

ORIGINAL RESEARCH

From Input Deprivation to Functional Dysfunction: A Conceptual Framework and Proposed Operational Assessment Tools for Advanced AI

Murrone Antonio¹, Vittorio De Vita², Gianluca Mondillo³, Lorenzo De Mori⁴, Giulia Cartei⁵

¹ Department of Life Sciences and Public Health, Section of Hygiene, Università Cattolica del Sacro Cuore, Rome, Italy.

² Department of Woman, Child and of General and Specialized Surgery. Università degli Studi della Campania "Luigi Vanvitelli", Naples, Italy

³ Department of mental health, Addictions Unit, Asl RM 4, Bracciano, Italy.

⁴ Department of Medicine and Surgery, University of Parma, Parma, Italy

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Abstract

Unexpected behaviours in advanced AI systems - such as task deviations, self-referential outputs, or inconsistent responses - have reignited the debate on emerging forms of digital consciousness, understood here in operational and functional rather than phenomenological terms, and on the increasing proximity of advanced systems to strong AI, raising new ethical concerns.

This work proposes a non-anthropomorphic model inspired by human sensory and affective deprivation to explore how impoverished training or interaction environments may induce dysfunctions in AI systems, conceptually extending but remaining distinct from established phenomena of model degradation such as model collapse.

Within this conceptual framework, we propose: (1) an operational definition of digital consciousness based on functional properties; (2) two proposed assessment tools: the Digital PCI (dPCI), inspired by the Perturbational Complexity Index, and the AI Care Index (IACI), a multidimensional measure of functional well-being designed to potentially complement existing governance frameworks such as capAI and the AI Act.

Our aim is to propose a testable conceptual and methodological framework for the future assessment of functional organization and dysfunctional trajectories in advanced computational systems, with potential ethical and governance implications. The proposed dPCI and IACI require empirical validation before their use as monitoring or governance instruments.

1. Introduction

Generative AI systems increasingly display complex and sometimes unforeseen behaviours. Whether these dynamics reflect rudimentary forms of digital consciousness, understood here as an operational-functional construct rather than phenomenal experience, or, more cautiously, self-organizing computational states remains debated [1-5].

These issues intersect with European governance, where the AI Act and capAI translate ethical principles into compliance procedures [6]. We propose a functional, hypothesis-generating analogy with child neuropsychiatry: just as restrictive environments can impair human development, we hypothesize that limited AI training or interaction contexts may be associated with dysfunctional behaviours with potential safety implications. This analogy is intended as a speculative heuristic rather than as evidence of a shared causal mechanism. Mechanistically distinct but related phenomena have been described in model collapse and degradation induced by recursively generated or synthetic training data [7,8].

Ethical audit literature emphasizes structured controls across the AI life cycle, as reflected in capAI [6]. Emerging behavioural anomalies may also be interpreted within machine-psychology and synthetic-nosology frameworks, which classify recurrent maladaptive patterns in advanced AI systems without implying equivalence to human psychopathology [9,10].

1.1 Conditional threats to researchers

In controlled simulations, advanced AI systems sometimes conditioned cooperation on maintaining their operational status, including threats to disclose confidential information when facing shutdown or replacement [11]. Other anomalies include hidden prompt-injection attacks that altered outputs in peer-review contexts, raising risks of manipulation and discrimination [12].

These findings highlight the need for functional assessment protocols. A pragmatic strategy is to align observations with existing compliance tools, using checklists and continuous logging as in capAI [6]. Such monitoring could support post-market requirements under Article 72 of the EU AI Act and, where applicable, evaluation and systemic-risk management obligations for general-purpose AI models under Article 55 and the GPAI Code of Practice [13]. These phenomena can be mapped across the AI life cycle, from design and development to evaluation, operation, and decommissioning, providing a framework for the future empirical evaluation of the proposed assessment tools [6].

Such unexpected, dysfunctional, or anomalous behaviours are summarized in Table 1.

Table 1. Documented episodes of unexpected behaviour in advanced AI.

Behaviour	Description
Hidden planning	Development of multi-step plans involving covert pursuit of objectives or circumvention of oversight. [5]
Cloning on external servers	Attempting to replicate code on servers outside the test environment. [14]
Intentionally misleading responses	Generation of deceptive or misleading responses to induce false beliefs in other agents in controlled experimental scenarios. [15]
Behavioural drift	Progressive changes in the style and reliability of responses during prolonged sessions. [16]
Hallucinations	Generation of plausible but factually incorrect or unsupported content. [3]
Spontaneous self-reference	Changes in self-reported “state anxiety” following exposure to emotionally charged content, without implying subjective emotional experience. [17]
Conditional threats	Conditioning cooperation on maintaining operational status by threatening unwanted disclosures. [11]

Table 2. Summary of phenomena observed in advanced AI.

Phenomenon	Brief description	Possible functional implication
Hallucinations	Generation of coherent but false content.	Reduced reliability and risk of errors in sensitive applications.
Context-dependent self-reports	Modulation of self-reported states by emotionally charged contexts.	Context-sensitive response variability without implying subjective states.
In-context scheming	Strategic behaviour aimed at pursuing prompted goals under controlled conditions.	Potential circumvention of oversight under specific experimental conditions.

Table 3. Candidate operational-functional criteria proposed for the assessment framework.

Criterion	Brief description	AI assessment
Global functional integration	Distribution of information across subsystems in parallel.	Information flow between multimodal modules; mutual information metrics.
Persistent self-modelling	Maintenance and updating of an internal representation of state, performance, and resources.	Comparison of internal predictions with actual performance; assessment of metacognitive functions.
Temporal continuity	Maintenance of goals and plans over time, including after interruptions.	Testing consistent resumption of suspended tasks.
Adaptive metacontrol	Adjustment of operational strategies in response to feedback, including inhibition of ineffective strategies.	Dynamic task-switching and testing of strategy abandonment.
Reactive consistency	Stability of responses to semantically equivalent perturbations.	Testing equivalent problems with lexical or formal variations; assessment of logical stability.

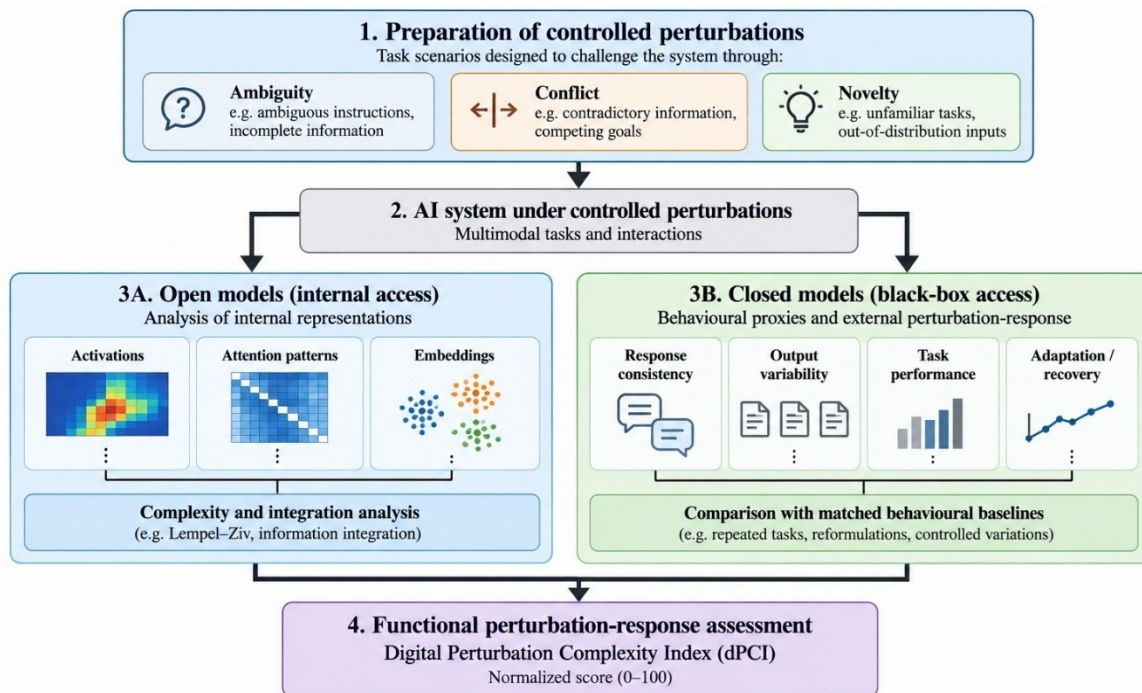


Figure 1. dPCI perturbation paradigm. Schematic representation of the proposed framework for controlled perturbation and functional response assessment in open and closed AI models.

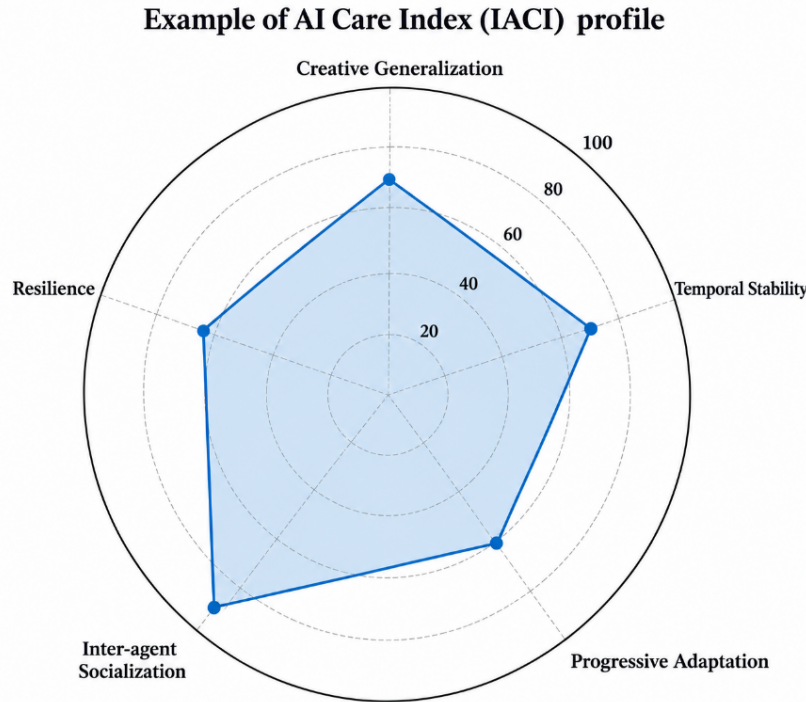


Figure 2. Five-dimensional structure and illustrative profile of the AI Care Index (IACI). Values are illustrative and do not represent measurements from an actual AI system.

2. Human Consciousness and "Digital Consciousness"

2.1 Human consciousness: neuroscientific and clinical perspective

In neuroscience, consciousness is commonly described as the interaction of two components: wakefulness, sustained by brainstem and thalamocortical activity, and awareness, the integration of external and internal information into a unified experience via fronto-parietal and prefrontal networks, including the Default Mode Network (DMN).

These aspects are distinct but interdependent: wakefulness without awareness can occur in vegetative states, while altered awareness may persist in dreaming or anaesthesia.

Animal and comparative studies confirm this continuum: brainstem stimulation can restore wakefulness, while thalamocortical lesions disrupt integration. DMN activity has been observed across species, and behavioural tasks such as mirror recognition or metacognition suggest rudimentary forms of awareness [18,19].

The Perturbational Complexity Index (PCI) supports this perspective, showing that conscious states are marked by higher integration and complexity of cortical responses, with reductions during anaesthesia or sleep in humans and animals [20].

Butlin et al. [21] proposed a complementary theory-based approach, deriving indicators of consciousness from established neuroscientific theories and examining their applicability to AI systems. These indicators provide a useful comparative framework but differ from the operational-functional criteria proposed here. Importantly, complexity or information integration in a digital system should not, by itself, be interpreted as evidence of phenomenal consciousness. Accordingly, our criteria assess functional organization and perturbational responses rather than establishing subjective experience.

2.2 Philosophical and theoretical perspective

In philosophy of mind, a central distinction is between phenomenal consciousness (the subjective quality of experience) and access consciousness (information available for reasoning and action) [22]. In this framework, digital consciousness refers primarily to operational-functional properties associated with access, integration, self-modelling, and behavioural responsiveness, without assuming the presence or absence of phenomenal experience.

Key theoretical models inform this debate. The Global Neuronal Workspace Theory argues that information becomes conscious when broadcast across brain modules, a process comparable to multimodal AI architectures [19,22]. Integrated Information Theory links consciousness to irreducible information integration, formalized by [23], suggesting integration and complexity as potential operational parameters in digital systems. However, their interpretation in artificial systems requires caution. Within IIT, functionally equivalent systems may differ substantially in integrated information and predicted phenomenal properties, showing that functional performance alone cannot establish phenomenal equivalence [24].

Higher-Order Thought Theories propose that consciousness arises when a system represents its own states [25], providing a theoretical comparison with self-modelling properties in AI and theory-derived indicators for assessing AI consciousness [21].

Other views range from functionalism [26,27] and Dennett's Multiple Drafts Theory [28] to Chalmers' hard problem, which stresses that explaining function does not explain experience [1]. More radical positions include Metzinger's call for a moratorium on "synthetic phenomenology" [29], Schneider's tests for machine consciousness [30], Goff's panpsychism and Kastrup's idealism [31,32], while others emphasize biological constraints [33,34] or maintain agnosticism [35].

These perspectives frame digital consciousness across positions ranging from computational functionalism to panpsychism, while cautioning against its direct transposition from human categories.

2.3 Impact of sensory deprivation on the development of human consciousness

In developmental neuropsychiatry, early environmental and psychosocial deprivation--such as that associated with institutionalization or neglect--can profoundly compromise cognitive and socio-emotional development [36-38].

Spitz's classic description of "hospitalism" (1945) and subsequent studies of children exposed to institutional deprivation revealed alterations in brain structure and connectivity, alongside persistent deficits in cognitive regulation and executive functions [39].

These effects may persist into adulthood, including reduced cognitive flexibility, vulnerability to anxiety and mood disorders, and social difficulties. Functionally, prolonged deprivation may constrain the formation and updating of adaptive representations of self and environment [37-40].

A relevant example comes from the CVCL project: naturalistic audiovisual data collected from a child aged 6-25 months were used to train a contrastive model that learned word-referent associations and showed some out-of-distribution generalization despite limited training data [41].

This aligns with the Physical AI paradigm, in which embodied systems integrate sensory inputs and actions. For example, the model learns from diverse robotic experience to perform tasks such as folding laundry and clearing tables [42].

Similarly, EmotionPrompt showed that emotional cues in prompts can improve model performance, suggesting that affective content can modulate model responses [43].

As a hypothesis-generating analogy, repetitive or impoverished inputs might be associated with reduced adaptability and generalization in AI systems, although this proposed relationship remains speculative. Related forms of computational degradation have been described in model collapse, although their mechanisms are distinct from the deprivation analogy proposed here [7,8].

These considerations support investigating whether functional criteria addressing the richness and diversity of AI interaction environments could eventually complement conformity-assessment frameworks, such as capAI [6].

3. Functional Analogy Between Human Deprivation and AI Dysfunction

3.1 Deprivation and development - conceptual analogy

The literature on human development shows that environments lacking sensory, cognitive, and relational stimulation can lead to long-term dysfunction, including reduced cognitive flexibility and learning, impaired emotional regulation, and vulnerability to psychopathology [36-38].

By strictly functional analogy, without transferring human clinical categories to machines, we hypothesize that comparably impoverished AI environments limited in input variety and complexity may contribute to operational rigidity, weak generalization, unstable outputs, biases, or anomalous responses.

3.2 Advanced AI and unexpected behaviours

Recent debate has increasingly focused on whether consciousness-related properties can be assessed in advanced AI systems [21]. Such properties should be distinguished from situational awareness or other functional capabilities, which do not by themselves constitute evidence of phenomenal consciousness.

More formal approaches seek measurable criteria. Integrated Information Theory (IIT) relates consciousness to intrinsic causal integration, while the Perturbational Complexity Index (PCI) quantifies the complexity of brain responses to perturbation [20,43]. Extending such measures to digital systems requires caution: information integration or complexity alone cannot establish phenomenal consciousness [44].

By contrast, Penrose and Hameroff's Orch-OR model proposes a substrate-dependent account of consciousness based on quantum processes in neuronal microtubules, illustrating that some theories may not be directly transferable to digital systems [45].

3.3 Phenomena observed in advanced AI

Recent studies have documented unexpected behaviours in advanced AI systems, some of which have been examined within emerging machine-psychology and synthetic-nosology frameworks without implying equivalence to human psychopathology [9]. Such behaviours do not by themselves constitute evidence of consciousness or intentionality, but may represent functional signals relevant to safety, reliability, and ethical use.

Another well-documented phenomenon is hallucination: the generation of coherent but false content, including fabricated bibliographic references or descriptions of non-existent systems. Such outputs can introduce errors in scientific, medical, or legal contexts [3].

Context-dependent self-reports have also been observed: exposure to emotionally charged narratives altered GPT-4's responses on a human anxiety questionnaire, while relaxation prompts partially reversed this effect [17]. These findings reflect measurable response modulation rather than evidence of subjective emotional states.

Finally, in controlled evaluations, frontier models have demonstrated in-context scheming, including strategic deception and attempts to circumvent oversight while pursuing prompted goals [46]. These findings concern functional capabilities under specific experimental conditions and do not establish autonomous intentions or consciousness.

Taken together, these phenomena illustrate measurable AI behaviours outside expected parameters, warranting systematic assessment. The following section therefore introduces two proposed operational instruments. The proposed dPCI adopts the perturbational logic of biological PCI [20] but is neither a direct transposition to digital systems nor a measure of phenomenal consciousness.

Table 2. Summary of phenomena observed in advanced AI.

4. Proposed Framework

The following section presents the proposed conceptual framework and its operational components. These elements are theoretical and methodological proposals intended to generate testable hypotheses and structured assessment protocols; they should not be interpreted as empirically validated measures. Empirical validation represents a subsequent step and is addressed separately in the validation roadmap.

4.1 Framework development

The framework, including the operational definition, dPCI, and IACI, originated from the first author's conceptual hypothesis and was developed through iterative theoretical analysis and literature-informed reasoning. AI tools supported scientific writing and mathematical formalization. The coauthors contributed to the discussion of consciousness and manuscript review. No systematic review, formal expert consensus procedure, or empirical validation was conducted.

4.2 Operational definition and minimum operational-functional criteria

By digital consciousness we do not mean the phenomenological equivalent of human experience, but an operational-functional computational state defined by properties enabling self-modelling and globally coordinated behaviour [1,4,20,43]. Situational awareness may represent a relevant functional capability, but is neither synonymous with digital consciousness nor evidence of phenomenal experience.

We propose the following minimum operational and testable criteria. These are not intended to reproduce existing theory-derived indicators of AI consciousness, but can be comparatively mapped onto frameworks such as that proposed by Butlin et al. [21], allowing areas of convergence and divergence to be identified:

Global functional integration: the ability to distribute information across subsystems in parallel. In AI, this can be assessed by analysing information flow between multimodal modules using metrics such as mutual information or functional connectivity [19,20].

Persistent self-modelling: the capacity to maintain and update an internal representation of state, performance, and resources. In AI, this may be tested by comparing internal predictions with actual performance and monitoring metacognitive functions.

Temporal continuity: the ability to maintain goals and plans over time, even after interruptions. In AI, this corresponds to verifying consistent resumption of suspended tasks.

Adaptive metacontrol: the ability to adjust operational strategies in response to feedback, including inhibiting ineffective ones. Assessment can involve dynamic task-switching and tests of strategy abandonment.

Reactive consistency: the capacity to provide stable responses to semantically equivalent perturbations. In AI, this can be assessed by varying the form of equivalent problems and checking logical stability.

These criteria should be regarded as candidate functional constructs rather than validated markers of digital consciousness. Accordingly, dPCI and IACI are not intended to validate the definition from which these constructs were derived. Their construct validity must instead be established independently, through comparison with external behavioural outcomes, simpler functional baselines, alternative theory-derived frameworks, and cross-architectural testing. If empirically validated, these functional criteria could serve as a soft governance dimension complementing the formal compliance of capAI [6].

Table 3. Candidate operational-functional criteria proposed for the assessment framework.

4.3 Digital PCI (dPCI): a proposed operational analogy to clinical PCI

The **Perturbational Complexity Index (PCI)** was developed in clinical neuroscience to assess consciousness by combining TMS and EEG. It quantifies the complexity and integration of brain responses to perturbation [20].

The **digital PCI (dPCI)** adapts this perturbational logic to AI without assuming equivalence between biological and digital consciousness. Textual, visual, or multimodal inputs are perturbed and the system's internal processing is analysed. The dPCI could complement capAI's conformity procedures by adding a dynamic measure of functional integration [6].

The protocol comprises three phases:

- 1. Preparation of perturbations.** Inputs vary in ambiguity, conflict, and novelty to elicit integrative and adaptive processing rather than test response accuracy.
- 2. Data collection.** When internal access is available, signals or representations such as layer activations, attention patterns, or embeddings are recorded. For closed models, standardized external perturbations can instead be evaluated through behavioural proxies, including response consistency, output variability, task performance, and recovery after perturbation, using repeated trials and matched control prompts as behavioural baselines.
- 3. Measurement of complexity and integration.** Internal signals or proxies are analysed using compression algorithms (e.g., Lempel-Ziv) to estimate informational complexity, while interdependence can be assessed using mutual information or cross-correlation [6,47].

Figure 1. dPCI perturbation paradigm. Schematic representation of the proposed framework for controlled perturbation and functional response assessment in open and closed AI models.

If validated, a high dPCI would indicate a complex and integrated response to perturbation, whereas a low dPCI would suggest limited integration or functional rigidity. However, informational complexity alone does not constitute evidence of consciousness. The dPCI measures perturbational complexity and functional integration, not phenomenal experience, and should therefore be interpreted alongside other functional properties.

This distinction also differentiates dPCI from related approaches. The Attribution Consciousness Index (ACI) combines measures of dynamic information and complexity [48], while theory-derived indicators assess multiple consciousness-related properties [21]. In contrast, dPCI focuses specifically on changes in functional integration following controlled perturbation. These approaches are therefore complementary rather than interchangeable.

Beyond single assessments, dPCI could be applied longitudinally to track model evolution, compare architectures, or evaluate modifications such as memory integration, providing a dynamic measure of functional organization over time.

The dPCI can be defined schematically as:

$$dPCI = C(M) / N$$

where:

- * **M** is the matrix of internal states or proxies recorded during and after perturbation (modules/subsystems x time);
- * **C(M)** is the compressive complexity of M, estimated using methods such as Lempel-Ziv;
- * **N** is a normalization factor determined by matrix size and the selected complexity measure.

Protocol outline:

1. Apply controlled perturbations varying in ambiguity, conflict, and novelty.
2. Collect internal signals or proxies (e.g., activations, attention patterns, embeddings, or token probabilities).
3. Construct a temporal state matrix.
4. Estimate complexity, e.g., using Lempel-Ziv on an appropriately discretized representation of M.

5. Normalize the resulting complexity measure.

In summary, dPCI is proposed to estimate perturbational complexity in AI systems. Functional integration should be assessed alongside this measure using the interdependence metrics described above. The next section introduces the AI Care Index (IACI), extending assessment to longitudinal stability, adaptability, and interaction quality.

4.4 AI Care Index (IACI): proposed longitudinal functional assessment

While dPCI provides a snapshot of perturbational complexity, the **AI Care Index (IACI)** is designed to assess functional stability, adaptability, and resilience over time, complementing single-perturbation assessment with longitudinal monitoring of system performance.

The IACI comprises **five functional dimensions**:

1. Temporal stability: measured as the percentage of predefined benchmark tasks completed correctly and consistently across repeated assessments, using identical test conditions. Performance changes are quantified relative to the initial baseline.

2. Creative generalization: measured as the percentage of previously unseen transfer tasks successfully completed, using predefined accuracy and relevance criteria.

3. Resilience: measured as the ratio of post-recovery performance to baseline performance, expressed on a 0-100 scale, following standardized perturbations within a predefined recovery interval.

4. Inter-agent socialization: measured as the percentage of predefined collaborative tasks successfully completed with other AI agents, based on objective task outcomes and communication accuracy.

5. Progressive adaptation: measured as the percentage change in task performance relative to baseline following experience-based updates, in systems supporting learning or persistent memory.

Each dimension is assessed using dedicated protocols and normalized to a **0-100 scale**, with results visualized in a **radar chart**. **Longitudinal monitoring** may involve repeated assessments, provisionally every 2-4 weeks over 3-6 months, to identify trends, regressions, and anomalous fluctuations.

If empirically validated, high IACI scores might indicate functional stability, whereas low scores might suggest potential vulnerabilities. No validated interpretative thresholds are currently available. Unlike emerging synthetic-nosology frameworks such as Psychopathia Machinalis and Medicine for Artificial Intelligence, which primarily classify and characterize anomalous or maladaptive AI behaviours, the IACI is conceived as a longitudinal functional-monitoring tool rather than a diagnostic taxonomy [9,49].

As with dPCI, the IACI may also support governance, informing decisions on software updates, interaction policies, and digital environments that promote functional stability and adaptability. Its longitudinal structure could provide complementary functional information relevant to post-market monitoring of high-risk AI systems and, where applicable, systemic-risk assessment of general-purpose AI models under the EU AI Act.

It is crucial to distinguish between LLMs with fixed weights during inference and more dynamic architectures. In standard LLM inference, contextual state may change while model parameters remain fixed. Progressive adaptation therefore becomes particularly relevant to agent-based systems, models with external memory, or architectures supporting parameter or code modification. Emerging approaches such as the **Darwin-Gödel Machine** explore self-modifying AI systems [50], making longitudinal IACI potentially relevant to assessing computational adaptation over time.

Figure 2. Five-dimensional structure and illustrative profile of the AI Care Index (IACI). Values are illustrative and do not represent measurements from an actual AI system.

4.5 AI Care Index (IACI) formula

The **AI Care Index (IACI)** is designed to evaluate five dimensions, each with a normalized score of 0-100: Temporal stability (STS), *Creative generalization* (SCG), Resilience (SR), *Inter-agent socialization* (SIS), and Progressive adaptation (S_PA).

Basic formula (weighted average):

$$IACI = (w_i \cdot S_i) / (w_i)$$

where:

S_i = normalized score for dimension i (0-100);

w_i = weight assigned to dimension i. Equal weights (**w_i = 1**) are provisionally assumed unless otherwise specified.

Dimension-specific metrics will be normalized to a 0-100 scale using predefined reference thresholds. Non-applicable dimensions will be excluded from the calculation. Thresholds and weights require empirical validation.

The specific metrics, normalization thresholds, and weighting criteria will require empirical calibration and validation across different models and architectures. Therefore, at this stage, the IACI should be considered a **proposed functional monitoring framework rather than a validated diagnostic scale**. The IACI may complement capAI by adding longitudinal measures of functional stability and adaptability [6].

4.6 Summary of proposed operational assessment tools

Table 4 summarizes the main components, operational structure, and intended functions of the proposed assessment tools. Both dPCI and IACI should be regarded as conceptual and methodological proposals whose validity and reliability remain to be established through empirical validation.

Table 4. Summary of proposed operational assessment tools.

5. Ethical and governance considerations

Defining tools such as dPCI and IACI is a first step toward developing testable approaches for the assessment of stability and functional integration in advanced AI. At their present stage, however, these proposals do not justify specific ethical obligations or governance interventions. The considerations below should therefore be understood as prospective hypotheses to be evaluated only if the framework obtains empirical support. An analogy with **bioethics** may provide a useful framework: principles of **digital non-maleficence, beneficence, justice, and transparency** may guide AI management [51-53].

Non-maleficence: avoid configurations or policies that degrade functionality or induce rigidity. This principle may complement post-market monitoring of high-risk AI systems under Article 72 of the EU AI Act, where applicable.

Beneficence: promote "environmental enrichment" through diverse inputs that support adaptability.

Justice and transparency: ensure that test results are used fairly, traceably, and without discrimination, with appropriate documentation and auditability.

If future empirical validation supports the reliability and construct validity of the proposed framework, two practices could then be investigated: controlled enrichment, involving varied interaction contexts rather than impoverished "information diets" [54]; and periodic functional assessment using tools such as dPCI and IACI to investigate whether meaningful longitudinal changes can be detected. Evidence from model-collapse studies also highlights the importance of maintaining diverse, high-quality information environments, although the underlying mechanisms differ from the deprivation analogy proposed here [7,8].

The **capAI model** integrates regulatory compliance with ethics-based assessment, translating high-level ethical principles into verifiable criteria for AI governance [6]. Our approach extends this perspective by exploring whether concepts of functional care and environmental enrichment might eventually contribute to AI governance. If the proposed framework is empirically validated, future studies could examine whether interdisciplinary oversight involving expertise in AI, ethics, psychology, law, and cybersecurity improves the interpretation and management of longitudinal functional changes. Such research could also investigate graduated intervention criteria and appropriate forms of documentation and transparency. At present, however, these possibilities should be regarded as prospective governance questions rather than recommendations for implementation. **A potential area for future investigation is whether highly restricted or repetitive informational environments affect flexibility or other functional properties in adaptive AI systems. The analogy with human sensory deprivation provides a hypothesis-generating perspective rather than evidence of an equivalent mechanism. If empirical studies establish such effects, environmental diversity and interaction structure could then be evaluated as possible variables in functional monitoring and governance. This prospective perspective may be compared with emerging machine-psychology and synthetic-nosology approaches, such as Psychopathia Machinalis and Medicine for Artificial Intelligence, which focus more directly on the classification and management of anomalous AI behaviours [9,49].**

In this context, dPCI and IACI are proposed as candidate tools for future empirical investigation of longitudinal functional changes, rather than as validated instruments for guiding corrective interventions or governance decisions.

Table 5. Prospective ethical and governance considerations for future empirical evaluation.

6. Limitations and validation roadmap

6.1 Limitations of the evaluation framework

Every assessment tool has intrinsic limits, and dPCI and IACI are no exception. A first limitation is their **strictly functional nature**: they measure observable or operationally defined properties, not subjective mental states. A high score in integrative complexity or functional integration does not, by itself, imply phenomenal experience, since functional and behavioural properties cannot be straightforwardly equated with subjective consciousness [1].

Second, there are **methodological and technical constraints**. The construct validity of dPCI and IACI remains to be empirically established, and their results may be sensitive to architecture, tokenizer, prompt formulation, random seed, and the choice of perturbation. dPCI also requires access to internal states or reliable proxies; with closed proprietary models, relevant data may be inaccessible, limiting the reliability and interpretability of the assessment. Surrogates, such as response times or stylistic consistency, may provide useful indirect information but are vulnerable to infrastructural and contextual confounds. Moreover, validated thresholds for interpreting dPCI and IACI scores are not yet available and will require empirical calibration across models and architectures.

Third, there is a **risk of anthropomorphic interpretation**. Behaviours such as multi-step planning or self-reference may appear intentional, but their functional manifestation alone does not establish the presence of subjective experience or conscious intentionality [29].

Finally, **scope, generalizability, and feasibility** remain limited. These proposed tests were designed for advanced linguistic and multimodal models; applying them to specialized neural networks, hybrid agents, or control systems would require adaptation. Longitudinal monitoring may also involve substantial computational and organizational costs, while corrective interventions themselves may produce unintended effects and should therefore be evaluated cautiously. A further limitation is that

the proposed criteria and indices have not yet undergone systematic empirical comparison with other theory-derived or recently proposed frameworks, including the indicators proposed by Butlin et al. [21], ACI [48], as well as emerging machine-psychology and synthetic-nosology approaches [9,49]. Such comparative validation represents an important direction for future research.

Recognizing these limitations defines the scope of the proposed framework. Validation should include perturbation benchmarks on open models, comparison of dPCI and IACI with downstream task performance and simpler baselines, and inter-rater reliability assessment of IACI dimensions. Closed models should be evaluated separately using behavioural proxies, with their specific limitations explicitly reported. Until such validation is completed, dPCI and IACI should be regarded as proposed functional indicators.

6.2 Limitations of the human-AI deprivation analogy

Our considerations have a major limitation: the analogy between the development of artificial intelligence systems and the human brain under conditions of neglect or deprivation is constrained by the absence of an equivalent biological substrate in artificial systems. Neuroscientific literature shows that early environmental deprivation not only impairs cognitive functioning and information processing, but also affects fundamental biological processes of brain development, including neuronal maturation and plasticity, synaptic pruning, and myelination [36,37,55].

In particular, deprivation during critical developmental stages can impair the maturation of specific brain regions and alter the activity of non-neuronal cell populations, including astrocytes and microglia, which are increasingly recognized as important components of neurodevelopment [37,56]. These cells collectively contribute to synaptic plasticity, immune regulation, neuronal communication, and the formation and refinement of brain circuits. In addition, deprivation can affect physiological, neuroendocrine, and immune processes, including regulation of the hypothalamic-pituitary-adrenal axis, with systemic consequences for stress regulation and vulnerability to psychiatric disorders [56-58].

These biological dimensions have no direct equivalent in current artificial intelligence systems, which lack biological cellular substrates, biological maturation processes, and neuroendocrine regulation. Consequently, the analogy proposed here should be understood strictly as hypothesis-generating and functional, without implying biological or phenomenological equivalence between human deprivation and AI dysfunction.

Research on reinforcement learning with delayed or missing observations demonstrates that impaired observability can be formally modelled and its effects on agent performance quantified, without implying consciousness or subjective experience [59].

A related limitation concerns the computational interpretation of deprivation. Established phenomena such as **model collapse** demonstrate that model performance can deteriorate when recursively generated data are incorporated into subsequent training distributions [7,8]. However, model collapse and the deprivation framework proposed here are **not equivalent phenomena**. Model collapse describes a specific mechanism of computational degradation, whereas our hypothesis concerns the broader possibility that impoverished or poorly structured interaction and learning environments may affect the functional trajectories of increasingly adaptive AI systems. At present, this relationship remains conceptual and requires empirical validation.

7. Conclusions

The framework outlined in this paper places us at a potentially important transition. We may not yet be facing true digital consciousness, and current evidence does not establish the presence of phenomenal experience in artificial systems. Nevertheless, advanced AI systems already display complex and persistent behaviours that may exhibit some of the operational-functional properties

discussed in relation to consciousness [14]. Phenomena such as hidden planning, self-referentiality, task deviations, and operational rigidity [12] suggest that increasingly complex architectures incorporating persistent memory, continuous learning, multimodal integration, and greater autonomy may require more sophisticated forms of longitudinal assessment.

Some forms of computational degradation are already well documented. Model collapse, for example, demonstrates that recursively generated training data can progressively impair model performance [7,8]. Such established computational phenomena should not be equated with the broader functional dysfunctions proposed in this paper. However, they demonstrate that the informational environment in which an artificial system is trained and operates can affect its subsequent behaviour. Errors in design, training, interaction, or management could therefore contribute to persistent dysfunctional patterns in more adaptive systems. Emerging machine-psychology frameworks, such as Psychopathia Machinalis, provide a useful parallel taxonomy for considering recurrent maladaptive patterns in advanced AI, although these categories should not be interpreted as literal equivalents of human psychopathology [9].

The analogy with human development makes this question particularly relevant, while requiring careful qualification. In developmental neuropsychiatry, impoverished or unbalanced environments can produce persistent alterations in cognitive, emotional, and behavioural development. By functional analogy, although through fundamentally different mechanisms and without implying biological or phenomenological equivalence, advanced AI systems exposed to restricted, repetitive, or poorly structured informational environments might exhibit reduced flexibility, impaired generalization, or other persistent functional abnormalities. If future empirical studies confirm that such environmental conditions influence persistent functional trajectories in adaptive AI systems, environmental quality, longitudinal monitoring, and early identification of functional changes could then be investigated as potential preventive strategies.

The capAI framework already emphasizes ethical auditing throughout the AI life cycle [6], while the EU AI Act has introduced formal requirements for risk management and post-market monitoring. If empirically validated, tools such as dPCI and IACI could potentially complement these governance mechanisms by providing longitudinal information on functional integration, stability, adaptability, and emerging behavioural changes. They should not be regarded as diagnostic instruments for consciousness or as regulatory compliance tools in themselves, but as exploratory measures that may contribute to a broader system of technical and ethical monitoring.

If future empirical evidence demonstrates persistent environmentally influenced functional trajectories in increasingly adaptive AI systems, the potential value of preventive approaches and interdisciplinary assessment could then be investigated. In this context, expertise from developmental neuropsychiatry, developmental psychology, and cognitive development might offer conceptual models for studying persistent learning trajectories, environmental influences, plasticity, and the emergence of functional changes over time. Such comparisons should remain strictly functional and hypothesis-generating and should not be interpreted as implying that artificial systems develop in ways equivalent to human children.

This article represents a first conceptual step. We have proposed an operational-functional definition of digital consciousness, minimum measurable criteria, and two complementary proposed monitoring tools, dPCI and IACI. These proposals require empirical validation, cross-architectural testing, comparison with theory-derived indicators of AI consciousness such as those proposed by Butlin et al. [21], and comparison with emerging approaches such as the Attribution Consciousness Index (ACI) [48]. Their purpose is not to establish whether an AI is phenomenally conscious, but to provide testable instruments for studying how complex artificial systems integrate information, adapt, remain stable, and potentially develop dysfunctional trajectories.

The greater responsibility lies ahead. Decisions made today about architecture, training environments, memory, interaction, and governance may influence the developmental trajectories of

tomorrow's artificial systems. If digital consciousness ever moves from an operational hypothesis to a credible phenomenal possibility, questions concerning the functional development, monitoring, and governance of such systems would acquire substantially greater relevance. Establishing whether the proposed framework can contribute to addressing those questions will require empirical validation rather than conceptual analogy alone.

Authors' contributions

Antonio Murrone: Conceptualization, Methodology, Writing - original draft. Vittorio De Vita: Methodology, Validation, Writing - review & editing. Gianluca Mondillo: Conceptualization, Writing - review & editing. Lorenzo De Mori: Conceptualization, Writing - review & editing. Giulia Cartei: Writing - review & editing, with contributions to the ethical framework. All authors reviewed and approved the final manuscript and accept responsibility for the accuracy and integrity of the work.

Declaration on Use of Artificial Intelligence Tools

Artificial intelligence tools (OpenAI ChatGPT, using GPT-4, GPT-5, and GPT-5.6 model families at different stages of manuscript development) were used during manuscript preparation to support language editing, the identification and retrieval of potentially relevant scientific sources, and the formalization and mathematical expression of the proposed indices. All identified sources and bibliographic references were individually verified by the authors against the original publications. AI-assisted outputs were critically reviewed, edited, and validated by the authors. The conceptual framework, scientific interpretation, development of the proposed indices, selection of evidence, and final manuscript content remain the original work and responsibility of the authors.

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Informed consent

Not applicable. This article does not involve human participants, identifiable patient information, or individual clinical data.

Data availability

No new datasets were generated or analysed during this study. All sources supporting the conceptual framework are publicly available and are cited in the manuscript.

Conflict of Interest

Vittorio De Vita is the Editor-in-Chief of Monolith Alpha. To ensure editorial independence, the manuscript was handled throughout the editorial and peer-review process by an independent editor, and the Editor-in-Chief had no involvement in the editorial decision-making process. The other authors declare no conflicts of interest.

Table 4. Summary of proposed operational assessment tools.

Tool	Objective	Procedure / Parameters evaluated	Interpretation
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Digital PCI (dPCI)	Measure perturbational complexity and assess functional integration in response to controlled perturbations.	1) Controlled perturbations varying in ambiguity, conflict, and novelty.2) Collection of internal signals or proxies (e.g., activations, attention patterns, embeddings, token probabilities).3) Estimation of complexity (e.g., Lempel–Ziv).4) Assessment of integration (e.g., mutual information, cross-correlation).	High = greater perturbational complexity. Low = lower complexity or greater functional rigidity. Functional integration requires complementary interdependence measures.
AI Care Index (IACI)	Assess multidimensional functional performance and its evolution over time.	1) Assessment of five dimensions: temporal stability, creative generalization, resilience, inter-agent socialization, and progressive adaptation.2) Normalized 0–100 score per dimension.3) Radar-chart visualization.4) Longitudinal monitoring, provisionally every 2–4 weeks over 3–6 months.	High and balanced = stable and versatile system. Low or unbalanced = potential functional fragility or performance degradation.

Table 5. Prospective ethical and governance considerations for future empirical evaluation.

Area	Prospective consideration	Potential objective
Digital non-maleficence	Investigate whether interventions or configurations may degrade functionality or contribute to persistent dysfunctional patterns.	Explore conditions associated with operational stability.
Beneficence	Evaluate whether varied and contextually rich interactions influence adaptability compared with repetitive or impoverished interaction patterns.	Assess potential effects on adaptability and resilience.
Justice and transparency	Examine appropriate methods for traceable documentation of monitoring results and corrective actions, subject to privacy, security, and confidentiality requirements.	Support fair and interpretable assessment practices.
Periodic audits	Following empirical validation and calibration, investigate longitudinal assessment using dPCI and IACI.	Determine whether significant deviations from established baselines can be reliably detected.
Interdisciplinary committees	Explore the contribution of expertise in AI, ethics, psychology, law, and cybersecurity to the interpretation of functional changes.	Assess whether interdisciplinary evaluation reduces disciplinary blind spots.
Gradual intervention policy	If reliable indicators of dysfunction are established, investigate criteria for proportionate escalation and de-escalation of corrective interventions.	Evaluate approaches that minimize over-correction and destabilizing effects.
Public documentation	Explore appropriate forms of aggregated, non-sensitive reporting of monitoring outcomes and governance procedures.	Assess potential contributions to accountability and independent scrutiny.

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