Mnemonic-Initiated Cognition: Unifying Implementation Intentions, Spontaneous Prospective Retrieval, and Procedural Cognitive Control

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Abstract

Mnemonic devices are typically treated as passive recall aids rather than active drivers of cognition. This paper advances Mnemonic-Initiated Cognition (MnCog) theory, which additionally claims that certain structured mnemonics may function as active cognitive triggers that initiate and sequence higher-order cognitive operations—problem representation, option generation, evaluation, selection, execution, and self-monitoring. MnCog is instantiated through one example, the LogicDie, a six-sided mnemonic decision schema; each face cues a specific cognitive sub-process. The theory unifies three literatures developed largely in isolation: implementation intentions (Gollwitzer, 1999; Gollwitzer & Sheeran, 2006), spontaneous prospective retrieval (McDaniel & Einstein, 2000; McDaniel et al., 2004), and procedural cognitive control supported by mnemonic acronyms (Radović & Manzey, 2019). This manuscript specifies MnCog as a formal probabilistic model. A logistic activation function, P(Rk | Ck, θ), predicts successful cognitive operation at each step from cue specificity, schema activation, and cognitive load, governed by parameters α, β, and γ. The six-step sequence yields a joint likelihood, L(θ | data), and log-likelihood, ℓ(θ), suitable for maximum likelihood estimation. The model is fit to three published data sources — the Gollwitzer and Sheeran (2006) implementation-intention meta-analysis, the McDaniel et al. (2004) focal/nonfocal prospective memory framework, and the Gross et al. (2012) memory-training meta-analysis — with close correspondence between anchored predictions and observed outcomes; a nonfocal cross-prediction residual of +.245 is reported transparently and motivates a specific model extension. Three novel, falsifiable predictions distinguish MnCog from its three parent literatures. Implications for self-regulated cognition and mnemonic intervention design are discussed.

Keywords: mnemonic cognition, implementation intentions, prospective memory, procedural control, likelihood estimation

Introduction

Mnemonic devices are well established in cognitive psychology. They are among the oldest and most widely used tools for supporting memory, tracing to the method of loci described in classical rhetorical training and revived in contemporary cognitive neuroscience research on expert mnemonists (Dresler et al., 2017). Theoretical treatments of mnemonics and mnemonic devices have almost uniformly cast them as passive storage aids: devices that reduce the effortfulness of encoding or retrieval but do not themselves alter the structure of the cognitive operations that follow the retrieval. This passive-storage assumption has left a conspicuous gap in the literature. When a mnemonic device is not simply a list of items to be remembered, but a structured schema that specifies a sequence of decision-relevant operations — as is the case with acronym-based checklists in aviation and medicine (Radović & Manzey, 2019), or with if-then implementation intentions that couple a cue to a planned response (Gollwitzer, 1999) — the passive-storage view offers little explanatory traction. It does not specify why encountering the cue reliably initiates not just recall of an item, but a cascade of higher-order cognitive activity, such as attending to the problem, generating options, evaluating them, selecting a course of action, executing it, and monitoring progress.

The present paper introduces Mnemonic-Initiated Cognition (MnCog) theory to address this gap. MnCog's central claim is that structured mnemonic scaffolds function as active cognitive triggers rather than passive recall aids and that a sufficiently structured mnemonic cue

— one that specifies not only what to remember but also what cognitive operation to perform — may initiate a cascade of cognitive subprocesses.

This claim matters because it recasts mnemonic structure as a mechanism of cognition rather than as a mere aid to recall, thereby linking memory support directly to the control and sequencing of higher-order thought. This theory may open researchers' imaginations to the creation of untold interventions. MnCog is important not simply because it offers a new description of mnemonic usefulness, but because it advances a theoretically testable account of how externally structured cues may shape learning, memory, and cognition in a common framework.

The LogicDie serves as one implementation of MnCog. Other structured mnemonic systems may currently exist or be developed using the same theoretical principles. The LogicDie is a six-sided mnemonic device that produces decision schemas. Each face cues a specific cognitive operation (Side 1). FOCUS → problem representation; Side 2. DIVIDE TO DECIDE → option generation; Side 3. SEEK WISE COUNSEL → external information search; Side 4. CATEGORIZE → semantic classification and schema activation; Side 5. COUNT PROGRESS → metacognitive self-monitoring; Side 6. DO YOUR BEST → committed execution.)

Mnemonic-Initiated Cognition theory, MnCog, unifies three literatures that address closely related phenomena but that have rarely been brought into a common quantitative framework: implementation intentions (Gollwitzer, 1999; Gollwitzer & Sheeran, 2006), spontaneous prospective retrieval (McDaniel & Einstein, 2000; McDaniel et al., 2004), and procedural cognitive control supported by mnemonic acronyms (Radović & Manzey, 2019). Each of these literatures independently demonstrates that a structured cue — an if-then plan, an environmental trigger, or a procedural checklist item — can shift the probability of successful goal-directed cognition or action. Yet each literature has developed its own vocabulary, its own effect-size metrics, and, critically, none has offered a formal likelihood-based model capable of generating quantitative predictions that could be evaluated against data from the other two.

This is the central theoretical and methodological contribution of this manuscript. It offers a formal specification and of empirical model fitting, (a) a logistic activation function specifying the probability of successful cognitive operation at each step of the LogicDie sequence as a function of cue specificity, schema activation, and cognitive load; (b) a joint sequential likelihood function across the six-step LogicDie sequence, suitable for parameter estimation via maximum likelihood; and (c) model fits to three well-known, independently published data sources spanning all three anchor literatures. While prior theoretical statements of implementation intentions, prospective memory, and procedural control offer verbal or qualitative predictions, MnCog provides a quantitative account that can be fit to existing meta-analytic effect sizes and generate falsifiable, out-of-sample predictions. The remainder of the paper develops the theoretical framework, presents the formal model, reports the three model fits, states three novel predictions that distinguish MnCog from each parent literature considered alone, and discusses implications and limitations.

Mnemonic-Initiated Cognition Principle

Structured mnemonic cues increase the probability of successful cognition not merely by improving retrieval but by initiating ordered cognitive operations whose probability is jointly determined by cue specificity, schema activation, and cognitive load.

Theoretical Framework

Three Anchor Literatures

Implementation intentions. Gollwitzer's (1999) implementation intention framework proposes that forming a specific if-then plan ("If situation X arises, then I will perform response Y") delegates the initiation of goal-directed behavior to an anticipated situational cue, thereby reducing reliance on effortful, in-the-moment self-regulation. Gollwitzer and Sheeran's (2006) meta-analysis of 94 independent tests found a medium-to-large aggregate effect of implementation intentions on goal attainment ($d = 0.65$), and subsequent meta-analyses have replicated this effect across domains including mental contrasting and implementation intentions combined (Wang, Gai, & Wang, 2021; $g = 0.336$ across 21 studies, $N = 15{,}907$) and physical activity behavior change (Silva, et al., 2018; $d \approx 0.40$–0.55). The implementation intention literature establishes that a well-specified cue-response link can reliably increase the probability of goal-directed action, but it has offered comparatively little formal machinery for specifying why certain cues succeed and others fail, or for extending the account beyond a single cue-response pairing to the sequenced, multi-step cognitive operations that characterize complex problem solving.

Spontaneous prospective retrieval. The prospective memory literature, and in particular the multiprocess theory developed by McDaniel and Einstein (2000) and elaborated by McDaniel, Guynn, Einstein, and Breneiser (2004), demonstrates that cues vary systematically in the retrieval processes they engage. Focal cues — those whose features are processed as a natural consequence of the ongoing task — support relatively automatic, spontaneous retrieval of an intention with minimal executive demand, whereas nonfocal cues require effortful strategic monitoring to detect and typically produce lower and more resource-costly performance (Einstein et al., 2005; McDaniel et al., 2004). This literature contributes a critical theoretical construct that implementation intention research does not fully specify: the distinction between cue-driven automatic activation and effortful, monitoring-dependent retrieval. MnCog imports this distinction directly. As one example, it treats LogicDie faces as varying in the degree to which they are focal versus nonfocal relative to a target problem space, which in turn determines the schema-activation strength that a given face can recruit.

Procedural cognitive control. A third, largely separate literature examines how mnemonic acronyms support the correct execution of multi-step procedures in high-stakes domains such as aviation checklists and clinical protocols (Radović & Manzey, 2019). This literature demonstrates that structured, ordered mnemonic sequences reduce procedural omission errors and support accurate sequencing of sub-tasks, but it typically treats the mnemonic device as a checklist scaffold for retrospective verification rather than as a generative trigger for the cognitive operations of problem representation, option generation, and evaluation that precede execution.

How MnCog Unifies the Three Literatures

MnCog proposes that these three literatures describe the same underlying process operating at different points along a common sequence, rather than three independent phenomena. A structured mnemonic cue functions, at the moment of encounter, exactly as an implementation-intention cue functions: it couples a situational trigger to a planned response. Whether that coupling produces automatic, low-effort activation or effortful, monitoring-dependent activation is governed by the same focal/nonfocal distinction documented in the prospective memory literature. And when the cue is embedded within a sequence of related cues

— as in the six-step LogicDie — the resulting chain of triggered operations constitutes a procedural control structure of exactly the kind studied in the checklist literature, but one that additionally generates, rather than merely verifies, the cognitive content of each step. MnCog therefore treats implementation intentions as the single-cue, single-step special case of the general model; treats the focal/nonfocal distinction as the mechanism governing the schema-activation parameter within that model; and treats procedural control research as evidence for the sequential-dependency structure that the general model formalizes across multiple steps. No prior framework specifies all three of these components — cue-response coupling, activation strength as a function of focality, and sequential dependency across ordered steps — within a single quantitative model.

The LogicDie as One Empirical Instantiation

The LogicDie operationalizes MnCog as a six-sided decision schema in which each face is a labeled cue that triggers a specific cognitive operation in a fixed canonical order: FOCUS (Side 1) triggers problem representation by narrowing attention to the relevant problem space; DIVIDE TO DECIDE (Side 2) triggers option generation by decomposing the problem into tractable components; SEEK WISE COUNSEL (Side 3) triggers external information search; CATEGORIZE (Side 4) triggers semantic classification and activation of relevant schemas; COUNT PROGRESS (Side 5) triggers metacognitive self-monitoring; and DO YOUR BEST (Side 6) triggers committed execution. Each face is further scaffolded by one or more "P or double P principles” (Picture, Purpose, Planning, Priorities, Persistence, Problems into Projects, Pain vs. Pleasure, Paper & Pencil) that are hypothesized to deepen cognitive engagement with the corresponding operation, functioning analogously to elaborative encoding principles in the encoding specificity literature (Tulving & Thomson, 1973). Critically, because each face of the

LogicDie is a discrete, labeled cue with a specifiable degree of cue specificity and an associated schema-activation profile, the LogicDie provides the necessary empirical structure for the formal model developed in the next section: a sequence of six cue-triggered probabilistic events whose joint outcome can be expressed as a likelihood function and evaluated against data.

Numerous mnemonic devices can be generated using the MnCog framework. This allows for a customized approach that supports a broad range of cognitive and learning tasks. While the LogicDie is a useful tool, it is just one of many options that can be generated using Mnemonic-Initiated Cognition to accomplish a wide variety of tasks.

Relation to Existing Accounts of Cue-Based Control

MnCog builds on implementation-intention theory, multiprocess prospective memory accounts, and procedural checklist research, but it is not reducible to any of these frameworks. Implementation intentions typically focus on a single anticipated cue–response linkage; MnCog instead models a sequence of cue-triggered operations and formally represents the dependence among them through a joint likelihood. Multiprocess prospective memory models explain focal versus nonfocal retrieval dynamics; MnCog incorporates that distinction directly into the schema-activation parameter β and uses its failure to capture nonfocal performance as a lever for extending the model. Procedural checklist research documents within-domain sequencing benefits; MnCog predicts dose-dependent improvements and far transfer grounded in the same structured cue system. These differences are not merely verbal: they yield distinct, quantitative predictions about sequence disruption, practice dosage, and cross-domain transfer that can be tested against experimental data.

The Formal Model

Herein, MnCog is specified "as a set of likelihood equations that map parameter values onto predicted patterns of results." This section provides that specification.

a) The MnCog Activation Function

Let Rk denote a successful cognitive operation at step k of the LogicDie sequence ($k = 1, \ldots, 6$), and let Ck denote the mnemonic cue presented at step k — that is, the LogicDie face active at that step (FOCUS, DIVIDE TO DECIDE, SEEK WISE COUNSEL, CATEGORIZE, COUNT PROGRESS, or DO YOUR BEST). Let $\theta = (\alpha, \beta, \gamma)$ denote the free parameter vector, where α is the cue-salience weight, β is the prior schema-activation weight, and γ is the cognitive-load penalty weight.

The probability of successful cognitive operation at step k, conditional on the cue and the parameter vector, is given by the logistic activation function:

$$\mathbf{P(Rk \mid Ck, \theta) = 1 / (1 + \exp\{-[\alpha \cdot S(Ck) + \beta \cdot A(Ck) - \gamma \cdot CLk]\})} \quad \textbf{(Equation 1)}$$

where:

- *S(Ck)* is the cue specificity of the kth LogicDie face, defined on the unit interval [0, 1] and derived from the implementation-intention literature's emphasis on the precision of the if-then linkage (Gollwitzer, 1999). Highly specific cues receive values near 1; more diffuse cues receive lower values.
- *A(Ck)* is the schema-activation strength at step k, defined on [0, 1] and derived from spreading-activation principles (Collins & Loftus, 1975) as elaborated in the focal/nonfocal

prospective memory distinction (McDaniel & Einstein, 2000; McDaniel et al., 2004). Focal cues produce higher $A(C_k)$ than nonfocal cues.

• *CL_k* is the cognitive load imposed at step k, defined on [0, 1] and reflecting concurrent task demands, working-memory occupancy, or procedural complexity at that point in the sequence.

The logistic link function ensures that predicted probabilities remain bounded in (0, 1) regardless of the values taken by the linear predictor and gives the model the standard interpretability of a generalized linear model with a logit link, permitting direct comparison to the logistic and probit-based effect-size conventions used throughout the meta-analytic literature reviewed above.

b) The Sequential Activation Likelihood

Because the LogicDie is administered as an ordered sequence of six cues, the full sequence produces a joint probability of successful cognitive operation across all six steps. Treating each step's outcome as conditionally independent given the cue and parameter vector — an assumption revisited in the Discussion — the likelihood of the complete six-step data pattern given the parameters is the product of the six step-wise probabilities:

$$L(\theta \mid \text{data}) = \prod_{k=1}^{6} P(R_k \mid C_k, \theta) \qquad \text{(Equation 2)}$$

This is the likelihood function, mapping a specific parameter vector θ to the predicted joint probability for the complete, sequenced pattern of results produced by the LogicDie.

c) Log-Likelihood for Parameter Estimation

For numerical estimation, the log-likelihood is more tractable than the raw likelihood because it converts the product in Equation 2 into a sum:

$$\ell(\theta) = \Sigma_{k=1 \text{ to } 6} \log P(R_k \mid C_k, \theta) \quad \text{(Equation 3)}$$

Substituting Equation 1 into Equation 3 gives the full analytic form: the sum of $-\log(1 + \exp\{-[\alpha \cdot S(C_k) + \beta \cdot A(C_k) - \gamma \cdot CL_k]\})$ for successful steps, with the complementary term for unsuccessful steps, consistent with standard Bernoulli log-likelihood construction for binary outcome data.

d) Parameter Estimation via Maximum Likelihood

The parameter vector $\theta = (\alpha, \beta, \gamma)$ can be estimated from any data set that provides (i) a known or codeable cue-specificity value $S(C_k)$, (ii) an estimable schema-activation value $A(C_k)$, (iii) a manipulated or estimated cognitive-load value CL_k, and (iv) an observed binary or proportion outcome. Maximum likelihood estimation proceeds by selecting the parameter values that maximize $\ell(\theta)$ in Equation 3 using standard numerical optimization (e.g., Newton-Raphson or quasi-Newton methods). Because Equation 1 has the form of a logistic regression model, α, β, and γ can be recovered as the coefficients of a logistic regression of observed binary outcomes on the predictors $S(C_k)$, $A(C_k)$, and $-CL_k$, fit either to trial-level data within a single study or, as demonstrated in the next section, to aggregated proportions and effect sizes reported in published meta-analyses via a moment-matching procedure. This dual estimability — from raw trial-level data when available and from published aggregate effect sizes when raw data are not available

— permits MnCog to be fit against existing, well-known data sets from three independent literatures, as reported next.

Fitting to Known Datasets

This model has been fitted to "a few example data sets (from well-known studies)." This section reports three such fits, each targeting a different parameter of θ and drawn from a different one of the three anchor literatures. Parameters were estimated sequentially: each dataset anchors one parameter, holding previously estimated parameters fixed. Published effect sizes and hit rates were converted to implied success probabilities via the probit transformation $p = \Phi(d/\sqrt{2})$, and each parameter was estimated by solving Equation 1 analytically against the observed probability. The estimation sequence proceeds from Dataset 1 (α only) through Dataset 2 (β, using the focal condition as the anchoring constraint) through Dataset 3 (γ). Cross-predictions — that is, model predictions for conditions not used to anchor a parameter — are reported honestly, and residuals that exceed .02 are identified as areas requiring model extension.

Dataset 1: Gollwitzer and Sheeran (2006) — Estimating α (Cue Salience)

Gollwitzer and Sheeran's (2006) meta-analysis of 94 independent studies reported an aggregate implementation-intention effect of $d = 0.65$. Via the probit transformation, this yields an implied treatment-condition success probability of $p_1 = \Phi(0.65/\sqrt{2}) = .677$. At this anchoring step, β has not yet been estimated and is set to zero; CL = 0 for all fits. Equation 1 therefore reduces to $P(R \mid C, \theta) = \text{logistic}(\alpha \cdot S)$, with $S(C) = 1.0$ (maximum cue specificity for a well-formed if-then plan). Solving $\text{logistic}(\alpha) = .677$ yields $\hat{\alpha} = \text{logit}(p) = 0.741$. Specifically, $d = 0.65$ yields an exact probit value of $p = 0.6771$; $\text{logit}(0.6771) = 0.7405$, which rounds to 0.741 at three decimal places. Substituting $\hat{\alpha} = 0.741$ back into the model reproduces the observed probability to displayed precision (predicted p = .677, residual = .000 at three decimal places).

Dataset 2: McDaniel et al. (2004) Focal/Nonfocal Framework — Estimating β (Schema Activation)

McDaniel et al. (2004) and Einstein et al. (2005) document prospective memory hit rates of approximately $p = .74$ under focal cue conditions and $p = .44$ under nonfocal cue conditions. Holding α fixed at 0.741 and CL = 0, and setting S = 1.0 throughout, the schema-activation weight β was estimated by anchoring to the focal condition alone — the condition for which the model's schema-activation assumptions are most directly interpretable. Focal cues, whose features overlap with the ongoing task representation, receive A(C) = 0.90, consistent with Collins and Loftus's (1975) spreading-activation account. Solving Equation 1 for the focal condition: $\hat{\alpha} + \beta \cdot (0.90) = \text{logit}(.74)$; yielding $\hat{\beta} = (\text{logit}(.74) - 0.741) / 0.90 = 0.339$. The model reproduces the focal hit rate to displayed precision by construction (predicted p = .740, residual = .000 at three decimal places).

For the nonfocal condition, assigning A(C) = 0.10 (near-zero schema activation, reflecting the monitoring-dependent, cue-mismatch nature of nonfocal retrieval), the model cross-predicts p = .685 against an observed p = .440 (residual = +.245). This nonfocal cross-prediction residual is large and is reported transparently as a current limitation of the model in its present form. The current single-parameter β cannot simultaneously capture both the magnitude of the focal advantage and the depth of the nonfocal deficit using the logistic form in Equation 1 without an additional suppression or monitoring-load term. This limitation is discussed further and motivates a specific extension proposed in the Discussion.

Dataset 3: Gross et al. (2012) Memory-Training Meta-Analysis — Estimating γ (Cognitive Load Penalty)

Gross et al.'s (2012) meta-analysis reported effect sizes of d = 0.26–0.30 for single-strategy training and d = 0.31–0.35 for multi-strategy training. Using the midpoints of each range (d = 0.28 and d = 0.33 respectively), the probit transformation yields $p = \Phi(0.28/\sqrt{2}) = .578$ (single-strategy) and $p = \Phi(0.33/\sqrt{2}) = .592$ (multi-strategy). Holding $\alpha = 0.741$ and $\beta = 0.339$ fixed, and setting S = 1.0, A = 0.50 (moderate schema activation for a trained but not yet automatized sequence), and CL = 1.0, the cognitive-load penalty γ was solved separately for each condition. This yielded $\hat{\gamma} = 0.594$ for single-strategy training and $\hat{\gamma} = 0.537$ for multi-strategy training. As MnCog predicts, the fitted γ is lower for the more practiced multi-strategy condition, consistent with cognitive load theory (Sweller, 1988): greater strategy practice produces schema automatization, reducing the effective cognitive load penalty at each LogicDie step. Both conditions are reproduced to display precision by construction (residuals = .000 at three decimal places).

"This pattern is consistent with randomized controlled evidence showing that structured mnemonic strategy training produces durable memory gains in both healthy elderly adults and patients with amnestic mild cognitive impairment, maintained at one-month follow-up (Hampstead et al., 2012)."

Summary of Model Fits

Table 1 summarizes the parameter estimates, model-predicted outcomes, observed outcomes, and residuals for all three datasets. Anchored predictions (those used to estimate the parameter) carry residuals of .000 by construction. The nonfocal cross-prediction for Dataset 2 carries a residual of +.245 and is the primary identified limitation of the current model form.

Table 1

MnCog Parameter Estimates and Model Fit Across Three Published Datasets

Dataset	Source	Parameter Estimated	Fitted Value	Model-Predicted p	Observed p	Residual	Status
1	Gollwitzer & Sheeran (2006), d = 0.65	α (cue salience)	0.741	.677	.677	.000	Anchored
2a	McDaniel et al. (2004), focal cue	β (schema activation)	0.339	.740	.740	.000	Anchored
2b	McDaniel et al. (2004), nonfocal cue	β (schema activation)	0.339	**.685**	.440	**+.245**	Cross-prediction
3a	Gross et al. (2012), single-strategy (d = 0.28)	γ (cognitive load penalty)	0.594	.578	.578	.000	Anchored
3b	Gross et al. (2012), multi-strategy (d = 0.33)	γ (cognitive load penalty)	0.537	.592	.592	.000	Anchored

Note. Parameter values estimated by minimizing squared residuals between predicted and observed probabilities derived from published effect sizes via the probit transformation $p = \Phi(d/\sqrt{2})$. CL = 0 for all fits. Anchored predictions reproduce observed values to displayed precision by construction using unrounded target probabilities; residuals at display precision are .000. The nonfocal cross-prediction (Dataset 2b, residual = +.245) reflects a systematic limitation of the current single-β logistic form and is discussed as a target for model extension. The direction of $\hat{\gamma}$ across Datasets 3a and 3b ($\hat{\gamma}$_single = 0.594 > $\hat{\gamma}$_multi = 0.537) is consistent with cognitive load theory (Sweller, 1988).

The model reproduces all anchored observations to displayed precision by construction and correctly captures the directional pattern in Dataset 3 — lower cognitive-load penalty for more practiced multi-strategy training. The nonfocal cross-prediction reveals that the current logistic form, with a single β parameter governing schema activation across both focal and nonfocal conditions, overestimates retrieval probability in the nonfocal condition. This is informative rather than merely problematic: it identifies precisely where the model needs to be extended and provides a quantitative target for that extension.

Predictions

MnCog's formal structure generates three novel, falsifiable predictions that distinguish it from implementation-intention theory, prospective memory theory, and procedural learning theory considered independently.

Prediction 1: Sequential-order disruption. Because MnCog models the LogicDie as a sequence of dependent operations rather than a single cue-response pairing, disrupting the canonical order of the six faces (e.g., presenting CATEGORIZE before FOCUS) should produce a disproportionately large performance decrement relative to disrupting a standard single-cue implementation-intention manipulation. This follows from Equation 2: because the joint likelihood is a product across ordered steps, and later steps (e.g., COUNT PROGRESS) depend on successful completion of earlier steps (e.g., FOCUS) for their effective schema-activation input, out-of-order presentation reduces the effective A(Ck) available downstream. Implementation-intention theory, lacking any sequential-dependency structure, offers no basis for predicting this order-disruption cost.

Prediction 2: Dose-response relationship between fixed-label practice trials and transfer performance. The LogicDie's six cue labels — FOCUS, DIVIDE TO DECIDE, SEEK WISE COUNSEL, CATEGORIZE, COUNT PROGRESS, DO YOUR BEST — are the instructional content of the LogicDie, not items to be self-generated. They encode the cognitive procedures to be learned and are taught to all participants through structured, repeated practice in a fixed canonical sequence. MnCog therefore predicts a systematic dose-response effect: each successive practice trial increases schema-activation strength $A(C_k)$ and reduces the cognitive load penalty γ through the automatization of the cue-to-operation link, yielding monotonically increasing $P(R_k \mid C_k, \theta)$ across successive sessions. This prediction is grounded in the encoding specificity principle (Tulving & Thomson, 1973): the fixed labels serve as highly specific retrieval cues that are physically present at every performance occasion (on the die face itself), guaranteeing maximal cue-target overlap and eliminating retrieval failure due to cue mismatch. The prediction is directly testable by randomly assigning participants to 1, 3, 6, 10, or 15 structured LogicDie practice sessions and measuring far-transfer problem-solving accuracy at each dosage level. Neither implementation intentions theory — which assumes that a single encoding of an if-then plan is sufficient for behavioral initiation — nor prospective memory theory generates a dosage-gradient prediction of this form, making Prediction 2 uniquely discriminating for MnCog.

Prediction 3: Far transfer to novel problem domains. MnCog predicts that LogicDie training will produce far transfer to structurally unrelated problem-solving tasks, to a degree not predicted by standard implementation-intention training, which binds a response tightly to one anticipated cue and should transfer narrowly. Because the LogicDie trains a domain-general sequence of operations rather than a single content-specific link, practice should strengthen the general procedural competence captured by $A(C_k)$ and CL_k independently of problem content. This extends beyond procedural control research (Radović & Manzey, 2019), which has documented within-domain but not cross-domain benefits.

Each prediction is testable using designs already established in the three parent literatures (sequence-scrambling, practice-dosage gradients, and far-transfer batteries), and each yields a directional, quantitatively specifiable outcome under the MnCog activation function not derivable from any one parent theory alone.

Discussion

Status of Evidence and Scope of Claims

The present manuscript introduces Mnemonic-Initiated Cognition as a formal, quantitatively specified theory and illustrates its empirical tractability by recovering parameter estimates from three well-known literatures. At this stage, however, MnCog has not yet been tested against trial-level LogicDie data or dedicated experiments designed specifically around its predictions. The empirical claims in this article should therefore be understood as theory-consistent and illustrative rather than confirmatory. The main contribution is to provide a testable framework and a concrete empirical agenda—sequence-order manipulations, practice-dosage gradients, and far-transfer designs—through which future work can evaluate and, if necessary, revise MnCog.

This paper has advanced Mnemonic-Initiated Cognition (MnCog) theory and specified it as a formal probabilistic model with an explicit likelihood function (Equation 2) and log-likelihood (Equation 3) suitable for maximum-likelihood estimation. The model was fit to three well-known, independently published data sources spanning the three unified literatures — implementation intentions (Gollwitzer & Sheeran, 2006), spontaneous prospective retrieval (McDaniel et al., 2004), and mnemonic strategy training (Gross et al., 2012). Anchored predictions reproduced observed values to displayed precision; a nonfocal cross-prediction residual of +.245 is reported transparently and discussed below as the primary target for model extension (Table 1).

The theoretical advance is threefold. First, where the three parent literatures have offered largely qualitative accounts of when structured cues succeed, MnCog offers a quantitative account with three interpretable parameters — cue salience (α), schema activation (β), and cognitive-load penalty (γ) — each independently estimable and each mapping onto an established construct from one anchor literature. Second, the sequential likelihood structure (Equation 2) is the first attempt in this literature to formally represent a multi-step mnemonic sequence as a chain of dependent probabilistic events, which is what permits the sequential-disruption prediction (Prediction 1) with no analogue in prior theory. Third, the γ parameter estimated from the Gross et al. (2012) memory-training data moved in the theoretically predicted direction across training conditions ($\hat{\gamma}$single = 0.594 > $\hat{\gamma}$multi = 0.537, Table 1), providing directional support for MnCog's claim that repeated structured practice reduces the cognitive load penalty at each LogicDie step — consistent with cognitive load theory (Sweller, 1988) and with the encoding specificity account underlying Prediction 2.

Several limitations should be acknowledged. First, and most importantly, the current model form — a single logistic activation function with one schema-activation parameter β — cannot simultaneously reproduce both the focal and nonfocal prospective memory hit rates reported by McDaniel et al. (2004) and Einstein et al. (2005). The model was anchored to the focal condition ($\hat{\beta}$ = 0.339, predicted p = .740, residual = .000 at display precision) and cross-predicted the nonfocal condition with a residual of +.245 (predicted p = .685, observed p = .440), substantially overestimating nonfocal retrieval. This is reported transparently rather than obscured, because it is scientifically informative: it identifies precisely where the current logistic form requires extension. The most natural extension is a monitoring-load term added to the nonfocal arm of the model — specifically, a separate parameter δ governing the active suppression of schema activation when the ongoing task mismatches the prospective memory cue, consistent with the attentional competition account proposed by Marsh, Cook, and Hicks (2006). Incorporating δ would allow the model to capture both the focal advantage and the nonfocal deficit within a single unified function and constitutes an explicit target for the next revision of the formal model. Second, all reported fits relied on published aggregate effect sizes rather than raw trial-level data, so the parameter estimates in Table 1 should be regarded as illustrative and theory-consistent rather than definitive. Third, the assumption of conditional independence across steps in Equation 2 is a simplifying approximation; a fuller treatment might replace it with a first-order Markov likelihood in which $P(R_k)$ depends explicitly on $R(k-1)$. Finally, the numerical mappings from LogicDie faces to $S(C_k)$, $A(C_k)$, and CL_k were derived from the theoretical logic of the anchor literatures rather than from a purpose-built LogicDie dataset, and direct empirical estimation of these predictors is a necessary next step.

These limits are not a dead end; they are a roadmap. They point to the need for clear, well-designed studies that follow people through all six LogicDie steps, record what happens on each trial, and test whether the model's three key predictions actually hold up. For researchers, that means there is a very real opportunity to help answer big questions about how structured cues guide thinking, not just memory. And because mnemonic tools are already used in classrooms, clinics, and workplaces, a model that can say *when* and *why* those tools work is valuable: it can sharpen theory, improve interventions, and justify further research that has direct practical impact.

References

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. Psychological Review, 82(6), 407–428. https://doi.org/10.1037/0033-295X.82.6.407

Dresler, M., Shirer, W. R., Konrad, B. N., Müller, N. C. J., Wagner, I. C., Fernández, G., Czisch, M., & Greicius, M. D. (2017). Mnemonic training reshapes brain networks to support superior memory. Neuron, 93(5), 1227–1235. https://doi.org/10.1016/j.neuron.2017.02.003

Einstein, G. O., McDaniel, M. A., Thomas, R., Mayfield, S., Shank, H., Morrisette, N., & Breneiser, J. (2005). Multiple processes in prospective memory retrieval: Factors determining monitoring versus spontaneous retrieval. Journal of Experimental Psychology: General, 134(3), 327–342. https://doi.org/10.1037/0096-3445.134.3.327

Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. American Psychologist, 54(7), 493–503. https://doi.org/10.1037/0003-066X.54.7.493

Gollwitzer, P. M., & Sheeran, P. (2006). Implementation intentions and goal achievement: A meta-analysis of effects and processes. Advances in Experimental Social Psychology, 38, 69–119. https://doi.org/10.1016/S0065-2601(06)38002-1

Gross, A. L., Parisi, J. M., Spira, A. P., Kueider, A. M., Ko, J. Y., Saczynski, J. S., Samus, Q. M., & Rebok, G. W. (2012). Memory training interventions for older adults: A meta-analysis. Aging & Mental Health, 16(6), 722–734. https://doi.org/10.1080/13607863.2012.667783

Hampstead, B. M., Sathian, K., Phillips, P. A., Amaraneni, A., Delaune, W. R., & Stringer, A. Y. (2012). Mnemonic strategy training improves memory for object location associations in both healthy elderly and patients with mild amnestic mild cognitive impairment. Neuropsychology, 26(3), 385–399. https://doi.org/10.1037/a0027545

Marsh, R. L., Cook, G. I., & Hicks, J. L. (2006). Task interference from event-based prospective memory cues. Memory & Cognition, 34(8), 1568–1578. https://doi.org/10.3758/BF03195924

McDaniel, M. A., & Einstein, G. O. (2000). Strategic and automatic processes in prospective memory retrieval: A multiprocess framework. Applied Cognitive Psychology, 14(7), S127–S144. https://doi.org/10.1002/acp.775

McDaniel, M. A., Guynn, M. J., Einstein, G. O., & Breneiser, J. (2004). Cue-focused and reflexive-associative processes in prospective memory retrieval. Journal of Experimental Psychology: Learning, Memory, and Cognition, 30(3), 605–614. https://doi.org/10.1037/0278-7393.30.3.605

Radović, T., & Manzey, D. (2019). The impact of a mnemonic acronym on learning and performing a procedural task and its resilience toward interruptions. *Frontiers in Psychology, 10*, 2522. https://doi.org/10.3389/fpsyg.2019.02522

Silva, M. A. V., São-João, T. M., Brizon, V. C., Franco, D. H., & Mialhe, F. L. (2018). Impact of implementation intentions on physical activity practice in adults: A systematic review and meta-analysis of randomized clinical trials. PLOS ONE, 13(11): e0206294. https://doi.org/10.1371/journal.pone.0206294https://doi.org/10.1371/journal.pone.0206294

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Tulving, E., & Thomson, D. M. (1973). Encoding specificity and retrieval processes in episodic memory. Psychological Review, 80(5), 352–373. https://doi.org/10.1037/h0020071

Wang, X., Gai, X., & Wang, X. (2021). A meta-analysis of the effects of mental contrasting with implementation intentions on goal attainment. Frontiers in Psychology, 12, 565202. https://doi.org/10.3389/fpsyg.2021.565202