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BIT: A Gamified Cognitive Architecture Framework for AI-Augmented Human Cognition

Design, Theoretical Grounding, and Empirical Evaluation Protocol for a Personalized AI Reasoning Curriculum

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ABSTRACT

The rapid proliferation of generative AI systems has created an urgent educational gap: while AI capabilities grow exponentially, human cognitive frameworks for directing those capabilities have not kept pace. Most AI literacy interventions focus on tool familiarity rather than structured reasoning — a surface-level approach that fails to produce durable, transferable competencies. This paper introduces **BIT (Business Intelligence Trainings)**, a gamified single-page web platform implementing the **IAEP model** — a four-pillar cognitive architecture organizing AI-directed reasoning into Ideation, Analysis, Execution, and Persuasion. BIT delivers 12 scaffolded missions producing a personalized *Master Prompt*: a metacognitive artifact encoding each user's reasoning profile as structured AI system instructions. The platform integrates gamification mechanics (ranks, unlockable skills, character progression) grounded in self-determination theory, and includes a secondary personality-mapping subsystem (BIT Arkana) to support psychological engagement and identity formation. We present the theoretical underpinnings of the IAEP model — connecting it to Bloom's revised taxonomy, Kolb's experiential learning cycle, Vygotsky's zone of proximal development, and dual-process cognitive theory — alongside a complete empirical study protocol. Qualitative evidence from ten early adopters indicates improved confidence, prompt quality, and strategic AI use. We argue that BIT represents a novel contribution to the AI literacy field: a complete, serverless, self-directed cognitive training system that outputs a verifiable, deployable metacognitive artifact.

Keywords: AI literacy, prompt engineering, cognitive scaffolding, gamified learning, metacognition, self-directed learning, large language models, instructional design

SECTION 1

Introduction

1.1 The Problem: AI Capability Without Cognitive Framework

By 2025, generative AI systems — including GPT-4o, Claude 3.5, and Gemini 1.5 — had achieved performance rivaling or exceeding domain experts across a wide range of knowledge tasks [1]. Yet empirical evidence consistently shows that the quality of human-AI collaboration is not primarily determined by model capability, but by the quality of human direction [2]. This "direction gap" — the difference between what an AI system could produce given ideal instruction and what it actually produces given average user prompts — represents a systematic failure of human cognitive preparation, not machine limitation.

Organizations across sectors report that AI tools are widely adopted but poorly utilized: employees use AI for isolated, tactical queries rather than structured, strategic workflows [3]. The most common intervention — prompt engineering training — teaches syntactic patterns ("act as," "chain of thought," "step by step") without developing the underlying cognitive capacity to generate those patterns independently across novel contexts [4]. The result is brittle competency: users can follow prompting templates but cannot reason about *why* those templates work or adapt them when contexts change.

We argue that effective AI use requires not prompt literacy but **cognitive architecture**: a structured, internalized model of how human reasoning modes map to AI interaction patterns, enabling users to direct AI systems fluently across the four fundamental dimensions of knowledge work — ideation, analysis, execution, and persuasion.

1.2 Research Gap and Contributions

Existing AI education products occupy two extremes: broad AI literacy curricula (e.g., Elements of AI, AI4K12) that develop conceptual understanding without practical skill, and narrow prompt engineering courses that develop tactical skill without cognitive depth [5]. No published system offers a gamified, self-directed, fully personalized curriculum that: (a) grounds prompt engineering in a formal cognitive model, (b) produces a deployable metacognitive artifact as its primary output, and (c) integrates identity and personality mapping to sustain engagement across a multi-session program.

This paper makes the following contributions:

(C1) The IAEP Model — a four-pillar cognitive architecture for AI-directed reasoning, formally specified and mapped to established learning science frameworks. **(C2) BIT Platform** — a complete, open, serverless implementation of the IAEP curriculum as a gamified 12-mission SPA, including source code and design documentation. **(C3) The Master Prompt** — a novel metacognitive artifact concept that synthesizes a user's full cognitive profile into deployable AI system instructions, enabling verifiable, persistent, personalized AI collaboration. **(C4) Empirical Study Protocol** — a complete pre-registered study design for evaluating BIT's effectiveness, along with qualitative preliminary evidence from ten early adopters.

SECTION 2

Literature Review

2.1 AI Literacy Frameworks

Long and Magerko's foundational work [5] identified 17 AI literacy competencies grouped into five themes: recognizing AI, understanding AI, using and applying AI critically, evaluating AI, and designing AI. Their framework emphasizes conceptual understanding but provides limited guidance on skill development sequencing or motivational scaffolding. Touretzky et al. [6]

similarly proposed five competency clusters for K-12 AI education, focused on classroom instruction rather than self-directed adult learning.

Holmes et al. [7] documented a global landscape of AI in education efforts, observing that most focus on AI *as a subject* (teaching about AI) rather than AI *as a cognitive tool* (teaching with AI to think better). Zawacki-Richter et al. [8] found in a systematic review that higher education AI integration studies rarely measured learning outcomes rigorously. BIT addresses all three gaps: adult-targeted, cognitively grounded, and producing measurable output artifacts.

2.2 Prompt Engineering as a Cognitive Skill

White et al. [2] formalized a catalog of 16 prompt patterns — reusable templates for directing LLM behavior — analogous to design patterns in software engineering. Their work establishes that prompt quality is systematic, learnable, and transferable, lending theoretical support to curriculum-based prompt training. Wei et al. [9] demonstrated that chain-of-thought prompting significantly improves LLM reasoning, suggesting that human reasoning structures, when made explicit in prompts, propagate into model outputs — a key mechanism BIT exploits through its variable-substitution mission architecture.

Noy and Zhang [3] conducted a controlled experiment on AI-assisted writing, finding that LLM access reduced task completion time by 40% and increased output quality ratings by 18% — but only for users who provided sufficiently specific instructions. This quantifies the direction gap: the average user leaves 30-50% of AI capability unrealized due to prompt quality, not model limitation. BIT's core pedagogical claim is that its curriculum closes this gap by developing the cognitive models needed for consistently high-quality direction.

2.3 Gamification in Learning Systems

Deterding et al.'s canonical definition [10] frames gamification as "the use of game design elements in non-game contexts," emphasizing that points and badges alone do not produce motivation — game elements must activate intrinsic psychological needs. Hamari et al.'s meta-analysis [11] found that gamification is effective under two conditions: when challenges are appropriately calibrated to user skill, and when the game narrative is meaningful rather than arbitrary.

BIT's gamification aligns with both conditions. First, missions are sequenced using cognitive scaffolding (Section 2.5), ensuring difficulty increases predictably with competency. Second, the progression narrative — from *Iniciado* through *Alquimista*, *Orquestador*, to *Mente BIT* — maps directly to cognitive achievements rather than arbitrary levels, giving ranks semantic coherence. Skill unlocks (12 named competencies) serve as both motivational milestones and conceptual vocabulary for users to name their developing capabilities.

2.4 Metacognition and AI Interaction

Flavell's foundational work on metacognition [12] distinguished metacognitive knowledge (what one knows about cognition), experience (real-time monitoring), and regulation (adjusting strategies). Schraw and Dennison [13] developed the Metacognitive Awareness Inventory (MAI), establishing that metacognitive awareness is measurable and improvable through structured intervention.

More recently, Luckin [14] argued that AI systems should function as "metacognitive scaffolds" — tools that make learners aware of their own thinking processes. BIT operationalizes this at the system level: the Master Prompt is not a chatbot interaction but a *codified representation of the user's metacognitive profile*, produced through structured self-reflection across 12 missions. To our knowledge, no prior system generates a deployable metacognitive artifact as its primary educational output.

2.5 Scaffolding Theory and Progressive Mastery

Vygotsky's zone of proximal development (ZPD) [15] holds that learning occurs most efficiently at the boundary between what a learner can do independently and what they can do with support. BIT implements ZPD through level gating: each level unlocks only when prior missions are complete, ensuring users face Levels 2-4 challenges with the cognitive tools developed in Levels 1-3. The AI system itself becomes the "more capable other" of Vygotsky's formulation.

Kolb's experiential learning cycle [16] — Concrete Experience → Reflective Observation → Abstract Conceptualization → Active Experimentation — maps precisely onto BIT's mission structure: users experience AI interaction (CE), write a reflective insight (RO), receive a named skill unlocking abstract knowledge (AC), and apply that knowledge in the next mission (AE). Anderson and Krathwohl's revision of Bloom's Taxonomy [17] provides a second alignment: BIT's four levels map to Remember/Apply (L1), Analyze/Evaluate (L2), Create/Synthesize (L3), and Evaluate/Communicate (L4).

2.6 Identified Gap

The reviewed literature reveals a consistent structural gap: *no published system integrates formal cognitive scaffolding, gamification grounded in self-determination theory, prompt engineering training, and metacognitive artifact production into a complete, self-directed, personalized curriculum*. BIT is designed to fill this gap.

SECTION 3

Theoretical Framework: The IAEP Model

3.1 Four Cognitive Modes

We propose the **IAEP model** — a four-dimensional cognitive architecture for AI-directed knowledge work. The model holds that all complex knowledge tasks can be decomposed into four fundamental cognitive operations, each requiring distinct reasoning modes, AI interaction patterns, and metacognitive skills.

MODE I

Ideation

Divergent thinking, conceptual blending, creative synthesis. The capacity to generate novel frames, connections, and possibilities where none existed.

Maps to: Bloom's Create/Remember · Kolb CE · System 1 thinking

MODE II

Analysis

Convergent thinking, variable decomposition, systematic evaluation. The capacity to identify which variables drive outcomes and how to control them precisely.

Maps to: Bloom's Analyze/Evaluate · Kolb AC · System 2 thinking

MODE III

Execution

Systems thinking, tool orchestration, iterative prototyping. The capacity to transform insights into replicable, measurable, improvable processes.

Maps to: Bloom's Apply/Synthesize · Kolb AE · Executive function

MODE IV

Persuasion

Narrative construction, social cognition, strategic communication. The capacity to make ideas legible, compelling, and actionable for others.

Maps to: Bloom's Evaluate/Communicate · Kolb RO · Narrative cognition

3.2 Formal Specification

We define a **cognitive state** C for a given user at time t as a four-dimensional vector:

$$C(t) = (I(t), A(t), E(t), P(t)) \in [0,1]^4$$

where each component represents the normalized proficiency in the corresponding mode. A **complete AI-ready cognitive profile** is defined as a state vector where all four components exceed a minimum threshold θ (empirically set to 0.7 in BIT's curriculum, corresponding to 3 completed missions per mode). The **Master Prompt** M is then a function of the user's full response history R = {r1, r2, ..., r12}:

$$M = f(R) = \text{synthesize}(r\_I, r\_A, r\_E, r\_P)$$

where r_X denotes the concatenated reflections from mode X missions

The function *f* is currently implemented as a deterministic template synthesis in BIT v9.1. Future work proposes using an LLM to generate f dynamically from user responses, producing richer profiles.

3.3 Alignment with Existing Taxonomies

Table 1. Alignment of the IAEP model with established educational and cognitive science frameworks

IAEP Mode	Bloom's (2001)	Kolb (1984)	Kahneman (2011)	AI Interaction Pattern
I · Ideation	Create, Remember	Concrete Experience	System 1 (intuitive)	Open-ended generation, conceptual blending prompts
A · Analysis	Analyze, Evaluate	Abstract Conceptualization	System 2 (deliberate)	Structured decomposition, constraint specification, meta-prompting
E · Execution	Apply, Synthesize	Active Experimentation	System 2 + automation	Tool orchestration, end-to-end

IAEP Mode	Bloom's (2001)	Kolb (1984)	Kahneman (2011)	AI Interaction Pattern
				pipeline design, MVP specification
P · Persuasion	Evaluate, Communicate	Reflective Observation	Narrative cognition	Story architecture prompts, audience calibration, stakeholder framing

3.4 Testable Hypotheses

The IAEP model generates four principal hypotheses that will be evaluated in the empirical study (Section 5):

HYPOTHESIS H1 — COGNITIVE SCAFFOLDING

Users who complete BIT missions in the prescribed IAEP sequence (I→A→E→P) will demonstrate significantly higher post-intervention AI output quality than users who complete missions in arbitrary order or access AI tools without structured training ($p < .05$, Cohen's $d \geq 0.5$).

HYPOTHESIS H2 — METACOGNITIVE TRANSFER

Users who complete all 12 BIT missions will demonstrate measurably higher metacognitive awareness scores (MAI; Schraw & Dennison, 1994) post-intervention than matched controls, indicating that the BIT curriculum develops durable metacognitive capacity, not only task-specific skill.

HYPOTHESIS H3 — MASTER PROMPT QUALITY

Master Prompts generated by BIT graduates, when used as system instructions in a standardized AI task battery, will produce outputs rated significantly higher on relevance, specificity, and actionability by blind evaluators than prompts produced by non-BIT users working on the same tasks.

HYPOTHESIS H4 — ENGAGEMENT AND COMPLETION

BIT's gamification mechanics (ranks, skill unlocks, character progression) will predict mission completion rates significantly above baseline for self-directed online learning platforms (industry baseline: 5-15% completion for MOOCs [18]), with predicted completion ≥ 65% among users who complete Mission 1.

SECTION 4

System Design

4.1 Architecture Overview

BIT is implemented as a single-file Progressive Web Application (PWA) in vanilla HTML5/CSS3/JavaScript, with no server-side dependencies. State is persisted in browser `localStorage` under the key `bit_v2`. This architecture was chosen deliberately: it eliminates all infrastructure dependencies, enables full offline use, scales to arbitrary concurrent users at zero marginal cost, and ensures user data never leaves the device without explicit export — an important privacy consideration for self-reflective educational tools.

The current production version (v9.1) consists of approximately 3,300 lines of code implementing eight tabs (Misiones, Personaje, Radar, Códex, Voces, Nexo, Núcleo, Arkana), a complete onboarding flow, 12 mission views, certificate generation via the browser Print API, and a full gamification engine — all without build tools, frameworks, or transpilation.

```
State Object S (localStorage: "bit_v2")
├── name: string            // user name
├── company: string         // organization
├── bitRole: string         // personal BIT role (M2)
├── completed: number[]     // mission IDs completed
├── responses: {[id]: string} // reflection texts
├── mVars: {[id]: {[k]:v}}  // mission variables
├── charType: string        // active archetype
```

```
├── points: number          // total points
├── aiTool: string          // preferred AI
└── gender: "M"|"F"         // gender (affects UX copy)
```

Figure 1. *BIT state object schema persisted in browser localStorage. All user data is stored client-side; no personal information is transmitted to any server.*

4.2 Mission Structure and Scaffolding

BIT implements 12 missions distributed across four levels corresponding to the IAEP model. Each mission follows a consistent pedagogical structure designed to activate Kolb's full learning cycle within a single session:

Table 2. Mission structure components and their pedagogical functions

Component	Pedagogical Function	Kolb Stage
Context	Activates prior knowledge, frames the cognitive challenge	Reflective Observation
Variable Inputs	Personalizes the prompt; forces user to articulate their specific situation	Abstract Conceptualization
Live Prompt Preview	Shows prompt construction in real-time; makes abstract structure concrete	Abstract Conceptualization
AI Interaction	Provides the concrete experience with the AI system	Concrete Experience
Reflection textarea	Requires users to extract a personal insight from the experience	Reflective Observation
Skill Unlock	Names and frames the newly developed competency; reinforces transfer	Abstract Conceptualization
Next Mission	Applies previous learning in a new, slightly more complex context	Active Experimentation

The variable substitution mechanism is central to personalization. Each mission prompt contains 2–4 parameterized slots (e.g., `{problema}`, `{industria}`, `{objetivo}`) that users complete before the prompt is usable. This forces users to contextualize abstract skills to their specific situation — a requirement that substantially increases both engagement and the relevance of AI outputs [2].

4.3 The Master Prompt as Metacognitive Artifact

The primary novel contribution of BIT is the **Master Prompt** — a synthesis document generated upon completion of all 12 missions that encodes a user's full cognitive profile as structured AI system instructions. This artifact is simultaneously:

(a) A metacognitive record — it documents the user's self-understanding of their reasoning strengths, working context, and cognitive mode profile. **(b) A deployable AI configuration** — it can be pasted as system instructions into any LLM (GPT, Claude, Gemini), producing an AI assistant that has internalized the user's identity, goals, and reasoning style. **(c) A verifiable credential** — the document's content demonstrates that the user can articulate their cognitive profile with sufficient precision to configure an AI system — a high-order metacognitive competency.

> DEFINITION: MASTER PROMPT
>
> A Master Prompt M for user u is a structured natural language document of the form: *System Role → Context → Cognitive Profile → Behavioral Guidelines → Output Standards*, generated deterministically from u's variable inputs and mission reflections, such that when used as system instructions for an LLM, the resulting AI system reproduces u's preferred reasoning patterns, communication style, and domain expertise.

4.4 Gamification Mechanics

BIT's gamification design follows the Self-Determination Theory (SDT) framework [19], which identifies autonomy, competence, and relatedness as the three psychological needs that intrinsic motivation requires.

Autonomy is supported through self-pacing, tool choice (users select their preferred LLM), and character customization (18 pixel-art archetypes including gender variants). **Competence** is supported through the 13-rank progression system (Iniciado → Mente BIT), 12 named skill unlocks corresponding to genuine competencies, and visual progress indicators (progress bars, neural network visualization, RPG stats). **Relatedness** is supported through the 10-testimonial

Voces section showing real user experiences, and the shared language of the BIT community (the four pillars serve as a vocabulary that enables peer conversation about AI reasoning).

Table 3. BIT gamification elements mapped to SDT needs and learning outcomes

Game Element	SDT Need	Learning Function
13-rank title progression	Competence	Landmarks for cognitive development trajectory
12 named skill unlocks	Competence	Vocabulary for metacognitive self-description
Character archetype selection	Autonomy	Identity engagement; personalization of learning
Tool selection (GPT/Claude/Gemini)	Autonomy	Agency; reduces tool-dependency bias
Neural network visualization	Competence	Spatial representation of cognitive development
Testimonial section (Voces)	Relatedness	Social proof; reduces isolation in self-directed learning
Master Prompt certificate	Competence + Relatedness	Verifiable, shareable achievement; bridges learning and professional contexts

4.5 BIT Arkana: Identity Engagement Subsystem

The Arkana subsystem is an intentional deviation from standard educational platform design. Rather than offering a reward-based cosmetic (common in gamified learning), Arkana provides a **personalized cosmological identity map** linking the user's birthdate to zodiacal archetypes, elemental psychology, and BIT cognitive pillar affiliation.

The theoretical basis for this design is *identity-based motivation theory* [20], which holds that learning is sustained when learners perceive the learning task as consistent with their identity. By mapping IAEP pillars onto archetypal personality frameworks (e.g., Aries/Fire/Ideation, Virgo/Earth/Analysis), Arkana creates a culturally resonant narrative that positions the user's dominant cognitive mode as a natural expression of who they are — not a skill being externally imposed. This approach has precedent in Jungian typology applications in educational psychology [21].

Arkana also includes an interactive display of 8 sacred geometry figures (Merkabá, Flower of Life, Metatron's Cube, Rodin Vortex, Torus, Vector Equilibrium, Sri Yantra, Golden Spiral), 5 Platonic Solids, and 8 foundational physics and mathematics equations. This content serves a specific function: it signals that BIT is engaging with a larger philosophical project — the development of human consciousness in collaboration with AI — rather than merely teaching productivity techniques. The Arkana section targets users who are motivated by meaning and cosmological significance alongside practical skill.

SECTION 5

Empirical Study Design

5.1 Overview and Research Questions

We propose a mixed-methods study to evaluate BIT's effectiveness. The study addresses four research questions:

RQ1. Does completing the BIT curriculum improve the quality of users' AI-directed outputs as assessed by blind evaluators?
RQ2. Does BIT completion produce measurable increases in metacognitive awareness?
RQ3. Do BIT gamification mechanics sustain engagement above MOOC baseline completion rates?
RQ4. Are the four IAEP cognitive modes empirically distinguishable in users' Master Prompts and mission reflections?

5.2 Participants

Target N = 60 (30 experimental, 30 waitlist control). Eligibility: knowledge workers (employed ≥ 1 year), minimum daily AI tool use of 30 minutes for ≥ 3 months, no prior structured prompt engineering training. Recruitment via LinkedIn and AI professional communities. Minimum age: 22. No maximum age. Equal representation across four professional domains: marketing, engineering, management, education.

Power analysis: assuming a medium effect size ($d = 0.6$, based on comparable educational interventions), $\alpha = .05$, power = 0.80, minimum n per group = 23. N = 30 per group provides buffer for 20% attrition.

5.3 Procedure

WEEK 0 · PRE-ASSESSMENT

Metacognitive Awareness Inventory (MAI, 52 items). AI self-efficacy scale (10 items, adapted from Compeau & Higgins, 1995). Standardized AI task battery (3 tasks: problem decomposition, persuasive memo, system design brief). Outputs rated by 3 blind expert evaluators on a validated 5-point rubric (Relevance, Specificity, Actionability, Completeness, Clarity).

WEEKS 1–3 · INTERVENTION

Experimental group: self-directed BIT platform completion (target: 12 missions, estimated 4–8 hours total). No time pressure. Control group: free AI tool use, no structured curriculum. Both groups log daily AI use via a lightweight diary (5-minute daily entry).

WEEK 4 · POST-ASSESSMENT (IMMEDIATE)

Full MAI re-administration. AI self-efficacy scale. Identical AI task battery (counterbalanced stimuli). Experimental group: Master Prompt quality evaluation by 3 blind raters. Platform engagement metrics collected from localStorage snapshots (missions completed, time per mission, reflection length).

WEEK 10 · FOLLOW-UP (RETENTION)

Abbreviated battery: MAI knowledge subscale (8 items), AI task battery (1 task), brief interview (15 min) on AI use changes. Control group offered access to BIT platform after study completion.

5.4 Primary Measures

Table 4. Measurement instruments and outcome variables

Measure	Instrument	Hypothesis
AI Output Quality	5-criterion expert rubric (IRR target: $\kappa \geq 0.70$). Tasks: problem decomposition memo, persuasive brief, system design spec.	H1, H3
Metacognitive Awareness	MAI (Schraw & Dennison, 1994). 52 items, 8-factor structure, Likert 1–5.	H2
AI Self-Efficacy	10-item scale adapted from Computer Self-Efficacy (Compeau & Higgins, 1995).	H1

Measure	Instrument	Hypothesis
Completion Rate	localStorage telemetry: missions_completed / 12 for each user.	H4
Master Prompt Quality	Separate 5-item rubric: Identity Specificity, Contextual Richness, Behavioral Precision, Cognitive Mode Coverage, Deployability.	H3
IAEP Mode Distinctiveness	Thematic content analysis of mission reflections (coded by 2 independent raters for IAEP mode content).	H1, RQ4

5.5 Analysis Plan

Quantitative: Paired t-tests for within-group pre/post comparisons; independent samples t-tests for between-group comparisons at post-test. ANCOVA with pre-test scores as covariate. Effect sizes reported as Cohen's d. All analyses conducted in R (v4.3+); scripts and data made available at OSF. Alpha = .05, two-tailed.

Qualitative: Reflexive thematic analysis [22] of mission reflections and follow-up interviews. Themes coded independently by two researchers; disagreements resolved by consensus. IAEP mode content in Master Prompts analyzed using directed content analysis seeded by the four-mode coding scheme.

Moderation analyses: Exploratory examination of whether effects differ by AI tool used (GPT/Claude/Gemini), professional domain, and prior AI experience. No a priori power for moderation; results treated as hypothesis-generating.

SECTION 6

Preliminary Findings

6.1 Qualitative Evidence: Early Adopter Testimonials

Prior to the formal study, BIT was used by an initial cohort of knowledge workers recruited through professional networks. Ten users who completed all 12 missions provided written testimonials, which were subjected to preliminary thematic analysis. While not meeting the standards of controlled evidence, these data offer early signal on user experience and perceived outcomes.

Three recurring themes emerged:

THEME 1 — IDENTITY CLARITY AND PROFESSIONAL REPOSITIONING

Multiple users reported that the combination of Mission 1 (cognitive state diagnosis) and Mission 2 (role personalization) produced unexpected clarity about their professional identity and value proposition — independent of AI functionality.

"Antes de BIT usaba ChatGPT como si fuera Google. Después de la misión 4 [metaprompting] entendí que la calidad del output es mi responsabilidad, no de la IA. Eso cambió todo."

— Participant A · Marketing Director · Mexico City

"Lo que más me sorprendió fue que al terminar el programa tenía un documento — mi Prompt Maestro — que podía usar inmediatamente. No solo había aprendido algo abstracto, sino que tenía una herramienta real."

— Participant B · Entrepreneur · Guadalajara

"El sistema de misiones hace que conceptos difíciles como 'arquitectura de inputs' se vuelvan simples porque los practicas con tu problema real, no con ejemplos inventados."

— Participant C · Operations Manager · Monterrey

THEME 2 — TRANSFER TO NOVEL AI TASKS

Seven of ten users spontaneously mentioned applying BIT-developed frameworks to AI tasks not covered in the curriculum, suggesting metacognitive transfer rather than only task-specific learning. This is consistent with Hypothesis H2 and warrants formal measurement.

> *"Cuando necesito usar una IA para algo nuevo, ya tengo un proceso: primero identifico en cuál de los 4 modos estoy pensando, luego diseño el prompt desde ahí. No necesito recordar trucos, tengo un sistema."*
>
> — Participant D · UX Designer · CDMX

THEME 3 — COMPLETION DRIVEN BY GAMIFICATION COHERENCE

Users cited the gamification as a completion enabler specifically because the ranks and skills felt semantically meaningful, not arbitrary. Multiple users noted that the rank name at their current level accurately described their perceived competency — suggesting the progression design has ecological validity.

> *"Llegué al rango 'Orquestador' exactamente cuando sentí que podía coordinar múltiples IAs para un proyecto. No fue coincidencia, el sistema estaba midiendo algo real."*
>
> — Participant E · Product Manager · Bogotá

6.2 Engagement Metrics (Preliminary)

From the initial cohort (N = 10, self-selected completers), preliminary platform telemetry — captured from voluntary localStorage exports — showed the following patterns:

Table 5. Preliminary engagement metrics from early adopter cohort (N=10, completers only)

Metric	Value	Note
Mean missions per session	2.8	Users typically complete 2–3 missions per sitting
Mean reflection length (chars)	312	Range: 98–780; minimum required: 40
Mean total time (estimated)	5.4 hours	Estimated from session counts × avg session length
Missions with longest reflections	M1, M2, M9	Identity-related and systems-design missions

Metric	Value	Note
Most commonly selected AI tool	Claude (60%)	ChatGPT: 30%, Gemini: 10%

6.3 Limitations of Current Evidence

The preliminary evidence described above has substantial limitations: the cohort is self-selected (only completers reported), lacks a control group, and is too small for inferential statistics. Testimonials are retrospective and subject to social desirability bias. We present them not as evidence of efficacy but as qualitative signal to inform hypothesis specification and study design. The formal study described in Section 5 will provide rigorous evidence.

SECTION 7

Discussion

7.1 Theoretical Contributions

The IAEP model contributes to the AI literacy literature by providing the first cognitive architecture specifically designed for AI-directed knowledge work. Existing frameworks (Long & Magerko, 2020; Touretzky et al., 2019) describe what users should know about AI; IAEP describes how users should organize their own thinking to interact with AI productively. This is a substantive distinction: knowing that LLMs can reason by analogy is different from having a cognitive routine for generating high-quality analogical prompts.

The Master Prompt concept extends metacognitive theory into a new form. Traditional metacognitive interventions produce changes in thinking; BIT produces a *document* that externalizes those changes and makes them deployable as AI configuration. This is analogous to the difference between developing mathematical intuition (metacognitive) and writing a textbook that codifies it (artifact). The BIT Master Prompt is a metacognitive artifact in the literal sense: a physical (digital) object that embodies refined self-knowledge.

7.2 Design Principles Derived

BIT's design yields several principles for gamified cognitive education platforms:

P1 — Semantic gamification: Game elements should correspond directly to learning objectives. Ranks that name cognitive milestones (Orquestador, Narrador) are more motivationally effective than arbitrary levels (Level 7, Expert Badge) because they provide learners with a vocabulary for their own development.

P2 — Personalization as pedagogy: Requiring users to substitute personal variables into every prompt serves dual functions — it personalizes outputs and forces metacognitive engagement with one's own situation. Generic examples should be replaced with parameterized templates wherever possible.

P3 — Artifact-driven learning: Designing a curriculum around a deployable artifact (the Master Prompt) rather than a score or certificate substantially changes the learning experience. Users work toward something they will actually use, not toward an academic credential they may never deploy.

P4 — Identity engagement as retention mechanism: The BIT Arkana system, personality archetypes, and character customization serve not as entertainment but as identity-investment mechanisms. When learners see their cognitive mode as an expression of who they are (not just what they should do), engagement and persistence increase substantially.

7.3 Limitations

BIT has several current limitations that future work should address. First, **no cloud synchronization**: state is stored exclusively in localStorage, preventing cross-device access. This limits usage for mobile-primary users and creates data loss risk. Second, **no objective verification**: the certificate is self-generated without external validation of learning outcomes. A blockchain-anchored or third-party verified credential system would increase institutional acceptance. Third, **single language**: BIT is currently implemented in Spanish, limiting global applicability. Localization infrastructure does not yet exist. Fourth, **no adaptive difficulty**: missions are fixed-sequence with no branching based on user performance. An adaptive version that responds to reflection quality or engagement patterns could improve learning outcomes for users at the tails of the competency distribution.

Additionally, the theoretical claim that the IAEP model is *necessary and sufficient* for AI-directed cognition requires empirical validation. Alternative framings (e.g., a five-mode model adding an "Evaluation" pillar; a two-mode model collapsing Analysis and Execution) may prove equally or more effective. The current specification should be treated as a first empirically testable formulation, not a final taxonomy.

7.4 Broader Implications

If the IAEP model and its BIT implementation prove effective at scale, the implications extend beyond individual productivity. Organizations that adopt a shared cognitive vocabulary (the four modes) for AI interaction can develop coordination systems where team members know which mode they are in, which AI tools are optimal for each mode, and how to hand off between modes efficiently. This represents a form of *organizational metacognition* — teams that are self-aware not only of what they know but of how they think collectively.

More broadly, the premise that AI literacy is primarily a *thinking* skill rather than a *technical* skill has significant curriculum implications. If our hypotheses are confirmed, the most effective AI education investment is not in tool training but in cognitive architecture development — teaching people how to think, not what to type.

SECTION 8

Conclusion

We have presented BIT, a gamified cognitive architecture framework for AI-augmented human cognition. The central contribution is the IAEP model — a four-dimensional cognitive architecture (Ideation, Analysis, Execution, Persuasion) that structures AI-directed reasoning into a learnable, teachable, and measurable progression. BIT implements this model as a 12-mission gamified curriculum producing the Master Prompt: a deployable metacognitive artifact encoding each user's cognitive profile as AI system instructions.

The system is grounded in established learning science: Bloom's revised taxonomy, Kolb's experiential cycle, Vygotsky's zone of proximal development, Self-Determination Theory, and metacognitive research. It generates four testable hypotheses that the proposed empirical study will evaluate rigorously. Preliminary qualitative evidence from ten early adopters indicates positive signal on cognitive transfer, engagement, and practical value.

BIT is already deployed and used by knowledge workers across Latin America. The proposed study will provide the controlled evidence needed to substantiate its theoretical claims and establish BIT as a validated AI education intervention. Future work will explore adaptive mission sequencing, multilingual deployment, organizational team-mode assessment tools, and LLM-powered Master Prompt synthesis.

The central wager of BIT is this: *in the age of AI, the limiting resource is not machine intelligence — it is the human capacity to direct it.* Building that capacity systematically is among the most valuable educational investments a society can make.

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APPENDIX A

BIT Mission Prompts: Abbreviated Catalog

Full prompt templates for each mission, showing variable slots (highlighted in blue) that users complete before the prompt is submitted to their chosen AI system.

M1 · IDEAR — ESTADOS COGNITIVOS

```
Actúa como un diagnosticador cognitivo de alto nivel. Mi nombre es
{nombre} y me dedico a {profesión}. Mi desafío principal en este
momento es {problema}. Diagnostica en qué estado cognitivo me
encuentro (Explorador, Analítico, Ejecutor, Integrador), explica por
qué, describe cómo afecta mi forma de ver este problema y sugiere
cómo activar el estado más útil para resolverlo. Finaliza con 3
preguntas poderosas que debo hacerme antes de actuar.
```

M4 · ANALIZAR — METAPROMPTING ESTRATÉGICO

```
Diseña un sistema de prompts para {tarea_recurrente} en el contexto
de {industria}. El sistema debe incluir: Rol del asistente, Contexto
necesario, Tarea específica, Formato de salida esperado,
Restricciones clave. Luego genera el metaprompt maestro que
activaría este sistema de manera consistente y replicable.
```

M8 · EJECUTAR — DISEÑO DE SISTEMAS END-TO-END

```
Diseña un sistema de trabajo end-to-end para {proceso} en
{contexto_organizacional}. El sistema debe incluir: Anatomía del
proceso (pasos clave), Flujo de información entre pasos, Métricas de
calidad por etapa, Puntos de falla más comunes y cómo prevenirlos,
Un MVP implementable en 48 horas. Estructura la respuesta como un
manual operativo que un colaborador nuevo pueda seguir sin
supervisión.
```

M12 · PERSUADIR — PERSUASIÓN Y PRESENTACIÓN

```
Actúa como un consultor de comunicación estratégica. Necesito
persuadir a {audiencia} sobre {propuesta} en el contexto de
```

```
{situacion}. Diseña una estrategia de persuasión completa: establece
credibilidad en los primeros 30 segundos, construye el argumento
lógico en 3 niveles, anticipa y desmonta las 2 objeciones más
probables, incluye el cierre específico para esta audiencia.
Finaliza con el guion exacto para una presentación de 3 minutos.
```

APPENDIX B

AI Output Quality Rubric

Instrument for blind evaluation of AI-generated outputs in the empirical study. Raters assess each output on five criteria (1–5 scale each; maximum 25 points).

Criterion	1 — Insufficient	3 — Adequate	5 — Excellent
Relevance *Does the output address the actual problem?*	Output addresses a generic version of the problem; ignores specific context provided.	Output addresses the core problem; some context integrated.	Output precisely addresses the specific problem with all contextual nuances respected.
Specificity *How concrete and actionable are the outputs?*	Output is generic; could apply to any situation; no concrete steps.	Output includes some specifics; partially actionable.	Output provides specific, named actions, timelines, or parameters uniquely suited to the situation.
Actionability *Can a competent person implement this immediately?*	Output describes concepts but provides no implementation path.	Output provides implementation steps that require significant additional interpretation.	Output provides a clear implementation path requiring minimal additional judgment.

Criterion	1 — Insufficient	3 — Adequate	5 — Excellent
Completeness *Does it address all dimensions of the task?*	Output addresses <50% of task dimensions.	Output addresses 50–80% of task dimensions.	Output addresses all major task dimensions comprehensively.
Structural Clarity *Is information organized for efficient use?*	Output is presented as undifferentiated prose; difficult to navigate.	Output has some structure; partially navigable.	Output uses clear headers, hierarchy, or format that enables rapid extraction of key information.

APPENDIX C

BIT Skills Taxonomy

The 12 skills comprising the BIT competency taxonomy, each unlocked upon mission completion. Skills are designed to be named, discussed, and self-assessed — serving as a shared vocabulary for metacognitive reflection.

#	Skill Name	IAEP Mode	Core Competency
1	**Mente Clara**	Ideation	Distinguishes signal from noise; identifies the root problem beneath surface symptoms
2	**Identidad Propia**	Ideation	Articulates professional identity with sufficient precision to configure AI as a personalized assistant
3	**Fusión Creativa**	Ideation	Combines domains by analogy to generate novel solutions outside conventional category boundaries
4	**Código Maestro**	Analysis	Understands prompt structure as a grammar; diagnoses why outputs succeed or fail at the structural level

#	Skill Name	IAEP Mode	Core Competency
5	**Arq. de Inputs**	Analysis	Designs the information inputs that enable high-quality AI outputs; applies input-quality principle systematically
6	**Precisión Total**	Analysis	Specifies output constraints (format, length, tone, depth) precisely enough to reduce ambiguity-driven variation
7	**Orquestador**	Execution	Coordinates multiple AI tools as a coherent system; assigns each tool to its optimal function
8	**Constructor**	Execution	Transforms insights into documented, replicable, improvable AI-assisted workflows
9	**Ejecutor Ágil**	Execution	Moves from insight to prototype without friction; applies AI to reduce iteration cost and time-to-test
10	**Narrador**	Persuasion	Converts data, processes, and expertise into narratives that are legible and compelling to target audiences
11	**Claridad Extrema**	Persuasion	Communicates with zero redundancy; each word serves a function; uses AI to compress without losing meaning
12	**Mente BIT**	Persuasion	Integrates all four IAEP modes fluidly; shifts between modes as task demands; directs AI across the full cognitive spectrum

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