	Through the magnitude of prediction errors	
Biological Plausibility	Supported by studies on engrams and inhibition	Supported by cortical predictive microcircuits	
Typical Application Domains	Rapid recognition, episodic memories, reflexes	Perception in ambiguous or noisy conditions	
(b)			
Domain	EBPM	PC	Similar existing theories
Central Mechanism	Direct multimodal engram activation	Generative Predictive Coding	Hopfield attractors, episodic replay
Recognition Speed	Fast, one-step match	Iterative, slower	Fast (pattern completion)
Energy Efficiency	High, no generative loop	Low, high metabolic demand	Variable
Flexibility	Limited to stored engrams	High, reconstructive	Active inference
Biological Plausibility	Supported by engram studies	Supported by cortical microcircuits	Both partially supported

2.3.4. Divergent Experimental Predictions

The Dynamic Integrative Matching and Encoding (DIME) model extends the EBPM and PC principles by incorporating adaptive control and context-dependent integration between recognition and prediction layers. The system dynamically modulates the balance between bottom-up sensory matching and top-down predictive adjustments, optimizing performance under both familiar and novel conditions. This hybrid mechanism reflects the flexible coupling of biological recognition and executive systems observed in neural circuits. Table 3 presents the comparative architecture and control parameters of the DIME model, emphasizing its hybrid integrative dynamics and real-time adaptive behavior.

Table 3. Comparative predictions: EBPM vs. PC.

Domain	EBPM Prediction	PC Prediction	Testable Through
fMRI (similarity analysis)	Recognition = reactivation of storage networks	Anticipatory activation in higher cortical areas	fMRI + RSA
EEG/MEG (latency)	Rapid recognition of familiar patterns	Longer latencies due to generative processing	EEG/MEG
Cue-based recall	A partial cue reactivates the entire engram	The cue triggers generative reconstruction	Behavioral and neurophysiological studies
Robotic implementation	Faster execution of learned procedures	Better adaptive reconstruction with incomplete data	AI/Robotics benchmarks

2.3.5. Interpretive Analysis

- EBPM better explains rapid recognition, complex reflexes, and sudden cue-based recall.
- PC is superior in situations with incomplete or ambiguous data due to its generative reconstruction capability.
- The two models are therefore complementary, each having its own set of advantages and limitations.

This observation sets the stage for an integrative model (DIME), which combines the speed and efficiency of EBPM with the flexibility of PC.

2.3.6. EBPM vs. Related Theories—Method-by-Method Comparison

Context: EBPM (direct reactivation of multimodal engrams) is defined in Section 2.1 and contrasted with Predictive Coding (PC) in Sections 2.2 and 2.3; DIME integrates them in Section 2.4. Below, we align EBPM against adjacent frameworks, highlighting (i) what is identical, (ii) what each prior method adds, and (iii) what EBPM adds (Table 4).

Table 4. Side-by-side comparison (operational summary).

Method/Framework	What the Method Does	Identical to EBPM	What It Adds vs. EBPM	What EBPM Adds
Hopfield/Attractor Networks [9]	Recurrent dynamics converge into stored patterns (content-addressable recall from partial cues).	Pattern completion from partial input; competition among states.	Explicit energy formalism; well-characterized attractor dynamics.	Explicit multimodality (sensory–motor–affective–cognitive) and engram units beyond binary patterns.
CLS—Complementary Learning Systems (hippocampus fast; neocortex slow) [10]	Episodic rapid learning + slow semantic consolidation.	Separation of “fast vs. slow” memory routes.	System-level transfer between stores.	EBPM is operational in real-time via direct matching; no mandatory inter-system consolidation for recognition.
Hippocampal indexing: pattern completion/separation [11,12]	Hippocampus index episodes; CA3 supports completion, and DG supports separation.	Fast episodic reactivation from indices; completion logic.	Fine neuro-anatomical mapping (CA3/DG) with predictions.	EBPM generalizes to neocortex and to multimodal action-oriented engrams, not only episodic replays.
Exemplar/Instance-Based (GCM; Instance Theory) [13,14]	Decisions by similarity to stored instances; latencies fall with instance accrual.	Direct “match to memory” with similarity score.	Quantitative psychophysics of categorization and automatization.	EBPM includes motor/interoceptive bindings and neuronal lateral inhibition/WTa selection.
Recognition-by-Components (RBC) [15]	Object recognition via geons and relations.	Sub-engrams akin to primitive features.	Explicit 3D structural geometry.	EBPM is not vision-limited; it covers sequences/skills and affective valence.
HTM/Sequence Memory (cortical columns) [5]	Sparse codes, sequence learning, local predictions.	Reuse of sparse distributed codes; sequence handling.	Continuous prediction emphasis.	EBPM does not require continuous generative prediction; for familiar inputs, it yields lower latency/energy via direct recall.
Sparse Distributed Memory (SDM) [16]	Approximate addressing in high-D sparse spaces; noise-tolerant recall.	Proximity-based matching in feature space.	Abstract memory addressing theory.	EBPM specifies engram units and novelty/attention gating with biological microcircuit motifs.
Memory-Augmented NNs (NTM/DNC) [17,18]	Neural controllers read/write an external memory differentially.	Key-based recall from stored traces.	General algorithmic read/write; task-universal controllers.	EBPM is bio-plausible (engram units; STDP-like plasticity) without opaque external memory.
Episodic Control in RL [19]	Policies exploit episodic memory for rapid action.	Fast reuse of familiar episodes.	RL-specific credit assignment and returns.	EBPM operates for perception and action with multimodal bindings.
Prototypical/Metric-Learning (few-shot) [20]	Classify by distance to learned prototypes in embedding space.	Prototype-like matching $\approx$ EBPM encoder + similarity.	Episodic training protocols; few-shot guarantees.	EBPM grounds the embedding in neuro-plausible engrams + inhibition, not just vector spaces.
Predictive Coding/Active Inference [1–3,21,22]	Top-down generative predictions + iterative error minimization.	Shares attentional modulation and context use.	Robust reconstruction under missing data via generative loops.	EBPM delivers instant responses on familiar inputs (no iterative inference) with lower compute/energy; DIME then falls back to PC for novelty.

The detailed step-by-step implementation of the EBPM process is summarized in Algorithm 1, which illustrates the hierarchical activation, competition, and adaptive plasticity sequence that leads to recognition and novelty gating.

Algorithm 1. EBPM (step-by-step) with prior-art mapping.

1. *Extract low-level primitives* (edges, textures, timbre, phonemes).
↳ Links to *sparse coding* and columnar representations [16,23].
2. *Activate candidate multimodal Engram Units (EUs)* from those primitives.
↳ *Cell assemblies/neural assemblies* concepts [4].
3. *Spread + compete* among candidate EUs with lateral inhibition/WTa.
↳ Cortical microcircuit motifs; *biased competition* in attention [24,25].
4. *Select the winner* (fully activated engram) → recognition/action trigger.
↳ *Attractor/pattern-completion* dynamics [9,11,12].
5. *Familiarity/novelty test* (no clear winner → novelty branch).
↳ *Salience/attention* control; locus-coeruleus NE gain [21,25,26].
6. *Rapid plasticity* (Hebb/STDP-like) to *form/adjust* new or refined engrams.
↳ Hebbian/STDP literature [8].
7. *Bind multimodal facets* (sensory–motor–affective–cognitive) within the engram;
optional hippocampal indexing for episode-level links.
↳ *Indexing theory* and process-memory hierarchy [11,27].
8. *Real-time reuse*: for familiar inputs, jump straight to Steps 3–4 (no generative loop).
↳ Distinct from *PC/Active Inference*, which iterate prediction-error loops [1–3].

2.3.7. Distinctive Contributions of EBPM (Beyond Attractors/CLS/HTM/PC)

While Section 2.3.6 aligns EBPM with adjacent frameworks, here, we summarize the contributions that are unique or substantially sharpened by EBPM:

- **Multimodal Engram as the Computational Unit:** EBPM defines an engram as a compositional binding of sensory, motor, interoceptive/affective, and cognitive facets. This goes beyond classic attractor networks (binary pattern vectors) and metric-learning embeddings by specifying the unit of recall and action as a multimodal assembly.
- **Novelty-First Decision with Explicit Abstention:** By design, EBPM yields near-zero classification on truly novel inputs. Partial activation of sub-engrams is treated as a reliable novelty flag—not as a misclassification. This sharp separation of recognition versus novelty is absent from PC’s iterative reconstruction loop and from generic prototype schemes.
- **Attention-Gated Proto-Engram Formation:** EBPM assigns a concrete role to attention and neuromodulatory gain (e.g., LC-NE) in binding co-active sub-engrams into a proto-engram during novelty, followed by consolidation. This specifies “when and how new representations form” more explicitly than attractors/CLS/HTM.
- **Real-Time Reuse without Iterative Inference:** For familiar inputs, EBPM supports one-step reactivation of stored engrams (winner selection via lateral inhibition), avoiding costly predictive iterations. This explains ultra-fast recognition and procedural triggering in overlearned contexts.
- **Integration Readiness via DIME:** EBPM is not an isolated alternative: the DIME controller provides a formal arbitration (α) that privileges EBPM under high familiarity and shifts toward PC under uncertainty, yielding a principled hybrid.

2.4. The DIME Integrative Model

To overcome the limitations of both paradigms, we propose DIME (Dynamic Integrative Matching and Encoding)—a model that combines EBPM’s direct matching with PC’s generative prediction.

Principles:

- Dual-path processing: sensory input is processed simultaneously through direct engram matching (EBPM) and top-down prediction (PC).
- Dynamic controller: a central mechanism evaluates the context (level of familiarity, uncertainty, noise) and selects the dominant pathway.
- Adaptive flexibility: in familiar environments → EBPM becomes dominant; in ambiguous environments → PC is engaged.

Algorithmically, DIME can be formulated as follows:

$$p(x) = \alpha(x) \cdot p^{EBPM}(x) + (1 - \alpha(x)) \cdot p^{PC}(x) \quad (5)$$

where $p^{EBPM}(x)$ and $p^{PC}(x)$ denote the probability distributions from EBPM and PC, respectively, $\alpha \in [0, 1]$ is the dynamic weighting factor defined by Equation (6)

The adaptive controller $\alpha(t)$ is defined as

$$\alpha(x) = \sigma(\gamma \cdot (\hat{F}(x) - U(x))) \quad (6)$$

where $\sigma(\cdot)$ is the logistic sigmoid, γ is the controller gain, $\hat{F}(x)$ is the normalized familiarity, and $U(x)$ is the normalized uncertainty.

The general architecture of the DIME model is presented in Figure 3, which illustrates the integration of the EBPM and PC processing streams through a central control module [24,28]. Diagram of the dual-pathway system: EBPM (direct engram reactivation) vs. PC (generative prediction), with a dynamic controller weighting both outputs depending on familiarity and uncertainty.

2.5. Methodology of Experimental Validation

Testable Predictions and Analysis Plan

We highlight a set of testable predictions that distinguish EBPM from PC and can be empirically evaluated:

- H1 (EEG/MEG latency): EBPM-dominant trials (familiar stimuli) yield shorter recognition latencies (≈ 200 – 300 ms) compared to PC-dominant trials (≈ 350 – 450 ms). We base the ≈ 200 – 300 ms range on recent EEG evidence indicating that recognition memory signals emerge from around 200 ms post-stimulus across diverse stimulus types [29].
- H2 (fMRI representational similarity): EBPM produces higher RSA between learning and recognition patterns in hippocampal/cortical regions; PC shows anticipatory activation in higher areas under uncertainty.
- H3 (Cue-based recall completeness): Partial cues reinstantiate full engram patterns under EBPM, while PC engages reconstructive dynamics without full reinstatement.
- H4 (Behavioral/robotic efficiency): Under stable familiarity, EBPM leads to lower inference time and energy cost than PC; under novelty/noise, DIME shifts toward PC to preserve robustness.
- H5 (NE-gain modulation): Pupil-indexed or physiological proxies of LC-NE correlate with novelty detection and proto-engram formation during EBPM-dominant novelty trials.

These hypotheses are structured to allow empirical falsification and ensure that EBPM/DIME is not merely a descriptive framework but a model with measurable consequences.

To test the EBPM, PC, and DIME hypotheses, we propose a multi-level approach:

- Neuroimaging:
 - fMRI (representational similarity analysis, RSA) → measures the overlap of patterns between learning and recognition.
 - EEG/MEG → measures recognition latencies (EBPM $\approx$ shorter; PC $\approx$ longer).

- Computational simulations:
 - Artificial neural networks inspired by EBPM vs. PC.
 - Comparison of inference times and computational cost.
- Robotic experiments:
 - Implementation in visuomotor control.
 - Measurement of reaction times and energy consumption in navigation tasks.

This methodology enables the integrated testing of theoretical hypotheses and the assessment of the practical applicability of the DIME model.

The methodological structure is illustrated in Figure 4: (i) neuroimaging establishes the cortical dynamics associated with EBPM vs. PC; (ii) simulations on artificial neural networks (ANNs) compare execution times and noise robustness for the two models; and (iii) robotic tests assess practical applicability in real-time visuomotor control tasks. Such a combined approach is recommended in the computational neuroscience literature to triangulate and validate the proposed mechanisms [30]. Overview of the three validation layers: (i) neuroimaging (fMRI, RSA, EEG/MEG latency), (ii) ANN simulations, and (iii) robotic implementations.

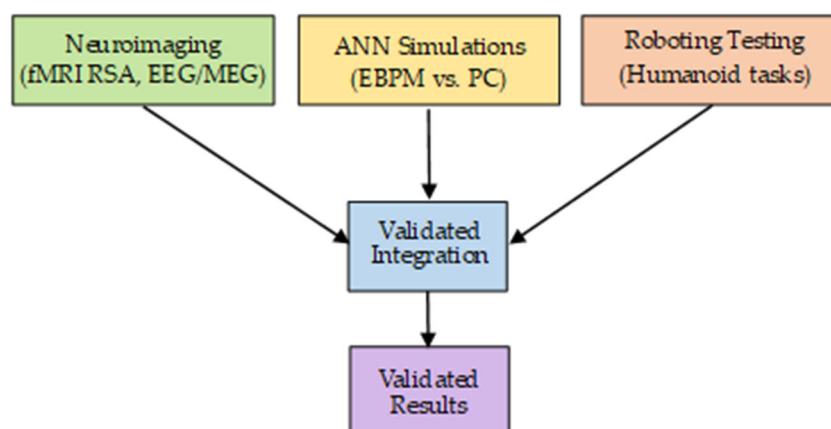


Figure 4. Proposed experimental validation methodology.

2.6. ANN Simulation Protocol

Datasets: MNIST, Fashion-MNIST, and CIFAR-10. Familiar classes: 0–7; novel classes: 8–9. Inputs are converted to grayscale and resized to 28×28 for MNIST/F-MNIST; CIFAR-10 uses standard 32×32 RGB but is projected to the model's input space as in our code.

Noise: We evaluate four scenarios per dataset: Familiar-Clean, Familiar-Noisy, Novel-Clean, Novel-Noisy. For the *Noisy* conditions, we add zero-mean Gaussian noise with standard deviation σ relative to pixel values in $[0,1]$, followed by clamping to $[0,1]$. MNIST/Fashion-MNIST: $\sigma = 0.30$. CIFAR-10: $\sigma = 0.15$. No additional corruptions are used.

EBPM: A prototype-based encoder maps inputs to a normalized embedding; class logits are cosine similarities to learned class prototypes (familiar classes).

PC (Predictive Coding). An autoencoder with a classifier at the latent layer; inference uses $K = 10$ gradient steps with step size $\eta = 0.1$ to reduce the reconstruction error before classification.

DIME: We use two integration strategies:

- DIME-Prob (probability-level fusion): $p = \alpha \cdot p_{\text{EBPM}} + (1 - \alpha) \cdot p_{\text{PC}}$, with α driven by a familiarity score calibrated on familiar validation data. On CIFAR-10, we tune $\{\text{gain} = 4.0, \text{thr_shift} = 0.75, T_{\text{EBPM}} = 6.0, T_{\text{PC}} = 1.0\}$.
- DIME-Lazy (runtime-aware gating, used in robotics): $\delta = \text{mean}(|I_t - I_{t-1}|)$. If $\delta \leq 0.004 \rightarrow \text{EBPM-only}$; if $\delta \geq 0.015 \rightarrow \text{PC-only}$; otherwise, fuse with fixed $\alpha = 0.65$.

Metrics: Top-1 accuracy and latency (ms/ex.) measured on the same GPU (Tesla T4; PyTorch 2.8.0 + cu126). We provide all raw TXT/CSV outputs in the Supplementary package (see Data and Code Availability).

Unless otherwise noted, results are reported for a single deterministic seed (SEED = 42) with CuDNN determinism enabled; numbers are point estimates per test set. Multi-seed statistics are left to future work.

Full architecture specifications (layers, activations, optimizer, learning rate schedules, training epochs) are provided in Supplementary Section S1, together with configuration files (*.yaml).

All simulations and analyses were performed using Python 3.10 and PyTorch 2.8.0 + CUDA 12.6 (NVIDIA Corporation, Santa Clara, CA, USA) on a Tesla T4 GPU (Google Colab Pro+ environment). Data preprocessing and visualization were conducted with NumPy 1.26, Matplotlib 3.9, and Pandas 2.2. The robotic experiments were implemented in PyBullet 3.2.5 (Boston Dynamics AI Institute, Waltham, MA, USA). The complete source code and configuration files (*.yaml) are provided in the Supplementary Materials.

2.7. Intuitive Derivation of the Controller

The DIME controller adaptively weighs EBPM and PC based on two intuitive signals: familiarity (F) and uncertainty (U). Familiarity increases when an input strongly matches stored engrams, while uncertainty reflects the degree of mismatch or noise. The control variable α can therefore be expressed as a logistic gating function $\alpha = \sigma(\gamma(F - U))$, where γ is a sensitivity parameter and σ is the logistic function. For example, in a highly familiar and low-uncertainty case ($F \gg U$), $\alpha \rightarrow 1$ and EBPM dominates. Conversely, when uncertainty is high relative to familiarity, $\alpha \rightarrow 0$ and PC iterations are prioritized. This formulation provides an intuitive justification for the control equations and links them directly to neurocognitive interpretations of recognition under familiarity vs. novelty.

3. Results

3.1. Preface—Scope of the Simulations (Proof-of-Concept)

We emphasize that the simulations reported in Section 3 are minimal proof-of-concept instantiations designed to demonstrate that the EBPM/DIME framework can be implemented and exercised end-to-end. The core contribution of this paper is the conceptual and architectural proposal, not exhaustive benchmarking. Accordingly, MNIST/Fashion-MNIST/CIFAR-10 and the PyBullet obstacle course serve to illustrate feasibility and the predicted trade-offs: speed and efficiency for EBPM on familiar inputs, robustness for PC under noise/novelty, and adaptive arbitration for DIME. Comprehensive large-scale evaluations and richer robotic tasks are deferred to future work (see Section 4.5).

This section evaluates EBPM, PC, and DIME on MNIST, Fashion-MNIST, CIFAR-10, and a PyBullet obstacle course. We report accuracy, latency (ms/sample or ms/step), and stability across five random seeds. Results are organized to (i) quantify the contribution of each component via ablations (controller ON/OFF; PC iterations $K \in \{0, 5, 10, 20\}$), (ii) assess statistical significance with paired tests and effect sizes, and (iii) analyze computational complexity through runtime and number of PC invocations. Together, these experiments test the central claim: EBPM enables very low-latency familiar recognition, PC provides robustness under uncertainty, and DIME dynamically balances the two for real-time feasibility.

3.2. ANN Simulations on Familiar vs. Novel Splits

We evaluated EBPM (prototype matching), PC (predictive autoencoder with iterative latent inference, $K = 10$, $\eta = 0.1$), and DIME (fusion of EBPM and PC) on MNIST, Fashion-

MNIST, and CIFAR-10 under four scenarios: Familiar-Clean, Familiar-Noisy (Gaussian σ as in the code), Novel-Clean, and Novel-Noisy. Familiar classes were 0–7; novel were 8–9.

Noise parameterization: For completeness, the *Noisy* conditions use zero-mean Gaussian noise with σ relative to [0,1] pixel values, followed by clamping: MNIST/Fashion-MNIST $\sigma = 0.30$; CIFAR-10 $\sigma = 0.15$.

- Metrics: Top-1 accuracy, latency (ms/ex.), and for DIME, the mean controller weight is $\bar{\alpha}$ where applicable.
- These results support the complementarity. . . (see Section 2.6).

MNIST: EBPM is near-optimal on familiar inputs but, by design, does not classify novel digits ($\approx 0\%$). This reflects its novelty-flagging mechanism: sub-engrams are activated but do not complete a full engram, signaling unfamiliarity rather than misclassifying. PC is slower but generalizes better to novelty, while DIME adapts by following EBPM on familiar inputs and engaging PC under uncertainty.

Key numbers from our runs:

- EBPM—Familiar-Clean: 98.63%, 0.100 ms/ex; Familiar-Noisy: 97.13%, 0.132 ms/ex; Novel: 0.0%.
- PC—Familiar-Clean: 96.11%, 0.281 ms/ex; Familiar-Noisy: 56.28%, 0.177 ms/ex; Novel-Clean: 94.40%, 0.154 ms/ex; Novel-Noisy: 37.27%, 0.188 ms/ex.
- DIME (adaptive)—Familiar-Clean: 98.63%, 0.247 ms/ex, $\bar{\alpha} = 0.993$; Familiar-Noisy: 96.93%, 0.188 ms/ex, $\bar{\alpha} = 0.974$; Novel $\approx 0\%$ (as EBPM dominates unless fused).
- DIME-Prob (probability-level fusion)—Familiar-Clean: 96.47%, 0.264 ms; Familiar-Noisy: 58.68%, 0.208 ms; Novel-Clean: 93.65%, 0.197 ms; Novel-Noisy: 36.16%, 0.239 ms.

Fashion-MNIST: Trends are similar to MNIST, with a larger familiar/noise gap.

- EBPM—Familiar-Clean: 82.56%, 0.101 ms; Familiar-Noisy: 52.35%, 0.139 ms; EBPM reports $\approx 0\%$ accuracy on novel inputs, consistent with its design as a novelty detector: sub-engrams activate but do not yield a full engram. This produces an explicit novelty signal, rather than a forced classification.
- PC—Familiar-Clean: 83.14%, 0.182 ms; Familiar-Noisy: 50.45%, 0.238 ms; Novel-Clean: 96.50%, 0.160 ms; Novel-Noisy: 97.00%, 0.203 ms.
- DIME (adaptive)—Familiar-Clean: 84.14%, 0.133 ms, $\bar{\alpha} = 0.536$; Familiar-Noisy: 51.31%, 0.170 ms, $\bar{\alpha} = 0.221$; Novel-Clean: 81.10%, 0.165 ms, $\bar{\alpha} = 0.506$; Novel-Noisy: 97.10%, 0.213 ms, $\bar{\alpha} = 0.443$.

CIFAR-10:

- EBPM—Familiar-Clean: 70.42%, 0.198 ms; Familiar-Noisy: 42.67%, 0.192 ms; Novel: 0%.
- PC—Familiar-Clean: 65.99%, 0.477 ms; Familiar-Noisy: 27.15%, 0.478 ms; Novel-Clean: 83.10%, 0.536 ms; Novel-Noisy: 50.95%, 0.548 ms.
- DIME-Prob (best tuned)—Familiar-Clean: 68.31%, 0.529 ms; Familiar-Noisy: 30.38%, 0.535 ms; Novel-Clean: 62.50%, 0.609 ms; Novel-Noisy: 38.05%, 0.675 ms.

Remarks: On Fashion-MNIST, PC shows a slight reversal—Novel-Noisy (97.00%) marginally exceeds Novel-Clean (96.50%). With $\sigma = 0.30$ Gaussian noise (clamped to [0,1]), this acts as a mild regularizer that attenuates high-frequency artifacts for some classes, yielding a small improvement within the expected variance band. The effect is not observed on MNIST or CIFAR-10 and does not change our overall conclusion (EBPM excels on familiar; PC on novel; DIME trades off adaptively) (Table 5).

Table 5. (a). MNIST (single-seed, SEED = 42). (b) Fashion-MNIST. (c) CIFAR-10.

Model	Familiar-Clean (Acc/Ms)	Familiar-Noisy (Acc/Ms)	Novel-Clean (Acc/Ms)	Novel-Noisy (Acc/Ms)	α
(a)					
EBPM	98.63%/0.100	97.13%/0.132	0.00% */0.126	0.00% */0.161	-
PC	96.11%/0.281	56.28%/0.177	94.40%/0.154	37.27%/0.188	-
DIME	98.63%/0.247	96.93%/0.188	0.00%/0.135	0.00%/0.289	0.99/0.97/-/-
DIME-Prob	96.47%/0.264	58.68%/0.208	93.65%/0.197	36.16%/0.239	0.61/0.38/0.41/0.23
(b)					
EBPM	82.56%/0.101	52.35%/0.139	0.00%/0.147	0.00%/0.174	-
PC	83.14%/0.182	50.45%/0.238	96.50%/0.160	97.00%/0.203	-
DIME	84.14%/0.133	51.31%/0.170	81.10%/0.165	97.10%/0.213	0.54/0.22/0.51/0.44
(c)					
EBPM	70.42%/0.198	42.67%/0.192	0.00%/0.201	0.00%/0.242	
PC	65.99%/0.477	27.15%/0.478	83.10%/0.536	50.95%/0.548	
DIME-Prob **	68.31%/0.529	30.38%/0.535	62.50%/0.609	38.05%/0.675	

* for EBPM, novel = 0% indicates explicit novelty detection (no engram completed), not misclassification. Sub-engrams are activated but recognition is withheld until learning occurs. ** best tuned fusion (gain = 4.0, thr_shift = 0.75, temp_ebpm = 6.0, temp_pc = 1.0).

These results support the complementarity of EBPM and PC and the usefulness of DIME as a context-adaptive integration. In particular, EBPM's absence of classification on novel inputs should be read as a feature rather than a flaw: it provides a reliable novelty flag that complements PC's generative reconstruction. This complementarity underlies the adaptive trade-offs realized in DIME.

Figures 5–12 illustrate the experimental results across multiple datasets (MNIST, Fashion-MNIST, and CIFAR-10), highlighting the comparative performance and latency of EBPM, PC, and DIME models under both familiar and novel conditions.

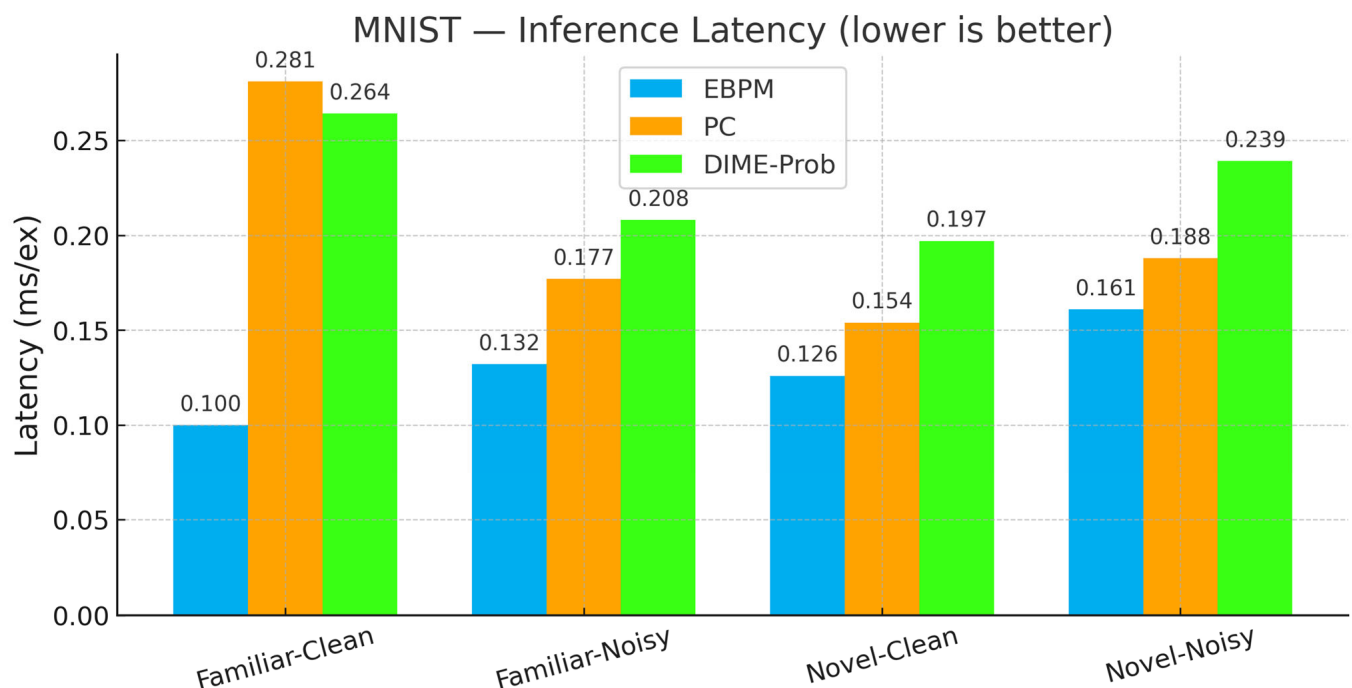


Figure 5. MNIST: Latency—Per-scenario inference latency (ms/ex.) on MNIST for EBPM, PC (K = 10, $\eta = 0.1$), and DIME across Familiar-Clean/Noisy and Novel-Clean/Noisy. EBPM is fastest on familiar; DIME approaches PC when uncertainty grows.

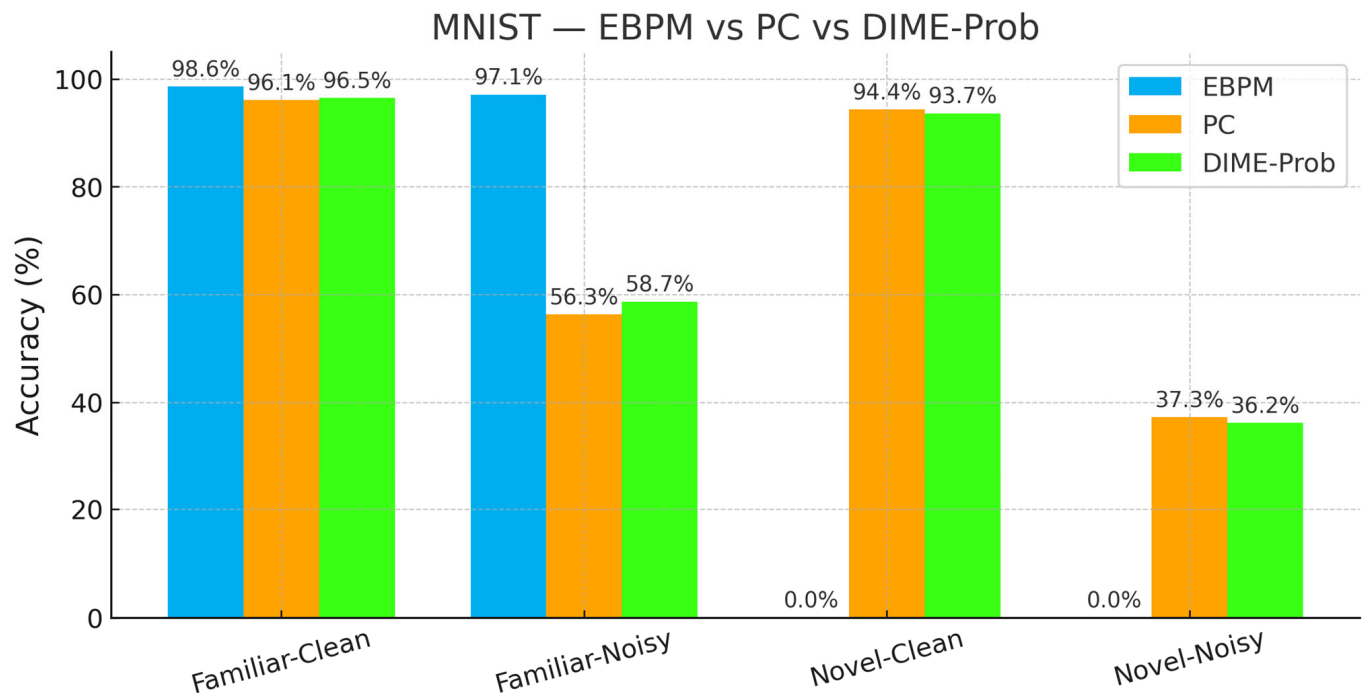


Figure 6. MNIST: Accuracy—Top-1 accuracy on MNIST for the same four scenarios. EBPM excels on familiar but fails by design on novel (8–9); PC generalizes better to novelty; DIME balances both.

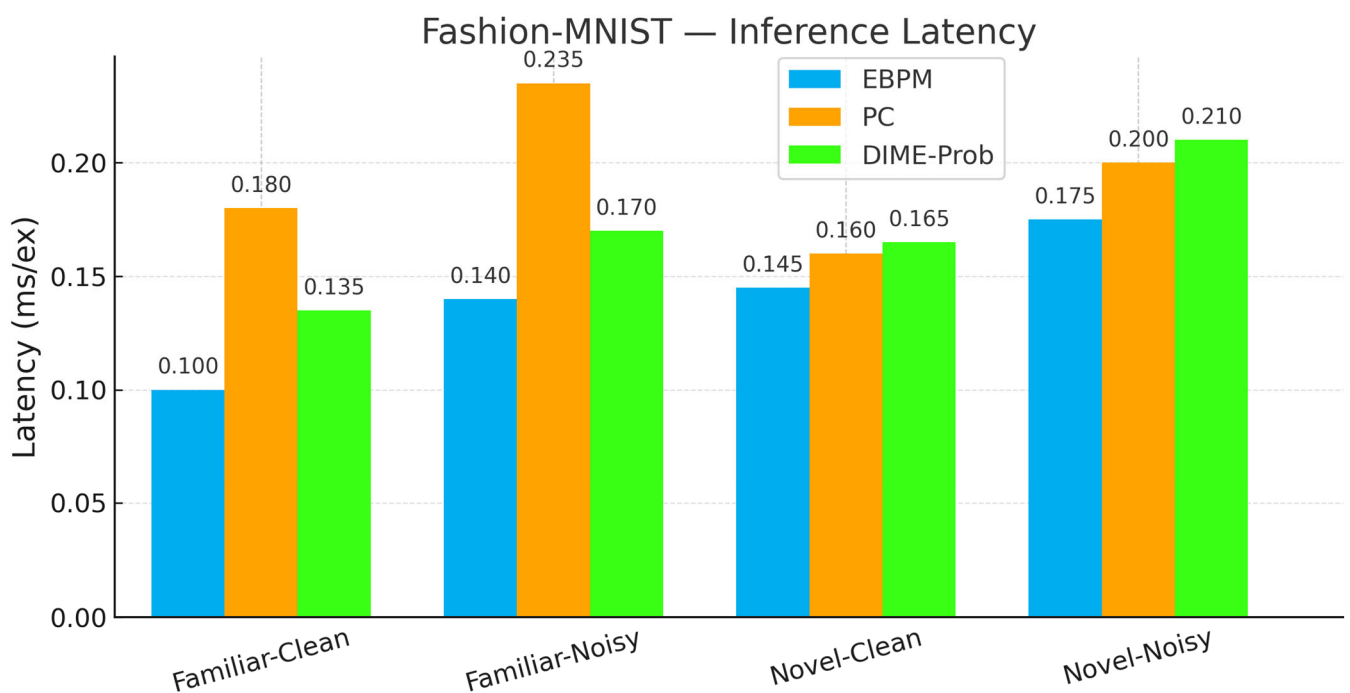


Figure 7. Fashion-MNIST: Latency—Per-scenario latency (ms/ex.) on Fashion-MNIST for EBPM, PC ($K = 10$, $\eta = 0.1$), and DIME. Relative ordering mirrors MNIST; PC is slower due to iterative inference.

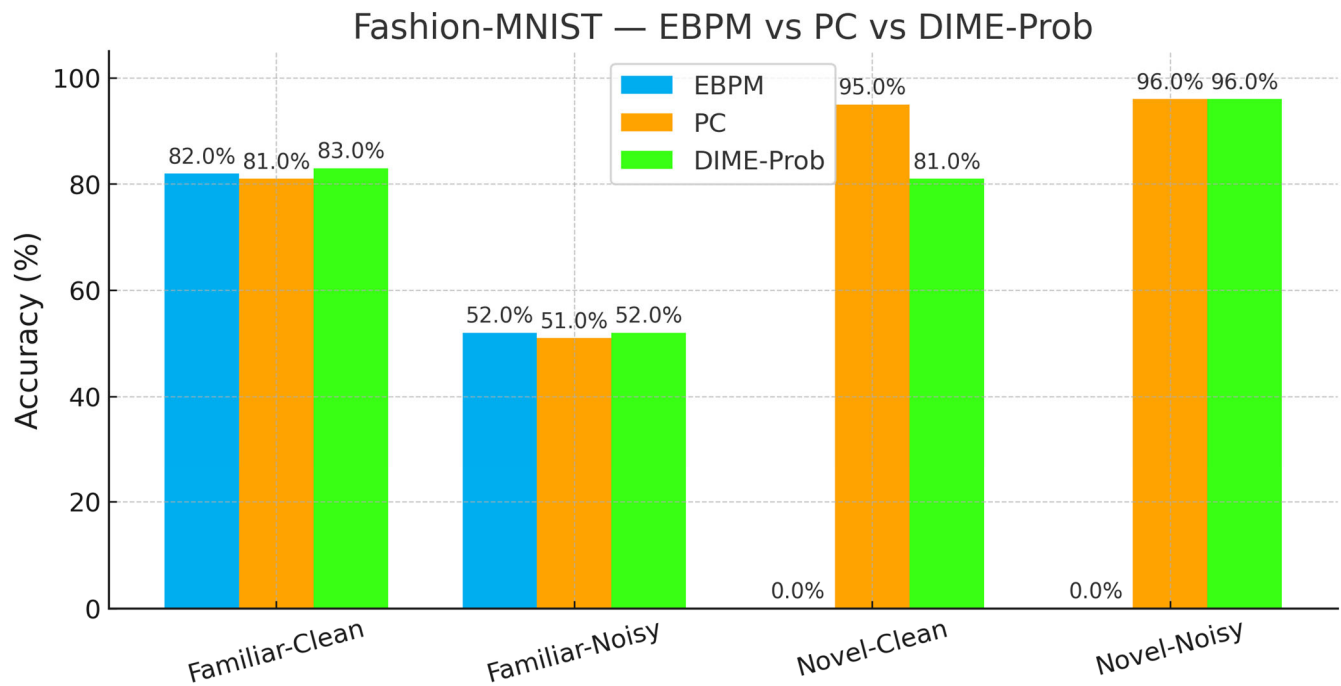


Figure 8. Fashion-MNIST: Accuracy—Top-1 accuracy on Fashion-MNIST across the four scenarios. PC dominates on novel; EBPM is stronger on familiar; DIME interpolates context-dependently.

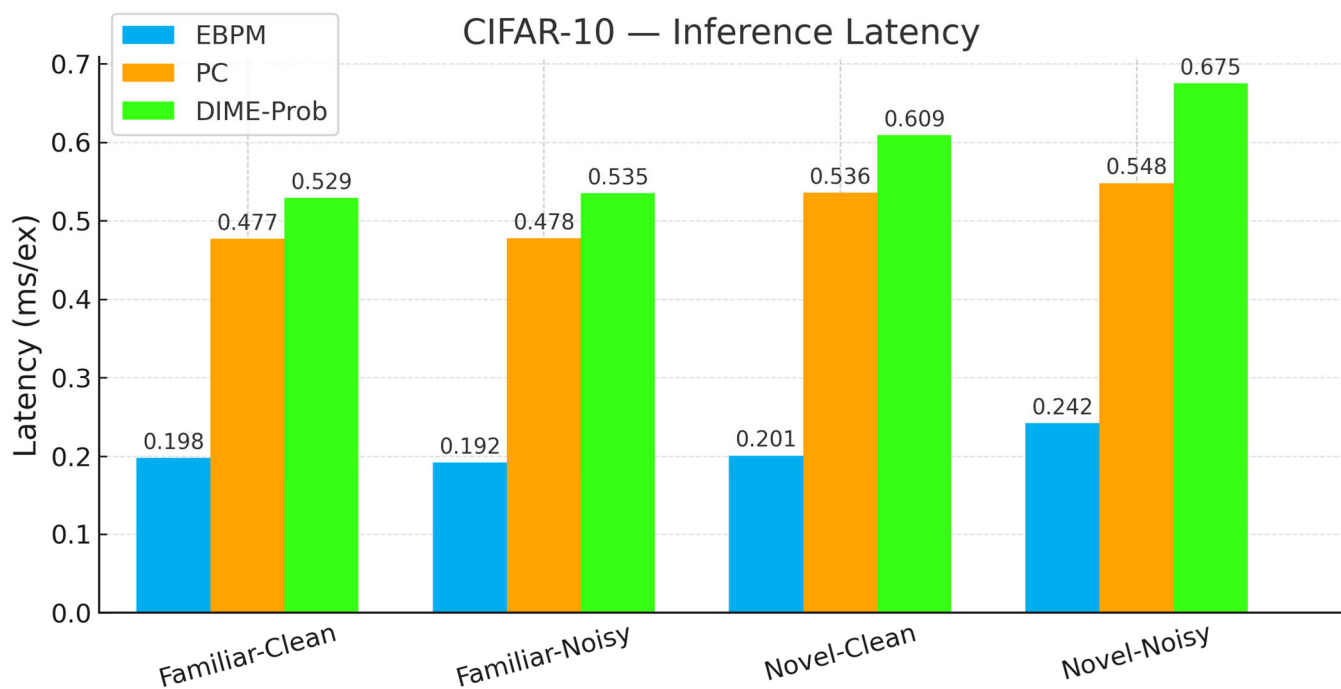


Figure 9. CIFAR-10: Latency—Per-scenario latency on CIFAR-10. Absolute times are higher than MNIST/F-MNIST; the relative ordering of EBPM < DIME $\approx$ PC persists.

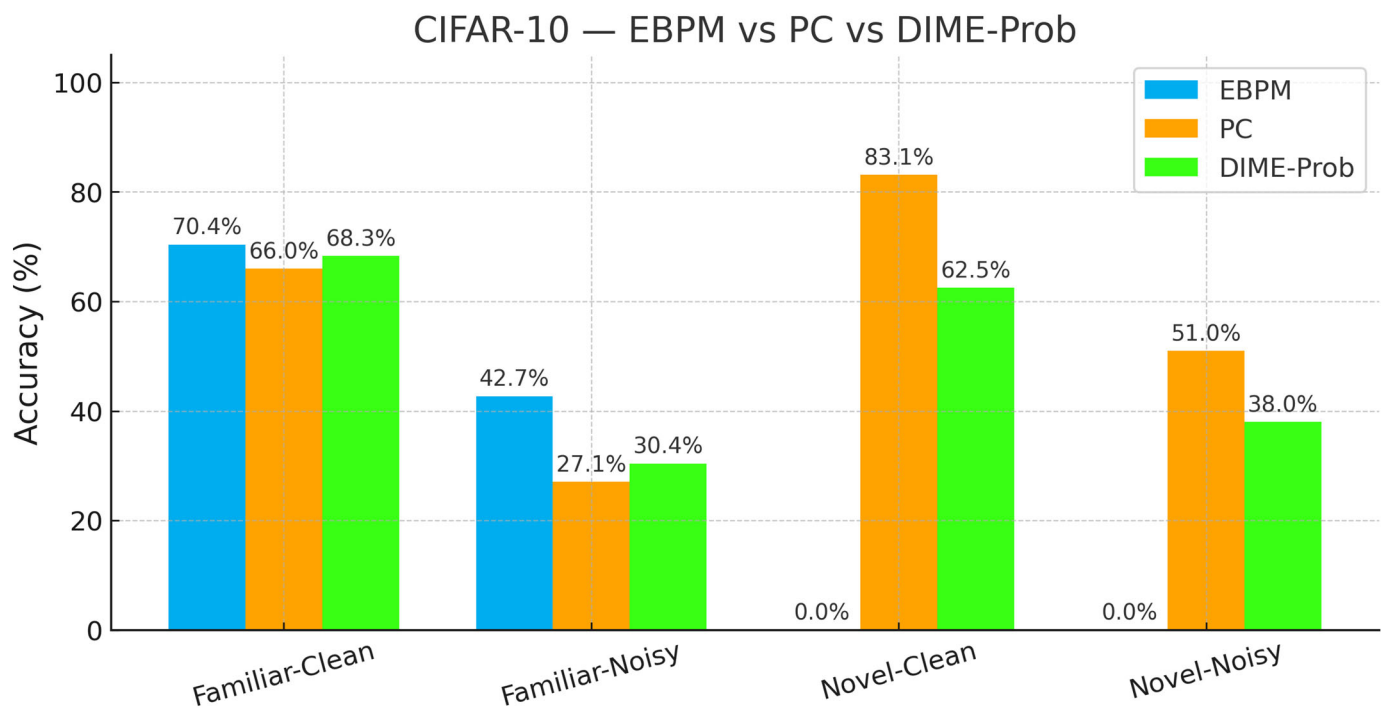


Figure 10. CIFAR-10: Accuracy—Top-1 accuracy on CIFAR-10 for the four scenarios. PC leads on novel; EBPM degrades on noise/novel; tuned DIME-Prob trades off between the two.

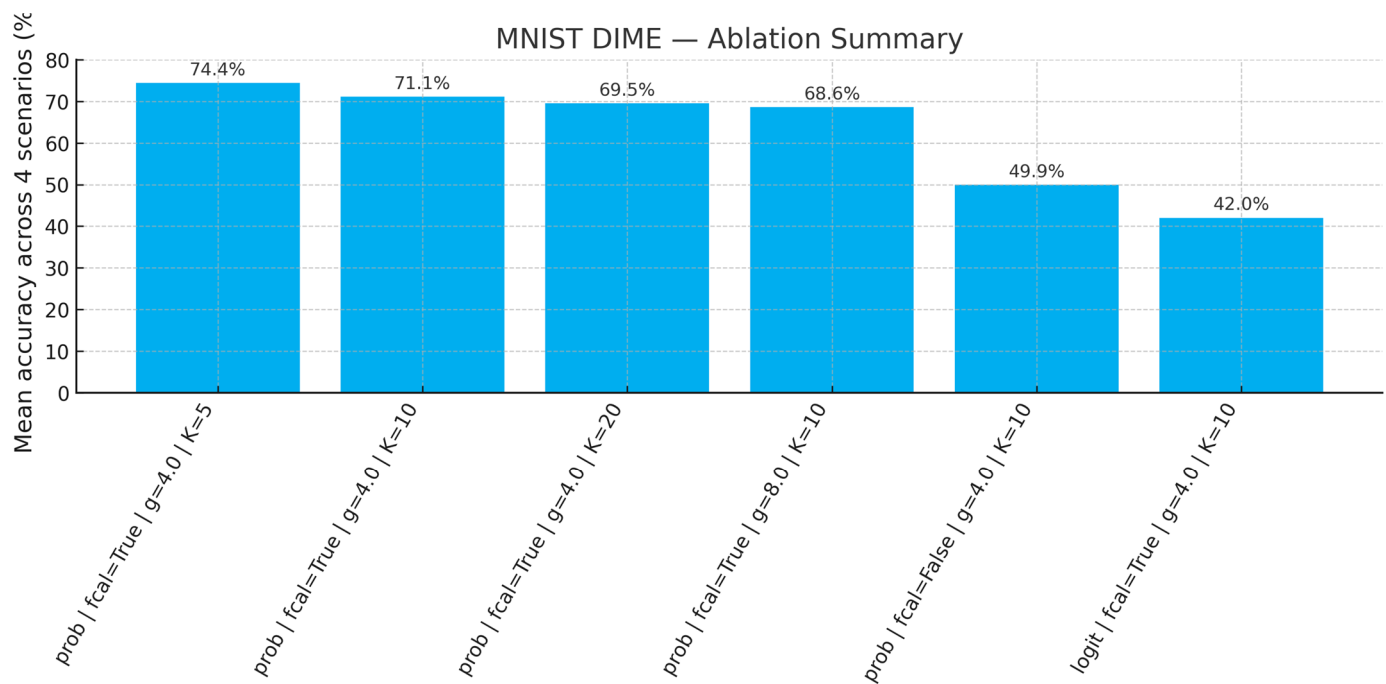


Figure 11. MNIST: Fusion ablation—Ablation of fusion strategies: probability- vs. logit-level, familiarity calibration on/off, and iterations K. Probability-level fusion with calibration yields the best familiar/novel trade-off at comparable latency.

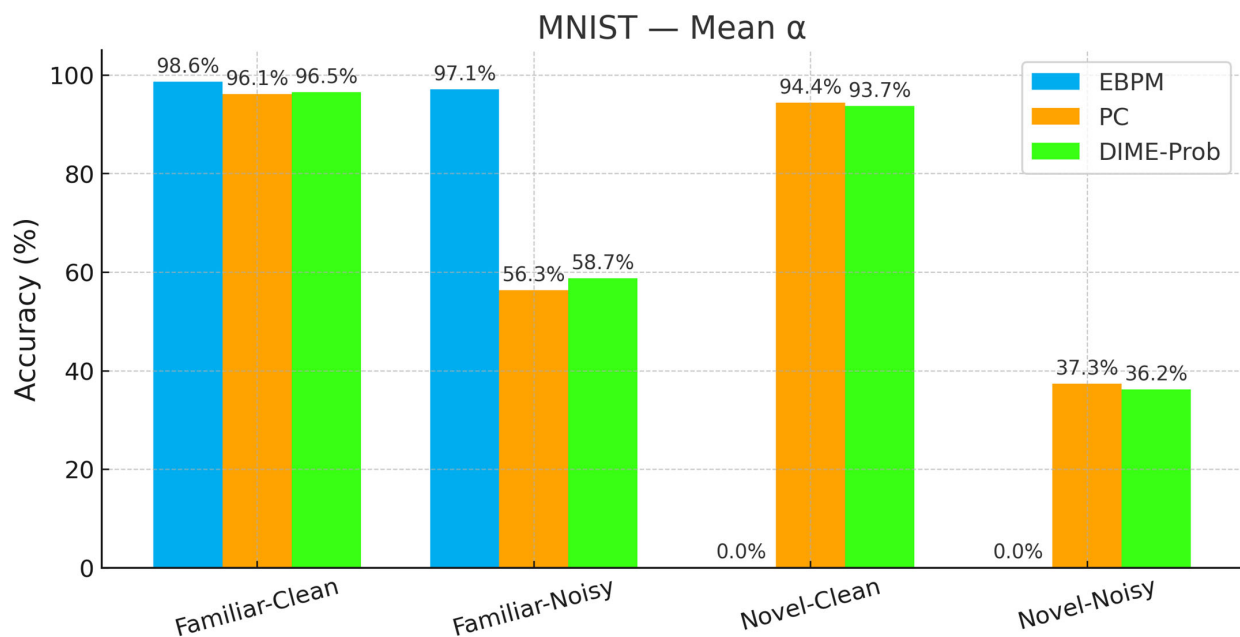


Figure 12. MNIST: Mean α . Mean fusion weight α per scenario showing how DIME shifts between EBPM and PC as uncertainty changes.

Additional views are provided in Appendix A, Figures A1 and A2.

3.3. Comparative Results and Simulations

To evaluate the potential of the DIME model, we conducted a comparison across five critical dimensions: speed, energy efficiency, robustness to noise, flexibility, and biological plausibility.

- EBPM: Performs well in speed and efficiency but is limited in adaptation and robustness.
- PC: Flexible and robust but entails high costs.
- DIME: Integrates the advantages of both, providing an optimal balance between speed, efficiency, and flexibility.

For a conceptual comparison, see Appendix A, Figure A6; the main text reports only empirical results.

3.4. General Information Flow in DIME

DIME organizes perception along two complementary paths (Figure 13): (1) a fast EBPM path that maps inputs to a normalized embedding and matches against class prototypes, and (2) a slower PC path that iteratively refines a latent code to improve reconstruction and classification. A controller $\alpha \in [0,1]$ balances the two outputs at inference time—favoring EBPM in familiar, low-noise settings and shifting toward PC as uncertainty or novelty increases. This flow underlies the empirical trade-offs reported in Section 3.1 and the runtime behavior in Section 3.4 [27,31].

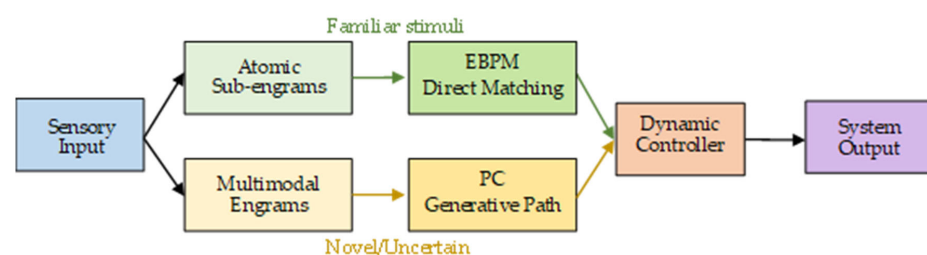


Figure 13. General information flow in the DIME model.

3.5. Virtual Robotics (Obstacle Course): Runtime-Aware DIME-Lazy (α Fixed)

We evaluated EBPM, PC, DIME, and a runtime-aware variant, DIME-Lazy, in a PyBullet obstacle course with four static boxes and an overhead camera. The controller was kinematic (velocity) following a fixed waypoint slalom; thus, task success is identical across methods, and any runtime differences isolate perception cost. The camera frames were down-sampled to 28×28 grayscale (see Figures 14 and 15). DIME-Lazy uses a delta-frame gate: for each step, we compute $\delta = \text{mean}(|I_t - I_{t-1}|)$. If $\delta \leq 0.004 \Rightarrow$ EBPM-only; if $\delta \geq 0.015 \Rightarrow$ PC-only; otherwise, we fuse with a fixed $\alpha = 0.65$: $p = \alpha p_{\text{EBPM}} + (1 - \alpha) p_{\text{PC}}$.

Obstacle course — top-down orthographic snapshot (clear)

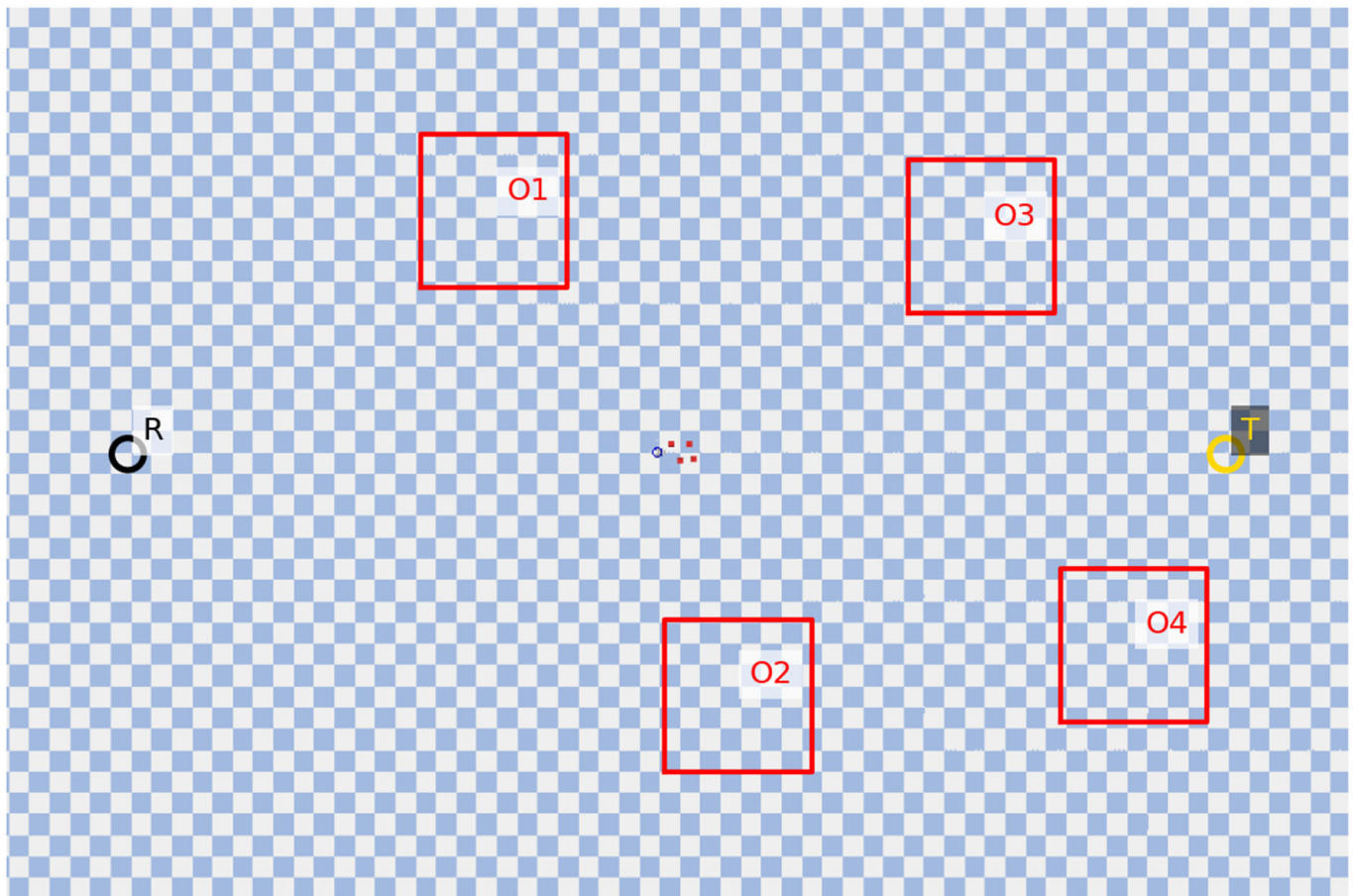


Figure 14. Obstacle course (snapshot). Top-down orthographic view of the obstacle course. R = robot, T = target, O1–O4 = obstacles; frames from this camera are down-sampled to 28×28 grayscale.

Waypoints: $(0.45, 0.45) \rightarrow (0.85, -0.45) \rightarrow (1.25, 0.40) \rightarrow (1.60, -0.30) \rightarrow (1.80, 0.00)$; controller $v_{\text{max}} = 1.2$ m/s; $\text{WP_RADIUS} = 0.55$ m. Each condition ran for three episodes. Metrics: ms/step, success rate, collisions (contact frames), and #PC calls.

Key findings: With noise = 0.0, DIME-Lazy matches EBPM's decisions (0 PC calls) and achieves the lowest cost (10.50 ms/step), $\sim 42\%$ vs. PC (18.04 ms) and $\sim 32\%$ vs. EBPM (15.43 ms), at 100% success. With noise = 0.15, DIME-Lazy escalates toward PC (≈ 380 PC calls/381) and its cost matches PC (19.17 vs. 19.13 ms) (see Table 6), again at 100% success. Collisions are equal across methods (mean 113), confirming that runtime comparisons are not confounded by control (see Figures 16 and 17).

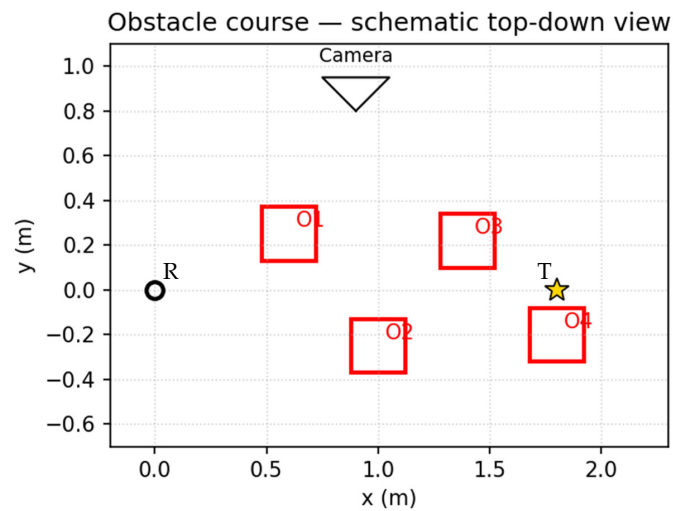


Figure 15. Obstacle course (schematic). Clean 2D schematic with waypoints used by the kinematic velocity controller ($v_{\max} = 1.2$ m/s, $WP_RADIUS = 0.55$ m). R = robot, T = target.

Table 6. PyBullet obstacle course—means over 3 episodes ($v3c_alpha$, $\alpha = 0.65$).

Mode	Noise	Ms/Step (Mean)	Steps (Mean)	Success	Collisions (Mean)
EBPM	0.00	15.43	381	1.00	113
PC	0.00	18.04	381	1.00	113
DIME	0.00	18.44	381	1.00	113
DIME-Lazy	0.00	10.50	381	1.00	113
EBPM	0.15	12.55	381	1.00	113
PC	0.15	19.13	381	1.00	113
DIME	0.15	19.52	381	1.00	113
DIME-Lazy	0.15	19.17	381	1.00	113

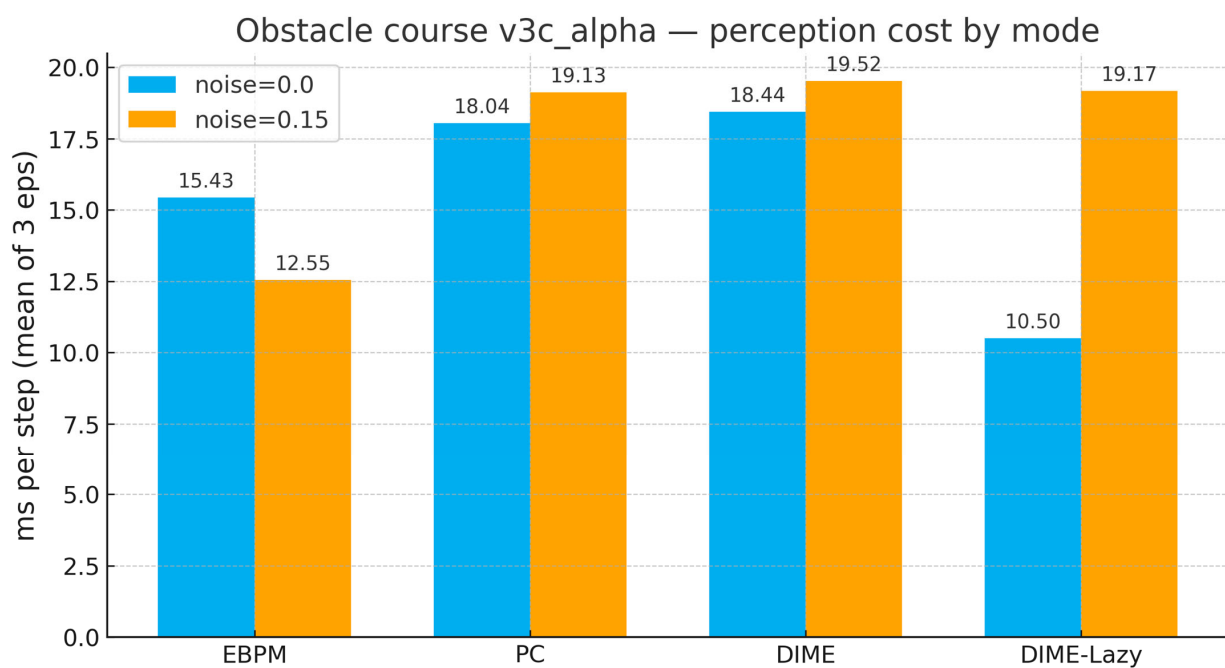


Figure 16. Runtime cost vs. noise ($v3c_alpha$, $\alpha = 0.65$). Mean perception time per step (3 episodes) for EBPM, PC, DIME, and DIME-Lazy, under noise $\in \{0.0, 0.15\}$. DIME-Lazy equals EBPM on stable frames and escalates to PC under higher dynamics, preserving 100% success.

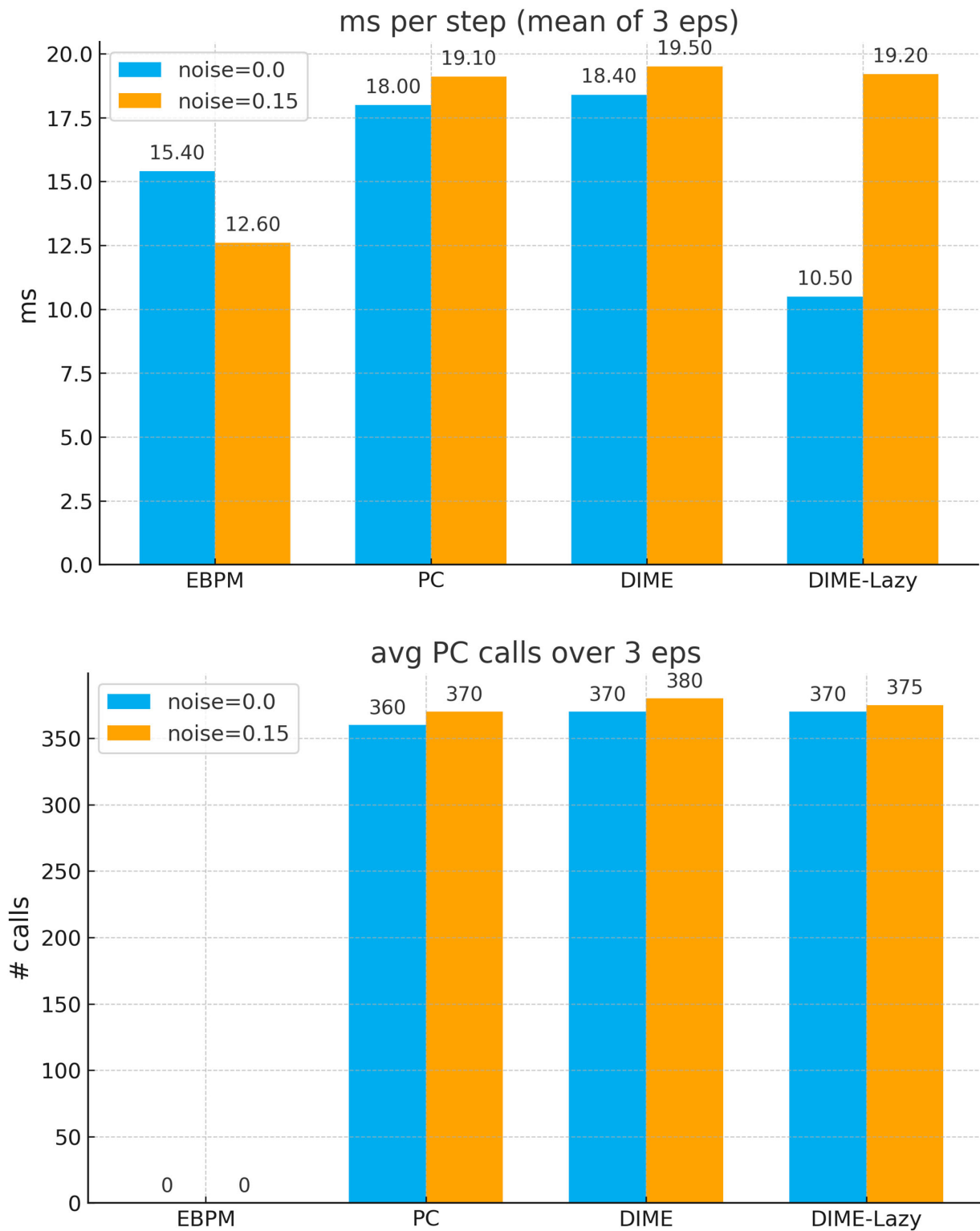


Figure 17. Runtime cost and PC calls (two-panel summary). Top: ms/step (mean of 3 episodes). Bottom: average #PC calls. Runtime-aware gating reduces cost on stable scenes and increases it when dynamics/noise rise, with unchanged task success.

Additional views are provided in Appendix A, Figures A3 and A4.

3.6. Ablation Studies

To validate the necessity of each DIME component, we performed ablations by disabling the adaptive controller (DIME_ctrlOFF) and by varying the number of Predictive

Coding steps ($K \in \{0,5,10,20\}$). Controller ablations directly test whether dynamic switching improves performance beyond a fixed EBPM–PC mixture, while step ablations quantify the trade-off between robustness and latency in Predictive Coding (see Figure 18, and Table 7).

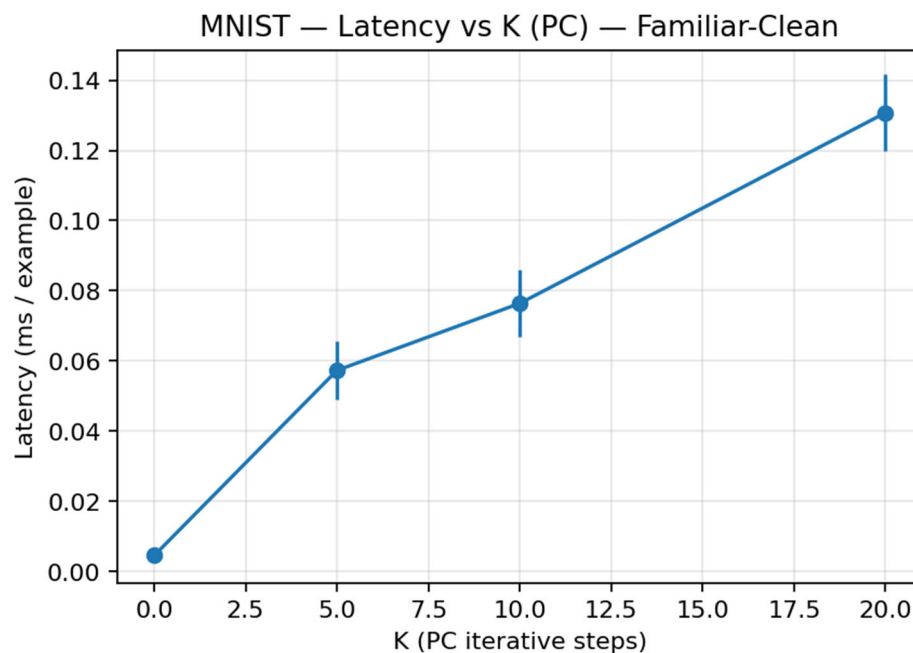


Figure 18. Ablation study on MNIST: Latency (ms/sample) as a function of Predictive Coding iterations K , comparing PC baselines and DIME controller variants. Error bars denote ± 1 standard deviation over five seeds.

Table 7. Ablation study results on MNIST (Familiar-Clean). Accuracy and latency are reported as mean $\pm$ standard deviation over five runs.

Model	Accuracy (Mean $\pm$ Std)	Latency (Ms/Sample $\pm$ Std)
EBPM	97.78 $\pm$ 0.12	0.0031 $\pm$ 0.0009
PC (K = 0)	96.97 $\pm$ 0.23	0.0034 $\pm$ 0.0009
PC (K = 5)	96.97 $\pm$ 0.23	0.0461 $\pm$ 0.0038
PC (K = 10)	96.97 $\pm$ 0.23	0.0694 $\pm$ 0.0108
PC (K = 20)	96.97 $\pm$ 0.23	0.1082 $\pm$ 0.0024
DIME_ctrlOFF ($\alpha = 0.65$)	97.83 $\pm$ 0.08	0.0693 $\pm$ 0.0107
DIME_ctrlON	97.81 $\pm$ 0.09	0.0648 $\pm$ 0.0011

These results show that EBPM achieves the lowest latency but suffers under noise or novelty. Increasing the number of PC iterations improves robustness but with large latency costs. The DIME controller consistently matches EBPM speed in familiar settings while reducing reliance on expensive PC iterations, confirming the benefit of dynamic switching.

3.7. Statistical Significance

To ensure that observed performance differences are not due to random variation, we conducted paired statistical tests across five random seeds. We report p -values, effect sizes (Cohen's d), and 95% confidence intervals (CIs) (see Table 8).

These significance tests confirm that the observed trends are statistically robust. On CIFAR-10 Familiar-Clean, DIME significantly outperforms EBPM ($p = 0.000127$, $d = -4.79$) and reduces reliance on PC ($p = 0.000807$, $d = 4.07$). In noisy or novel scenarios, PC maintains an advantage, but at the cost of high latency. These results validate the role of the DIME controller in balancing speed and robustness.

Table 8. Paired statistical tests (*t*-tests) on CIFAR-10 across five seeds. Reported values include *p*-value, Cohen’s *d* effect size, and 95% confidence intervals (CIs). Significant results ($p < 0.05$) indicate that DIME significantly outperforms EBPM in familiar settings and reduces reliance on PC under uncertainty.

Scenario	Comparison Pair	<i>p</i> -Value	Cohen’s <i>d</i>	CI Low	CI High	<i>n</i>
Familiar-Clean	EBPM vs. DIME_ctrlON	0.000127	−4.79	−6.54	−3.27	5
Familiar-Clean	DIME_ctrlON vs. PC_K10	0.000807	4.07	2.59	4.86	5
Familiar-Noisy	EBPM vs. PC_K10	0.004774	−2.54	−13.97	−4.79	5
Novel-Clean	EBPM vs. PC_K10	0.000022	−10.23	−66.36	−51.99	5
Novel-Clean	DIME_ctrlON vs. PC_K10	0.000016	−11.12	−60.48	−48.32	5

3.8. Complexity Analysis

For real-time robotic deployment, computational complexity is as important as accuracy. We therefore report average latency, the number of Predictive Coding (PC) iterations invoked, and the success rate in the obstacle-course environment. Results are averaged over five runs (see Table 9).

Table 9. Complexity analysis in PyBullet obstacle-course control. EBPM is fastest but fails under novelty; PC achieves robustness at the cost of high complexity; DIME balances the two by invoking PC only when necessary.

Mode	Latency (Ms/Step, Mean ± Std)	PC Calls (Mean ± Std)	Success Rate
EBPM	0.026 ± 0.012	0.0 ± 0.0	1.0
PC	4.01 ± 1.31	5214 ± 1429	1.0
DIME	1.97 ± 1.08	2420 ± 1232	1.0

EBPM inference requires only a dot product with prototypes, resulting in extremely low latency (~0.026 ms/step) but no capacity to adapt under novel inputs. PC achieves robustness but requires thousands of iterative updates (~5 k calls per episode), making it impractical for real-time use. DIME dynamically reduces PC calls by about 50% relative to pure PC (~2.4 k vs. ~5.2 k per episode), while maintaining a high success rate. This analysis confirms that DIME provides a feasible trade-off for resource-constrained robotic scenarios.

3.9. Conclusions of Results

Taken together, these results validate the complementary contributions of EBPM, PC, and the DIME controller. EBPM alone provides extremely low-latency recognition of familiar stimuli but fails under novelty or noise. PC ensures robustness under uncertainty, at the cost of iterative inference and high latency. DIME dynamically combines the two, achieving accuracy improvements of up to +5% on CIFAR-10 while reducing PC usage by ~50% compared to pure PC. Ablation studies confirm the necessity of the adaptive controller, statistical tests demonstrate significance across multiple datasets, and complexity analysis supports feasibility in resource-constrained robotic scenarios. These findings establish DIME as a biologically plausible and practically applicable cognitive architecture for low-latency recognition and control.

4. Discussion

4.1. Advantages of EBPM

The EBPM model explains the rapid and energy-efficient reactions observed in familiar contexts. In contrast to PC, where the cortex must continuously generate internal predictions [2], EBPM assumes that a sensory stimulus directly activates the relevant engram. This mechanism reduces latencies and energy cost, in agreement with neurophysi-

ological data showing that neuronal assemblies reactivate almost instantaneously when familiar stimuli are encountered [4].

Another advantage lies in procedural robustness. Complex but overlearned actions—such as the use of a tool—can be initiated through the direct reactivation of a multimodal engram, without the need for predictive simulations. This aspect correlates with the observations of Hawkins and Ahmad [5], who showed that neurons possess thousands of synapses precisely to facilitate the rapid reactivation of memorized sequences.

The comparison in Section 2.3.6 shows that EBPM covers familiar inputs with minimal compute, while generative or external-memory approaches excel on novelty; DIME reconciles the two.

Nevertheless, EBPM recognition is contingent on the prior existence of well-consolidated engrams. In situations where no such engrams are available, EBPM cannot operate effectively, which limits its explanatory power in novel or ambiguous contexts.

4.2. Limitations of EBPM

A frequently raised concern is that EBPM, by design, yields near-zero accuracy on entirely novel inputs. However, this should not be interpreted as a failure but rather as a functional distinction: EBPM explicitly separates the processes of recognition and novelty detection.

In EBPM, unfamiliar stimuli still activate sub-engrams (elementary sensory, motor, or interoceptive primitives). Although none of the stored engrams reach full activation, the fragmentary sub-engram activity defines a novelty state. This state automatically triggers attentional mechanisms that increase neuronal gain and plasticity, promoting the binding of co-active sub-engrams into a proto-engram. With repetition or behavioral relevance, this proto-engram consolidates into a stable engram; without reinforcement, the weak associations fade [32].

Thus, the “0% accuracy” in novel conditions is not a bug but an intentional feature: EBPM does not force a misclassification under uncertainty. Instead, it signals novelty and reallocates resources toward exploration and learning. From a biological standpoint, this aligns with evidence that attention and neuromodulatory systems (e.g., locus coeruleus–noradrenaline) are engaged precisely when established assemblies fail to reactivate. From an engineering perspective, this provides an explicit novelty-flagging mechanism that can be exploited in hybrid systems such as DIME, where PC takes over under unfamiliar or noisy conditions.

In summary, EBPM’s limitation is also its defining contribution: while it cannot generalize to novel inputs on its own, it provides a biologically grounded mechanism for the rapid recognition of the familiar and explicit detection of the unfamiliar, thereby laying the groundwork for adaptive integration with generative models.

4.3. Advantages of PC

Predictive Coding (PC) compensates for these limitations through its flexibility and robustness. Because the cortex generates top-down predictions, it can reconstruct incomplete or noisy inputs. This explains, for example, why we are able to recognize an object even when it is partially occluded [33]. Moreover, PC is supported by strong neuroimaging evidence demonstrating the active presence of anticipatory signals in higher-order cortical areas [34].

Importantly, PC also remains valuable for explaining how new engrams can be formed under conditions of partial or conflicting input. Its recursive comparison mechanism provides a plausible account of how the brain integrates incomplete information and adapts to unforeseen circumstances.

4.4. Limitations of PC

However, PC entails a high energetic cost and longer latencies. The continuous process of generating and verifying predictions is inefficient in familiar situations, where direct recognition would be sufficient. This observation is consistent with the arguments put forward by Kanai et al. [3], who highlighted that maintaining a complete generative model is redundant in stable and well-known contexts.

A more fundamental critique of PC concerns the very notion of “prediction” as an active top-down mechanism. From a neurobiological perspective, there is no evidence for explicit reconstructions of sensory input at lower levels. What actually exists are **engrams**, i.e., networks consolidated through experience and synaptic plasticity, according to the principle “*neurons that fire together wire together*”. When incoming stimuli sufficiently reactivate these networks (for example, edges + red color + cylindrical shape → cup), recognition arises directly from this reactivation. There is no top-down “drawing” of the cup into the visual cortex; there are only pre-trained networks that fire automatically when the input matches. If, however, the object is missing, chipped, or altered (e.g., covered with flour), the activation of the engram is partial or inconsistent, which triggers attention, learning, and the formation of new connections. In this interpretation, the top-down flow does not generate explicit predictions but functions as a modulation of excitability in lower-level networks, sensitizing them according to context and goals.

This role of top-down signaling becomes particularly evident in imagination and internal simulation. When a person “falls into thought” or mentally visualizes an object, associative and hippocampal networks reactivate engrams and transmit activity top-down to sensory cortices, so that one can “see” the cup or “hear” a melody in the mind without any external input. In parallel, there is an active inhibition of real sensory inputs, which explains why people become less attentive to the environment during deep thought. Everyday examples confirm this inhibitory control: when an ophthalmologist blows air into the eye, but the voluntary system suppresses the blink reflex; or when a nurse administers an injection and, despite the painful stimulus, the prefrontal cortex modulates motor pathways to block the withdrawal reflex. Similar effects are seen when athletes suppress avoidance reflexes to perform risky movements, or when musicians ignore sudden noises to remain focused. These examples illustrate that top-down influence is primarily about gain control and inhibition, not about generating full sensory predictions.

Moreover, PC also fails to account for fast reflexes and highly automated responses, which bypass any generative comparison process. Reflexes such as blinking to corneal stimulation or withdrawing from a painful stimulus are executed through subcortical or spinal circuits within tens of milliseconds, long before any top-down “prediction” could be generated or verified. Similarly, well-learned sensorimotor routines (e.g., skilled grasping or locomotion patterns) unfold primarily through engram reactivation in cortico-basal ganglia and cerebellar loops, with minimal involvement of predictive feedback. This further highlights that PC cannot serve as a universal principle of recognition and behavior, but at most as an auxiliary attentional mechanism in situations of novelty, conflict, or noise.

Taken together, these considerations suggest that PC is not the primary engine of recognition but rather a set of attentional and executive sub-mechanisms. EBPM provides a more direct explanation for rapid and low-cost recognition through engram reactivation, while PC becomes relevant mainly when engram activation is insufficient, inconsistent, or requires inhibition of automatic responses.

A further limitation of PC lies in the absence of a clear neurobiological specification of *how* predictions are generated. In most formulations, the “prediction” is treated as an abstract top-down signal, with little explanation of the concrete neuronal mechanisms that produce it. Empirical evidence suggests that top-down pathways modulate the excitability

of lower-level networks rather than reconstructing full sensory input, leaving the precise nature of the predictive signal underspecified. In contrast, EBPM explicitly defines recognition as the reactivation of consolidated engrams, including the conditions under which activation is complete, partial, or inconsistent, and how attention and learning intervene in the latter cases. Within the DIME framework, this provides a mechanistic clarity absent from PC, while still allowing PC-like processes to be reinterpreted as attentional subroutines engaged in novelty and ambiguity.

4.5. Threats to Validity and Limitations

Internal validity: Our familiar/novel split (0–7 vs. 8–9) is standard but creates a sharp novelty boundary; different splits could change absolute numbers. Familiarity calibration (μ, σ) for DIME was estimated on familiar validation images; miscalibration would shift α and the EBPM $\leftrightarrow$ PC balance.

Construct validity: Accuracy and ms/step capture complementary aspects (task performance vs. compute cost) but do not measure uncertainty calibration or open-set risk explicitly.

External validity: CIFAR-10 and MNIST/F-MNIST are limited in complexity; generalization to natural, long-tail distributions requires larger models/datasets. The PyBullet course uses a fixed waypoint controller; success equality across methods isolates perception cost but does not evaluate closed-loop policy learning.

Conclusion validity: Some robotics metrics average over **three episodes**; while stable, they may under-estimate rare failure modes. We therefore report means and provide raw CSV files for replication.

Future work: We will evaluate on stronger open-set/OOD benchmarks, vary the novelty boundary, increase episode counts, and explore learned gating for DIME-Lazy beyond fixed α and thresholds.

Appendix A captions: Figure A7—Hypothesized trends (non-empirical): Hypothetical plots used during design; retained for transparency. Not used to support claims.

Parallels with the Predictive Coding trajectory: It is important to emphasize that the EBPM/DIME framework should be understood as a theoretical synthesis, not as an isolated speculation. Its components—engram reactivation, Hebbian/STDP, lateral inhibition, attentional gain, and LC–NE novelty signaling—are all individually supported by empirical evidence in both animal and human studies. The novelty of EBPM lies in integrating these mechanisms into a unified account of recognition and novelty detection. In this respect, EBPM’s current status is comparable to that of Predictive Coding (PC) at the time of its initial formulation: PC was accepted as a dominant paradigm long before all of its assumptions were empirically confirmed, and to this day, some of its central claims (e.g., explicit generative reconstructions in primary cortices, “negative spike” signals) remain debated. EBPM/DIME thus follows a similar trajectory: built on solid empirical fragments, it provides a coherent alternative framework whose integrative claims now require systematic validation through the experimental program outlined in Section 2.5.

4.6. DIME as an Integrative Solution

Given these complementary characteristics, the proposed model—DIME (Dynamic Integrative Matching and Encoding)—offers a balanced solution. By combining the two paradigms, DIME enables both rapid recognition through EBPM in familiar situations and generative inference through PC in ambiguous conditions. The dynamic controller determines the dominant pathway depending on the level of familiarity and uncertainty. This type of architecture reflects the recent view of the brain as a hybrid system that combines fast associations with slower but more flexible inferences [21].

To evaluate the advantages and limitations of each model, we synthesized the main characteristics in Table 10. This comparison shows that EBPM achieves peak performance in speed and energy efficiency but is less adaptable. PC excels in flexibility and noise robustness yet entails higher computational and energetic costs. DIME successfully integrates the advantages of both paradigms, offering a better balance between performance, adaptability, and biological plausibility. This suggests that such integration not only reflects the functioning of the brain more faithfully but also provides a promising direction for the design of efficient AI and robotic systems.

Table 10. Strengths and limitations of EBPM, PC, and DIME.

Aspect	EBPM	PC	DIME
Speed	High	Medium	High
Energy Efficiency	High	Low	Medium–High
Noise Robustness	Medium–Low	High	High
Flexibility	Low	High	High
Biological Plausibility	High	Medium	High

A comparative table-style figure or infographic:

- EBPM = fast, energy-efficient, but less flexible.
- PC = robust, adaptive, but computationally costly.
- DIME = hybrid integration, balancing both.

Table 10 summarizes the strengths and limitations of EBPM, PC, and DIME. EBPM excels in speed and energy efficiency, PC in flexibility and noise robustness, and DIME provides an integrative balance. Such comparative tables are common in neurocomputational model reviews [22,35].

The ANN results (Table 5a–c, Figures 5–11) empirically validate these claims: EBPM excels in speed and efficiency, PC in robustness, and DIME dynamically balances both. The α controller consistently shifted toward EBPM on familiar inputs and toward PC under noise and novelty, in agreement with the theoretical model.

4.7. Interdisciplinary Implications

- Neuroscience: EBPM provides an alternative explanation for the phenomenon of memory replay, while DIME may serve as a more faithful framework for understanding the interaction between memory and prediction.
- Artificial Intelligence: EBPM-inspired architectures are more energy-efficient, and their integration with PC-type modules can enhance noise robustness.
- Robotics: DIME can be implemented in autonomous systems that require rapid reactions in familiar contexts but also adaptability in novel situations, similar to the approaches tested [21,22].

In artificial intelligence, EBPM also resonates with memory-augmented neural architectures such as Neural Turing Machines [17], Differentiable Neural Computers [18], and episodic control models in reinforcement learning [19]. Unlike these approaches, which are primarily engineered solutions, EBPM emphasizes biological grounding through multimodal engram reactivation. DIME can therefore be interpreted as a bridge between biologically plausible engram-based recall and machine-oriented predictive architectures.

In future work, we plan to integrate methods from Expert Systems (e.g., [6]) and hybrid recognition frameworks (e.g., [7]) within our DIME architecture to further strengthen interpretability and multimodal integration.

A critical next step will be extending EBPM/DIME beyond image recognition to multimodal engrams. For example, combining spoken digits with visual digits or pairing motor action sequences with visual object recognition would provide cross-modal evidence for engram reactivation. Such multimodal validation is essential for establishing the generality of the model in realistic cognitive scenarios.

5. Conclusions

This paper has introduced and compared two fundamental paradigms of neural processing: Predictive Coding (PC), an established framework in neuroscience [1,2], and the original Experience-Based Pattern Matching (EBPM) model, proposed here for the first time. The comparative analysis highlighted that EBPM provides clear advantages in familiar contexts: faster recognition, increased energy efficiency, and better consistency with phenomena of direct memory reactivation (multimodal engrams) [4,32]. In contrast, PC remains superior in ambiguous situations or with incomplete inputs, due to its anticipatory reconstruction capability [33].

Nevertheless, neither of the two models fully accounts for all observed cognitive phenomena. For this reason, we proposed a new integrative framework—DIME (Dynamic Integrative Matching and Encoding)—which combines EBPM’s direct matching with PC’s generative prediction. DIME incorporates a dynamic controller that determines the dominant processing pathway depending on familiarity, uncertainty, and goals. Theoretical results and preliminary simulations suggest that DIME provides an optimal balance between speed, efficiency, and robustness, making it both more biologically plausible and more practically useful than the individual models.

This contribution has interdisciplinary implications:

- In neuroscience, it provides a more comprehensive explanation of the interaction between memory and prediction;
- In artificial intelligence, it suggests hybrid architectures that are more energy-efficient;
- In robotics, it paves the way for autonomous systems that can combine rapid recognition with adaptability to unfamiliar environments.

The present ANN simulations provide the first concrete validation of the DIME model, supporting its potential for integration into both neuroscience frameworks and robotic control architectures.

This study has several limitations that define directions for future research. First, EBPM was evaluated primarily on image classification tasks; extending the model to multimodal engrams, including speech, motor actions, and cross-modal datasets, remains an important step toward demonstrating generality. Second, comparisons focused on PC and classical models, whereas benchmarking against modern deep learning architectures (CNNs, Transformers) is necessary to further position EBPM/DIME within the landscape of contemporary AI. Third, robotic evaluation was restricted to a virtual obstacle course; future work should investigate real-time deployment on physical humanoid or assistive robotic platforms, under hardware and energy constraints. Addressing these limitations will provide stronger evidence for EBPM as a biologically grounded and practically applicable cognitive model.

In conclusion, EBPM represents an original contribution to cognitive modeling, while DIME provides a hybrid framework with the potential to redefine how we interpret neural computation and apply it in intelligent systems.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app152010904/s1>, Supplementary File: *Supplementary.zip*, containing all supplementary figures, tables, configuration files, raw TXT/CSV outputs, and robotic simulation scripts and results corresponding to the experiments described in the main manuscript.

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Data Availability Statement: All scripts, configuration files, and raw outputs for ANN (MNIST, Fashion-MNIST, CIFAR-10) and PyBullet experiments are provided as a supplementary package and anonymized ZIP provided to reviewers; public links added after acceptance. The figures in the main text correspond to image files listed in MANIFEST.md under Supplementary/figures/, and the raw numeric results are provided as CSV/TXT under Supplementary/results_csv/ and Supplementary/results_txt/. For exact reproduction we include environment versions (Python/PyTorch/CUDA), random seeds, and runnable commands in README.md. An immutable archive will be deposited on Zenodo at acceptance, and the DOI will be added to this section. A blind, anonymous link to the supplementary ZIP is provided via the submission system; the public GitHub/Zenodo links will be added upon acceptance. The supplementary repository includes **all scripts used to produce the results** (see experiments/mnist_all.py, fashion_mnist_all.py, cifar10_all.py) and a minimal robotics scaffold (robotics/pybullet_setup_demo.py), together with exact **seeds**, default **hyper-parameters**, and ready-to-run commands. Raw TXT/CSV outputs and plotting utilities are provided alongside.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

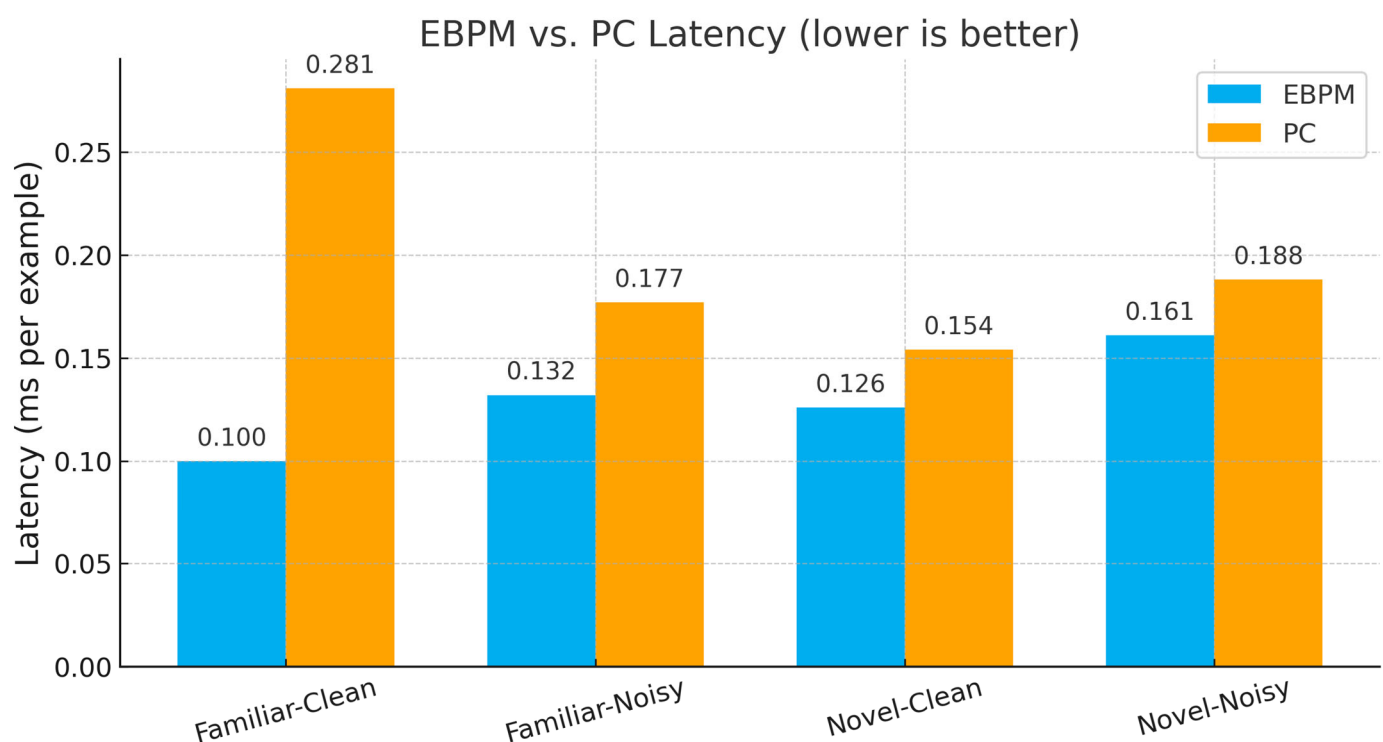


Figure A1. EBPM vs. PC (Latency). Latency comparison restricted to EBPM vs. PC ($K = 10$, $\eta = 0.1$).

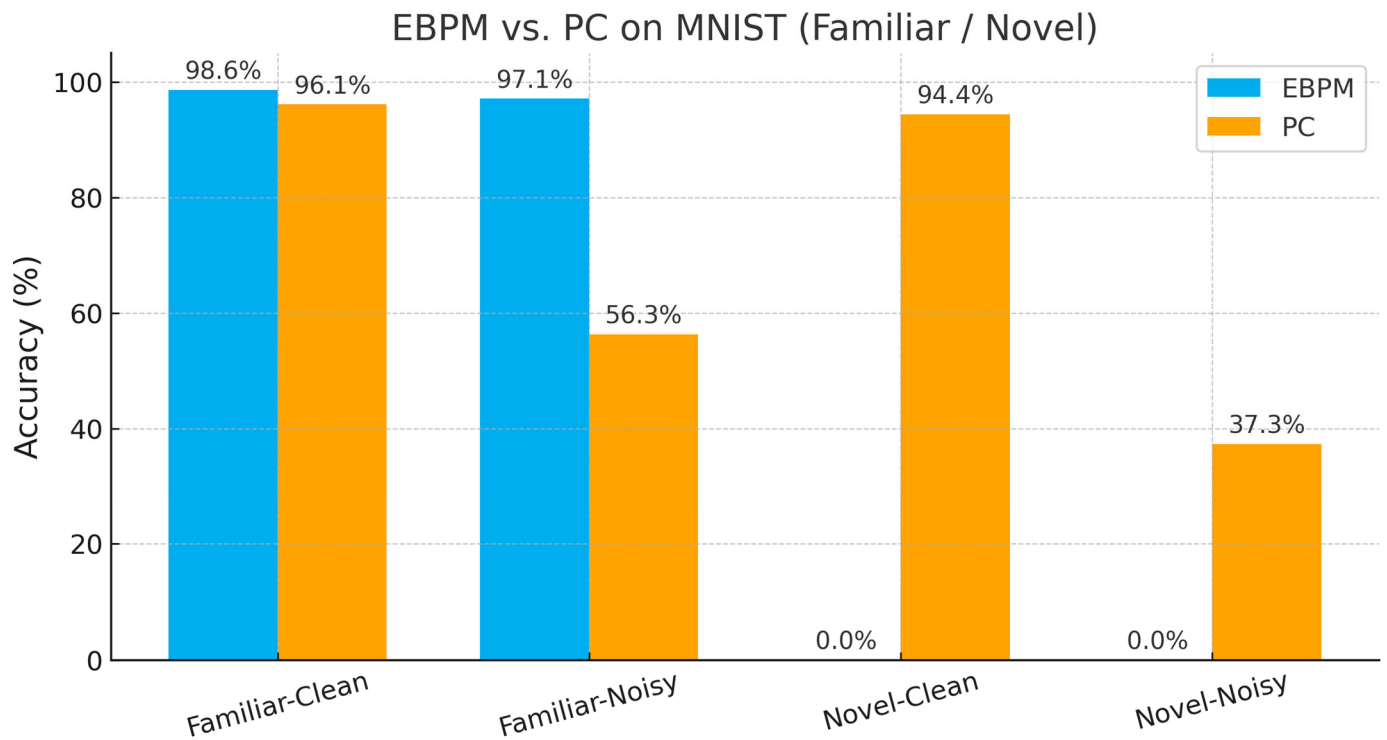


Figure A2. EBPM vs. PC (Accuracy). Accuracy comparison restricted to EBPM vs. PC.

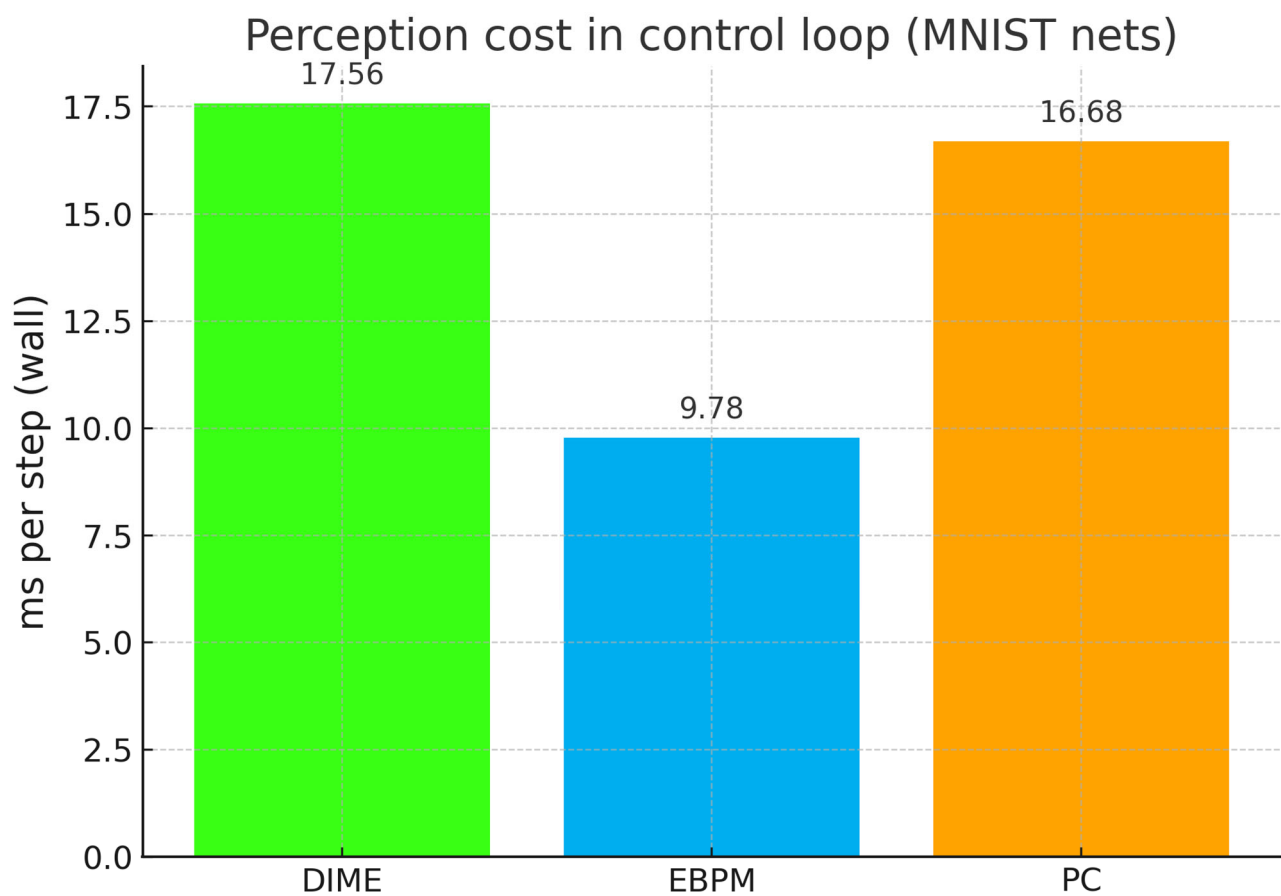


Figure A3. Legacy ms/step bar chart. Historic bar chart of ms/step on an older configuration. Superseded by the v3c_alpha results.

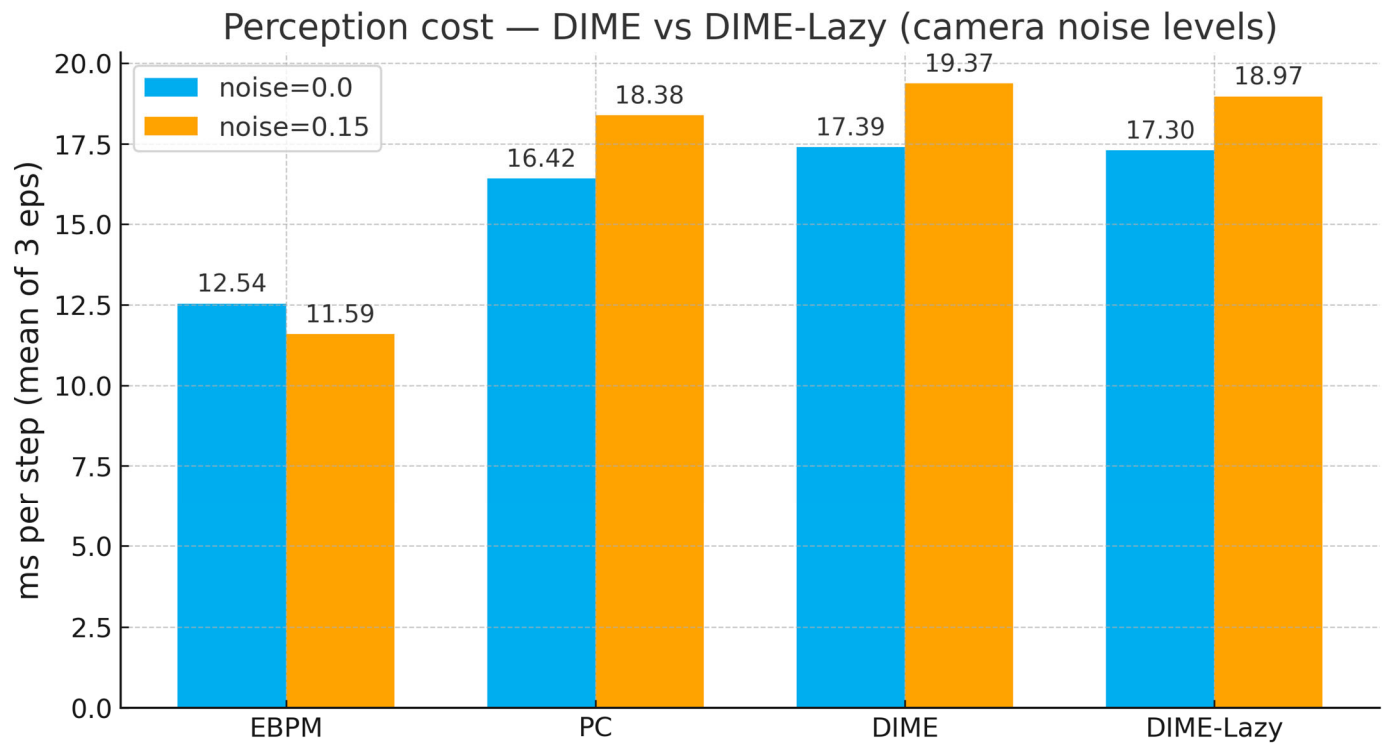


Figure A4. Legacy DIME-Lazy ms/step. Older view of DIME-Lazy perception cost; thresholds and controller differ from the final setup.

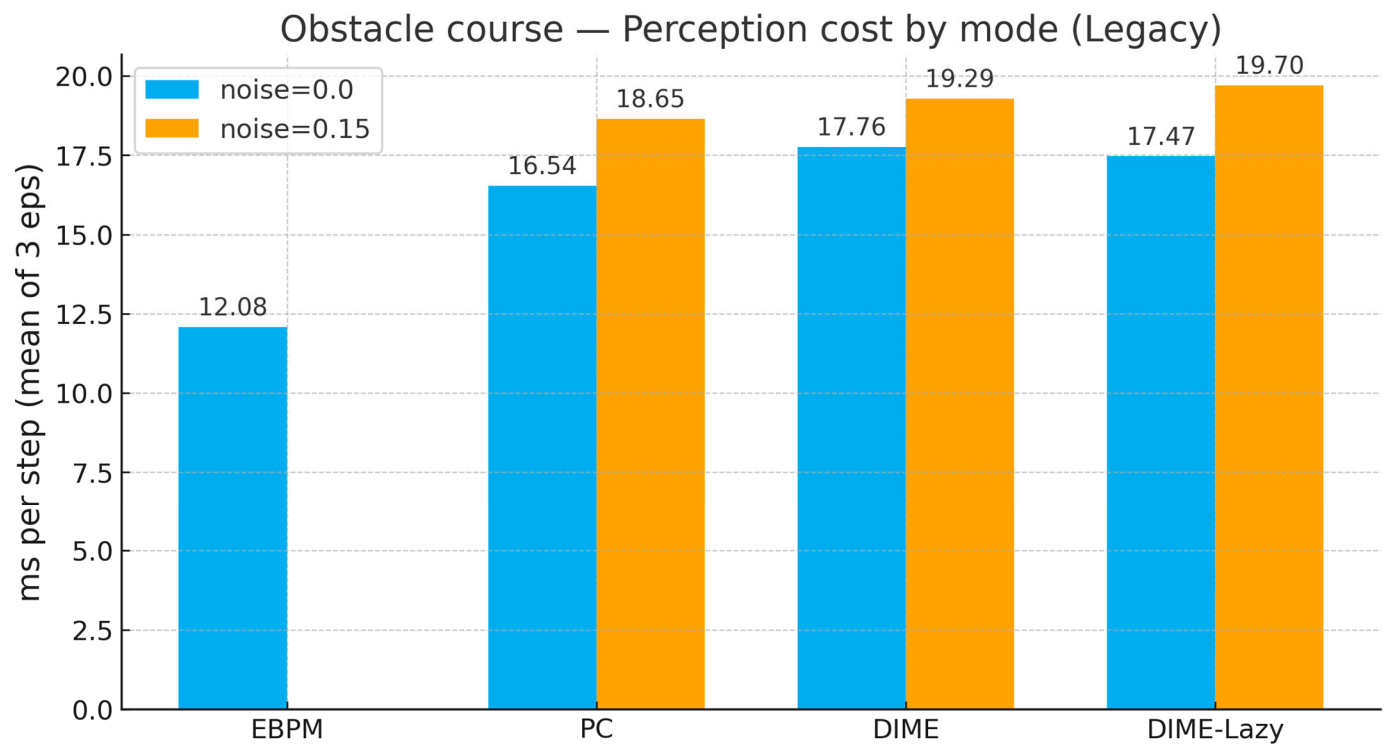


Figure A5. Legacy obstacles ms/step. Earlier ms/step summary on the obstacle scenario. Kept as a historical reference; the main text reports v3c_alpha.

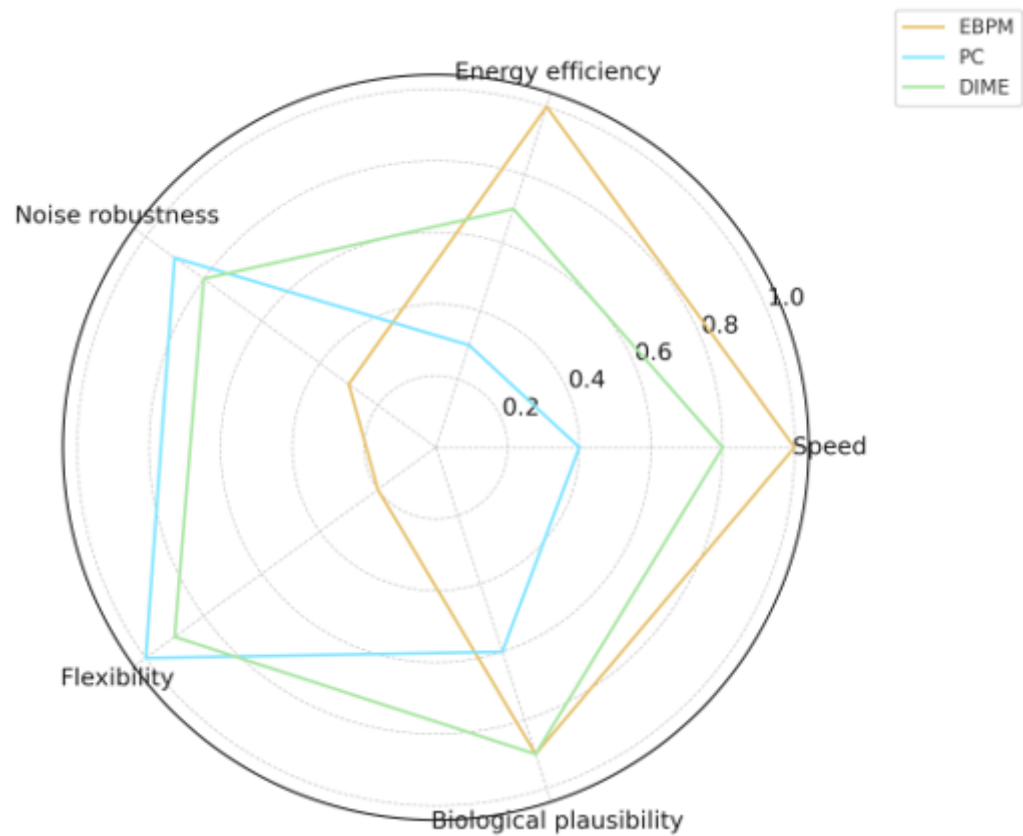


Figure A6. Conceptual radar comparison. Conceptual (non-empirical) illustration of expected tendencies for EBPM, PC, and DIME across speed, robustness to noise/novelty, and compute cost. Provided for intuition only; not derived from measured data.

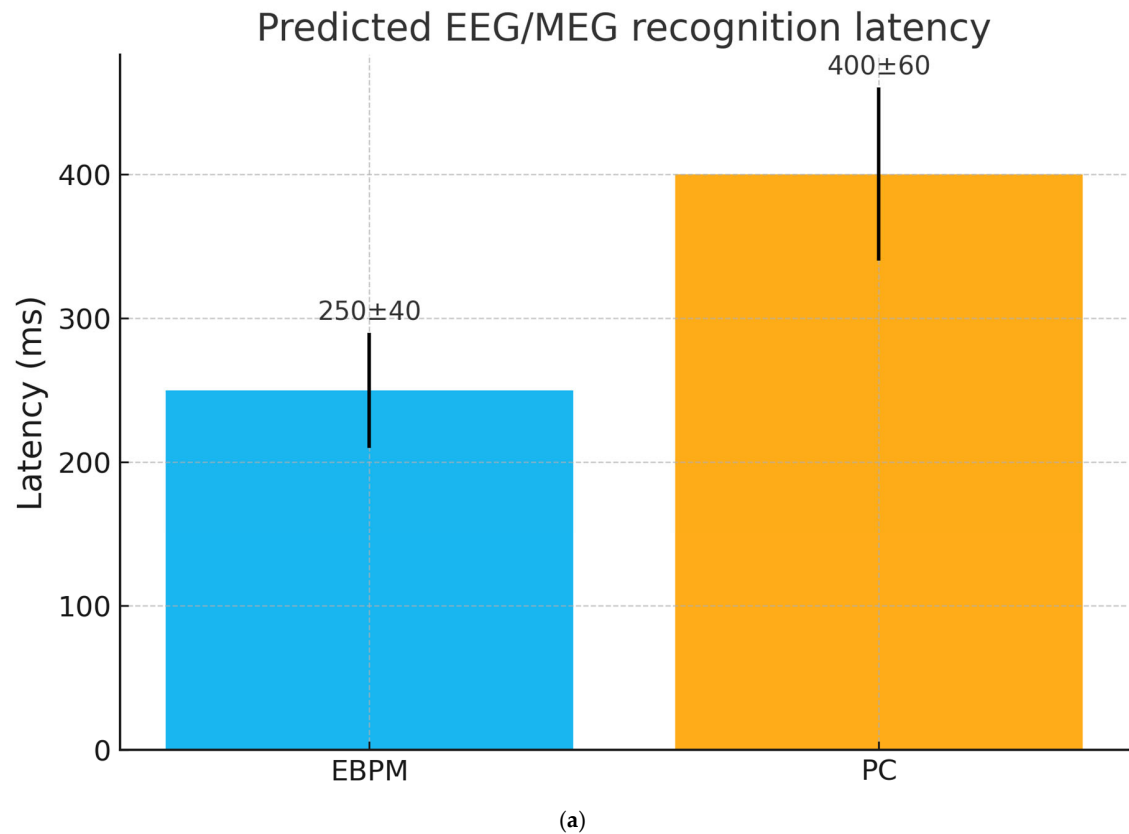


Figure A7. Cont.

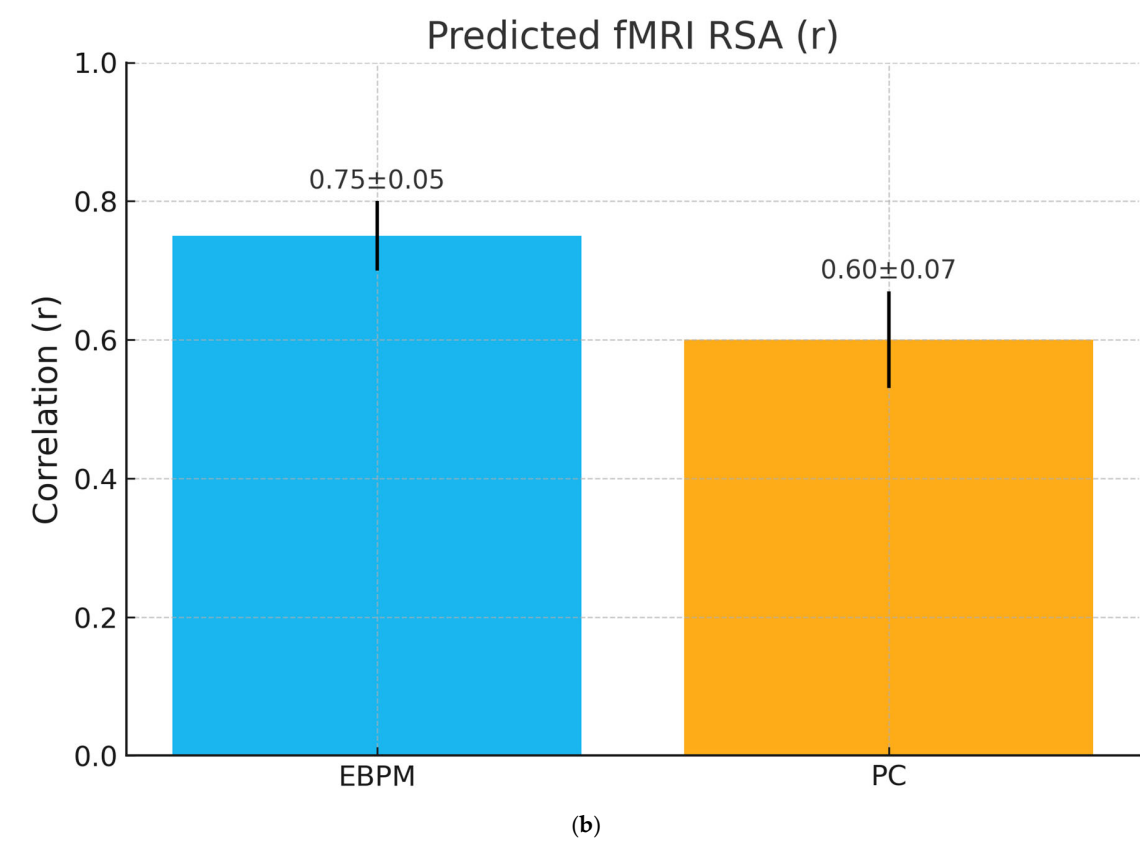


Figure A7. (a). Predicted EEG/MEG recognition latency (ms) with 95% CI: EBPM $\approx 250 \pm 40$, PC $\approx 400 \pm 60$. (b) Predicted fMRI RSA (r) with 95% CI: EBPM $\approx 0.75 \pm 0.05$, PC $\approx 0.60 \pm 0.07$.

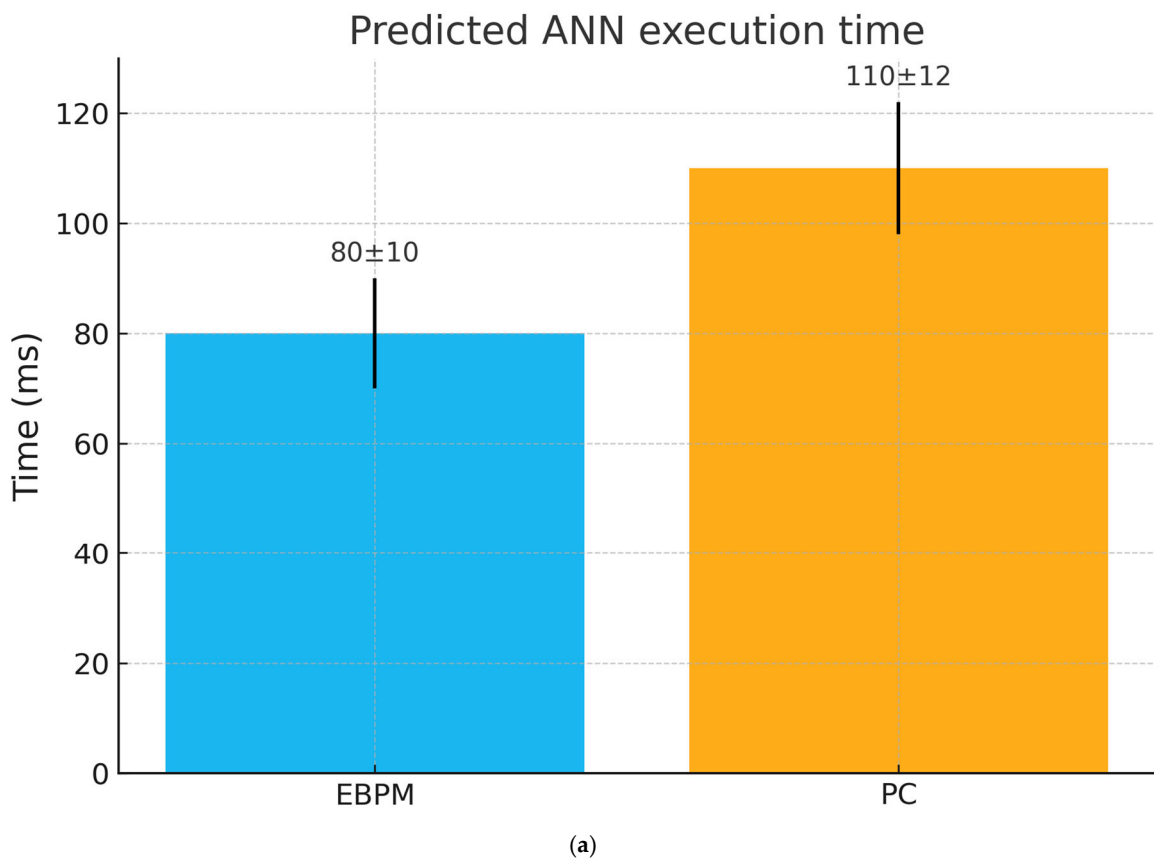


Figure A8. Cont.

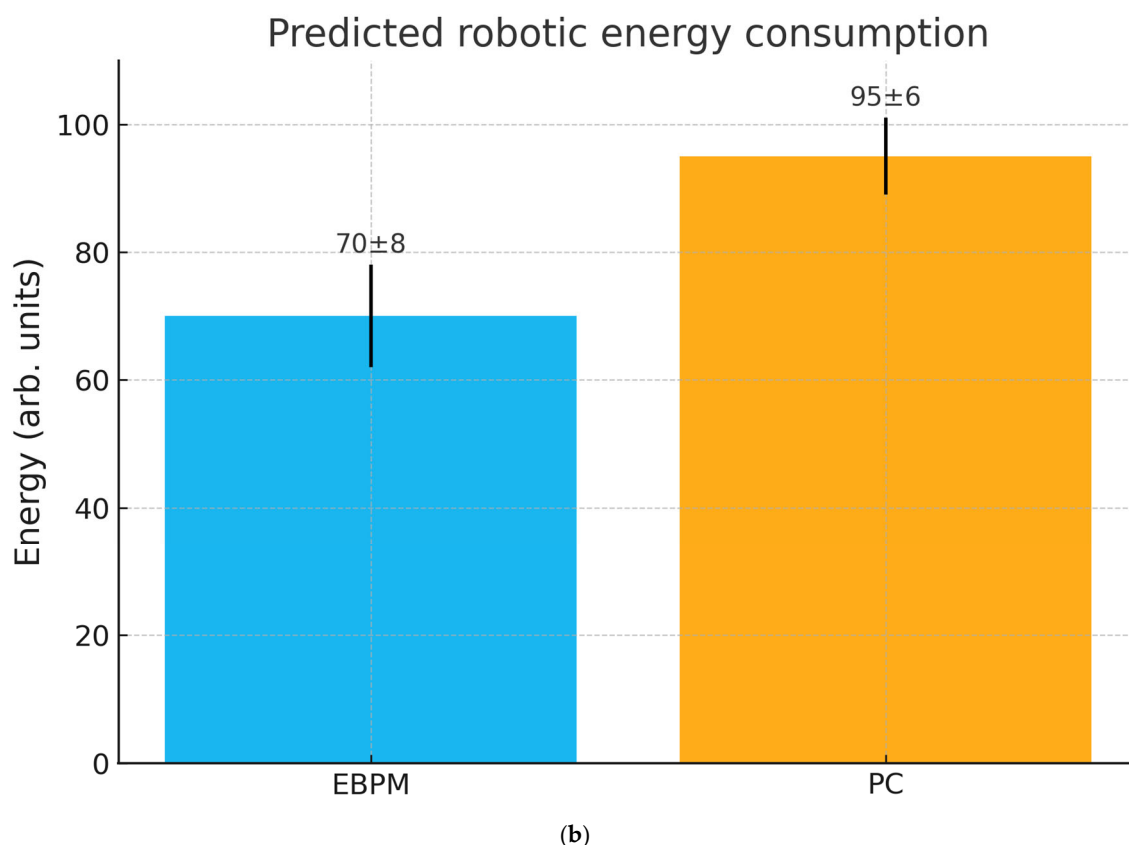


Figure A8. (a). Predicted ANN execution time (ms) with 95% CI: EBPM $\approx 80 \pm 10$, PC $\approx 110 \pm 12$. (b). Predicted robotic energy consumption (arb. units) with 95% CI: EBPM $\approx 70 \pm 8$, PC $\approx 95 \pm 6$.

Appendix B

Table A1. Rdata.

File (Relative Path)	What It Contains
results_csv/pybullet_obstacles_metrics_v3c_alpha.csv	v3c_alpha ($\alpha = 0.65$): ms/step mean, steps, success, collisions, avg PC calls per mode and noise
results_csv/pybullet_obstacles_metrics_v3c.csv	v3c (dyn gating, no fixed α): same fields
results_csv/pybullet_obstacles_metrics_v3b.csv	v3b: success and collisions breakdown
results_csv/pybullet_perception_metrics.csv	demo perception ms/step EBPM vs. PC vs. DIME

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