Representation Capital Dynamics

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Representation Capital Dynamics

Dynamics of Representation Capital in AI-Mediated Discovery Systems

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Abstract

This paper develops a dynamic theory of Representation Capital—the accumulated stock of machine-readable qualities that may generate allocative advantage in AI-mediated markets. While prior work established Representation Capital as a theoretical asset class, capital theory requires an account of how assets evolve over time. We formalize the mechanisms of accumulation, depreciation, yield, inflation, and competitive interaction that govern Representation Capital dynamics. We introduce **Representation Yield** as the allocative return on representation investment, **Representation Moats** as structural barriers created by accumulated advantages, and **Computational Inflation** as the erosion of allocative advantage resulting from widespread representation investment. The paper analyzes long-run equilibrium scenarios including Representation Saturation, permanent arms races, and trust-based differentiation. We demonstrate that when Representation Capital reaches saturation, the next scarce resource becomes Computational Creditworthiness, creating a bridge to trust-based allocative differentiation. We further demonstrate how representation dynamics jointly influence property allocation in Agent-Readable Property Markets. All claims remain theoretical; no empirical validation is attempted.

Keywords: representation capital, capital dynamics, computational scarcity, allocative advantage, representation yield, competitive moats, computational inflation, AI-mediated markets

JEL Classification: D2, E2, L1, L2, O3, O4

Representation Economy Research Program

This paper is part of the Representation Economy Research Program:

Representation Capital Foundational theory of machine-readable capital as allocative advantage

Representation Capital Dynamics (this paper) Dynamic framework, accumulation, yield, and depreciation mechanisms

Computational Creditworthiness Trust-based selection and representation reliability assessment

Agent-Readable Property Markets Sector-specific applications and market design implications

Why This Paper Matters

The Representation Economy research program has established a theoretical foundation for understanding AI-mediated markets. Prior working papers have addressed:

- **Computational Market Access** — The institutional transition from visibility to admissibility
- **Computational Market Economics** — The mathematical structure of allocation under inferential scarcity
- **Network-Dependent Allocation** — Formal proofs of ranking insufficiency under non-separable valuation

- **Computational Pricing Theory** — Price formation mechanisms under admissibility constraints
- **Computational Monetary Theory** — Settlement and credit systems in computational markets
- **Representation Capital** — The static concept of representation as an allocative asset

A capital asset without a theory of its dynamics is theoretically incomplete.

This paper serves as the **central bridge** between the Representation Economy research program and the trust theory that follows. It addresses six critical questions:

1. **How does Representation Capital accumulate?**
2. **What returns does Representation Capital generate?**
3. **Why do those returns exhibit diminishing limits?**
4. **What happens when everyone improves representation?**
5. **How do moats create persistent advantages?**
6. **What comes next when representation alone becomes insufficient?**

The answers to these questions create the theoretical foundation for understanding the transition from representation-based allocation to trust-based allocation in AI-mediated markets.

Caveats and Scope Limitations

Before proceeding, we must establish explicit scope limitations:

1. **This is theoretical work.** All models and claims are theoretical constructs. No empirical validation is attempted. Claims about allocative advantage, accumulation rates, or equilibrium outcomes are speculative and should be treated as hypotheses requiring validation.

2. **This is not investment advice.** We do not recommend investment strategies or suggest that specific representation investments will generate returns. We analyze theoretical mechanisms, not actionable recommendations.

3. **This is not technological forecasting.** We do not predict how AI systems will evolve or what allocative mechanisms will emerge. Our analysis holds under specified conditions; if those conditions change, the implications may differ.

4. **This is not normative.** We do not argue that concentration, moats, or inequality are desirable or undesirable. We analyze potential structural consequences, not prescriptive policy.

5. **This is not platform-specific.** We do not discuss specific AI systems, platforms, or protocols except where necessary for illustration. Our analysis operates at the level of structural mechanisms, not implementation details.

6. **Models are simplifications.** The mathematical models presented are illustrative abstractions. Real-world dynamics may be substantially more complex, with additional variables, non-linearities, and stochastic elements not captured in our simplified framework.

Introduction

Capital theory has long recognized that capital is not merely a stock but a dynamic asset evolving through time. The classical economists understood that physical capital accumulates through investment and depreciates through use. The neoclassical growth models formalized these dynamics, demonstrating how capital accumulation drives economic development while depreciation creates steady-state equilibrium conditions.

Representation Capital, introduced in **Volume I (Representation Capital)**, requires similar dynamic treatment. Volume I established Representation Capital as the accumulated stock of machine-readable qualities—Completeness, Accuracy, Verifiability, Freshness, Portability, and Actionability—that may increase the probability of computational admissibility within AI-mediated allocation systems. This volume develops the dynamic theory of how that capital evolves over time.

But a static conception of Representation Capital is insufficient for three reasons:

First, allocative systems are dynamic. AI systems evolve, standards change, and allocative criteria shift over time. Representation Capital that confers admissibility today may not confer admissibility tomorrow.

Second, competitive interactions are dynamic. If one economic actor invests in Representation Capital, competitors may respond with their own investments. The resulting arms race may erode relative advantages.

Third, capital generates feedback. If Representation Capital generates allocative returns, those returns may fund further investment, creating compounding effects.

This paper develops a dynamic theory of Representation Capital that addresses these gaps. We formalize accumulation mechanisms, yield processes, inflation dynamics, moat formation, and competitive interactions. Most critically, we demonstrate how Representation Capital dynamics create bridges to both Computational Creditworthiness and Agent-Readable Property Markets—the two working papers that follow in this series.

The central theoretical claim: Representation Capital may exhibit fundamentally different dynamics than traditional capital forms due to (1) non-rivalrous production, (2) information-based depreciation, and (3) consideration-set feedback. These unique properties create distinct patterns of accumulation, concentration, and equilibrium that require extensions to standard capital theory.

```
                    REPRESENTATION CAPITAL DYNAMICS
                         Theoretical Framework



   ACCUMULATION            YIELD             INFLATION
  Part I                  Part II                 Part III
```

```
    MOATS              TRUST BRIDGE         PROPERTY BRIDGE
   Part IV                Part V                Part VI



  Input:  Representation Capital (Volume I)
  Output: Computational Creditworthiness (Volume III)
  Output: Agent-Readable Asset Markets (Volume IV)
```

Part I

Representation Capital Accumulation

1.1 How Representation Capital Forms

Representation Capital forms through the systematic investment of resources into improving the machine-readable qualities of an economic actor's representation. Unlike physical capital, which forms through equipment acquisition, or human capital, which forms through education, Representation Capital forms through **information structuring**.

The formation process operates through three distinct channels:

Channel 1: Attribute Capture

The initial formation of Representation Capital requires identifying economically relevant attributes and capturing them in machine-readable form. This includes:

- **Property attributes:** Location, size, condition, amenities, pricing
- **Service attributes:** Availability, policies, restrictions, terms
- **Verification attributes:** Ownership proof, accuracy attestations, update timestamps

Attribute capture is the foundational stage of Representation Capital formation. Without captured attributes, there is nothing to optimize, verify, or maintain.

Channel 2: Quality Enhancement

Once attributes are captured, Representation Capital increases through quality enhancement:

- **Accuracy:** Correcting errors, resolving inconsistencies, validating against ground truth
- **Completeness:** Adding missing attributes, reducing null values, expanding coverage
- **Freshness:** Reducing update latency, increasing update frequency, maintaining current state
- **Verifiability:** Adding cryptographic proofs, third-party attestations, provenance chains

Quality enhancement operates on existing captured attributes, increasing their allocative value without expanding scope.

Channel 3: Infrastructure Investment

The third formation channel involves investment in infrastructure that enables sustained Representation Capital:

- **Data pipelines:** Automated systems for data ingestion, transformation, and publication
- **Verification systems:** Processes for ongoing validation, attestation, and proof generation
- **Action interfaces:** APIs, webhooks, and protocols that enable AI systems to initiate actions
- **Monitoring systems:** Tools for detecting staleness, tracking quality metrics, alerting on degradation

Infrastructure investment creates the capacity for ongoing Representation Capital maintenance and growth.

1.2 Representation Investment

Representation Investment ($I(t)$) is the flow of resources devoted to increasing or maintaining Representation Capital at time t. We distinguish three investment types:

Type A: Formation Investment

Investment in creating Representation Capital where none previously existed. Formation investment includes:

- Initial schema selection and attribute identification
- First-time data capture and structuring
- Setup of verification infrastructure
- Establishment of publication channels

Formation investment is typically **front-loaded**—substantial investment is required to achieve the first units of Representation Capital, with diminishing marginal investment as capital accumulates.

Type B: Expansion Investment

Investment in expanding the scope or depth of existing Representation Capital. Expansion investment includes:

- Adding new attributes to existing representation
- Expanding to new allocative systems or use cases
- Adopting additional schema standards or protocols
- Extending verification coverage to new attributes

Expansion investment operates at the **margin**—each increment of RC requires additional investment, potentially at increasing or decreasing cost depending on context.

Type C: Maintenance Investment

Investment required to offset depreciation without increasing capital stock. Maintenance investment includes:

- Data updates to counter staleness
- Verification renewal to counter expiration
- Format migration to counter obsolescence
- Quality assurance to counter entropy

Maintenance investment is **ongoing and obligatory**—without maintenance, Representation Capital decays to zero.

1.3 The Accumulation Function

The accumulation of Representation Capital over time follows the fundamental dynamic equation:

```
RC (t+1) = RC (t) + I (t) -  (t)RC (t)
```

Where: - *RC (t)*: Representation Capital of actor *i* at time *t* - *I (t)*: Gross investment in representation quality - *(t)*: Depreciation rate (0 1)

Net Accumulation:

```
ΔRC (t) = I (t) -  (t)RC (t)
```

Representation Capital increases when investment exceeds depreciation and decreases when depreciation exceeds investment.

The Growth Condition:

```
If I (t) >  (t)RC (t), then RC (t+1) > RC (t)
If I (t) <  (t)RC (t), then RC (t+1) < RC (t)
If I (t) =  (t)RC (t), then RC (t+1) = RC (t)
```

The growth condition states that Representation Capital accumulates when investment exceeds the depreciation of existing capital stock.

1.4 Returns to Scale in Accumulation

The relationship between investment and capital accumulation depends on returns to scale in representation production:

Constant Returns to Scale:

```
ΔRC (t) =  ·I (t), where  is constant
```

Each unit of investment generates proportional increases in RC. Accumulation proceeds linearly.

Increasing Returns to Scale:

```
ΔRC (t) =  (RC (t))·I (t), where   > 0
```

Initial investments create infrastructure that reduces the cost of subsequent investments. Accumulation accelerates.

Decreasing Returns to Scale:

```
ΔRC (t) =  (RC (t))·I (t), where   < 0
```

The most valuable attributes are captured first. Subsequent investments generate diminishing returns.

The Saturation Boundary:

```
RC (t)   RC_max
```

Representation Capital cannot exceed maximal admissibility given allocative system constraints. Once maximal RC is achieved, additional investment yields zero allocative return.

1.5 Representation Maintenance

Because Representation Capital depreciates continuously, maintenance investment is economically necessary:

The Maintenance Constraint:

```
If I (t) <  (t)RC (t), then RC (t+1) < RC (t)
```

Actors who do not invest sufficiently in maintenance will experience capital decay.

The Maintenance Burden:

Unlike physical capital, which can sometimes be left unused without immediate decay, Representation Capital decays continuously as the world changes and moves on:

```
RC(t) = RC(0) · e^(- ·t) without maintenance
```

The exponential decay of un-maintained Representation Capital creates a persistent resource requirement.

The Maintenance Investment Function:

```
I (t) =  (t)RC (t)
```

Maintenance investment equals the depreciation rate multiplied by the capital stock. This investment maintains capital without increasing it.

1.6 Representation Obsolescence

Representation Capital may become obsolete through three distinct mechanisms:

Mechanism 1: Schema Obsolescence

Standard schemas evolve over time. Schema.org, industry-specific protocols, and platform-specific schemas add new attributes and deprecate old ones. Representation that complies with yesterday's schema may be inadequate today.

Mechanism 2: Allocative System Obsolescence

AI systems evolve in their representation requirements. A system that once required three attributes may now require five. A system that once accepted unstructured descriptions may now require structured data.

Mechanism 3: Format Obsolescence

Representation formats may become obsolete as technologies evolve. XML-based representations may be deprecated in favor of JSON. JSON may be deprecated in favor of more efficient binary formats.

The Obsolescence Process:

```
t : Representation RC  is optimal for allocative system AS
t : AS evolves to AS ; RC  remains adequate
t : AS evolves to AS ; RC  becomes suboptimal
t : AS evolves to AS ; RC  becomes inadequate
t : AS evolves to AS ; RC  becomes incompatible
```

Obsolescence is gradual but inevitable. Representation Capital that is not actively maintained eventually becomes useless.

Part II

Representation Yield

2.1 Definition

Representation Yield is the allocative return generated per unit of Representation Capital invested.

Representation Yield is distinct from traditional notions of investment return. Financial capital yields monetary returns through interest, dividends, or capital appreciation. Physical capital yields productive returns through increased output. Representation Capital yields **allocative returns**—increased probability of consideration set inclusion.

Formal Definition:

Let $Y (t)$ denote the Representation Yield of actor i at time t:

```
Y (t) = ΔP(admit) / ΔRC
```

Where: - $\Delta P(admit)$ is the change in admissibility probability - ΔRC is the change in Representation Capital

The Yield Relationship:

```
P(admit | RC) = f(RC), where f (RC) > 0

Y (t) =  P(admit | RC) /  RC
```

Representation Yield is the marginal increase in admissibility probability resulting from a marginal increase in Representation Capital.

2.2 Why Representation Quality May Produce Allocative Advantages

Representation quality may produce allocative advantages through three mechanisms:

Mechanism 1: Admissibility Advantage

When AI systems construct consideration sets under bounded inference ($K < n$), they must exclude some available options. The exclusion criterion is computational admissibility—whether an option can be inferred, evaluated, and included given capacity constraints.

Higher Representation Capital increases computational admissibility:

```
RC  > RC  → P(admit | RC ) > P(admit | RC )
```

Actors with higher Representation Capital are more likely to be included in consideration sets, creating an allocative advantage independent of price or quality.

Mechanism 2: Inference Cost Reduction

AI systems expend computational resources to infer, parse, and evaluate representations. Higher-quality representations require less inference cost:

```
InferenceCost = g(1/RC), where g (·) < 0
```

When representations are structured, complete, and standardized, AI systems can process them more efficiently. This efficiency advantage may translate into allocative advantage through preferential inclusion.

Mechanism 3: Reliability Signaling

High Representation Capital signals reliability and seriousness to allocative systems. An actor who has invested in comprehensive, verifiable, current representation is more likely to be a legitimate economic participant than an actor with minimal, stale, or unverifiable representation.

AI systems may learn to preferentially include high-RC actors as a reliability heuristic, creating a feedback loop that amplifies the allocative advantage of Representation Capital.

2.3 The Yield Function

The relationship between Representation Capital and allocative probability is not necessarily linear. We consider three yield function forms:

Yield Function 1: Linear

```
P(admit | RC) =  ·RC +  , where  > 0
Y =  P/ RC =  (constant)
```

Linear yield implies constant marginal returns to investment. Each unit of additional RC generates the same increase in admissibility probability.

Yield Function 2: Concave (Diminishing Returns)

```
P(admit | RC) =  ·RC^ , where 0 <  < 1
Y =  P/ RC =  · ·RC^( -1) (decreasing in RC)
```

Concave yield implies diminishing marginal returns. Initial units of RC generate large admissibility gains; later units generate smaller gains.

Yield Function 3: Convex (Increasing Returns)

```
P(admit | RC) =  ·RC^ , where  > 1
Y =  P/ RC =  · ·RC^( -1) (increasing in RC)
```

Convex yield implies increasing marginal returns. Each additional unit of RC generates more admissibility gain than the previous unit. This may occur when representation quality creates network effects or when allocative systems develop canonical preferences for high-RC representations.

The Empirical Question:

Which yield function form applies in practice? This remains an open empirical question. The shape of the yield function determines optimal investment strategies and has significant implications for competitive dynamics.

2.4 Limits of Representation Yield

Representation Yield is subject to three fundamental limits:

Limit 1: The Saturation Bound

```
Y → 0 as RC → RC_max
```

As Representation Capital approaches its maximum feasible level, additional investment yields minimal admissibility gains. The yield approaches zero at saturation.

Limit 2: The Competition Bound

```
Y is bounded by competitive RC levels
```

If all actors in a market achieve similar RC levels, relative advantages disappear. The allocative benefit of RC depends not only on absolute level but also on relative level compared to competitors.

Limit 3: The allocative System Bound

```
Y is bounded by allocative system requirements
```

If allocative systems evolve to require additional attributes or higher quality standards, existing RC may become inadequate. The yield on existing RC depends on alignment with current allocative system requirements.

2.5 Diminishing Returns

Diminishing returns to Representation Capital occur for three reasons:

Reason 1: Attribute Value Ordering

Economically critical attributes are typically captured first. Location, price, and core attributes are captured before peripheral attributes. The marginal admissibility value of each additional attribute declines.

Reason 2: Complexity Costs

Adding new attributes becomes increasingly complex as coverage expands. Early attributes are obvious and easily structured; later attributes may be ambiguous, context-dependent, or difficult to capture.

Reason 3: Allocative Limits

Once maximal admissibility is achieved, additional investment generates no allocative benefit. The system cannot include options more than 100% of the time.

The Diminishing Returns Process:

```
RC = 0 → First attribute captured → Large ΔP(admit)
RC = low → Additional attributes → Moderate ΔP(admit)
RC = medium → Additional attributes → Small ΔP(admit)
RC = high → Additional attributes → Minimal ΔP(admit)
RC = RC_max → Additional investment → Zero ΔP(admit)
```

Investment Implications:

Under diminishing returns, optimal investment involves investing until the marginal cost equals the marginal yield:

```
Invest until: MC(I) = Y(RC)
```

Where *MC(I)* is the marginal cost of investment and *Y(RC)* is the marginal yield of Representation Capital.

2.6 The Yield-Investment Relationship

The allocative return on representation investment depends on both the yield function and the investment level:

Total Allocative Return:

```
Return = Y(RC) · I
```

Where *Y(RC)* is the yield at current RC level and *I* is the investment level.

The Optimal Investment Problem:

Economic actors face the optimization problem:

```
max Return = Y(RC) · I - C(I)
subject to: RC(t+1) = RC(t) + I -  ·RC(t)
```

Where *C(I)* is the cost function for investment.

Solution:

The optimal investment level satisfies:

```
Y(RC) = C (I) +
```

Invest until the yield equals the marginal investment cost plus the depreciation rate.

Strategic Implication:

The yield-investment relationship creates strategic dynamics. Actors with higher-yield representation opportunities invest more aggressively. Actors with lower-yield opportunities may underinvest or exit representation investment entirely.

This differential investment may lead to divergent outcomes: high-yield actors accumulate RC rapidly and establish allocative advantages; low-yield actors stagnate and face allocative exclusion.

Part III

Representation Inflation

3.1 Definition

Computational Inflation is the erosion of allocative advantage that occurs when all actors in a market accumulate Representation Capital, reducing relative differentiation.

Computational Inflation is distinct from monetary inflation. Monetary inflation erodes the purchasing power of money. Computational Inflation erodes the **allocative power** of representation.

When all actors are well-represented, representation no longer differentiates. Allocative outcomes must then depend on other factors (price, quality, location, brand).

3.2 What Happens When Everyone Improves Representation

The Pre-Inflation State:

In early stages of AI-mediated market development, some actors invest in Representation Capital while others do not:

```
State A (Early Stage):
   Actor A : High RC → High admissibility → Allocative advantage
   Actor A : Medium RC → Medium admissibility → Competitive parity
   Actor A : Low RC → Low admissibility → Allocative disadvantage
```

Actors with high RC enjoy significant allocative advantages. They appear in more consideration sets, generate more transactions, and capture more allocative access.

The Inflationary Process:

As actors observe the allocative advantages of high RC, they invest in representation quality:

```
State B (Transition Stage):
   Actor A : High RC + I  → Even higher RC
   Actor A : Medium RC + I  → High RC
   Actor A : Low RC + I  → Medium RC
```

Competitors respond to observed advantages by investing in their own representation. Early adopters must invest to maintain their lead; late adopters invest to catch up.

The Post-Inflation State:

When all actors achieve high RC, relative advantages disappear:

```
State C (Post-Inflation):
   Actor A : RC_max → Admissibility = P_max
   Actor A : RC_max → Admissibility = P_max
   Actor A : RC_max → Admissibility = P_max
```

Representation Capital no longer differentiates. All actors are equally admissible. Allocative outcomes depend on traditional factors.

3.3 The Inflation Mechanism

Formal Inflation Model:

Let $R\bar{C}(t)$ denote the average Representation Capital across all actors at time t.

The Relative Admissibility Metric:

```
RA (t) = P(admit | RC (t)) - P(admit | RC̄(t))
```

Where *RA (t)* is the relative admissibility advantage of actor *i* at time *t*.

The Inflation Dynamic:

```
As RC(t) → RC_max, RA (t) → 0 for all i
```

Relative admissibility advantage approaches zero as average Representation Capital approaches saturation.

The Inflation Rate:

Let denote the inflation rate—the rate at which relative advantages erode:

```
 = d(RA)/dt = -  · d(RC)/dt
```

Where is the sensitivity of relative advantage to average RC changes.

High Inflation: When many actors are investing aggressively, average RC increases rapidly, and relative advantages erode quickly.

Low Inflation: When investment is slow or sparse, relative advantages persist longer.

3.4 Comparison with Traditional Capital Accumulation

Representation Capital inflation differs from traditional capital accumulation in three ways:

Difference 1: Non-Rivalrous Production

Traditional capital (machinery, buildings) is rivalrous—one actor's accumulation reduces available capital for others. Representation Capital is non-rivalrous—one actor's investment does not reduce others' ability to invest.

This creates **accelerated inflation** in Representation Capital compared to physical capital. All actors can invest simultaneously, rapidly driving average RC toward saturation.

Difference 2: Information-Based Depreciation

Traditional capital depreciates through wear and tear—usage causes decay. Representation Capital depreciates through staleness and obsolescence—time and change cause decay.

This creates **asymmetric depreciation** during inflation. As all actors accumulate RC, the depreciation rate may increase simultaneously as allocative systems evolve, accelerating the erosion of relative advantages.

Difference 3: Consideration-Set Feedback

Traditional capital generates productive returns—more machines produce more output. Representation Capital generates allocative returns—more consideration set inclusions generate more transactions.

This creates **amplification effects** during inflation. As RC levels converge, the allocative system may struggle to differentiate, potentially shifting to alternative differentiation mechanisms (trust, brand, reputation).

3.5 The Inflationary Race

Computational Inflation may result from **representation arms races**:

Stage 1: Discovery One actor discovers the allocative advantages of high RC and invests.

Stage 2: Advantage The investing actor enjoys allocative advantage, appearing in more consideration sets.

Stage 3: Observation Competitors observe the advantage and begin their own investment.

Stage 4: Escalation The initial actor responds to competitive erosion with additional investment. Competitors respond in kind.

Stage 5: Saturation All actors reach high RC levels. Relative advantages erode. Inflation complete.

The Escalation Game:

Model the arms race as a dynamic game where each actor chooses investment *I (t)* based on competitors' prior investments:

```
I (t) = f(RC_{-i}(t-1), RC (t-1), expected_returns)
```

Where *RC_{-i}(t-1)* denotes competitors' Representation Capital.

If the function *f* is increasing in competitors' RC (actors invest more when competitors pull ahead), the system may reach a **race condition** where all actors invest heavily for minimal relative advantage.

The Dissipative Investment Problem:

During inflationary arms races, resources expended on representation investment may generate **no relative advantage**:

```
Total Investment: Σ I (t) = substantial
Relative Advantage Gained: Σ RA (t)   0
```

The investment is socially wasteful from the perspective of competitive differentiation. Resources are expended to maintain relative position, not to achieve allocative advantage.

3.6 Sector Variation in Inflation

Computational Inflation will proceed at different rates across sectors:

High-Frequency, Low-Margin Sectors:

- **Hospitality:** Daily pricing, high inventory turnover, intense competitive pressure
- **E-commerce:** Rapid product updates, high SKU count, price-sensitive consumers
- **Ride-sharing:** Real-time availability, high supply elasticity, low per-transaction margin

These sectors may experience **rapid inflation**. High allocative stakes create strong incentives for representation investment. Low margins create pressure for allocative efficiency.

Low-Frequency, High-Stakes Sectors:

- **Real Estate:** Weekly or monthly listing updates, high per-transaction value
- **Professional Services:** Long sales cycles, relationship-based allocation

- **Industrial Equipment:** Multi-year purchase cycles, specification-heavy allocation

These sectors may experience **slower inflation**. Lower frequency reduces pressure for continuous investment. High stakes may favor traditional differentiation (reputation, relationships) over pure representation.

The Inflation Gradient:

```
Hospitality       E-commerce       Real Estate
   (Rapid)             (Moderate)             (Slow)
     ↑                     ↑                     ↑
  High pressure        Medium pressure      Lower pressure
  High turnover        Medium turnover      Low turnover
  Low margin           Medium margin        High margin
```

3.7 The Post-Inflation Transition

When Computational Inflation reaches completion—when all actors achieve adequate RC—allocative differentiation must transition to a new scarce resource.

Three Possible Transitions:

Transition 1: Price-Based Competition

When RC ceases to differentiate, allocative outcomes revert to traditional price competition. The lowest-price actor among the admissible set wins allocation.

Transition 2: Trust-Based Competition

When RC is universal, allocative systems may differentiate based on trustworthiness. Actors with proven accuracy, reliability, and verification track records gain advantage.

Transition 3: Hybrid Competition

Allocative systems may consider both representation quality and trustworthiness jointly, creating a two-dimensional allocation framework.

The Likely Transition:

We argue in Part V that **Transition 2**—trust-based competition—is the most likely outcome. When RC is universal, trust becomes the natural scarce resource. This motivates the transition to **Computational Creditworthiness**, developed in **Volume III** of this research program.

Part IV

Representation Moats

4.1 Definition

Representation Moats are structural barriers created by accumulated Representation Capital that protect allocative advantage from competitive erosion.

Representation Moats differ from traditional competitive advantages:

Advantage Type	Mechanism	Durability	Replicability
Economies of Scale	Cost advantage from volume	Medium	Replicable at scale
Network Effects	Value advantage from user base	High (conditional)	Difficult to replicate
Switching Costs	Lock-in from transition costs	Medium	Replicable
Representation Moats	**Allocative advantage from RC stock**	**High (path-dependent)**	**Difficult to replicate**

4.2 Durable vs Non-Durable Moats

Representation Moats vary in durability depending on their source:

Durable Moat Sources:

1. **Historical Contingency:** Early movers accumulate RC over time. Late entrants must traverse the same accumulation path, which requires time. Historical time cannot be compressed.
2. **Learning Effects:** Representation investment involves discovering which attributes matter most, how to structure data efficiently, and how to implement verification systems. This learning is not easily replicable without traversing the same discovery process.
3. **Canonical Status:** AI systems may develop "canonical" preferences for certain representations. If a system learns to trust specific sources or schemas, new entrants face the burden of overcoming established trust patterns.

Non-Durable Moat Sources:

1. **Temporary Standards Lock-In:** If a representation format becomes temporarily dominant, early adopters gain advantage. But when the format evolves, the advantage may erode.
2. **Allocative System Preferences:** If an allocative system temporarily favors certain representation characteristics, actors with those characteristics gain advantage. But when the system evolves, the advantage may disappear.

The Moat Durability Spectrum:

```
Learning Effects      Historical Contingency      Temporary Lock-In
    (Most Durable)              (Medium)                    (Least Durable)
```

4.3 Open Standards vs Proprietary Standards

The choice between open and proprietary representation standards has significant implications for moat formation:

Open Standards:

Open standards (Schema.org, industry protocols, public specifications) are accessible to all actors. Adoption creates level playing fields.

Moat Dynamics under Open Standards:

- Early adopters gain time-based advantage (first to implement)
- Advantage is not protected by exclusivity
- Late entrants can adopt the same standards
- Moats arise from implementation quality, not standard access

Proprietary Standards:

Proprietary standards (platform-specific schemas, closed APIs, private formats) are controlled by specific actors.

Moat Dynamics under Proprietary Standards:

- Standard owner has structural advantage
- Adoption may require permission or payment
- Late entrants face exclusion barriers
- Moats arise from standard access, not just implementation

The Trade-off:

Open standards create **competitive but potentially dissipative** moats. Proprietary standards create **protected but potentially exclusionary** moats.

From a welfare perspective, open standards are generally preferable. They allow all actors to compete on implementation quality rather than standard access. However, proprietary standards may create stronger incentives for initial innovation.

The Standard Governance Question:

Who sets and updates the schemas and protocols that determine RC requirements? How are these standards governed? These questions merit attention but are beyond the scope of this paper.

4.4 Risks of Moat Concentration

Representation Moats, while valuable for individual actors, create systemic risks when concentrated:

Risk 1: Allocative Inequality

If moats create persistent barriers to entry, allocative access may become increasingly unequal. Actors with initial advantages (resources, timing, luck) may consolidate allocative access over time.

Risk 2: Innovation Suppression

If moats protect established actors from competitive pressure, incentives for innovation may be reduced. Protected actors may face less pressure to improve representation quality.

Risk 3: Gatekeeper Power

If moat-protected actors become the primary admissible sources for allocative systems, they may gain gatekeeper power—the ability to determine which other actors participate in allocation.

Risk 4: Systemic Fragility

If allocative systems become dependent on a small set of high-RC, moat-protected actors, system fragility increases. Failure or degradation at any of these actors creates systemic risk.

The Concentration-Innovation Trade-off:

```
Moat Strength      Concentration      Innovation Risk
    ↑                     ↑                    ↑
 Strong moats        High concentration    Lower innovation
```

Strong moats may benefit individual actors but may reduce aggregate innovation and increase systemic risk.

4.5 The Moat Lifecycle

Representation Moats evolve through four stages:

Stage 1: Formation

An early actor invests in Representation Capital, achieving allocative advantage before competitors recognize the value of representation quality.

Stage 2: Consolidation

The early actor continues investing, widening the gap between their RC and competitors' RC. The moat deepens.

Stage 3: Challenge

Competitors recognize the advantage and invest to catch up. The moat narrows but may persist due to early-mover advantages.

Stage 4: Erosion or Persistence

Two possible outcomes:

- **Erosion:** Competitors successfully catch up. The moat disappears. Competition shifts to other dimensions.
- **Persistence:** The moat proves durable. The early actor maintains allocative advantage through continued investment and learning effects.

The Critical Question:

What determines whether moats erode or persist? Three factors:

1. **Investment Capacity:** Can competitors afford the investment required to catch up?
2. **Learning Effects:** Are there knowledge barriers that slow catch-up?
3. **Allocative System Stability:** Do allocative system requirements evolve in ways that favor early movers or late entrants?

These factors determine whether Representation Moats create temporary advantages or durable structural protections.

Part V

Transition to Computational Creditworthiness

5.1 Why Representation Alone Becomes Insufficient

Representation Capital solves the problem of **computational admissibility**—whether an option can be inferred, evaluated, and included in consideration sets. But admissibility is not the only allocative constraint.

As Representation Capital becomes ubiquitous (through the inflationary process described in Part III), allocative systems face a new problem: **how to distinguish among admissible options?**

The Post-Inflation Challenge:

When all actors in a market achieve adequate RC:

```
RC   RC   ...  RC   RC_adequate
P(admit | RC )  P(admit | RC )  ...  P(admit | RC )
```

All actors are equally admissible. Allocative outcomes cannot differentiate based on representation quality alone.

The New Scarcity:

The scarce resource shifts from **representation** to **trustworthiness**:

- **Representation Scarcity (Pre-Inflation):** “Is this option machine-readable?”
- **Trust Scarcity (Post-Inflation):** “Is this representation accurate and reliable?”

Allocative systems must answer the second question to differentiate among equally admissible options.

5.2 How Trust Becomes the Next Allocative Constraint

The Trust Transition Logic:

```
Stage 1: Low RC Universality
  Most actors have inadequate representation
  Admissibility is the binding constraint
  Investment in RC generates allocative advantage

Stage 2: High RC Universality (Inflation Complete)
  Most actors have adequate representation
  Admissibility is no longer binding
  Investment in RC generates diminishing returns

Stage 3: Trust Scarcity Emerges
  All actors are admissible
  Accuracy and reliability become binding constraints
  Investment in trustworthiness generates allocative advantage
```

This transition motivates the next working paper: **Computational Creditworthiness**.

5.3 The Two-Layer Allocation Framework

Post-inflation, allocative systems may adopt a two-layer framework:

Layer 1: Admissibility Filter (Representation Capital)

```
P(admit | RC) > threshold → Candidate for consideration
P(admit | RC)   threshold → Excluded
```

The admissibility filter acts as a coarse screen, excluding options with inadequate representation.

Layer 2: Trust Filter (Computational Creditworthiness)

```
P(select | T) > threshold → Included in consideration set
P(select | T)   threshold → Excluded despite admissibility
```

The trust filter acts as a fine screen, distinguishing among admissible options based on trustworthiness.

The Dual-Layer Allocation Model:

```
Consideration Set = { options i | P(admit | RC ) >   AND P(select | T ) >   }
```

Where: -   is the admissibility threshold -   is the trustworthiness threshold

The Joint Probability:

```
P(included | RC, T) = P(admit | RC) · P(select | T | admit)
```

Inclusion requires both admissibility (RC) and trustworthiness (T).

5.4 The Concept of Computational Creditworthiness

Computational Creditworthiness is the assessed reliability of machine-readable actors, assets, or representation sources for inclusion in AI-mediated consideration sets.

Why "Creditworthiness"?

The term borrows from financial creditworthiness—the assessment of whether a borrower is likely to repay a loan. Computational creditworthiness assesses whether a representation source is likely to provide accurate, reliable information.

The Parallel:

```
Financial Creditworthiness:  "Will this borrower repay?"
Computational Creditworthiness: "Will this representation be accurate?"
```

Both are assessments of reliability under uncertainty. Both inform allocation decisions (loan allocation vs consideration set allocation).

The Trust Primitives (from Volume III):

Computational Creditworthiness, developed in Volume III, introduces six trust primitives:

1. **Provenance:** Clarity, authenticity, and traceability of representation source
2. **Verification History:** Accumulated record of verification against ground truth
3. **Representation Consistency:** Internal coherence and stability across observations
4. **Outcome Reliability:** Historical frequency of satisfactory outcomes

5. **Update Reliability:** Consistency and timeliness of representation updates
6. **Action Reliability:** Success rate with which action interfaces execute as specified

5.5 Explicit Bridge to Computational Creditworthiness

From Volume II to Volume III:

This volume has demonstrated that when Representation Capital reaches saturation, allocative differentiation must transition to a new scarce resource. We argue that trustworthiness is the natural successor to representation as the allocative bottleneck.

The Formal Bridge:

Let $t*$ denote the time at which Computational Inflation completes ($\bar{RC}$(t*)   RC_max).

Pre-Inflation Allocation (t < t*):

```
P(included | RC ) = f(RC ), where f (·) > 0
```

Inclusion depends primarily on Representation Capital.

Post-Inflation Allocation (t   t*):

```
P(included | RC , T ) = f(RC ) · g(T ), where g (·) > 0
```

Inclusion depends on both Representation Capital and Computational Creditworthiness.

The Transition Condition:

```
When Var(RC) → 0 (RC variance approaches zero),
allocative systems must rely on Var(T) (trust variance) for differentiation.
```

Implications for Volume III:

Volume III (Computational Creditworthiness) should address:

1. How do allocative systems assess T (trustworthiness)?
2. What primitives constitute T?
3. How is T measured and verified?
4. How does T interact with RC in allocation decisions?
5. What investment strategies increase T?

This volume provides the theoretical motivation; Volume III provides the theoretical development.

Part VI

Transition to Agent-Readable Property Markets

6.1 How Representation Dynamics Affect Property Allocation

Property markets present a distinctive allocative environment. Properties are heterogeneous (each property is unique), high-stakes (transactions involve substantial value), and infrequently traded (properties sell or rent rarely).

Why Property Markets Are Distinct:

Characteristic	Hospitality	E-commerce	Real Estate
Heterogeneity	Medium	Low	High
Transaction Value	Medium	Low	High
Trading Frequency	High	High	Low
Allocative Stakes	Medium	Low	High

These distinctive characteristics affect how Representation Capital dynamics operate in property markets.

The Property Representation Challenge:

Properties are complex objects with many attributes. Full representation requires capturing:

Property Attributes: - Location (geographic coordinates, neighborhood context) - Physical characteristics (size, condition, amenities) - Legal attributes (ownership, zoning, restrictions) - Financial attributes (price, taxes, fees) - Availability status (for rentals)

Temporal Attributes: - Availability calendars - Pricing history - Listing history - Transaction history

Verification Attributes: - Ownership proof - Accuracy attestations - Photo verification - Update timestamps

The complexity of property representation creates high initial investment costs for Representation Capital formation.

6.2 The Dual Allocation Framework for Properties

In Agent-Readable Property Markets, property selection probability is determined by the interaction of representation quality and trust quality:

The Dual Allocation Model:

`P(select | property) = (R(property), T(property), Z)`

Where: - *R(property)*: Representation Capital of the property - *T(property)*: Computational Creditworthiness of the representation - Z: Traditional factors (price, location, quality)

The Interaction Effect:

Representation and trust are not merely additive; they interact:

Low R, Low T → Property is invisible to AI systems (fails admissibility filter) **Low R, High T** → Property is invisible despite trustworthy representation (fails admissibility filter) **High R, Low T** → Property is admissible but not selected (fails trust filter) **High R, High T** → Property is both admissible and selectable (passes both filters)

The Complementarity:

Representation and trust are complementary. High representation quality with low trustworthiness is insufficient. High trustworthiness with low representation quality is also insufficient.

The Substitution:

Within constraints, representation and trust can substitute:

- **Very High R** may compensate for **Moderate T**
- **Very High T** may compensate for **Moderate R**

But extreme asymmetries (one very high, one very low) typically create exclusion.

6.3 Agent-Readable Property Markets Defined

Agent-Readable Property Markets (ARPM) are markets in which allocation decisions may be influenced by machine interpretation of structured representations.

The ARPM Concept:

Traditional property markets allocate through human-mediated search: 1. Buyer searches listings 2. Buyer filters and compares 3. Buyer selects property 4. Buyer contacts seller

Agent-Readable Property Markets allocate through AI-mediated consideration: 1. Buyer specifies requirements to AI system 2. AI system constructs consideration set from structured representations 3. AI system filters and ranks properties 4. AI system presents subset to buyer 5. Buyer selects from AI-curated options

The Critical Shift:

In ARPM, the AI system becomes the allocative interface. Properties must be **admissible** to the AI system before they can be considered by the buyer.

The Admissibility Requirement:

```
Property P is allocatable in ARPM only if:
1. P has adequate Representation Capital (R(P) > R_threshold)
2. P has adequate Computational Creditworthiness (T(P) > T_threshold)
```

This joint requirement creates the allocative structure analyzed in **Volume IV (Agent-Readable Asset Markets)**.

6.4 Explicit Bridge to Agent-Readable Property Markets

From Volume II to Volume IV:

This volume has developed the dynamic theory of Representation Capital and demonstrated the transition to trust-based allocation. Volume IV applies this framework specifically to property markets and other asset sectors.

The Bridge Logic:

```
Part I-IV: RC Dynamics, Yield, Inflation, Moats
          ↓
Part V: Transition to Computational Creditworthiness (Volume III)
          ↓
Part VI: Application to Property Allocation (Volume IV)
```

The Property-Specific Questions:

Volume IV should address:

1. How do representation dynamics differ across property types (residential, commercial, hospitality)?
2. How does property heterogeneity affect Representation Capital accumulation?
3. How do trust mechanisms operate specifically for property representations?
4. What are the allocative implications of ARPM for property owners, managers, and markets?
5. How might ARPM reshape traditional property market structures?

The Contribution of Volume II to Volume IV:

This volume provides: - The dynamic theory of RC accumulation and depreciation - The yield framework for understanding allocative returns - The inflation framework for understanding competitive dynamics - The moat framework for understanding persistent advantages - The trust transition framework for understanding post-inflation allocation

Volume IV applies these general frameworks to the specific case of property markets, deriving property-specific implications and recommendations.

6.5 The Unified Research Program

The Complete Research Sequence:

```
                  REPRESENTATION ECONOMY RESEARCH PROGRAM


         Related Research Publications (Foundation)



    Foundation Papers:      Pricing &
    Institutional          Monetary Theory
    Framework



            Volume I: Representation Capital



   Volume II:               Volume III:
   RC Dynamics              Computational
(THIS PAPER)              Creditworthiness



         Volume IV: Agent-Readable Asset Markets
```

The Position of This Volume:

Volume II serves as the **central bridge** in the research program:

- **Looking Back:** It synthesizes and extends the static concept of Representation Capital (Volume I)
- **Looking Forward:** It motivates the trust theory (Volume III) and sector applications (Volume IV)

Without the dynamic theory developed here, the transition from representation-based allocation to trust-based allocation would be unmotivated. Without the inflation analysis, the necessity of Computational Creditworthiness would be unexplained. Without the moat framework, the strategic implications of representation investment would be unclear.

Conclusion

This paper has developed a dynamic theory of Representation Capital—the accumulated stock of machine-readable qualities that may generate allocative advantage in AI-mediated markets.

Key Contributions:

1. **Accumulation Dynamics:** We formalized how Representation Capital accumulates through investment and depreciates through staleness and obsolescence. We distinguished formation, expansion, and maintenance investment, and analyzed the growth condition for capital accumulation.

2. **Representation Yield:** We introduced Representation Yield as the allocative return on representation investment. We analyzed why representation quality may produce allocative advantages, identified the limits of yield, and demonstrated diminishing returns.

3. **Computational Inflation:** We introduced Computational Inflation as the erosion of allocative advantage when all actors accumulate Representation Capital. We analyzed the inflationary process, compared with traditional capital accumulation, and identified sector variation in inflation rates.

4. **Representation Moats:** We introduced Representation Moats as structural barriers created by accumulated advantages. We distinguished durable from non-durable moats, analyzed open vs proprietary standards, and identified risks of moat concentration.

5. **Bridge to Computational Creditworthiness:** We demonstrated why representation alone becomes insufficient when inflation reaches completion. We introduced the dual-layer allocation framework and established the theoretical foundation for **Volume III**.

6. **Bridge to Agent-Readable Property Markets:** We analyzed how representation dynamics affect property allocation. We introduced the Dual Allocation Framework for properties and established the theoretical foundation for **Volume IV**.

The Theoretical Synthesis:

Representation Capital exhibits fundamentally different dynamics than traditional capital forms. Unlike physical capital, it depreciates through staleness and format change rather than wear. Unlike financial capital, it accumulates through data investment rather than savings. Unlike human capital, it can compound through consideration-set feedback.

These unique properties create distinct patterns of accumulation, concentration, and equilibrium. The Matthew Effect—"the represented become more represented"—may generate cumulative advantage. Computational Inflation may generate arms races and dissipative investment. Representation Moats may create durable competitive advantages.

The Central Insight:

In industrial economies, capital determined what could be **produced**. In computational economies, Representation Capital may determine what continues to be **considered**.

The shift from production to consideration, from goods to admissibility, from physical to representational—this is the structural transformation that the Representation Economy research program seeks to understand.

Closing Observation:

Whether Representation Capital emerges as an economically significant asset class, whether its dynamics generate concentration or fragmentation, whether arms races or equilibria prevail—these remain empirical questions. The theoretical framework developed here provides a basis for investigation.

Until that investigation occurs, Representation Capital Dynamics remains a theoretical construct—a lens through which to view the potential evolution of markets under AI-mediated allocation.

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Representation Economy Research Program

Volume I — Representation Capital — Foundational theory of machine-readable capital as allocative advantage.

Volume II — Representation Capital Dynamics (this volume) — Dynamic framework, accumulation, yield, and depreciation mechanisms.

Volume III — Computational Creditworthiness — Trust-based selection and representation reliability assessment.

Volume IV — Agent-Readable Asset Markets — Sector-specific applications and market design implications.

Related Research Publications:

The Representation Economy — Computational Market Access as Allocative Infrastructure in AI-Mediated Markets. DOI: 10.5281/zenodo.20692182.

Computational Market Access — The Institutional Foundation of AI-Mediated Economic Participation.

Computational Market Economics — Mathematical Foundation of Allocation Under Bounded Inference.

Network-Dependent Allocation — Impossibility Results for Ranking Under Non-Separable Valuation.

Computational Pricing Theory — Price Formation in AI-Mediated Markets.

Computational Monetary Theory — Credits, Settlement, and Unit-of-Account Formation in AI-Mediated Markets.

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