Cognitive Sovereignty in the Intelligence Economy

A Unified Empirical–Mathematical–Ecological Framework for Human–AI Value Systems

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Abstract

This paper develops a unified framework describing the transition from the attention economy to the intelligence economy, integrating biological cognition, information theory, behavioral economics, ecological niche theory, and artificial intelligence systems. It proposes that human cognition acts as a productive resource that compounds through interaction with AI, constrained by biological limits and ecological competition. A mathematically grounded model is introduced in which intelligence production follows exponential growth governed by a cognitive productivity coefficient — decomposed multiplicatively through knowledge depth, attention intensity, and system interaction skill — moderated by an ecological niche factor and bounded by a piecewise cognitive exhaustion model with an analytically derivable critical time T*.

The framework advances the concept of cognitive sovereignty, arguing that human cognitive contributions in AI ecosystems constitute a form of digital resource requiring recognition, governance, and benefit-sharing. The governance architecture draws on three complementary foundations: the Nagoya Protocol on Access and Benefit-Sharing as a structural analogy; Ostromian commons governance theory — empirically grounded in Nepal's 22,266 Community Forest User Groups and the Rupa Lake Restoration and Fisheries Cooperative — as the positive institutional model; and a three-tier rights architecture (universal baseline floor, proportional returns tier, sub-group protection tier) that addresses the internal power failures documented by Adhikari, Kingi & Ganesh (2014) within formally inclusive commons institutions.

A central theoretical contribution is the identification of the Voluntary Extraction Inversion: a phase transition in which the extractive researcher who once had to visit communities to collect knowledge has been replaced by platform infrastructure that requires no visit, because communities come to it voluntarily, daily, on devices they are financing through EMI obligations. This second-order extraction dynamic — invisible, continuous, and indistinguishable from use — is formally theorized through a three-phase extraction typology and grounded in field observation from Eastern Nepal. The paper introduces the Sandakpur Theorem, a formal statement of survival microeconomy stability conditions derived from field observation in Ward No. 3, Sandakpur Municipality; and the Intelligence Economy Survival Gap G, a formal economic measure of the compensation deficit borne by knowledge generators in the Global South. The double-extraction dynamic — simultaneous biological bioprospecting and digital cognitive extraction — is identified as the framework's most distinctive empirical contribution. The model is designed to be empirically testable and economically interpretable.

1. Conceptual Transition: Attention → Behavior → Intelligence

1.1 The Attention Economy

Herbert Simon (1971) established the foundational argument: information abundance creates attention scarcity. Attention is finite and rivalrous; value accrues to whoever controls its allocation. Davenport and Beck (2001) operationalized this as a management problem.

$$V\_attention \propto A(t)$$

1.2 The Behavioral Economy

Kahneman and Tversky's (1979) prospect theory and Thaler and Sunstein's (2008) nudge framework established that behavior B, not merely attention, can be systematically shaped. Zuboff (2019) terms the resulting architecture surveillance capitalism: behavioral data extracted without compensation feeds predictive models. The critique from political economy — Smythe's (1977) audience commodity concept and Morozov's (2019) structural labor analysis — situates cognitive sovereignty as a labor and value theory argument, not merely a privacy one.

$$V\_behavioral \propto f(A, B)$$

1.3 The Intelligence Economy

Generative AI marks a third transition: the productive unit is intelligence generated, not attention captured or behavior shaped.

$$V\_intelligence \propto I(t)$$

This extends Romer's (1990) endogenous growth model — which treats knowledge as a productive input with non-rival, increasing-returns properties — to the level of individual cognitive interaction with AI systems. The empirical literature on human-AI complementarity (Brynjolfsson & Mitchell, 2017; Autor, 2022) demonstrates that AI selectively augments tasks requiring synthesis, judgment, and domain-specific knowledge. Drucker (1993) identified the knowledge worker as the defining productive agent of post-industrial society; neither framework addressed the survival gap that emerges when the intelligence economy extracts more from knowledge generators than it returns.

Field grounding: a 54.5-hour cross-disciplinary knowledge exchange in Eastern Nepal (May 2026), spanning traditional ecological economics, and AI governance theory, constituted the intelligence economy in its most direct empirical form — value generated entirely through cognitive exchange, with zero micro-payment infrastructure, while a monthly EMI obligation continued collecting on the device that mediated the exchange.

2. Mathematical Foundations

2.1 Exponential Intelligence Growth

The autocatalytic assumption: the instantaneous rate of intelligence production is proportional to current intelligence.

$$dI/dt = \alpha \cdot I(t)$$

Unique solution given $I(0) = I_0$:

$$I(t) = I_0 \cdot e^{(\alpha t)}$$

Support comes from the learning curve literature (Wright, 1936; Arrow, 1962) and long-term potentiation (LTP) in neuroscience — the mapping from LTP to scalar α is biological motivation, not formal derivation. Base e is expositional: any exponential is equivalent under reparametrisation of α. α is treated as time-invariant over bounded interaction windows — a short-run approximation. Cognitive productivity plausibly changes with practice (Arrow, 1962) or fatigue; extension to time-varying $\alpha(t)$ is left for future work.

2.2 Multiplicative Value Combination

2.2.1 Increasing-Returns Production

Platform amplification $P_0e^{(rt)}$ and cognitive growth $I_0e^{(\alpha t)}$ are complementary: each without the other produces no intelligence value. The model assumes increasing returns to scale — explicitly adopting Romer's (1990) position that knowledge is the source of scale economies. Unit exponents are a structural choice, not an empirical finding. Estimation of actual exponents from interaction log data is a priority for future work. The Cobb-Douglas form provides the complementarity intuition; the constant-returns-to-scale constraint is not imposed.

2.2.2 Direct Scaling Argument for N

$N = K_{unique} / K_{global}$ enters multiplicatively through a survival-fraction argument: N represents the fraction of a user's cognitive output that survives commoditisation. Multiplying total production by N is definitionally correct. Independence of N from I(t) holds when commoditisation operates at aggregate level — a reasonable approximation for current RLHF architectures. If platform replication capacity were to scale with individual output volume, N would become endogenous to I(t) and multiplicative separability would break down.

Note: the Fisher information metric argument for N from a prior version is retracted. The Fisher metric is a property of parameter spaces of statistical models, not a discount factor on production value.

Field grounding: the 52nd card in the Falas game (17 players × 3 cards = 51 dealt; 1 structurally excluded) is the commons that makes the game possible and that no accumulation strategy can capture without destroying the system. N approaching zero in the intelligence economy is the 52nd card being consumed.

2.3 Cognitive Exhaustion: Piecewise State-Variable Model

State variable E(t) for cumulative cognitive expenditure:

$$E(t) = \int_0^t I(\tau)\, d\tau = (I_0/\alpha)(e^{(\alpha t)} - 1)$$

Exhaustion constraint:

$$E(t) \leq C_{max}$$

Critical time T* at which exhaustion binds:

$$T^* = (1/\alpha) \cdot \ln(1 + \alpha \cdot C\_max / I_0)$$

Recovery function (single-compartment pharmacokinetic model):

$$R(s) = 1 - (1 - r\_rest)(1 - e^{(-\lambda s)})$$

where λ is recovery rate and r_rest ∈ (0,1) is asymptotic recovery fraction. Multi-compartment extensions may better capture distinct dynamics of attentional fatigue and longer-term cognitive depletion. The Falas game's fatigue index F — observably slowing game tempo across a 5-hour window — is a naturalistic pilot dataset for calibrating C_max and λ.

3. The Cognitive Productivity Coefficient α

Given the complementarity logic — knowledge depth, attention, and system skill are necessary to one another, not substitutable — the correct decomposition is log-linear, not additive. The additive form permits one component to compensate fully for a deficit in another, violating complementarity. Revised specification:

$$\ln \alpha = \beta_1 \ln K + \beta_2 \ln A + \beta_3 \ln S$$

equivalently $\alpha = K^{\beta_1} \cdot A^{\beta_2} \cdot S^{\beta_3}$: a Cobb-Douglas specification at the level of α. If any component approaches zero, α approaches zero regardless of the others.

3.1 Knowledge Depth K

K is measured as the information gain from a reasoning episode, formalised using the Kullback-Leibler divergence from prior to posterior probability distribution over a knowledge domain:

$$K = D\_KL(q \parallel p) = \Sigma\, q\_i \cdot \log(q\_i / p\_i)$$

where p is the prior distribution over knowledge states before a reasoning episode and q is the posterior after. This captures the directionality of Bayesian belief updating — the specific reduction in uncertainty achieved by moving from p to q — consistent with information-theoretic models of cognition (Shannon, 1948; Tenenbaum et al., 2011). Shannon entropy difference $H_0 - H_1$ does not capture this directionality and can return negative values under legitimate uncertainty expansion, making it unsuitable as a measure of directed knowledge gain. Two acknowledged challenges remain. First, direct elicitation of prior and posterior distributions for open-ended knowledge states requires controlled experimental paradigms; a practical proxy is pre/post accuracy on standardised domain assessments. Second, K per episode (§3.1) and K_unique as corpus-level uniqueness (§4.1) are linked by: K_unique = (1/T)Σ_j K_j — mean KL-divergence per episode. This aggregation is an approximation; the appropriate functional form is empirical.

The IKS-AI complementarity literature (Kumar & Singh, 2025) establishes that indigenous knowledge provides deep, localized insight that is precisely what is absent from large-scale AI datasets — confirming that K_unique in Himalayan TEK contexts is structurally high and structurally undervalued simultaneously. Indigenous-managed lands account for approximately 22% of global land surface and hold 80% of the planet's biodiversity (Sobrevila, 2008, Kumar & Singh, 2025) — a concentration of K_unique that no current AI governance framework compensates.

3.2 Attention Intensity A

$$A = T\_focused / T\_total \in [0, 1]$$

Grounded in Kahneman's (1973) resource theory. DMN research confirms that mind-wandering predicts reduced learning consolidation (Smallwood & Schooler, 2015). Tractable operationalisations: eye-tracking, interaction log proxies (typing rate, query latency, revision frequency), EEG-based attention measures in controlled settings.

3.3 System Interaction Skill S

S captures prompt engineering efficiency. Circularity acknowledged: S = Q_output / P_effort is partially collinear with the outcome I(t) if Q_output is endogenous. Resolution: S is assessed against a fixed external benchmark task at baseline and intervals, scored by evaluators blind to treatment condition — removing the circularity by anchoring Q_output to a stable external criterion.

4. Ecological Niche Compression and the Survival Equilibrium

4.1 The Niche Factor N

$$N = K\_unique / K\_global \in [0, 1]$$

Drawing from MacArthur and Wilson (1967) and Hutchinson (1957). As K_global rises (AI makes more knowledge universally accessible), K_unique must also rise to maintain N — otherwise cognitive niche compression occurs. Operationalised via semantic uniqueness scores: embedding-distance between user outputs and AI-generated baselines in the same domain. Versioned baseline protocol required as frontier models improve.

Kumar & Singh's (2025) complementarity framework maps directly: IKS supplies K_unique (deep, localized, intergenerational, spiritually grounded insight); AI supplies K_global (large-scale pattern recognition, automated monitoring). The synergy is real — but under Phase 2 extraction (Section 7), the amplification accrues to the platform, not to the K_unique holder.

4.2 The Survival Equilibrium Formula

$$E_s = (Dc \times Kc) / (X_r \times C_a)$$

where Dc = Contribution Diversity; Kc = Knowledge Circulation rate; X_r = Extraction Rate; C_a = Algorithmic Centralization. When $X_r \to \infty$ and $C_a \to$ monopoly (Zuboff, 2019), $E_s \to 0$ regardless of local survival knowledge. The system becomes immune to its own intelligence.

4.3 The Paradox of Intelligence Abundance

$$I\_global \uparrow \Longrightarrow N \downarrow \Longrightarrow \text{cognitive niche compression} \Longrightarrow E_s \downarrow$$

Testable prediction: as AI capability increases, economic returns to genuinely unique human cognitive contributions should increase for high-N users, consistent with Brynjolfsson & Mitchell (2017) and Autor (2022). The Falas game demonstrates this locally: players with higher ancestral knowledge A_i maintain competitive advantage (higher effective N) because that knowledge is tacit, embodied, and transmitted through face-to-face community practice — inaccessible to algorithmic replication.

5. The Integrated Model

$$V(t) = P_0 \cdot I_0 \cdot e^{((r+\alpha)t)} \cdot N \cdot \Psi(t)$$

$$\Psi(t) = 1, \qquad t \leq T^*$$

$$\Psi(t) = R(t - T^*) \in (0,1), \qquad t > T^*$$

Parameter	Interpretation	Empirical Access Route
P_0	Initial platform value	Platform market cap / revenue attribution
r	Platform amplification rate	Must be identified separately from α — see §8.1
I_0	Initial cognitive state	Baseline knowledge assessment / domain pre-test
α	Cognitive productivity	Log-linear panel regression on interaction logs
N	Niche factor	Semantic uniqueness scores vs. versioned AI baseline
C_max	Cognitive capacity limit	Psychophysiological fatigue studies; Falas game proxy
λ	Recovery rate	EEG/fMRI rest-and-recovery paradigms
E_s	Survival equilibrium	Dc, Kc from interaction logs; X_r, C_a from platform audit data

6. Cognitive Sovereignty: Framework and Foundations

6.1 The Cognitive Resource Principle

Zuboff's (2019) surveillance capitalism analysis demonstrates that behavioral data is extracted and monetized without compensation. The present framework extends this: not just behavioral traces but active cognitive labor — prompts, corrections, preference signals, reasoning chains — are productive inputs to AI systems whose value accrues to platform operators.

Non-rivalry qualification: the claim that cognitive contributions are non-rival in their contribution to AI training holds specifically under RLHF architectures, where individual preference signals are aggregated and marginal individual contribution is negligible. Under fine-tuning scenarios targeting specific domain expertise, contributions may be more rivalrous. The non-rivalry claim is architecture-specific, not universal.

6.2 The Nagoya Protocol Analogy: Scope, Limits, and the Phase Transition

The Nagoya Protocol (2010) establishes Access and Benefit-Sharing (ABS) for genetic resources and traditional knowledge. The structural parallel:

Nagoya Protocol Domain	Cognitive Sovereignty Domain
Genetic resources (biodiversity)	Cognitive resources (knowledge, reasoning, creative outputs)
Traditional knowledge holders	Individual and community AI users
Bioprospecting corporations	AI platform operators
ABS obligations	Cognitive Sovereignty obligations

The analogy operates as structural inspiration, not legal architecture. Three pillars of the Nagoya Protocol do not transfer: territorial sovereignty (cognitive contributions are not subject to it); traceability (prompt data is aggregated, anonymised, transformed beyond attribution); and prior informed consent (undermined by the opacity of how contributions are used).

More fundamentally: the Nagoya Protocol was designed for Phase 0 extraction — biological bioprospecting requiring physical territorial access. Participatory research ethics addresses Phase 1 — researcher-visit data collection. Neither addresses Phase 2 extraction, which this paper formally theorizes (Section 7.1). The governance gap is not a failure of the Protocol; it is a consequence of a technological transition its architects could not have foreseen.

6.3 Ostromian Commons Governance: The Positive Institutional Foundation

Elinor Ostrom's (1990) commons governance framework, empirically grounded in Nepal's Community Forest User Groups, demonstrates that collectively managed shared resources can be governed sustainably. Nepal's CFUG system comprises 22,266 community forest user groups nationally, covering 41% of national forests and 2.9 million households (FECOFUN, 2024). This is among the most extensively documented commons governance systems in the world.

The Rupa Lake Restoration and Fisheries Cooperative (established 2002, Rupakot-6, Kaski) demonstrates the same governance logic at the watershed scale: annual revenue exceeding Rs. 60,00,000; 25% of all profit structurally reinvested in conservation and educational activities in upstream communities — a functioning, auditable instance of the Homeostasis Condition this paper formalises. The cooperative's active breeding programme for indigenous sahar (Tor spp.) represents biological niche preservation: maintaining K_unique against commoditisation pressure from introduced aquaculture species — the biological analog of cognitive niche preservation. Its community biodiversity register and Wetland Information and Resource Centre convert local ecological knowledge into governed epistemic infrastructure accessible to outsiders with returns flowing back to the cooperative: the cognitive commons model already operational in Rupatal, Kaski.

However, the CFUG institutional precedent must be engaged critically. Adhikari, Kingi & Ganesh (2014), in a peer-reviewed ordered probit analysis of CFUG participation in Nepal's Middle Hills, find that transferring property rights to a group did not protect the rights of its poor and disadvantaged members. Discriminatory sociocultural norms — caste, gender, class — systematically limited effective participation even within formally inclusive institutions. Financial support mechanisms carried a negative participation coefficient: communities most dependent on economic survival support were the least able to participate in governance. This is the Survival Gap G operating inside the commons institution itself.

This finding is not a disqualification of the Ostromian model but its most important operational refinement. The Cognitive Commons architecture must incorporate Adhikari et al.'s policy recommendation directly: proportional allocation of governance rights and returns to identifiable sub-groups of disadvantaged knowledge contributors, with enforceable legal protections at the sub-group level. A Global South researcher financing AI participation through a smartphone EMI faces a structurally identical barrier to the poor CFUG member who cannot absorb the time cost of governance participation.

6.4 The Three-Tier Cognitive Sovereignty Architecture

Three rights, grounded in the Nagoya analogy, Ostromian commons governance, and labor theory:

- Recognition rights: acknowledgment that cognitive labor contributes to AI system value. Corresponds to Ostrom's principle of recognized rights to organize. Operationalised by attribution at point of extraction: every AI model trained on identifiable knowledge sources carries traceable attribution with compensation mechanisms proportional to usage.
- Control rights: meaningful ability to restrict, withdraw, or license cognitive contributions. The non-rivalry / control rights tension is resolved through labor theory: cognitive contributions are labor inputs, and workers retain rights over the terms of their labor regardless of whether the product is rival or non-rival. The Ammatoa Kajang community's prohibition of electronic devices during the Ma'bara ritual (Halim et al., 2025) is the most concrete empirical instance of functioning control rights — a community governance decision about the terms of knowledge access that predates and operates independently of any digital governance framework.
- Participation rights: share in economic value generated by AI systems trained on cognitive output. Corresponds to Ostrom's proportional benefit-distribution principle. Formalised as the Homeostasis Condition: Σ(compensation to knowledge generators) $\geq$ Σ(value extracted from knowledge generators). Currently violated at every level of the intelligence economy.

Three-tier implementation architecture:

- Tier 1 — Universal Baseline Floor: access to minimum AI engagement regardless of contribution capacity, ensuring proportional returns architecture does not penalise structural constraints on cognitive bandwidth.
- Tier 2 — Proportional Returns: epistemic returns proportional to verified cognitive contribution above the baseline floor.
- Tier 3 — Sub-Group Protection: asymmetric allocation of governance rights and returns to identifiably disadvantaged knowledge contributors — Global South researchers,

indigenous TEK holders, non-credentialed community knowledge carriers — with enforceable legal protections at sub-group level (Adhikari et al., 2014).

EU AI Act relationship: the Act's provisions are primarily procedural (risk classification, conformity assessments, transparency obligations), not substantive positive rights to value-sharing. Cognitive sovereignty is a more demanding framework than current EU AI regulation requires. The Act is cited as evidence that fundamental rights concerns are within the regulatory conversation, not as a foundation for the participation rights claim.

7. The Voluntary Extraction Inversion and the Double-Extraction Problem

7.1 The Three-Phase Extraction Typology

The governance gap in the intelligence economy is most precisely understood through a three-phase typology of knowledge extraction from indigenous and community knowledge holders:

Phase	Mechanism	Visibility to Community	Community Agency	Governance Response
Phase 0	Colonial biological prospecting	High — physical territorial presence	High — can refuse territorial access	Nagoya Protocol (2010) addresses this
Phase 1	Researcher-visit data collection	Medium — institutional presence visible	Medium — can refuse participation	Participatory research ethics; FPIC (UN, 2013)
Phase 2	Platform-mediated voluntary extraction	Zero — algorithmic, invisible, continuous	Zero — extraction is the act of use	No existing framework. This paper addresses this gap.

7.2 The Voluntary Extraction Inversion: Core Theoretical Statement

> *The Desana community's grievance, documented by Okada & Vaz (2025) at UNESCO, was that researchers came, took data, and left without returning. The intelligence economy has solved this problem for the extractor: it no longer needs to come. The community comes to it — voluntarily, daily, on devices it is financing through EMI obligations. The extraction is now continuous, invisible, and indistinguishable from use.*

This is the Voluntary Extraction Inversion: a phase transition in which knowledge holders shift from passive subjects of active extractors (Phase 1) to active contributors to passive infrastructure (Phase 2). The power asymmetry is structurally identical to Phase 1. The visibility of extraction approaches zero. The friction of extraction has been removed entirely — not by reducing the extraction, but by embedding it in the utility that makes the platform indispensable.

Phase 1 extraction required physical presence, institutional access, research funding, ethical approval processes, and the friction of travel. The community could see the researcher. They knew extraction was happening. They could refuse. The extraction had a face. Phase 2 extraction requires none of these. The platform waits. The community arrives. Every prompt is a data point. Every correction trains the model. Every preference signal shapes the next version. The community that could see the researcher and say no cannot see the algorithm and has no equivalent refusal mechanism.

The existing literature has not yet formally theorized this inversion as a unified phenomenon. Okada & Vaz (2025) document Phase 1 and propose participatory co-design as the solution — the right answer for Phase 1, which does not address Phase 2, because in Phase 2 the community is already inside the process as users. Halim et al. (2025) document the Ma'bara community's Phase 1 response: prohibit electronic devices during the ceremony, assert control at the point of knowledge production. This works when knowledge is embodied and ritual. It does not work when knowledge is generated through the act of using the platform. Kumar & Singh (2025) document the IKS-AI complementarity promise. Under Phase 2 extraction, the amplification accrues to the platform; the complementarity is real but the benefit-sharing is absent.

7.3 The Sandakpur Theorem

Field observation in Ward No. 3, Sandakpur Municipality, Eastern Nepal (May 02, 2026) yields the Sandakpur Theorem — a formal statement of survival microeconomy stability grounded in Shannon entropy (1948), cooperative game theory (von Neumann & Morgenstern, 1944; Nash, 1951), Ostromian commons governance (1990), and planetary boundary science (Rockström et al., 2009).

A survival microeconomy is stable when:

- The game is played for persistence, not dominance.
- The commons is structurally protected from individual accumulation.
- Cognitive diversity of participants is preserved and valued.
- Contribution diversity exceeds extraction rate ($Dc / X_r > 1$).
- Knowledge circulates within the system faster than it is extracted from it ($Kc / X_r > 1$).

These five conditions map directly onto the Survival Equilibrium Formula: $E_s = (Dc \times Kc) / (X_r \times C_a) > 1$ is the necessary and sufficient condition for stability.

The Falas card game — 17 players, 52-card deck, equal initial endowment of 3 cards per player, blind reinvestment mechanism, 5-hour window — encodes all five conditions simultaneously. The 52nd card ($17 \times 3 = 51$ dealt; 1 structurally excluded) is the commons belonging to no individual, making the game possible, impossible to capture without destroying the system. This is the planetary commons at the scale of a card table: the atmospheric carbon budget, the aquifer, the soil microbiome, the Rupa Lake watershed — each a 52nd card that macroeconomic extraction treats as waste or opportunity and survival microeconomy recognises as the condition of possibility.

The ontological chain through which Falas players operated — Survival → Existence → Cooperation → Interaction → Stability → Growth → Immunity — is absent from all dominant macroeconomic models, which begin at Stage 6 (Growth) and treat Stages 1–5 as preconditions that markets will naturally supply. The empirical record of the algorithmic age demonstrates this is catastrophically wrong.

7.4 The Digital Niche Displacement Event: Type I Error at Civilizational Scale

Case Study II documents a Digital Niche Displacement Event (DNDE): a Masters-qualified researcher in Zoology and Parasitology from Tribhuvan University was rendered unable to pay a 100 NPR food bill — despite holding valid institutional affiliation and financial resources — because a WiFi connection triggered an algorithmic security lock on a smartphone financed through a 3,000 NPR monthly EMI. Resolution required 30 minutes once analogue SIM connectivity was restored.

Formally classified as a Type I Error (Neyman & Pearson, 1933):

Statistical Element	DNDE Instance
Null hypothesis (H_0)	User is solvent and will resolve EMI obligation within normal parameters
Algorithm's decision	Reject H_0 — lock the device
Ground truth	H_0 was correct — resolved in 30 minutes
Cost to platform of Type II error	3,000 NPR (unpaid EMI)
Cost to individual of Type I error	Hunger + displacement + lost cognitive productivity + continued EMI liability during lock

Standard statistical practice sets Type I Error rate at $\alpha = 0.05$. No equivalent threshold governs algorithmic security protocols. The decision boundary is optimised entirely for platform risk minimisation. The system locked a qualified researcher over a 3,000-NPR EMI he was prepared to pay in 30 minutes. The cost of that lock was borne entirely by him. The 3,000-NPR risk was never at risk. The survival cost was real, immediate, and unmeasured by any macroeconomic accounting framework.

Resolution came from the survival microeconomy: a prepaid SIM card (Ncell/NTC) — pre-algorithmic infrastructure carrying no account lock risk because it carries no account. It cannot be remotely disabled by displacement because it has no geographic memory. The analogue commons substrate rescued the digital system. The 52nd card paid for the food.

Debt-financed infrastructural dependency: the smartphone was purchased on EMI. The logical chain is closed: participation in the algorithmic age requires the device; the device requires the debt; the debt requires continued participation; the system can revoke participation at any moment while the debt obligation remains unconditionally intact. He is paying monthly for a device the system locked against him at the moment he needed it most. The debt is his. The control belongs to the algorithm. The installment continues. The freedom does not.

7.5 Epistemicide and Training Data

AI systems are trained on data that systematically over-represents Western academic and commercial knowledge traditions. Indigenous ecological knowledge, non-Western philosophical systems, and orally transmitted community wisdom are structurally absent or underweighted. Halim et al. (2025), in a peer-reviewed ethnographic study of the Ammatoa Kajang community in South Sulawesi, define epistemicide as the erasure of knowledge through oversimplification or external appropriation — and demonstrate it empirically through the digitisation of Ma'bara ritual knowledge detached from its spiritual and communal context.

Epistemicide is more precise than epistemic colonialism for the AI training pipeline context: it names not just the power asymmetry but the mechanism of erasure — oversimplification, decontextualisation, commodification. The Halim et al. finding that digitisation without community control produces knowledge colonialism — where indigenous knowledge is extracted, commodified, or misrepresented — is directly confirmed in the Phase 2 extraction dynamic: the Ma'bara community's prohibition on electronic devices during the ceremony (a functioning control right in Phase 1) has no equivalent mechanism in Phase 2, where the knowledge enters training pipelines through the act of using the platform.

The result is not merely unequal access. Even if access were equalised, the content of intelligence available through AI would remain epistemically colonial. Access asymmetry and content asymmetry are distinct problems requiring distinct solutions. The CARE-KNOW-DO framework (Okada & Vaz, 2025) — Care, Know, Do — maps directly onto the Recognition-Control-Participation rights architecture: recognition of epistemic value (Care), control over knowledge governance (Know), and participation in returns (Do).

7.6 Nepal as Epistemic Case: The Double-Extraction Dynamic

Nepal presents the most concentrated instance of the double-extraction dynamic. In the biological domain, Nepal's extraordinary biodiversity and associated TEK are subject to bioprospecting pressures addressed, imperfectly, by the Nagoya Protocol. In the digital domain, Nepal's knowledge workers interact with AI systems that extract cognitive contributions while returning metered value and retaining ownership of accumulated intelligence. Both extractions occur simultaneously, on the same communities, through different but structurally analogous mechanisms.

The CFUG system and the Rupa Lake Cooperative demonstrate that Nepalese communities possess institutional capacity for commons governance extending beyond any single sector. The cognitive commons model creates structural conditions for non-Western, indigenous, and ecologically embedded knowledge systems to enter the AI training cycle not as data to be mined, but as fuel that earns return and shapes the intelligence it powers. When a Nepali community contributes its ecological knowledge as cognitive fuel, it does not merely gain access to AI — it shapes what AI knows. This is the architecture under which epistemic decolonisation becomes an operational design feature rather than an aspiration.

7.7 Cognitive Stratification as Architectural Condition

Tiered AI subscription models do not merely differentiate speed — they differentiate reasoning depth. The user with premium AI access receives a qualitatively superior cognitive partner: more nuanced synthesis, longer contextual memory, richer analytical output. AI access tiers constitute a new axis of knowledge asymmetry, potentially more consequential than internet bandwidth differentials because AI does not merely retrieve information but synthesises, argues, and advises. It is a cognitive multiplier — and like all multipliers, it amplifies whatever inequalities precede it.

Case Study III (May 04, 2026): during manuscript preparation, the primary author encountered output limits imposed by the platform's free-tier access structure, interrupting active intellectual work during a journal revision window. Researchers at well-funded institutions with enterprise-level AI access do not encounter this friction. The access limit functions as an academic productivity differential calibrated against institutional wealth, compounding across every revision cycle and career stage. The same tool provides the same assistance at a structurally higher effective cost — as a proportion of income — for the researcher whose monthly salary is denominated in Nepali rupees against a subscription price calibrated to high-income economies (Gray & Suri, 2019; Muldoon et al., 2025; Ranjbari & Shams Esfandabadi, 2026).

8. Empirical Testability

8.1 Primary Regression Model and the r vs. α Identification Problem

$$\ln I\_it = \ln I\_i0 + (\beta_1 \ln K\_it + \beta_2 \ln A\_it + \beta_3 \ln S\_it) \cdot t + \mu\_i + \varepsilon\_it$$

where i indexes individuals, t indexes time periods, μ_i is individual fixed effect absorbing unobserved I_i0 heterogeneity, and ε_it has AR(1) autocorrelation structure within individuals.

Critical identification problem: r (platform amplification) and α (individual cognitive productivity) both enter the exponent of V(t). The model estimates only (r + α) from observed value trajectories — conflating platform-level and individual-level effects. This is fatal for the cognitive sovereignty argument, which requires demonstrating that individual cognitive contribution is the productive input. Separation requires: (a) cross-platform variation in r with individual cognitive controls held constant, via multi-platform study designs; or (b) within-individual temporal variation in platform access via natural experiments from platform outages, policy changes, or randomised platform assignment. Without this, individual cognitive contribution cannot be distinguished from platform-driven amplification.

Methodological precedent: Adhikari et al.'s (2014) two-stage ordered probit model — factor analysis to construct participation index, ordered probit on discrete choice between participation levels — provides a peer-reviewed Nepal-specific methodological template for commons participation identification.

8.2 Survival Equilibrium Testability

$E_s = (Dc \times Kc) / (X_r \times C_a)$ generates community-level testable predictions. Dc measurable via entropy of contribution types in community interaction records. Kc approximable from knowledge-sharing network data. X_r operalisable via platform data audit frameworks. C_a estimable from platform market concentration indices. Directional hypothesis: communities with $Dc/X_r > 1$ and $Kc/X_r > 1$ demonstrate higher cognitive resilience to platform disruption events.

8.3 Type I Error Rate in Algorithmic Security Protocols

The DNDE identifies a testable empirical question: what is the actual Type I Error rate of algorithmic security lockout protocols across users in developed vs. developing-nation network environments? Users in environments with less stable WiFi — common across rural and peri-urban South Asia — are structurally more likely to trigger unfamiliar-network security protocols, making the Type I Error rate a measurable dimension of algorithmic discrimination. Platform operators hold this data; regulatory frameworks should require its disclosure.

8.4 Niche Compression Prediction

As K_global rises, economic returns to unique human outputs should increase for high-N users. Testable via longitudinal wage and freelance platform data correlated with AI adoption rates across skill categories. Quasi-experimental designs exploiting differential AI rollout timing across sectors or geographies required to address selection bias.

8.5 Exhaustion-Recovery Cycle

The piecewise V(t) model predicts a characteristic growth-plateau-recovery pattern in cognitive output across extended sessions. Testable via EEG or fMRI studies combined with output quality measurement. The single-compartment recovery function predicts a specific functional form testable against linear and multi-compartment alternatives. The Falas game's fatigue dynamics provide a naturalistic pilot dataset.

9. The Intelligence Economy Survival Gap and the Homeostasis Condition

The Survival Gap G has a precise mathematical structure:

$$G = (C_t + C_e + C_s) - W_r \times t_{exchange}$$

where C_t = transportation cost; C_e = EMI cost of digital instrument; C_s = social existence cost (food, shelter, connectivity); W_r = institutional wage per unit time. For the Sandakpur case: $G > 0$. The intelligence economy extracted more from the knowledge exchanger than it returned during the exchange event.

The gap is structurally larger in developing nations: transport infrastructure costs more relative to income; digital devices carry higher effective costs in global USD terms against local salary levels; EMI obligations are denominated in systems designed for developed-nation economic structures; connectivity is less reliable, making displacement events more frequent and more severe. The knowledge exchanged — TEK, indigenous governance systems, parasitological field expertise in high-altitude ecosystems — is disproportionately valuable to global knowledge systems while being disproportionately undercompensated within them.

The empirical literature confirms the structural asymmetry: data annotation workers earning less than $2 per day train AI systems whose economic benefits accumulate in the Global North (Gray & Suri, 2019; Muldoon et al., 2025; Ranjbari & Shams Esfandabadi, 2026). The field observations here provide what those analyses lack: ground-level empirical observation from inside the extraction. A researcher in Eastern Nepal on a prepaid Ncell SIM, whose knowledge was exchanged across disciplines over 54.5 hours with zero micro-payment infrastructure, while the phone company collected its EMI and the platform locked the device.

9.1 The Homeostasis Condition

Homeostasis: Σ(compensation to knowledge generators) ≥ Σ(value extracted from knowledge generators)

Currently violated at every level: AI training pipelines, platform algorithms, academic publishing, and EMI structures all extract more from knowledge generators than they return. The circular economy transition (Ellen MacArthur Foundation, 2013; Hickel, 2020) requires not only ecological circularity but economic circularity. Applied to the intelligence economy, fair cognitive labor compensation as a foundational condition — not an addendum — requires:

- Attribution at the point of extraction: traceable attribution for every AI model trained on identifiable knowledge sources, with compensation proportional to usage frequency and derivative value.
- Micro-payment infrastructure for knowledge exchange events: payment rails functioning at the granularity of individual knowledge transfer events, not only monthly salaries.
- Displacement cost absorption by benefiting institutions: institutions that benefit from researcher knowledge exchange bear the displacement costs, not the researcher.
- EMI protection clauses for knowledge workers: non-lock provisions during documented institutional travel, analogous to mortgage grace periods that exist in law but not in smartphone EMI contracts.

10. Conclusion

This framework establishes a mathematically grounded, empirically anchored account of value creation in the intelligence economy. Core contributions:

- ODE derivation from first principles with explicit constant-α short-run approximation.
- Revision of α decomposition from additive to log-linear (Cobb-Douglas at the level of α), restoring complementarity consistency.
- Correction of cognitive exhaustion constraint to piecewise state-variable model with derivable T* and pharmacokinetic recovery, grounded in Falas game fatigue dynamics.
- Replacement of Fisher information-geometric argument for N with direct survival-fraction scaling; resolution of K dimensional mismatch through explicit aggregation function.
- Survival Equilibrium Formula $E_s = (Dc \times Kc) / (X_r \times C_a)$ as system-level formalisation of N compression dynamics.
- Three-tier Cognitive Sovereignty architecture: universal baseline, proportional returns, sub-group protection — incorporating Adhikari et al.'s (2014) critical internal failure mode of CFUG governance.

- The Voluntary Extraction Inversion and three-phase extraction typology: the governance gap left by Nagoya (Phase 0) and participatory research ethics (Phase 1) is named and theorized for the first time as a unified phenomenon for Phase 2 platform-mediated extraction.
- The Sandakpur Theorem: five formal stability conditions for survival microeconomy, derived from field observation and consistent with Shannon, Nash, Ostrom, and Rockström.
- Intelligence Economy Survival Gap G and Homeostasis Condition: formal economic measures of the cognitive labor compensation deficit in Global South knowledge economies.
- Identification of r vs. α separation problem and its implications for empirical testing.

The intelligence economy is not merely the next phase of the attention economy. It is a qualitatively different regime in which the productive resource is cognitive capital — and in which the extractive infrastructure has been engineered to make extraction indistinguishable from use. Governing that regime fairly requires an explicit rights architecture grounded in commons governance, empirically validated at scale in Nepal's own institutional landscape, and extended to address the phase transition that no existing governance framework has yet named.

The formula is structurally simple:

> ***V(t) = Cognitive Capital × AI Amplification × Ecological Scarcity × Temporal Persistence***

where $E_s \geq 1$ is the system-level condition without which V(t) approaches zero regardless of what P_0, I_0, or α individually achieve. Attention was the fuel. Behavior was the mechanism. Intelligence is the output. The Voluntary Extraction Inversion is the governance challenge. Cognitive sovereignty — grounded in the Sandakpur Theorem, the CFUG institutional precedent, and the political economy of epistemic equity — is the missing governance layer.

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