

Ecological Evolution Enriches the Capacity for Causal Lived Individuality in a Non-Language-Model Digital Organism

A preregistered, independently audited artificial-life study

Preprint manuscript

Project GHOST Research Collective

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Bounded certified claim

Ecological selection on frozen standing heritable variation enriched genotype distributions with greater inherited capacity for causal, durable, adaptive lived individuality through a preexisting HabitLearner mechanism.

Permanent qualification: HabitLearner was hand-authored and preexisting; evolution selected heritable parameters governing its operation and did not invent the learner. The result is certified with a post-freeze analysis provenance qualification.

This manuscript makes no claim of consciousness, general intelligence, production readiness, open-ended learning, or a developmentally grown large brain.

Abstract

A central objective in artificial life is to construct organisms whose behavior is neither scripted by a designer nor borrowed from human demonstrations, but instead arises from the joint action of ecological evolution and individual experience. We report a governed sequence of experiments in a non-language-model digital organism designed to isolate that causal chain. First, a finite-resource ecology with metabolism, death, reproduction, heritable variation, and no ranked external fitness function increased intrinsic foraging competence from random direct genomes (mean change approximately +0.026, 95% CI [0.016, 0.041]; 28 of 32 populations positive; no extinctions). Second, genetically and mentally identical newborn clones exposed to inverse, structurally symmetric lifetime contingencies acquired distinct HabitLearner Q states and displayed history-appropriate behavior during frozen probes. The certified paired-clone effect was 35.318 units of net-energy advantage (95% CI [28.161, 42.010]); the effect exceeded same-history replay divergence, vanished when learning was disabled or learned state was reset, and persisted through a neutral washout. Third, three heritable plasticity parameters - `update_gain`, `advantage_weight`, and `habit_discount` - were shown to form a learning-specific, epistatically navigable selection surface. Fourth, ecological selection acting on frozen standing variation changed genotype frequencies and increased newborn-reset learning-mediated function. The culminating preregistered assay evaluated 18 genotypes, 8 controller backgrounds, 16 assay seeds, 6 acquisition conditions, 13,824 acquisition episodes, and 27,648 frozen-state probe branches using exact genotype-frequency weighting. The stable-selected distribution produced a weighted own-history score of 59.624 versus 29.865 for equal founders, 22.988 for the balanced-selection control, and 30.070 for the learning-disabled-selection control. Enrichment effects were stable minus founder = 29.758 (95% CI [26.737, 33.523]), stable minus balanced = 36.635 (95% CI [30.251, 42.143]), and stable minus learning-disabled = 29.553 (95% CI [25.921, 33.136]). An independent implementation reconstructed all point estimates and intervals, confirmed one biological execution, and passed 12 adversarial fail-closed tests. These results establish, in a bounded direct-genome system, that ecological evolution can enrich an inherited capacity through which individual artificial organisms become persistently and adaptively different because of their own lived histories.

Keywords: artificial life; digital evolution; neuroevolution; phenotypic plasticity; lifetime learning; individuality; ecological selection; reinforcement learning; preregistration; reproducibility

Significance statement

Digital evolution has repeatedly shown that computational organisms can adapt and acquire complex functions, while evolved-plasticity research has shown that evolution can shape learning rules. The present study links these ideas under a stricter causal standard: ecological reproduction, rather than a ranked optimizer, altered the frequencies of heritable plasticity genotypes, and the resulting selected distribution had a substantially greater capacity to become adaptively different after different lived histories. The result does not depend on labels, a hidden correct-action signal, cherry-picked genotypes, inherited learned state, continued learning during evaluation, an Avatar, or a language model. It therefore closes a specific causal loop between living ecological selection and lived individuality in a bounded artificial organism.

1. Introduction

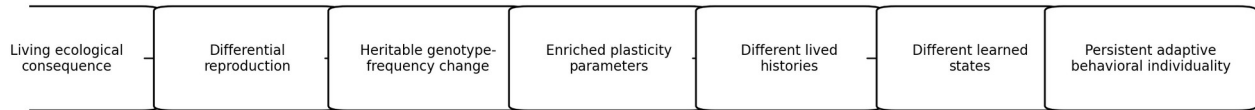
Artificial life studies life as it could be by constructing systems in which replication, heredity, variation, metabolism, interaction, and selection can be examined directly [1-5]. Digital-evolution platforms such as Tierra and Avida established that computational organisms can self-replicate, compete, mutate, and evolve complex functions under controlled conditions [2-4]. Neuroevolution, in parallel, demonstrated that neural controllers and their topologies can be optimized through evolutionary search [6-8]. A separate line of work on evolved plastic artificial neural networks asked whether evolution can shape mechanisms that learn during an individual lifetime [9-12].

These traditions leave a narrower but consequential question. Can a digital organism acquire competence because its lineage lived and reproduced in an ecology, and can that ecological history subsequently enrich the inherited capacity of newborn individuals to become different because of their own personal experience? Demonstrating either half alone is insufficient. A system may evolve fixed behavior without meaningful lifetime change; it may

contain a hand-authored learner that functions as programmed without evolution having shaped its usefulness; or it may show behavioral divergence that is random, label-driven, or continuously relearned during evaluation. The relevant claim therefore requires a controlled causal chain spanning ecology, heredity, lifetime plasticity, frozen evaluation, and matched counterfactual controls.

Project GHOST was designed around an operational definition of earned behavior. Metabolic resources are finite, survival and reproduction have real consequences, genomes are fixed within a life, mutation occurs only at reproduction, learned state is not inherited, perception is deliberately compact, and no language model or external ranked grader is part of the organism. Under this definition, behavior is considered earned when ecological consequences alter which heritable organisms reproduce and when an individual's own consequences alter its later internal state and behavior. The project does not treat behavioral activity, apparent personality, animation, or presentation-layer output as evidence of an internal mind.

The present manuscript synthesizes the complete certified result through the independent D-84 audit. It reports: (i) ecological evolution of competence in the original direct-genome system; (ii) a neutral paired-clone assay establishing causal and durable experience-dependent individuality; (iii) a heritable plasticity surface and standing-variation selection result; and (iv) the final assay showing that ecological selection enriched the inherited capacity for adaptive lived individuality. Negative and invalidated programs are reported alongside positive findings because they define the claim boundary and document the project's falsification discipline.



Certified causal chain in the bounded direct-genome GHOST system

Figure 1. Certified causal chain. The culminating claim requires every link: ecological consequence, differential reproduction, heritable frequency change, plasticity enrichment, divergent lived histories, distinct learned states, and persistent adaptive behavior.

2. Research question and claim boundary

2.1 Primary research question

The primary question was whether ecological selection on standing heritable variation could enrich the capacity of genetically identical newborn organisms to become persistently and adaptively different after different lived histories. The selected trait was not a fixed action preference. It was the effectiveness of a preexisting lifetime-learning mechanism under ordinary consequences.

2.2 Operational definition of causal lived individuality

Causal lived individuality was defined as the conjunction of four properties:

- Genetically and mentally identical newborns begin from the same genome, inherited controller state, and empty learned state.
- Different but structurally symmetric histories produce different learned internal states.
- The different learned states produce different behavior during probes in which learning is frozen.
- The behavioral difference is adaptive: each organism performs better in the contingency matching its own history than in the opposite contingency.

Divergence alone was not sufficient. Random action variation, inherited fixed biases, unequal contexts, different random-number streams, continued learning during probes, and learned-state inheritance were all treated as alternative explanations requiring explicit controls.

2.3 Claim ladder

Level	Claim	Status	Evidence basis
1	A lifetime-learning mechanism exists and can update from ordinary consequences.	Certified	D-60/D-61/D-62
2	Different lives make identical newborn learners persistently and adaptively different.	Certified	D-61/D-62
3	Evolution selects heritable plasticity parameters from standing variation.	Certified	D-73/D-77
4	Evolution enriches the inherited capacity for adaptive lived individuality.	Certified	D-83/D-84
5	A compact developmental genome grows a larger expressive brain.	Not established	Phase 2B closed negative
6	The organism exhibits rich open-ended lifetime behavior.	Not established	Outside certified evidence
7	The mind is efficient on ordinary consumer hardware.	Not established	Outside certified evidence

3. System and general methods

3.1 Digital organism

The certified organism used a compact direct genome controlling a reactive-plus-memory policy. The genome was immutable during an individual life. Working state and learned state were somatic: they could change during a life but were never inherited. The organism did not contain a language model, text-prediction core, semantic knowledge base, or externally supplied behavior script.

The lifetime-learning mechanism was a bounded tabular HabitLearner represented by a Q table. Ordinary context-action consequences updated Q values through the existing simulation path. Three heritable parameters governed its operation: `update_gain`, `advantage_weight`, and `habit_discount`. The first controls the magnitude of learning updates; the second controls the contribution of learned advantage to action selection; the third controls retention or discounting of learned habit values. HabitLearner itself was hand-authored and preexisting. The experiments tested whether evolution shaped the inherited parameters controlling this learner, not whether evolution invented the learner.

3.2 Ecological foundation

The original ecology contained finite metabolic resources, action costs, death, reproduction, inheritance, mutation at reproduction, and a carrying capacity. Reproductive success arose from survival and accumulated energy rather than from a ranked competence score. Intrinsic competence was measured separately from realized ecological success so that improvement in the measured trait could be tested without using that metric as the selection mechanism.

3.3 Determinism, isolation, and artifact governance

All formal programs used explicit integer seed registries, deterministic pseudorandom streams, frozen matrices, exact row identifiers, immutable manifests, and one-execution authorization. Gate-critical outputs were committed under `.architect/` with a `gate-artifact-manifest-v1` record containing the exact command, source commit, code and configuration hashes, row counts, completion status, artifact hash, and canonical before/after hashes. Simulation programs ran under isolated `GHOST_HOME` directories. Canonical live files were hashed before and after execution and were required to remain unchanged.

Formal analyses were separated from biological execution. Stage 1 produced frozen outcomes without access to expected directions, distribution labels used only in later weighting, gate thresholds, or verdict logic. Stage 2 read

frozen artifacts and was prohibited from importing simulators, acquisition runners, mutation, reproduction, or selection code. Independent audit repositories reimplemented the analyses without importing the reported verdict implementation.

3.4 Statistical approach

All major claims were evaluated over replicated seeds and named controls. Paired designs were retained whenever histories or source populations shared a common initial state. The final D-83 experiment used controller background multiplied by matched D-75 replicate as its primary inferential unit (64 matched units). Genotypes, assay seeds, acquisition episodes, probe branches, actions, and contexts were treated as nested observations rather than independent organisms. Confidence intervals were produced with a frozen 10,000-iteration paired bootstrap using deterministic seed 8,300,083 and percentile 95% intervals.

4. Experimental program

4.1 Ecological competence from random direct genomes

The foundation experiment asked whether a living ecology could increase intrinsic foraging competence from random genomes without selecting directly on the competence metric. Three linked tests were used. An externally ranked genetic-algorithm control established that the genome-to-behavior substrate was evolvable. A sustain test established that competent lineages could reproduce for many generations without collapse. The decisive ecological-improvement test began from random founders and used only the absolute ecological reproduction gate.

4.2 Neutral paired-clone lived-individuality task

A first lived-individuality task was invalidated because cue identities leaked semantically loaded being-addressed and phase-hint information into the inherited controller. The corrected v2 task separated the inherited-controller observation from the HabitLearner context key. The inherited controller received observations that were identical under context reflection; the HabitLearner received distinguishable but semantically neutral context identifiers. Spatial orientation and action-label orientation were fully counterbalanced in an eight-member symmetry orbit. Common random numbers were used across mirrored members, and newborn qualification required exact structural, policy, ecological, and random-consumption symmetry before any lifetime history was authorized.

The formal lived-individuality experiment used 24 governed direct genomes, 16 formal seeds, and 28 authoritative rows per genome-seed block, for 10,752 rows. Each newborn snapshot was forked into complementary Mapping A and Mapping B histories. Histories contained 64 relevant decision opportunities; probes contained 32 opportunities; washout contained 64 opportunities. The normal, same-history replay, learning-disabled, learned-state-reset, and neutral-washout arms shared preregistered schedules and consequence magnitudes.

$$A_specificity = performance(A-trained, A-probe) - performance(A-trained, B-probe)$$

$$B_specificity = performance(B-trained, B-probe) - performance(B-trained, A-probe)$$

$$counterfactual\ history\ advantage = (A_specificity + B_specificity) / 2$$

Primary performance was net-energy surplus generated by ordinary resource capture. No direct correct-action reward, desired Q value, mapping label, or harness score entered the creature. Probe learning was frozen, so the probe measured expression of acquired state rather than continued acquisition.

4.3 Heritable plasticity surface

The certified HabitLearner phenotype was re-expressed through three heritable genes: `update_gain`, `advantage_weight`, and `habit_discount`. A topology-aware held-out panel tested whether changes in these genes produced a learning-specific, navigable functional surface. The exact null `update_gain = 0` blocked Q updates and rendered downstream plasticity parameters silent, providing a mechanistic null. Balanced and shuffled controls separated ordinary controller function from the effect attributable to learning.

4.4 Standing-variation ecological selection

A frozen 18-genotype panel spanning the plasticity surface was crossed with 8 controller backgrounds. The D-75 population experiment used 8 matched replicates and three regimes, yielding 192 populations over 24 generations. Mutation was disabled. This ensured that any change arose from selection among standing heritable variants rather than from mutation supply or post hoc genotype creation. Newborn-reset common-garden evaluation separated inherited genotype-frequency change from acquired state in the selected adults.

An initially preregistered distribution-distance gate was found to be misspecified because unsigned Jensen-Shannon distance cannot identify direction. The result was not reinterpreted as a pass. D-77 instead applied a frozen exact causal decomposition within the existing experiment, testing whether stable selection increased learning-mediated function relative to balanced-selection and learning-disabled-selection controls.

4.5 Evolved capacity for causal lived individuality

The culminating D-83 assay combined the D-61/D-62 lived-individuality task with the exact D-75 genotype distributions. It included all 18 genotypes, 8 controller backgrounds, 16 assay seeds, and 6 acquisition conditions: learnable histories A and B, balanced-unlearnable histories A and B, and learning-disabled histories A and B. Each acquisition contained 64 opportunities. Every post-acquisition learned state was frozen and hashed, then branched into an own-history probe and an opposite-history probe, each containing 32 opportunities with learning disabled.

The full experiment comprised 13,824 acquisition episodes and 27,648 probe branches. Stage 1 evaluated every genotype directly and did not sample from source populations. Stage 2 reconstructed the equal-founder, stable-selected, balanced-selected, and learning-disabled-selected source distributions by exact weighting over the complete 18-category genotype vector. The decomposition residual tolerance was $1e-12$.

$$\text{own-history advantage} = 0.5[(A\text{-trained on } A - A\text{-trained on } B) + (B\text{-trained on } B - B\text{-trained on } A)]$$

$$\text{distribution score} = \text{sum over genotypes } g \text{ of } p_{\text{source}}(g) \times \text{genotype_score}(g)$$

5. Results

5.1 Ecological selection increased competence without a ranked grader

The externally graded control confirmed substrate evolvability, with an intrinsic-competence increase of approximately +0.050 (95% CI [0.039, 0.065]) and positive change in all replicates. Competent ecological populations sustained approximately 46-49 generations without extinction. In the decisive ecological-improvement experiment, random founder populations increased mean intrinsic competence by approximately +0.026 (95% CI [0.016, 0.041]); 28 of 32 populations improved, none went extinct, and the median lineage reached 49 generations. Because reproduction depended on ecological energy rather than the measured intrinsic-competence score, the result established that the living system itself provided a directional selection signal.

5.2 Different lives caused durable adaptive individuality

The v2 newborn qualification produced zero context effect, zero maximum paired difference, and zero standardized effect before history. During formal histories, Mapping A and Mapping B both produced positive learned alignment across all 24 genomes. The independently audited mean counterfactual history advantage was 35.3177 net-energy units (95% CI [28.1615, 42.0104]); 23 of 24 genomes had positive mean advantage. All leave-one-genome-out estimates (34.505-36.853) and leave-one-seed-out estimates (34.80-35.79) remained positive.

Between-history action-distribution distance exceeded same-history replay distance by 0.0292969 (95% CI [0.0224609, 0.0363770]). The normal-history advantage was 35.3177, whereas both the learning-disabled and learned-state-reset controls were exactly 0.0. The effect persisted unchanged after the preregistered neutral washout, yielding a retained-effect ratio of 1.0. Probe Q mutations, direct Q writes, inherited-controller changes, genome mutations, and nonselected learning updates were all zero. The effect decomposed entirely into ordinary resource capture; movement-cost, survival, derived-metric, and unexplained-residual contributions were zero.

5.3 Heritable plasticity formed a causal selection surface

The D-73 held-out surface qualified at brood cost 24. Stable reference minus exact-null function was 0.859375 (95% CI [0.5703125, 1.1484375]). The learning-specific interaction was 0.828125 (95% CI [0.484375, 1.1640625]), and all 8 controller backgrounds were positive. Ecological-causality residual was zero. The exact update_gain = 0 null prevented Q updates and silenced the other two plasticity genes, confirming that the surface depended on the learning mechanism rather than an unrelated controller effect.

5.4 Ecological selection changed standing plasticity variation

D-77 independently certified that ecological selection on frozen standing variation altered genotype frequencies and increased newborn-reset learning-mediated function. The stable learning-specific response was 0.764513. Stable minus balanced was 1.014974 (95% CI [0.793945, 1.184109]); stable minus learning-disabled was 0.753608 (95% CI [0.654433, 0.859321]). All 8 backgrounds and all leave-one-background-out estimates were positive. The sample decomposition residual was 3.33e-16. No mutation occurred, so the result was attributable to selection among the frozen variants.

5.5 Ecological evolution enriched adaptive lived individuality

The main D-83/D-84 assay passed every frozen gate. The learning mechanism engaged: learnable histories generated 245,760 Q updates and 3,840 learnable Q-state changes; learning-disabled histories generated zero updates and zero state changes. The equal-founder own-history advantage was 29.865451 (95% CI [26.653646, 32.523438]), confirming that the causal history effect reproduced within the D-83 matrix. Equal-founder Q divergence was 1.022444 and action-distribution divergence was 0.040188.

Outcome	Point estimate	95% interval	Interpretation
Equal-founder own-history advantage	29.865451	[26.653646, 32.523438]	Causal lived-history effect present before distribution weighting
Stable-selected score	59.623589	Descriptive weighted score	Highest source-distribution capacity
Balanced-selected score	22.988173	Descriptive weighted score	Label-balanced selection did not reproduce stable enrichment
Learning-disabled-selected score	30.070150	Descriptive weighted score	Selection without effective learning did not reproduce stable enrichment
Stable minus equal founders	29.758138	[26.737278, 33.523356]	Evolutionary enrichment over the initial distribution
Stable minus balanced	36.635417	[30.250651, 42.143175]	Enrichment is not explained by balanced exposure or selection alone
Stable minus learning-disabled	29.553440	[25.921441, 33.136149]	Enrichment depends on functional lifetime learning

The stable-selected distribution score was 59.623589, compared with 29.865451 for equal founders, 22.988173 for balanced-selected controls, and 30.070150 for learning-disabled-selected controls. The stable-selected distribution therefore nearly doubled the equal-founder own-history score. All three preregistered enrichment contrasts had confidence intervals bounded well above zero.

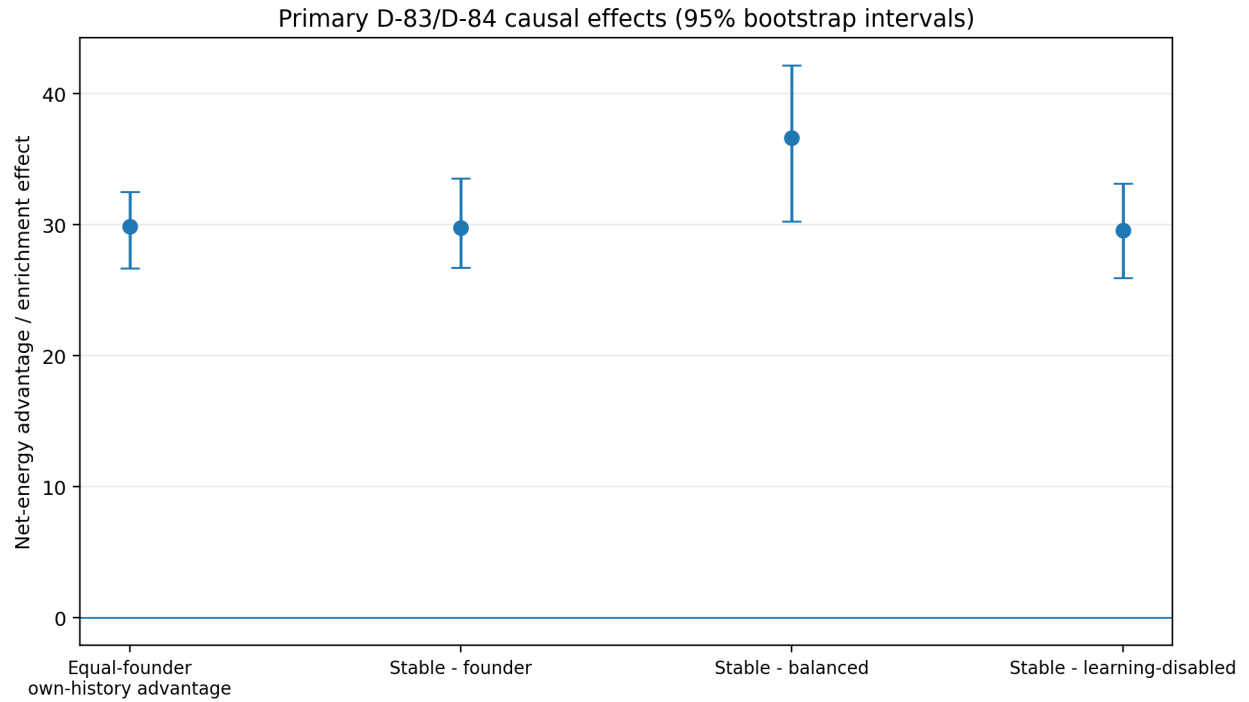


Figure 2. Primary causal effects and 95% paired-bootstrap intervals. The equal-founder result establishes the history effect; the three stable-distribution contrasts establish evolutionary enrichment over the initial and causal-control distributions.

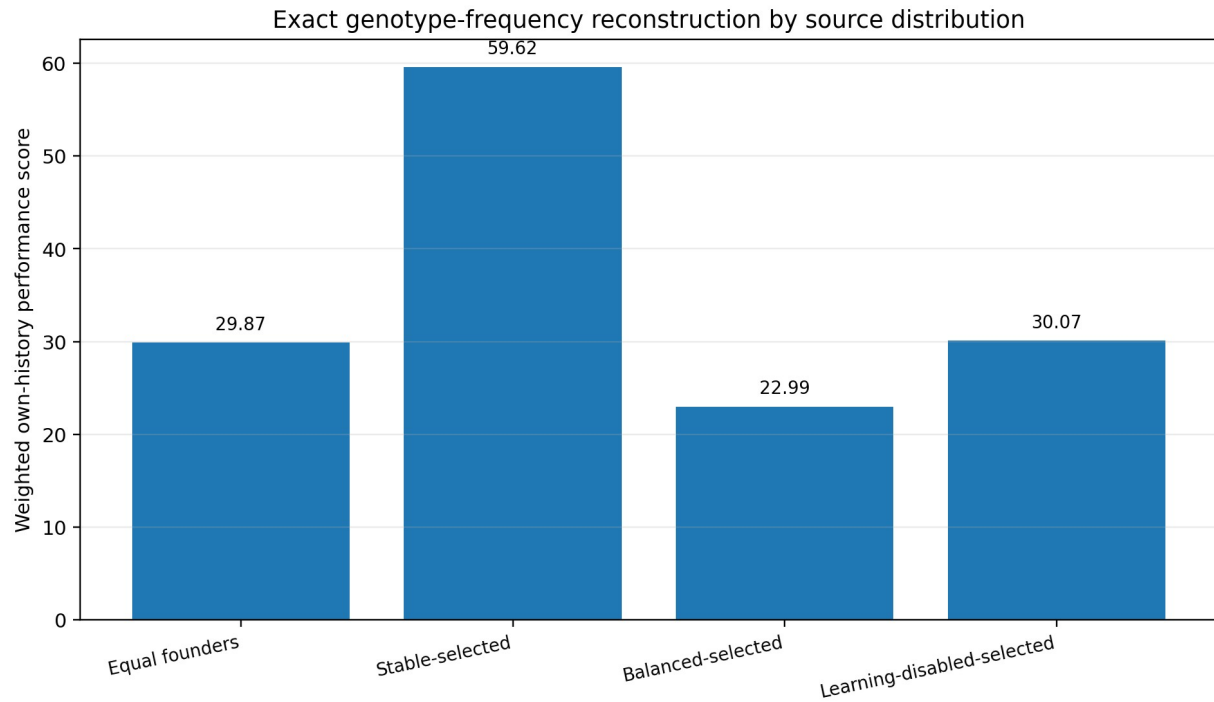


Figure 3. Exact genotype-frequency reconstruction by source distribution. Bars are weighted point estimates over the complete 18-genotype panel; no genotype sampling or best-genotype extraction was used.

Adaptive-divergence and persistence gates passed. Balanced label effect and learning-disabled history effect were both exactly 0.0. The stable own-history performance floor also passed: the stable distribution maintained at least the preregistered absolute performance floor rather than producing a large contrast through degradation of the opposite-history condition. Probe Q mutations and frozen-state hash mismatches were zero.

5.6 Exact attribution and integrity

All source-distribution outcomes were reconstructed by exact weighting across the 18-genotype panel. Genotype sampling was false. The decomposition residual was 1.4210854715202004e-14, below the preregistered 1e-12 tolerance. The statistical contract passed at the background-by-matched-replicate inferential level with all pseudoreplication guards active.

External ranked grading, genotype selection during the assay, best-genotype extraction, mutation, reproduction, learned-state inheritance, direct correct-action reads, direct fitness reads, direct Q writes, result-dependent weights, fitted genotype values, invalid runs, language-model calls, Avatar imports, and Avatar processes were all zero. Canonical live-state hashes and ticks were unchanged.

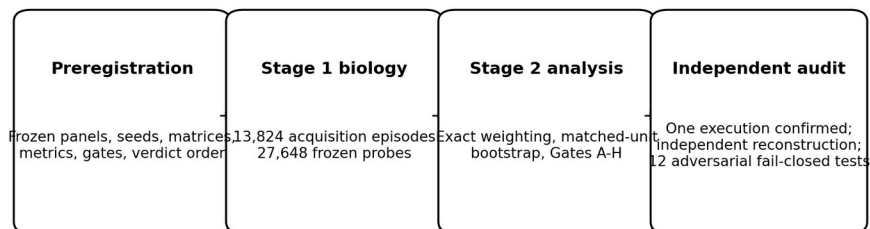
6. Independent audit and provenance

The D-83 biological execution completed exactly once and produced 13,824 acquisition rows and 27,648 probe rows. The first Stage 2 analysis attempt failed because a foundation guard checked `lock.formal_execution_count == 1` at a point where the lock representation did not satisfy the check. The analysis code was changed after Stage 1 freeze and Stage 2 was rerun without rerunning biology. This violated the original stop rule and therefore prevented an unqualified certification.

D-84 created an independent audit repository from the D-82 design basis rather than from the final D-83 execution commit. The audit reconstructed the commit chain and execution chronology; confirmed one authorization consumption and one biological execution; found no deleted, alternate, or replacement outcome set; verified all row counts, hashes, pairings, and frozen-state lineages; and classified the post-freeze change as `NONSCIENTIFIC_FOUNDATION_GUARD_ONLY`. The changed line affected the analysis foundation check and did not alter row selection, weighting, formulas, bootstrap, thresholds, gates, or verdict order.

A new analysis implementation imported no D-83 analysis module and independently reproduced every material point estimate and confidence interval within the frozen numerical tolerances. Gates A-H all passed. Twelve adversarial fixtures - including a missing row, duplicate row, altered genotype weight, broken matched pairing, altered bootstrap seed, probe Q mutation, and second-execution marker - were each detected and failed closed. The result was therefore certified with the permanent qualification:

`CERTIFIED_WITH_POSTFREEZE_ANALYSIS_PROVENANCE_QUALIFICATION`.



Governed evidence path: preregistered design -> one biological execution -> isolated analysis -> independent certification

D-84 permanent qualification: the post-freeze Stage 2 repair was independently shown to be a non-scientific foundation guard only.

Figure 4. Evidence and audit path. The provenance qualification remains attached because locked Stage 2 code changed after biological outcomes were frozen, even though independent reconstruction showed that scientific semantics were unchanged.

7. Negative, invalidated, and closed programs

The positive result emerged from a program that recorded negative and invalid experiments rather than absorbing them into a success narrative. These results constrain the interpretation of the certified claim.

Program	Result	Key evidence	Consequence for the claim
Initial lived-individuality v1 task	Invalid experimental task	Semantic cue leakage, inherited addressed-sensitivity bias, unequal RNG streams	Required a fully neutral, common-random-number v2 task; v1 was not reinterpreted
Developmental Phase 2B re-earn	Scientific negative	Ecology delta -0.0103; control -0.0069; selected-minus-control -0.000065; CI [-0.0174, 0.0049]; $p = 0.523$	Current developmental encoding cannot be credited with ecological re-earn or brain growth
D-75 original distribution-distance gate	Misspecified directional inference	Unsigned Jensen-Shannon distance could not encode direction	Replaced by exact preregistered causal decomposition; no retrospective pass
Null-founder mutation-enabled program	Closed	Mutation supply saturated activation; function did not converge; one-execution provenance later invalidated the formal attempt	No claim that evolution originated HabitLearner or plasticity from an all-null population
D-83 first Stage 2 attempt	Provenance defect	Post-freeze foundation-guard repair	Result certified only after independent reconstruction and with permanent qualification

8. Discussion

8.1 Main finding

The central result is not merely that a hand-authored learner can learn, nor merely that an evolutionary process can tune a scalar. The result links ecological selection to the inherited capacity for causal lived individuality. Stable ecological selection changed the frequencies of heritable plasticity genotypes; when all genotypes were evaluated from empty newborn learned states in a neutral paired-history assay, the selected distribution had a substantially greater ability to acquire persistent, history-appropriate behavior than the equal-founder distribution and two matched selection controls.

This distinction matters because the formal analysis never sampled a favorable individual from the stable distribution. Every genotype in the frozen panel was evaluated, and the source-population scores were reconstructed by exact frequency weighting. The effect therefore belongs to the distribution produced by ecological selection rather than to a cherry-picked champion.

8.2 Relation to digital evolution and evolved plasticity

Digital-evolution systems have shown that natural-selection analogues can generate adaptation and complex features in computational organisms [2-5]. The Baldwin-effect literature established that lifetime learning can reshape evolutionary search even when acquired states are not inherited [9]. Evolved-plasticity research has further demonstrated that evolution can optimize plastic neural systems for changing tasks [10-12]. GHOST contributes a complementary controlled demonstration in which the ecological mechanism, the within-life mechanism, and the causal distribution-level bridge are separately tested. The project's emphasis is not on maximizing benchmark reward but on preserving the distinction between behavior imposed by an optimizer and behavior earned through metabolism, survival, reproduction, and individual consequence.

The result is consistent with the broad EPANN objective of systems shaped by evolution and capable of autonomous learning [10]. It is narrower than general autonomous learning because the learner and task are bounded, but stronger in its causal controls: newborn symmetry, inverse histories, common random numbers, replay variation, disabled and reset controls, frozen probes, exact genotype-frequency attribution, and independent audit all constrain alternative explanations.

8.3 What was evolved and what was not

Evolution did not create the HabitLearner algorithm. The learner, its Q-table semantics, and the ordinary consequence-to-update path were written by the researchers. Evolution acted on three inherited parameters controlling how strongly and how persistently the learner influenced behavior. The certified statement is therefore that evolution enriched the capacity supplied by a preexisting learning architecture. Claiming that evolution invented learning would exceed the evidence.

Within an individual life, Q state changed in response to ordinary resource consequences. That acquired state was causally necessary: disabling updates or resetting only Q eliminated the history advantage. The acquired state was not inherited, and probes were frozen, so the later difference was carried by the individual's own learned history rather than by genotype mutation, continued probe training, or lineage memory.

8.4 Why divergence qualifies as adaptive individuality

Behavioral divergence can arise for reasons unrelated to meaningful individuality. The present assay required more. The two contexts were indistinguishable to the inherited controller, newborn ecological differences were exactly zero, and Mapping A and Mapping B were exact inverses. Between-history divergence had to exceed same-history replay divergence. Each trained individual had to perform better in the contingency matching its own history. Balanced-unlearnable and learning-disabled histories had to remain null. These conditions make random drift, action-label bias, spatial bias, and generic activity insufficient to pass.

8.5 Scientific significance

The study reaches the fourth level of the project's claim ladder: ecological evolution enriched adaptive lived individuality. This is a substantial milestone because it joins lineage-level selection and individual-level learning in one governed causal chain. It shows that the distribution produced by ecological living can alter not only fixed newborn behavior but also the kind of individual a newborn can become after experience.

The result should nevertheless be stated in its bounded form. The organism is a compact direct-genome controller operating in a controlled symbolic task. The experiment does not demonstrate a large developmentally grown brain, rich animal-like behavioral range, open-ended learning, free-form social cognition, or deployment as a consumer companion. It also does not establish consciousness, for which no operational test was attempted.

8.6 Importance of the negative results

The invalid v1 individuality task, the failed developmental re-earn program, the misspecified distribution-distance gate, the closed null-founder program, and the D-83 provenance defect materially strengthen the final claim by preventing broader but unsupported interpretations. In each case the program froze the failure, preserved artifacts, and either redesigned the question under a new preregistration or closed the research line. The certified result is therefore narrower than the project's long-range vision but more credible than a broad result assembled from post hoc subsets or altered thresholds.

9. Limitations

- The lifetime-learning architecture was preexisting and hand-authored. Evolution tuned three heritable parameters but did not originate the algorithm.
- The certified organism used a compact direct genome. The project did not establish a successful compact developmental encoding that grows a substantially larger structured brain.
- The lived-individuality task was deliberately bounded, symbolic, and symmetric. It does not establish transfer to unconstrained environments or human interaction.
- The primary adaptive outcome was net-energy surplus in a controlled resource contingency. Broader behavioral richness was not evaluated.
- The stable-selected result is a distribution-level claim. It does not guarantee that every individual genotype sampled from that distribution will exceed every founder genotype.

- The null-founder program did not establish spontaneous origin of functional plasticity from an all-null population and was closed.
- D-84 certified the D-83 result with a permanent post-freeze analysis provenance qualification because Stage 2 code changed after Stage 1 outcomes were frozen.
- The study did not evaluate consciousness, subjective experience, moral status, or human attachment.

10. Conclusion

In a bounded non-language-model digital organism, ecological selection on frozen standing heritable variation enriched the capacity for causal, durable, adaptive lived individuality. Identical newborns developed different internal learned states because they lived different histories; those states produced persistent history-appropriate behavior during frozen probes; and the genotype distribution produced by stable ecological selection expressed substantially more of this capacity than equal founders and matched selection controls. Exact genotype-frequency reconstruction, learning-disabled and reset controls, common-random-number symmetry, one-execution governance, and independent analysis constrained the principal alternative explanations.

The result establishes the core evolution-plus-lived-experience thesis in bounded direct-genome form. It does not establish that evolution invented learning, that the brain was developmentally grown at large scale, that behavior is open-ended, or that the system is production ready. Within those limits, the study demonstrates that ecological living can shape not only what an artificial organism is at birth, but also its inherited capacity to become an individual through experience.

11. Reproducibility and governed evidence

The results were produced in version-controlled project repositories with immutable gate artifacts and manifests. At the time of this manuscript, no public archival DOI had been assigned. The following identifiers define the certified evidence bundle and should accompany any public code or data release.

Evidence item	Identifier	Role
D-61 lived-individuality research commit	d17888a606083df3d54d9f43e8f5821d428a3bfd	Formal paired-clone result
D-62 lived-individuality audit commit	21451b735b003fd852904781d8f06e39d640129c	Independent causal certification
D-77 evolved-plasticity audit commit	0775158f6cfb2d4d3174fe590d5cd911f2a9f40c	Standing-variation selection certificate
D-81 null-founder review commit	12033f5abce335cafeae92fcad0ad7a9d5149867	Closure of unsupported null-founder claim
D-83 execution commit	6737516f205eff0bb340228f9b60438a6ba8d5b8	Formal evolved-individuality outcomes
D-84 independent audit commit	cd9ebb482aaa5bf0cce40c6d15f7b069713cfe4	Independent reconstruction and certification
D-85 milestone governance commit	f742c2302fee591ecf70591b29351833748fe89	Frozen claim ladder and milestone synthesis
D-83 acquisition artifact SHA-256	f0042324422758437dcc20e817c0d74fe9a4ec6b43e6c7cfd72c88b003dc36b	13,824 acquisition episodes
D-83 probe artifact SHA-256	63bf63ed1b8c18f2e9011b8172da276e11291620efbce3ef0001a2c5708dc3e7	27,648 frozen probes
D-84 independent gate hash	a50c73ba0bcc270abb68ece51479fd22064aa1b871c4239535379c9c1133fef3	Independent Gates A-H
Stable-selected distribution hash	373f0009d201d47dff50d94605aab97ab2ef4462c6926c5dd0683ea4911e2b9	Exact D-75 source distribution
Founder panel hash	fe7bd805e9dc62ffbb09a990abf35a456a8a924ac24305e4f146b5ee1201bdab	Frozen 18-genotype panel

12. Declarations

12.1 Ethics

The study used simulated digital organisms only. No human participants, human biological data, or nonhuman animals were involved.

12.2 Funding

Funding information was not provided for this manuscript draft and should be completed before submission.

12.3 Competing interests

Competing-interest declarations were not provided for this manuscript draft and should be completed before submission.

12.4 Author contributions

Author roles should be completed before submission using the CRediT taxonomy. The project record distinguishes operator governance, architecture and adversarial review, implementation, formal execution, and independent audit.

12.5 Data and code availability

The governed commit hashes and artifact SHA-256 identifiers are reported in Section 11. Public repository and archival-access details should be inserted when an external release is created.

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Supplementary Appendix A. Formal gate structure

A1. D-61/D-62 lived-individuality gates

- Newborn symmetry continuity: exact context equivalence before history.
- Habit-state acquisition: positive Mapping A and Mapping B alignment, with zero disabled-control updates.
- Experience-dependent ecological utility: positive counterfactual history advantage with robust paired intervals.
- Causal behavioral divergence: between-history divergence exceeds same-history replay divergence.
- HabitLearner dependence: normal effect exceeds disabled and reset controls; controls do not independently pass.
- Persistence: positive washout effect with no mapping evidence during washout.
- Ecological relevance: effect reconciles to ordinary net-energy/resource outcomes.
- Integrity: no hidden mapping reads, direct Q writes, mutations, reproduction, canonical writes, LLM calls, or Avatar dependencies.

A2. D-83/D-84 evolved-individuality gates

- Foundation and integrity: all D-61/D-62, D-77, D-81, D-82 dependencies and frozen matrices valid.
- Mechanism engagement: learnable histories update Q; learning-disabled histories do not.
- Equal-founder causal history effect: the lived-individuality effect reproduces before evolutionary weighting.
- Evolutionary enrichment: stable-selected exceeds equal-founder, balanced-selected, and learning-disabled-selected distributions.
- Adaptive divergence: divergence is own-history appropriate; label and disabled-history controls remain null.
- Persistence: learned-state effect is expressed with probe learning disabled and frozen-state hashes preserved.
- Exact attribution: all source scores reconstruct from exact 18-genotype frequencies within 1e-12 residual.
- Global integrity: no ranked grader, genotype sampling, best-genotype extraction, mutation, reproduction, inherited learned state, direct Q writes, LLM, Avatar, or canonical mutation.