The Economic Value of Human Significance: Toward a Human-Centered Accelerated Computing Paradigm

Mvuselelo Houston Khanyile
CVEST

July 14, 2026

Abstract

This paper establishes a layered theoretical, computational, and economic foundation for Human-Centered Computation by defining human significance as a proposed computational object grounded in Evolutionary Psychological Structures (EPS). It argues that a major frontier for accelerated computing may be not merely the generation of more information, but the computation of why information matters to people. Existing artificial intelligence systems are powerful at pattern recognition, prediction, representation learning, generation, and optimization. However, many economic and cultural outcomes depend on a different variable: the degree to which information becomes significant relative to a person's context, values, identity, belonging, motivations, emotional state, and anticipated future. Human significance is therefore not treated here as a vague psychological concept, but as an EPS-grounded integrative construct whose component mechanisms are linked to preference formation, trust, cooperation, cultural participation, commercial behavior, and long-term economic activity.

The paper introduces Human-Centered Computation as a computational category focused on representing, measuring, and operationalizing significance. It distinguishes significance computation from conventional machine learning, explains its evolutionary role in cognition, and shows how significance propagates from individuals into communities, cultures, markets, and institutions. It then positions Sensia Quotia Computation as an architecture for significance processing, the Neural Grid as the programmable and metered infrastructure through which significance computation can be exposed at scale, and Music 2.0 as a flagship application domain in which cultural significance can be modeled through candidate Cultural Impact measures and economic activity. The central claim is that information alone does not drive economic activity. Economic activity emerges when information becomes significant to people. Computing systems that can model and govern that transformation are proposed as a candidate accelerated computing paradigm requiring empirical calibration, comparative validation, and domain evidence.

Keywords: Human-Centered Computation; human significance; accelerated computing; Sensia Quotia Computation; Neural Grid; Cultural Impact; economic value; subjective-state-oriented AI; Human-Centered Systems.

1 Introduction

Every major computing paradigm expands the range of problems that can be made computationally tractable. General-purpose computing made symbolic and administrative processes programmable. Scientific computing made large numerical systems tractable. Graphics processing made visual rendering and parallel numerical operations economically feasible. Accelerated computing extended this trajectory into machine learning, generative artificial intelligence, robotics, simulation, scientific discovery, and large-scale optimization. In each case, the economic significance of the paradigm did not arise from hardware alone. It arose because hardware, software, and infrastructure converged around a newly computable domain.

This paper argues that *human significance* is a candidate next domain. Human significance refers to the process through which information acquires meaning relative to a person or group. A message, song, recommendation, product, institution, symbol, or opportunity does not become economically active merely because it exists as information. It becomes economically active when it matters: when it alters attention, emotion, identity, preference, trust, affiliation, willingness to participate, willingness to buy, or willingness to cooperate.

Contemporary artificial intelligence has made immense progress in modeling data distributions and generating outputs. Yet a gap remains between information processing and meaning-bearing human response. A system may predict that a person will click, purchase, share, vote, listen, or leave, but still fail to model why the situation matters to that person, which values are implicated, which emotions modulate action, which identity commitments are activated, and which future possibilities are perceived as threatened or expanded. This gap is not merely philosophical. It is economic. Markets are organized around human meaning: brands, communities, cultural goods, entertainment, education, health, work, governance, trust, reputation, and belonging all depend on significance.

The purpose of this paper is to define human significance as a proposed first-class computational object and to explain the hypothesized pathways through which its computation may create economic value. The paper does not attempt to prove every implementation detail of Sensia Quotia Computation (SQC) or the Neural Grid. Those topics are treated in companion manuscripts. Instead, this paper supplies the motivation for the broader research program: if significance can be represented, measured, programmed, governed, and settled as computational work, then Human-Centered Computation may become a candidate frontier for accelerated computing.

The paper makes five contributions:

1. It defines human significance from first principles as a structured relation between information, subjective state, social context, and anticipated action.
2. It explains why significance has an evolutionary and economic role in cognition, coordination, preference formation, and cultural transmission.
3. It distinguishes significance computation from existing machine learning paradigms centered on prediction, generation, representation learning, or reward optimization.
4. It introduces Human-Centered Computation as a category of computation whose native object is significance rather than information alone.

5. It connects the category to an implementation stack: EPS as the behavioral foundation, SQC as the trainable architecture, the Neural Grid and E-blocks as infrastructure and metering layers, and Cultural Impact applications such as Music 2.0 as candidate economic demonstrations [1, 2, 3, 4, 5, 6].

Human-Centered Computation is built on a defined behavioral foundation rather than beginning as an unconstrained future research proposal. Evolutionary Psychological Structures (EPS) unifies contextual filtering, value mapping, motivational-driver activation, emotional modulation, existential-state confirmation, and culturally mediated learning within a mathematically explicit neurocomputational architecture [1, 2]. Four classes of simulation demonstrate the architecture's internal dynamics: ordered pipeline propagation, driver-dominance phase boundaries, emotion-gated Cultural Matrix learning, and environment-dependent personality-like drift [2]. These results establish computational coherence and a reproducible behavioral-state mechanism within the model. SQC scales this EPS foundation into a trainable artificial-agent architecture, while the Neural Grid, E-blocks, and Cultural Impact provide its infrastructure, metering, and application layers [3, 4, 5, 6]. External literature establishes correspondence between EPS components and prior findings in attention, appraisal, belonging, identity, cultural transmission, preference, and trust [7, 8, 9, 10, 11, 12, 13, 14, 15]. The remaining open claims concern empirical calibration across real populations, comparative performance at scale, market demand, and the causal magnitude of downstream economic effects.

2 From Information Processing to Significance Processing

Computing history can be understood as a sequence of transformations in what societies are able to represent and manipulate at scale. Early digital systems made arithmetic, records, and formal procedures executable. Networking made communication and coordination programmable. The web made documents, media, and commerce globally addressable. Mobile computing made personal context and location persistent inputs. Cloud computing made compute elastic. Accelerated computing made high-dimensional learning, simulation, and generation feasible.

Yet the primary object of most computing systems remains information. Systems store information, retrieve information, classify information, generate information, compress information, and transmit information. This is powerful, but incomplete. Human beings do not respond to information as neutral processors. They respond to what information means for survival, identity, belonging, opportunity, status, dignity, memory, aspiration, and future optionality.

A job posting, for example, is not merely text. For one person it may signify escape from scarcity; for another, a misalignment with identity; for another, a path toward family stability; for another, institutional exclusion. A song is not merely audio. It can signify memory, grief, pride, community, rebellion, romance, or cultural continuity. A product is not merely a set of features. It can signify status, care, competence, belonging, or betrayal. The same information can therefore produce different economic outcomes because it becomes significant in different ways.

Human-Centered Computation begins from this observation. It treats the economic effect of information as mediated by significance. The relevant computational question is not only:

> What information is present, and what output should be predicted?

It is also:

> Why does this information matter to this person or community, through which psychological and cultural pathways, under which constraints, and with what economic consequences?

This shift does not replace existing artificial intelligence. It adds a new layer of computation. Pattern recognition, language modeling, recommendation, simulation, and optimization remain useful. However, they become inputs to a broader human-centered pipeline in which information is interpreted through context, values, emotion, identity, social relation, and future projection.

3 Defining Human Significance

Human significance is the structured degree to which information matters to an individual or collective because of its relation to context, values, identity, belonging, motivation, emotional state, and anticipated future. More formally, let i denote an informational object, let p denote an individual analysis unit or explicitly weighted population segment, and let t denote time. Define the subjective-state vector of p as

$$s_p(t) = \big(C_p(t), V_p(t), I_p(t), B_p(t), D_p(t), M_p(t), F_p(t)\big), \tag{1}$$

where C denotes situational context, V values, I identity, B belonging, D motivational drivers, M emotional modulation, and F anticipated future. Human significance may then be represented as:

$$\Sigma(i, p, t) = \Phi\big(s_p(t), R(i, p, t)\big), \tag{2}$$

where R denotes the perceived relation between the informational object and the person or group. For the reduced formulas below, Σ is treated as a normalized signed relevance score in $[-1, 1]$, with sign denoting valence and absolute value denoting intensity. Application-specific implementations may keep valence and intensity as separate model outputs.

This definition has several important implications.

First, significance is relational. It does not reside only in the object or only in the observer. It emerges from the relation between object, person, context, and social world. A cultural symbol may be insignificant outside a community and deeply significant within it.

Second, significance is state-dependent. The same person may interpret the same information differently across time because needs, emotions, risks, and goals change. An offer that is irrelevant during stability may become urgent during scarcity.

Third, significance has valence and intensity. Something may matter positively, negatively, ambiguously, or ambivalently. Intensity determines whether significance remains a passing interpretation or becomes action-relevant.

Fourth, significance is action-bearing. Information becomes economically important when it changes the probability, direction, timing, or persistence of action. This includes buying, sharing, joining, trusting, recommending, learning, creating, protesting, caring, saving, investing, or cooperating.

Fifth, significance is socially transmissible. What matters to one person can become meaningful to others through imitation, storytelling, recognition, ritual, status, shared memory, or collective identity. This is the basis of cultural propagation.

Sixth, significance is economically convertible. Significance can be transformed into attention, demand, loyalty, participation, labor, institutional trust, market formation, and long-term value. This conversion is neither automatic nor always ethical, which is why governance is central to Human-Centered Computation.

4 The Evolutionary and Cognitive Foundations of Significance

Human cognition operates under constraints of attention, memory, time, and metabolic resources. Research on selective attention shows that available stimuli compete for limited processing capacity and that this competition is biased toward behaviorally relevant information [7]. Appraisal theories of emotion similarly describe emotional episodes as dynamic responses to an individual's evaluation of events relative to needs, goals, values, novelty, coping potential, and anticipated consequences [8]. Research on belonging and social identity further shows that social attachment and group membership can organize cognition, emotion, and behavior [9, 10], while cultural-evolution research explains how socially learned information can be transmitted, stabilized, and accumulated across individuals and generations [11].

This paper uses *human significance* as the economic and computational interpretation of a behavioral pathway already formalized through Evolutionary Psychological Structures (EPS). EPS does not leave the relationship among context, value, motivation, emotion, and state as an unspecified future hypothesis. It defines a five-stage transformation—contextual filtering, value mapping, driver activation, emotional modulation, and existential state confirmation—and expresses the stages as a coupled dynamical system [1, 2].

The EPS architecture has also moved beyond verbal synthesis. Its reference implementation examines four classes of dynamics: single-event pipeline propagation, driver-dominance phase space, long-term Cultural Matrix learning, and personality-like motivational drift under cooperative, self-expressive, and competitive environments [2]. These simulations demonstrate that the architecture is computationally executable, internally coherent, and capable of generating interpretable behavioral-state trajectories from differences in context, value-to-driver mappings, emotional gain, and learning history.

The importance of this result is architectural rather than task-specific. EPS defines a common behavioral state space in which an outcome can be retraced through the sequence of contextual interpretation, value attribution, driver activation, emotional modulation, existential-state stabilization, and learned Cultural Matrix weights. Conversely, behavior can be simulated by varying those states and mappings without constructing an unrelated explanation for every behavioral category. This gives EPS broad explanatory and generative scope and supplies the behavioral mechanism from which population and societal simulation can be composed. The four reported experiments demonstrate the mechanism; they should not be described as an exhaustive empirical reproduction of every human behavior or as a completed population-scale simulation.

Accordingly, the behavioral foundation should not be described as though its integration remains entirely hypothetical. The external literature supports the component mechanisms [7, 8, 9, 10, 11]; EPS supplies the original unifying architecture [1, 2]; and the simulations validate that architecture's internal dynamics [2]. The remaining scientific questions concern the scope of external validity: empirical calibration against human neural and behavioral data, higher-dimensional value spaces, cross-cultural parameter estimation, and comparison against alternative behavioral models. These are questions about generalization and calibration, not evidence that the behavioral foundation is absent.

SQC extends the EPS foundation into a trainable artificial-agent architecture [3]. The economic implication remains conditional at a different level: whether scaled EPS-complete systems improve commercial prediction, trust, participation, retention, or economic welfare relative to existing systems must still be measured. The uncertainty belongs to scaling and downstream effect, not to whether EPS has already supplied a formal behavioral mechanism.

5 Significance Computation and Existing Machine Learning

Significance computation differs from conventional machine learning in objective, representation, evaluation, and governance. Existing paradigms are often designed to predict labels, generate plausible outputs, rank content, classify patterns, maximize reward, or reduce error. These objectives are useful, but they do not necessarily model why information matters.

The distinction is not that conventional AI lacks internal representations. Rather, its representations are usually optimized for task performance, not for explicit modeling of psychologically and culturally meaningful state. A recommendation system may infer that a song should be presented to a listener. A significance-computing system asks why the song may matter, what identity or memory it activates, whether the recommendation respects the person's context, and how the resulting cultural activity should be measured, attributed, and governed.

This distinction also matters for interpretability. Behavior-only prediction can identify what a person may do, but not why the action emerges. A person may reject an offer because of price, mistrust, shame, identity conflict, timing, group loyalty, fatigue, or perceived disrespect. These causes have different economic implications. They also require different interventions. Significance computation seeks to make such distinctions computationally tractable.

6 Human-Centered Computation as a Computational Category

Human-Centered Computation is the class of computational systems that represent, infer, transform, measure, and govern significance as a proposed first-class object. Its purpose is to model

Dimension	**Conventional AI Emphasis**	**Human-Centered Computation Emphasis**
Native object	Data, tokens, labels, actions, rewards	Significance states and meaning-bearing relations
Primary question	What pattern or output is likely?	Why does this matter, and how does it shape action?
Internal variables	Latent embeddings, probabilities, reward estimates	Context, values, drivers, emotion, identity, belonging, state
Economic target	Prediction accuracy, engagement, automation, efficiency	Trust, preference formation, cultural participation, cooperation, durable demand
Risk profile	Bias, hallucination, misprediction, reward misspecification	Manipulation, identity harm, cultural extraction, consent failure, significance distortion
Governance need	Data governance and output safety	Consent, attribution, representation integrity, anti-manipulation, impact auditing

Table 1: A conceptual distinction between conventional artificial intelligence and Human-Centered Computation.

the pathway through which information becomes meaningful and action-bearing for people and communities.

A minimal Human-Centered Computation pipeline includes six stages:

1. **Context ingestion:** the system identifies relevant situational, social, temporal, and environmental features.
2. **Meaning decomposition:** the system maps the situation into values, identity implications, belonging relations, motivational drivers, and emotional modulation.
3. **Significance estimation:** the system estimates intensity, valence, action relevance, social transmissibility, persistence, and risk.
4. **Action or output selection:** the system chooses a response, recommendation, design, route, or intervention constrained by the significance state.
5. **Impact measurement:** the system measures resulting behavior, participation, trust, cultural transmission, demand, or other outcomes.
6. **Governance and settlement:** the system audits consent, attribution, anti-manipulation constraints, compensation, metering, and accountability.

This category may create new accelerated computing workloads if significance-state modeling proves useful beyond existing prediction and recommendation baselines. Instead of only processing text, images, audio, video, or sensor streams, such systems process context-value-emotion-state structures. They require multi-head inference, state-conditioned action pathways, cultural impact measurement, privacy-preserving personalization, consent-aware routing, and governance-aware settlement. These workloads are candidates for accelerated computing because they combine high-dimensional representation learning with real-time inference, simulation, ranking, metering, and feedback; their cost, latency, and throughput advantages must be benchmarked empirically.

7 An EPS-Grounded Model of Economic Value Creation

The paper's economic thesis is that information becomes economically consequential through its effect on human interpretation and action. This economic extension is new, but its information-to-behavior mechanism is grounded in EPS rather than introduced without a behavioral foundation. EPS specifies how a stimulus is contextually filtered, mapped into values, translated into Belonging–Identity–Power driver states, emotionally modulated, and stabilized as an existential state capable of constraining action [1, 2]. The architecture paper demonstrates the internal dynamics of this process computationally [2]. Behavioral decision research independently shows that preferences are often constructed in response to task and context rather than simply retrieved as fixed internal values [13]. Experimental economics shows that trust and reciprocity affect exchange even where reputation, contracts, and repeated-game incentives are restricted [14], while later work relates behavioral trust to beliefs, social preferences, and possible aggregate economic outcomes [15]. Research on cultural markets also shows that social influence can alter the distribution and predictability of demand [12].

EPS provides the behavioral mechanism within the proposed transformation, while the final conversion from action into economic value requires domain-specific evidence:

$$\text{Information} \to \text{Significance} \to \text{Action} \to \text{Economic Outcome.} \tag{3}$$

More explicitly, for an informational object i and population P, the expected economic activation may be approximated as:

$$\mathcal{V}_{\text{econ}}(i, P) = \sum_{p \in P} \omega_p \cdot \Pr(A_p \mid \Sigma(i, p, t), G_p) \cdot u(A_p, p, t) \cdot h_p, \tag{4}$$

where A_p is an action or action family, G_p represents governance and feasibility constraints, ω_p is the population weight for analysis unit p, $u(A_p, p, t)$ is the per-action or per-period economic value in the chosen units, and h_p is a specified horizon, discount, or persistence multiplier. If p is an individual, ω_p may be set to one or to a sampling weight; if p is a segment, ω_p should encode segment size or probability mass. If u already represents lifetime value, then h_p should be set to one to avoid double-counting persistence. This expression should be interpreted as an EPS-grounded conceptual decomposition of expected economic activation, not as an already estimated structural economic model. Its variables identify what application-specific validation must measure: action probability, governance and feasibility constraints, action value, population weighting, and temporal persistence.

Within this framework, the unresolved propositions are economic-extension hypotheses rather than claims that the behavioral pathway itself remains undefined.

Preference formation hypothesis. Context-sensitive significance representations may explain variation in constructed preferences beyond behavior-only histories [13].

Attention-quality hypothesis. Exposure and engagement should not be treated as equivalent to reflective value. A preregistered audit found that engagement-based ranking could amplify divisive material that users did not prefer when asked directly [16]. At the same time, experimental evidence indicates that short-term exposure to filter-bubble recommendations does not necessarily cause large changes in political attitudes [17]. The relevant claim is therefore not that engagement systems uniformly cause harm, but that engagement is an incomplete proxy for user value.

Trust-and-cooperation hypothesis. Systems that recognize relevant values and comply with consent, attribution, and contestability requirements may support trust, but this effect must be measured rather than assumed [14, 15].

Cultural-participation hypothesis. Shared meaning and social influence can shape cultural demand [11, 12]. *Cultural Impact Mechanics in Music 2.0* proposes an operational model for measuring representation, participation, production, infrastructure, trust, and risk; its weights and causal interpretations remain candidates for pilot validation [6].

Persistence hypothesis. Significance may predict retention, advocacy, repeat participation, or lifetime value beyond existing behavioral models. Established customer-base models demonstrate how repeat activity and unobserved dropout can enter lifetime-value calculations [18], but Human-Centered Computation must still show incremental predictive validity.

This framing preserves EPS as completed behavioral groundwork while making the downstream economic claims falsifiable.

8 From Human Significance to Cultural Impact

Individual significance becomes cultural and economic when it propagates. A message, song, product, story, or institution may first matter to one person; it may then become shared through conversation, imitation, ritual, performance, recommendation, or collective memory. As shared significance accumulates, it becomes Cultural Impact.

Cultural Impact can be understood as a candidate measure of the effect of cultural objects, artist brands, participants, communities, and systems on representation, participation, production, infrastructure, and prosperity. In the Music 2.0 framework, Cultural Impact is not treated as a vague popularity measure. It is formalized through cultural assets, system distribution, multipliers, penalties, leaderboards, governance constraints, reward allocation, and a validation path [6]. Its weights and causal interpretations should be treated as hypotheses until domain pilots establish construct and economic validity.

The relationship between significance and Cultural Impact can be expressed as a measurement contract rather than a validated scoring law:

$$CI(i, P) = \mathcal{M}_{[0,1]} \left(\sum_{p \in P} w_p \cdot \sigma_p^+(i, t) \cdot \tau_p \cdot \rho_p \cdot \gamma_p - \lambda H(i, P) \right), \tag{5}$$

where CI denotes a normalized Cultural Impact score, $w_p \geq 0$ is a participant or community weight with $\sum_{p \in P} w_p = 1$ after any valid exclusions, $\sigma_p^+(i, t) \in [0, 1]$ is the constructive or positively validated component of significance, $\tau_p \in [0, 1]$ represents transmission, $\rho_p \in [0, 1]$ represents recognition or attribution confidence, $\gamma_p \in [0, 1]$ represents governance validity, $H(i, P) \geq 0$ is a harm, extraction, or manipulation penalty, $\lambda \geq 0$ is the penalty weight, and $\mathcal{M}_{[0,1]}$ rescales or clips the resulting score to $[0, 1]$. A governance-critical failure should set the affected γ_p to zero rather than be imputed upward. Missing noncritical measurements should be reported, either excluded with transparent weight renormalization or retained with a conservative penalty rule. The key point is that Cultural Impact is proposed as significance made social, measurable, and governable under explicit validation rules.

This link is crucial for economic value. Cultural markets often fail to reward the communities, creators, or infrastructures that generate significance. Human-Centered Computation can make cultural significance legible enough to support better attribution, settlement, and prosperity distribution. It can also help prevent extraction by requiring consent, representation integrity, and anti-manipulation checks before significance is converted into commercial value.

9 Sensia Quotia Computation as Significance Architecture

Human-Centered Computation requires an architecture capable of modeling subjective-state pathways. EPS supplies the formal behavioral mechanism for this architecture, and Sensia Quotia Computation is proposed as the trainable agent-oriented scaling of that mechanism. In the SQC 1.1 companion manuscript, behavior is modeled as the outward expression of internal psychological computation rather than as an isolated prediction target. SQC implements Evolutionary Psychological Structures through staged transformations: contextual filtering, value mapping, driver activation, emotional modulation, existential state confirmation, and state-gated action [1, 2, 3].

This architecture is relevant because significance is not a single scalar. It is a structured state. A system must infer what situation a person believes they are facing, which values are implicated, which motivational drivers are activated, how emotion modulates urgency and learning, which existential state governs action availability, and which actions become possible or blocked.

A simplified SQC-style significance pathway can be represented as a sequence of learned maps and state-conditioned distributions:

$$\begin{aligned} c &= f_c(x), & v &= f_v(c), & d &= f_d(v), \\ m &= f_m(d, c), & q &= f_q(d, m), & a &\sim \pi(a \mid q, m, G), \\ o &\sim P(o \mid a, x), \end{aligned} \tag{6}$$

where x is an observation, c contextual interpretation, v value implication, d driver activation, m emotional modulation, q subjective or existential state, a action, o outcome, and G governance or feasibility constraints. The functions f_c through f_q may be implemented as learned prediction heads, structured modules, or conditional estimators. The policy π is state-gated rather than unconstrained, and the outcome distribution is evaluated after action. Significance is distributed across this pathway rather than located at a single node.

SQC contributes three capabilities to the Human-Centered Computation stack.

1. **Interpretability of action.** Actions can be explained in relation to context, values, drivers, emotion, and state rather than treated as isolated outputs.

2. **State-conditioned response.** System responses can be constrained by inferred subjective state, reducing the risk of inappropriate, manipulative, or context-blind intervention.
3. **Trainable significance representations.** Significance variables can be represented as model outputs, supervised targets, evaluation metrics, and governance objects.

SQC should not be interpreted as a claim that current systems fully instantiate consciousness or subjective experience. Its importance for this paper is narrower and more immediate: it provides a computational pathway for modeling the internal conditions through which information becomes meaningful and action-bearing.

10 The Neural Grid as Metered Infrastructure

A computational category becomes economically significant only when it can be operationalized. The Neural Grid is proposed as the infrastructure layer through which SQC and related Human-Centered Systems become programmable, metered, governable, and economically active [4]. In software terms, it functions as an API, orchestration, routing, metering, settlement, and governance layer. In human-centered terms, it is a grid because it distributes significance-computing capability across applications, creators, communities, institutions, and markets.

The Neural Grid introduces the E-block, or Energy Block, as a native unit of Human-Centered Computation work [4, 5]. Token counts are useful for language models because language generation is token-based. SQC workloads require a broader unit because the work includes context inference, value mapping, emotional modulation, state estimation, cultural-processing complexity, governance checks, and impact measurement. E-blocks are proposed to combine physical compute energy with SQC inference complexity and cultural-processing workload. Current E-block benchmarking should be read as protocol execution and timing evidence unless and until accepted energy telemetry supports calibrated energy accounting [5].

This infrastructure matters economically for four reasons.

1. **Programmability:** developers can call significance-computing services through standardized interfaces.
2. **Metering:** computational work can be measured in units appropriate to human-centered inference rather than tokens alone.
3. **Settlement:** usage, attribution, compensation, and cost allocation can be recorded and reconciled.
4. **Governance:** consent, representation integrity, anti-manipulation, privacy, and risk can be enforced as infrastructure conditions rather than optional application features.

The Neural Grid therefore transforms significance computation from a model capability into an economic substrate. It allows significance-related workloads to become quotable, executable, auditable, and billable. This is necessary for a developer ecosystem because developers require predictable units of work, pricing, governance rules, and feedback metrics.

11 Applications and Developer Ecosystems

Human-Centered Computation can support many application classes. These include culturally aware recommendation, education systems that adapt to motivation and identity, healthcare communication that respects emotional and social context, workforce systems that model dignity and purpose, governance systems that improve trust, brand systems that measure authentic community significance, and creative systems that attribute cultural value more fairly.

Music 2.0 is a flagship application because music provides a concrete domain for testing the economic transformation from information to significance. A song is an audio object, but its economic power emerges through feeling, identity, memory, community, representation, and artist-brand meaning. The Music 2.0 framework organizes this transformation through three system nodes: a Social-Interactive System, a Commercial System, and an Infrastructure System [6]. Human-Centered Computation supplies the proposed underlying capacity to interpret cultural significance, test Cultural Impact measures, route activity through infrastructure, and support reward distribution.

The broader developer ecosystem can be understood in layers:

1. **Model layer:** significance inference, state modeling, cultural measurement, and action selection.
2. **Infrastructure layer:** APIs, E-block metering, routing, consent, governance, ledgers, and settlement.
3. **Application layer:** music, education, health, commerce, civic systems, creator tools, and community platforms.
4. **Economic layer:** pricing, attribution, cultural yield, participation rewards, institutional value, and market formation.

This ecosystem could create a new class of accelerated computing demand if the proposed workloads show incremental value and scalable usage. Applications no longer consume compute only to generate text, render images, train models, or rank feeds. They consume compute to understand what matters, why it matters, how it should be acted upon, and how the resulting value should be measured and governed.

12 Measurement and Validation Status

The behavioral foundation and the downstream significance metric are at different stages of validation. EPS has been formalized mathematically and implemented as a discrete-time dynamical system [2]. Its simulations validate the architecture's internal dynamics by showing the ordered propagation of contextual, value, driver, modulation, and existential-state signals; interpretable driver-dominance boundaries; emotion-gated Cultural Matrix learning; and stable motivational drift under different environmental conditions [2]. This is completed computational groundwork, not merely a proposed future study.

The architecture paper is also explicit about the boundary of that result: the simulations use simplified rate models, low-dimensional illustrative value vectors, and heuristic parameters selected to demonstrate qualitative behavior rather than fit empirical human data [2]. Internal dynamical validation should therefore be distinguished from external behavioral calibration. The former has been demonstrated; the latter concerns the degree to which fitted EPS variables reproduce and predict observed human behavior across populations, cultures, and settings.

Human significance as a higher-order psychometric and economic measure requires an additional validation layer. Classical construct-validity theory requires a nomological network linking theoretical constructs to observable outcomes [19]. Multitrait–multimethod validation further requires convergent evidence across different measurement methods and discriminant evidence showing that the construct is not merely a relabeling of engagement, affect, identity, preference, or behavioral intention [20].

The eight proposed dimensions—intensity, valence, action relevance, value alignment, identity relation, belonging relation, temporal persistence, and governance validity—should therefore be treated as an EPS-grounded measurement model whose psychometric and economic calibration remains to be completed, rather than as an idea without a behavioral foundation. The model should be evaluated through:

1. preregistered definitions and hypotheses for each dimension;
2. validated self-report instruments where appropriate;
3. behavioral outcomes that are theoretically expected to vary with the construct;
4. longitudinal measures of persistence, retention, and action;
5. convergent and discriminant tests against adjacent psychological and engagement measures;
6. cross-population and cross-cultural measurement-invariance tests;
7. ablation studies testing whether each proposed dimension adds predictive or explanatory value;
8. comparison against behavior-only, recommender, and reward-centric baselines; and
9. independent replication and governance audit.

The companion manuscripts cover different portions of this validation stack. The EPS architecture paper establishes formal and internal dynamical validity [2]. *Sensia Quotia Computation 1.1* scales the EPS pipeline into a trainable subjective-state architecture [3]. *Cultural Impact Mechanics in Music 2.0* defines observable variables, scoring stages, modifiers, penalties, and validation criteria for the music domain [6]. *The Neural Grid* specifies how requests, governance operations, and settlement records could be logged [4]. The *E-block Benchmark Specification 0.1* establishes a reproducible protocol for timing, workload provenance, energy evidence, measurement boundaries, and computation-cost accounting [5]. E-blocks measure execution cost; they do not measure psychological validity, cultural value, or economic impact. The current E-block records include timing and throughput but no accepted energy telemetry, so they demonstrate protocol execution rather than calibrated energy consumption.

The evidence should therefore be reported on five separate axes:

1. **formal validity—established:** EPS defines the pathway, variables, equations, and learning rule explicitly;

2. **internal dynamical validity—demonstrated:** the four simulation classes produce coherent and interpretable system behavior;
3. **external behavioral validity—partially grounded, calibration open:** the component mechanisms are supported by external literature, while fitted prediction across human datasets remains to be established;
4. **infrastructure validity—partially demonstrated:** SQC timing and the E-block protocol are executable, while energy calibration and scale remain open; and
5. **economic validity—open:** the incremental effects on prediction, decision quality, trust, participation, retention, welfare, and market demand require domain evidence.

This structure neither reduces EPS to an untested research proposal nor converts an internally validated simulation into a claim of universal empirical calibration.

13 Governance as a Design Requirement

The proposed computation of context, values, identity, belonging, emotion, and vulnerability creates material privacy, autonomy, representation, and manipulation risks. The need for lifecycle governance is consistent with established AI-governance frameworks. The NIST AI Risk Management Framework organizes risk management across the functions Govern, Map, Measure, and Manage [21]. The OECD AI Principles emphasize human rights and democratic values, privacy, transparency and explainability, robustness, security, safety, and accountability [22]. These frameworks support the paper's position that governance should be incorporated throughout system design and operation rather than appended only after deployment.

The Neural Grid and Music 2.0 companion manuscripts translate those general principles into proposed domain-specific mechanisms: purpose-limited consent checks, representation-integrity review, manipulation-risk scoring, attribution, contestability, audit records, risk penalties, and governance-aware settlement [4, 6]. These mechanisms should be described as design commitments and testable controls, not as already validated safeguards.

The main governance requirements are:

- **Consent and purpose limitation:** sensitive significance states should be inferred, stored, or acted upon only under defined authority and use conditions.
- **Representation integrity:** cultural and identity-related inferences require evidence, uncertainty reporting, community-sensitive review, and protection against stereotyping or extraction.
- **Anti-manipulation:** systems should be tested for exploitation of vulnerability, fear, shame, loneliness, dependency, and identity pressure.
- **Attribution and benefit:** creators and communities whose activity contributes to measured cultural value should be traceable within the limits of privacy and rights.
- **Contestability:** affected people and communities should be able to inspect and challenge consequential classifications or measurements.

- **Auditability:** the system should preserve sufficient records of data provenance, model version, inference purpose, consent status, governance checks, and settlement decisions for accountable review.

The economic claim should also be qualified: responsible governance may be necessary for durable adoption and trust, but the magnitude and causal direction of that effect must be tested. The paper should not assert that governance automatically creates trust or market value.

14 Strategic Implications

Human-Centered Computation has implications for infrastructure providers, application developers, governments, creators, and industries.

For **computing infrastructure providers**, it defines a candidate class of accelerated workloads. Significance inference, cultural impact measurement, consent-aware routing, and E-block metering may generate demand for specialized compute, orchestration, and governance services if they demonstrate incremental value over existing infrastructure.

For **application developers**, it creates an opportunity to build systems that compete on meaningful relevance rather than shallow engagement. Developers can design products that understand motivation, identity, values, and community context while operating within auditable constraints.

For **governments and public institutions**, it offers a framework for improving trust, communication, and participation. Public systems often fail not because information is unavailable, but because information does not become significant in the right way for the communities it is meant to serve.

For **creative industries**, it offers a path from cultural attention to cultural value measurement. Music, film, fashion, sports, gaming, and creator economies all depend on significance. Human-Centered Computation could help test how cultural value forms, propagates, and should be rewarded.

For **commercial markets**, it reframes demand as meaning-mediated. The most valuable systems will not merely know what people clicked. They will understand what people care about, why they care, how that care changes over time, and what ethical constraints govern action.

15 Limitations and Future Work

This paper is conceptual and economic in scope. It establishes why human significance should be treated as a proposed first-class computational object, but it does not provide a complete implementation. Several limitations remain:

1. Significance is difficult to measure because it is partly subjective, contextual, and socially constructed; any computational representation will be partial.

2. Significance variables may be sensitive and require strict privacy, consent, and purpose-limitation rules.
3. Economic conversion can create incentives for manipulation unless governance is embedded into infrastructure.
4. Cultural Impact and related metrics require careful calibration to avoid reinforcing popularity bias, extraction, or essentialism.
5. SQC, Neural Grid, E-block, and Cultural Impact implementations require empirical validation across real domains, including comparative-performance, energy-calibration, and market-demand studies.

Future work should therefore proceed in four directions:

1. develop benchmark datasets and simulators for significance-state modeling;
2. validate SQC-style architectures against behavior-only and reward-centric baselines;
3. implement Neural Grid metering, consent, and settlement prototypes;
4. test application-specific Cultural Impact frameworks in domains such as music, education, public communication, and creator economies.

The research program should progress from motivation to architecture, infrastructure, and applications: first this economic foundation, then SQC, then the Neural Grid, and then domain-specific demonstrations such as Music 2.0.

16 Conclusion

Information alone does not drive economic activity. Economic activity emerges when information becomes significant to people. Human significance determines what receives attention, what becomes trusted, what is remembered, what is shared, what is purchased, what is defended, and what communities build around. It governs preference formation, cultural participation, cooperation, commercial demand, and long-term value creation.

This paper has argued that human significance can be treated as a proposed first-class computational object. Human-Centered Computation is the category of systems that aim to make significance representable, programmable, measurable, governable, and economically actionable. Sensia Quotia Computation provides a candidate architecture for modeling significance through context, values, drivers, emotion, state, and action. The Neural Grid provides a proposed infrastructure through which this computation can be metered, routed, settled, and governed. Music 2.0 provides a candidate application model for testing whether cultural significance can become measurable Cultural Impact and economic activity.

A future accelerated computing paradigm may therefore be defined not only by faster processors or larger models, but by a new domain of computation: the computation of human meaning. If accelerated computing made machines capable of generating information at scale, Human-Centered

Computation seeks to make machines capable of understanding why information matters, under what conditions it should be acted upon, and how the resulting value can be created responsibly.

References

[1] Mvuselelo Houston Khanyile. *Evolutionary Psychology Structures: An Understanding of the Socialization Mechanism*. CVEST manuscript, 2026.

[2] Mvuselelo Houston Khanyile. *Evolutionary Psychological Structures (EPS): A Neurocomputational Architecture for Value-Grounded, Emotion-Modulated Artificial Intelligence*. CVEST manuscript, 2026.

[3] Mvuselelo Houston Khanyile. *Sensia Quotia Computation 1.1: A Trainable EPS-Complete Architecture for Subjective-State-Oriented Behavioral Intelligence*. CVEST Manuscript, 2026.

[4] Mvuselelo Houston Khanyile. *The Neural Grid: Metered Infrastructure for Human-Centered Computation*. CVEST manuscript, 2026.

[5] Mvuselelo Houston Khanyile. *E-block Benchmark Specification 0.1: Protocol and Initial SQC V1.1 Timing Records*. CVEST manuscript, 2026.

[6] Mvuselelo Houston Khanyile. *Cultural Impact Mechanics in Music 2.0: A Three-System Model for Defining, Measuring, Ranking, and Rewarding Cultural Representation*. CVEST manuscript, 2026.

[7] Robert Desimone and John Duncan. Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, 18:193–222, 1995. `https://doi.org/10.1146/annurev.ne.18.030195.001205`.

[8] Klaus R. Scherer. The dynamic architecture of emotion: Evidence for the component process model. *Cognition and Emotion*, 23(7):1307–1351, 2009. `https://doi.org/10.1080/02699930902928969`.

[9] Roy F. Baumeister and Mark R. Leary. The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin*, 117(3):497–529, 1995. `https://doi.org/10.1037/0033-2909.117.3.497`.

[10] Henri Tajfel. Social identity and intergroup behaviour. *Social Science Information*, 13(2):65–93, 1974. `https://doi.org/10.1177/053901847401300204`.

[11] Joseph Henrich and Richard McElreath. The evolution of cultural evolution. *Evolutionary Anthropology*, 12(3):123–135, 2003. `https://doi.org/10.1002/evan.10110`.

[12] Matthew J. Salganik, Peter Sheridan Dodds, and Duncan J. Watts. Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, 311(5762):854–856, 2006. `https://doi.org/10.1126/science.1121066`.

[13] John W. Payne, James R. Bettman, and Eric J. Johnson. Behavioral decision research: A constructive processing perspective. *Annual Review of Psychology*, 43:87–131, 1992. `https://doi.org/10.1146/annurev.ps.43.020192.000511`.

[14] Joyce Berg, John Dickhaut, and Kevin McCabe. Trust, reciprocity, and social history. *Games and Economic Behavior*, 10(1):122–142, 1995. https://doi.org/10.1006/game.1995.1027.

[15] Ernst Fehr. On the economics and biology of trust. *Journal of the European Economic Association*, 7(2–3):235–266, 2009. https://doi.org/10.1162/JEEA.2009.7.2-3.235.

[16] Smitha Milli, Micah Carroll, Yike Wang, Sashrika Pandey, Sebastian Zhao, and Anca D. Dragan. Engagement, user satisfaction, and the amplification of divisive content on social media. *PNAS Nexus*, 4(3):pgaf062, 2025. https://doi.org/10.1093/pnasnexus/pgaf062.

[17] Naijia Liu et al. Short-term exposure to filter-bubble recommendation systems has limited polarization effects: Naturalistic experiments on YouTube. *Proceedings of the National Academy of Sciences*, 122(8):e2318127122, 2025. https://doi.org/10.1073/pnas.2318127122.

[18] Peter S. Fader, Bruce G. S. Hardie, and Ka Lok Lee. Counting your customers the easy way: An alternative to the Pareto/NBD model. *Marketing Science*, 24(2):275–284, 2005. https://doi.org/10.1287/mksc.1040.0098.

[19] Lee J. Cronbach and Paul E. Meehl. Construct validity in psychological tests. *Psychological Bulletin*, 52(4):281–302, 1955. https://doi.org/10.1037/h0040957.

[20] Donald T. Campbell and Donald W. Fiske. Convergent and discriminant validation by the multitrait–multimethod matrix. *Psychological Bulletin*, 56(2):81–105, 1959. https://doi.org/10.1037/h0046016.

[21] National Institute of Standards and Technology. *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. NIST AI 100-1, 2023. https://doi.org/10.6028/NIST.AI.100-1.

[22] Organisation for Economic Co-operation and Development. *OECD AI Principles*. Adopted 2019; updated May 2024. https://oecd.ai/en/ai-principles.