Affordance–Experimentation–Actualization-Evolution for AI-based Support of Innovation

Fatou Ndiaye MBODJI*, Amadou Lo NIANG†, Alioune DIALLO*, Jacques KLEIN*, Tegawendé F. BISSYANDE*
*University of Luxembourg, Luxembourg
†Canada

***Abstract*—Artificial Intelligence (AI) holds significant promise for supporting decision-making in innovation ecosystems. However, this potential is constrained by fragmented and limited data, often scattered across industrial actors and restricted by concerns of sovereignty, confidentiality, and regulation. These limitations hinder the development of robust and generalizable AI system to evaluate early-stage ventures.**

To address these challenges, we introduce `datA-Inno`, an adaptive AI-based decision-support system designed to assist decision-makers in evaluating early-stage ventures operating within fragmented data environments. To formalize the operational logic of `datA-Inno`, we extend the traditional Affordance–Experimentation–Actualization (AEA) framework with an explicit Evolution phase, resulting in the `2*AE` model. This extension enables improved management of AI system transitions across multiple contexts without premature appropriation. We illustrate the applicability of `datA-Inno` and the `2*AE` framework through scenarios in which the AI system evolves from prompt-based models to federated and decentralized architectures, demonstrating how it can support effective venture evaluation.

***Index Terms*—AI, Large Language Models (LLMs), Blockchain, federated learning, Affordance theory**

I. Introduction

Artificial Intelligence (AI) is increasingly leveraged by organizations and innovation ecosystems to support problem-solving, enhance decision-making, and create new value streams [1], [2]. However, the development and appropriation of AI systems across diverse operational contexts remain highly challenging. In early project stages, limited access to real, high-quality industrial data [3] due to fragmentation, sovereignty concerns, confidentiality, and regulatory constraints hampers the creation of robust, context-relevant systems.

To address these challenges, this paper introduces `datA-Inno`, an adaptive AI-based decision-support system designed to guide and evaluate early-stage ventures within fragmented data environments. `datA-Inno` structures AI system evolution into four progressive phases, each characterized by distinct organizational configurations and data integration mechanisms.

Phase 1: involves prompt-based AI models that rely on crafting input prompts to guide pretrained language models. In this phase, organizations operate in isolation with fragmented datasets due to sovereignty and confidentiality constraints.

Phase 2: encompasses fine-tuning large language models (LLMs) by leveraging increasingly available domain-specific data. This phase involves adapting pretrained LLMs to industry-specific contexts through the use of internal or accessible sectoral data, thereby enhancing model specialization and accuracy.

Phase 3: introduces federated learning, and it enables decentralized training across multiple entities without raw data exchange. Blockchain technology is integrated to enforce privacy protection.

Phase 4: establishes Decentralized Autonomous Organization (DAO)-governed ecosystems that support decentralized data sharing and AI co-governance, enabling collective intelligence and adaptive, stakeholder-driven innovation.

While these phases represent a typical developmental trajectory, they are not strictly sequential: organizations may bypass or combine phases based on their capabilities, strategic goals, and context-specific constraints. To formalize the logic underlying `datA-Inno`, we extend the traditional Affordance–Experimentation–Actualization (AEA) framework [4], which provides a useful lens for understanding technological appropriation. However, AEA lacks mechanisms to manage transitions between heterogeneous contexts, especially during preparatory phases when technologies must be assessed and prepared without premature deployment in the target environment. We therefore introduce an Evolution phase, resulting in the `2*AE` framework.

This formalization through the `2*AE` framework equips `datA-Inno` with the ability to systematically analyze AI systems adaptability and transition readiness. It ensures that evolving systems are strategically prepared for deployment across diverse operational settings.

Through this integration, the paper contributes to both theory and practice: theoretically, by extending affordance-based models to account for multi-contextual evolution formalized as `2*AE`; practically, by providing decision-makers, such as incubators or investors, with `datA-Inno`, an AI-based system whose adaptability, evolutionary potential, and long-term viability enable systematic evaluation of early-stage ventures in fragmented and various data environments.

II. Theoretical Background and Foundations

A. Contextual Adaptation of LLMs and the Need for a Multi-Contextual Affordance Framework

Large Language Models (LLMs) have emerged as a foundational component of AI-driven automation. Their effectiveness, however, critically depends on their adaptation to specific usage contexts. Best practices favor customizing general-purpose LLMs through either (1) fine-tuning, adjusting the model using task-specific data or (2) prompt engineering by crafting prompts that guide the model without modifying its weights [5].

The fine-tuning approach assumes the availability of substantial, context-relevant datasets, as well as appropriate governance structures to manage access, privacy, and reuse. This raises fundamental questions about how organizations and innovation ecosystems can structure, customize, and evolve their use of LLM deployment in alignment with data availability and collaboration models.

To address this challenge, we propose analyzing LLM deployment contexts along two critical dimensions: *data accessibility* (ranging from scarce to abundant) and *organizational configuration* (from isolated entities to distributed ecosystems). These dimensions are not static but *inherently dynamic*, as organizations evolve their data infrastructures and collaborative arrangements over time.

The intersection of these dimensions reveals distinct deployment contexts, each characterized by specific technical capabilities, governance requirements, and strategic opportunities:

- Organizations operating with limited data and isolated structures face constraints that preclude traditional fine-tuning approaches, necessitating alternative adaptation strategies.
- Entities possessing proprietary datasets within standalone configurations can leverage internal resources for model specialization, though remaining constrained by the boundaries of their own data.
- Multi-organizational partnerships with privacy-preserving mechanisms enable collaborative model improvement while maintaining data sovereignty, requiring sophisticated coordination protocols.
- Distributed ecosystems support autonomous actors in co-creating AI capabilities through interoperable architectures, demanding new forms of governance and value distribution.

These contexts represent potential evolutionary trajectories rather than discrete categories. Organizations may transition between configurations as their capabilities mature, partnerships form, or strategic priorities shift.

This dynamic perspective reveals that LLM deployment is not merely a technical implementation challenge but an *evolutionary process* where organizations must navigate shifting affordance landscapes.

B. Limitations of the AEA Model in Multi-Contextual Settings

AEA (Affordance–Experimentation–Actualization) Model: Affordance theory has been widely used in information systems research to conceptualize how digital technologies offer action possibilities to goal-oriented actors [4], [6]. Affordances are not fixed properties of technologies but are relational: they emerge from interactions between the technological artifact, the actor, and the environment.

The AEA framework provides a dynamic process view of how affordances are perceived, tested, and institutionalized within organizations. The model consists of three stages:

- **Affordance Perception:** actors identify potential opportunities for action based on their goals and contextual understanding.
- **Experimentation:** This phase includes two key activities: *conceptual adaptation*, where the technology is aligned with the organizational context, and *constraint mitigation*, which involves identifying and addressing contextual constraints that hinder affordance realization. This is the phase during which organizations make new technologies ready for effective use.
- **Actualization:** defined as the goal-oriented actions taken by actors as they use a technology to achieve an outcome [4]. Actualization turns potential into organizationally meaningful outcomes.

While the AEA model has provided a robust foundation for analyzing how organizations perceive and appropriate digital technologies, it assumes relatively bounded and stable context, where actors, goals, and infrastructures are coherent and aligned. As such, AEA captures well the *intra-contextual logic of appropriation*, but does not account for scenarios where: multiple contexts coexist, organizations must operate across or migrate between contexts, affordances themselves evolve in light of broader ecosystemic transformations. This theoretical limitation is particularly salient in the case of AI infrastructures, where contextual fragmentation and strategic evolution represent significant design and governance challenges.

Contemporary Challenges in Multi-Contextual Environments: Contemporary organizational realities increasingly challenge the fundamental assumptions underlying traditional affordance frameworks. The assumption of bounded and homogeneous implementation contexts, while analytically useful, fails to capture the complexity of modern innovation ecosystems where multiple operational environments coexist, interact, and evolve simultaneously.

Contextual Multiplicity: Modern organizations frequently operate across multiple, simultaneous contexts that exhibit distinct technological infrastructures, regulatory environments, stakeholder configurations, and institutional logics. These contexts may coexist within a single organization (e.g., different business units with varying technological capabilities) or emerge as organizations expand their operational scope across geographical, regulatory, or market boundaries. Traditional AEA models, with their assumption of singular implementation contexts, cannot adequately capture the affordance variations that emerge as organizations navigate such diverse environments.

Evolutionary Affordance Landscapes: Contemporary AI technologies exhibit dynamic capabilities that evolve through machine learning processes, algorithmic updates, and changing data availability. Unlike traditional information systems whose affordance properties remain relatively stable, AI systems continuously adapt their capabilities based on usage patterns, training data, and environmental feedback. This evolutionary character introduces temporal dimensions to affordance theory that are underexplored in current frameworks especially concerning how affordances shift as technologies transition between contexts.

Stakeholder Heterogeneity: Innovation ecosystems involve diverse actor networks with varying technological capabilities, resource constraints, institutional logics, and strategic objectives. This heterogeneity creates complex affordance negotiations that extend beyond single organization boundaries, requiring theoretical frameworks capable of modeling inter-organizational affordance dynamics and the emergence of collective affordances that transcend individual organizational contexts.

C. Research Positioning

Our work builds upon established affordance scholarship by introducing essential theoretical extensions for multi-contextual environments, while simultaneously providing practical insights for designing adaptive AI infrastructures in complex stakeholder networks.

Unlike previous affordance studies that focus on technology adoption within bounded contexts, we explicitly model affordance evolution across concurrent and emergent contexts. This approach goes beyond additive extensions, offering a fundamental reconceptualization of how affordances emerge, stabilize, and evolve across contextual boundaries.

By addressing this limitation, our research enhances both the theoretical understanding of contemporary technology adoption processes and the practical ability to design adaptive technology architectures, such as AI infrastructures. Specifically, it presents an AI infrastructure for evaluating and supporting early-stage ventures, targeted at actors like incubators and investors, thereby bridging theory and practice through rigorous validation.

III. Our Proposals

A. Theoretical Framework: The `2*AE` Model

To respond to these challenges, we introduce a novel methodological extension to existing affordance-based models, namely the `2*AE` framework (Affordance–Experimentation–Actualization–**Evolution**).

1) Conceptual Foundation: Our first contribution introduces the `2*AE` framework, a novel methodological extension of the established AEA model that addresses its fundamental limitation: the assumption of bounded, homogeneous implementation contexts. The `2*AE` framework maintains the core insights of traditional affordance theory while introducing critical extensions for multi-contextual environments. It preserves the relational ontology of affordances understanding them as emerging from the interaction between technological capabilities and organizational contexts while recognizing that these interactions can occur across multiple, concurrent contexts that may exhibit different affordance potentials. The `2*AE` framework introduces an Evolution Dimension that explicitly models how AEA cycles can transition across concurrent or emergent contexts, each offering distinct affordance landscapes. This evolution is not just an extension of AEA cycles; it represents a distinct process where affordances transform as technologies move across contexts.

2) The Evolution Dimension: We formalize this step around three components.

Candidate Context: The Evolutionary Dimension envisions the possible future environment toward which a system may evolve. This candidate context constitutes a strategic or operational configuration distinct from the current state, characterized for example by altered information availability or reconfigured constraints. It embodies the target evolutionary state envisioned for the system, serving as the directional anchor for transformation processes.

Transition Preconditions: Before transitioning to the candidate context, a thorough evaluation of the technical and organizational prerequisites is necessary. This starts with a technical feasibility assessment that examines compatibility, highlights gaps, maps constraints, estimates resource requirements, and assesses risks. Following this, adaptive technical preparation ensures that the system is architecturally flexible and equipped with the necessary tools and infrastructure to support migration, while preserving strategic options.

Added Value denotes the concrete and measurable benefits that materialize when a system transitions from its current configuration to the candidate context. In contrast to affordances, which represent potential action possibilities perceived by goal-oriented actors, added value constitutes an outcome-oriented construct that evaluates realized improvements relative to the system's present state. It reflects the degree to which the new configuration enhances performance metrics, scalability parameters, robustness indicators, or alignment with strategic objectives, independent of individual stakeholder perceptions. The ultimate objective of evolutionary processes within this dimension is to realize substantive added value through successful migration to the candidate context.

3) Theoretical Contributions and Generalizability: In fig. 1 we present the `2*AE` framework. It makes several important theoretical contributions to affordance theory. First, it extends the temporal dimension of affordance analysis beyond single-context cycles to encompass cross-contextual evolution patterns. Second, it introduces spatial dimensions that account for the geographic, organizational, and institutional distribution of contexts. Third, it incorporates relational complexity by modeling how affordances emerge not only from technology-context interactions but also from context-context interactions within multi-contextual environments.

Importantly, the `2*AE` framework maintains the theoretical generalizability of traditional AEA models. It is not domain-specific but applicable to any digital technology deployment

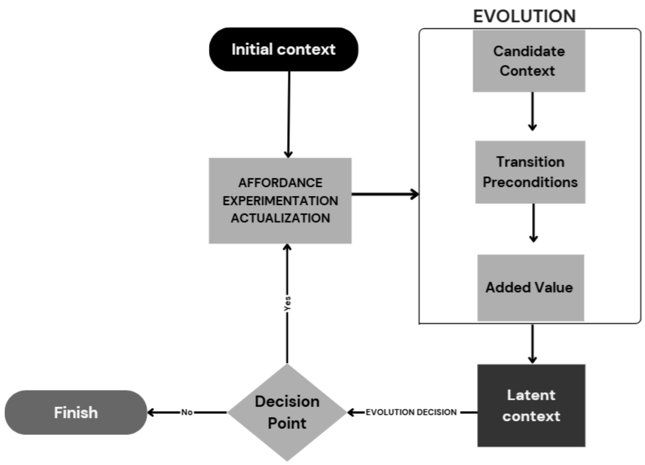

Fig. 1: The `2*AE` Framework for Multi-Contextual Digital Transformation

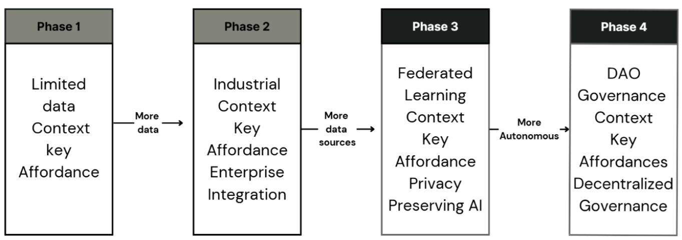

Fig. 2: The `datA-Inno` Framework

scenario where multiple operational contexts coexist, interact, or can be strategically developed. This generalizability ensures broad theoretical applicability while addressing the specific challenges of contemporary multi-contextual environments.

B. *Practical Framework:* `datA-Inno` *Architecture*

The proposed system establishes an intelligent framework, designed to optimize decision-making processes within innovation ecosystems, serving both institutional entities and project proponents. Functionally, it comprises a strategic decision support module, which assists organizations in identifying, evaluating, and optimizing their project portfolios by transforming heterogeneous data into actionable insights. Concurrently, a Project Enhancement Module acts as an interactive agent for innovators, refining their deliverables, providing constructive feedback, and preparing them for critical interactions. The technological foundation relies on Artificial Intelligence (AI), with an inherently adaptive implementation. The implementation of AI varies based on the nature and volume of available data, making it inherently context-dependent.

Design Principles and Conceptual Foundations: Our second contribution presents `datA-Inno`, a specialized AI infrastructure designed to support the complex stakeholder networks characteristic of modern innovation ecosystems. `datA-Inno` operationalizes the theoretical insights of the `2*AE` framework through a practical architecture that addresses the fragmented nature of innovation environments in which diverse actors operate under varying data access patterns, regulatory constraints, and operational requirements.

The platform's design philosophy centers on three core principles: modularity to enable contextual adaptation, scalability to support ecosystem growth, and reflexivity to facilitate continuous learning and improvement. These principles guide architectural decisions across all system components and ensure that the platform can evolve alongside the innovation ecosystems that it supports. The modular architecture of `datA-Inno` enables contextual adaptation across four distinct deployment phases, each designed to accommodate different stakeholder configurations, technical requirements, and governance models.

IV. Methodological Integration

This section presents our integrated methodology that combines the synergistic application of the `2*AE` and `datA-Inno` frameworks with multi-site empirical validation across diverse innovation environments.

A. *Synergistic Application*

While the `2*AE` framework and `datA-Inno` architecture are conceptually independent contributions, they demonstrate powerful synergies when applied in combination. We employ the `2*AE` framework as our methodological lens for analyzing and designing `datA-Inno`, while using `datA-Inno` implementation to validate and refine the theoretical propositions of the `2*AE` model. This integration creates a bidirectional validation process: the `2*AE` framework provides theoretical guidance for the design decisions of `datA-Inno`, while the implementation of `datA-Inno` provides evidence for the effectiveness and limitations of the `2*AE` approach. This methodological integration strengthens both theoretical and practical contributions while demonstrating the value of combining theoretical development with practical implementation.

B. *Multi-Site Immersion Strategy*

To validate the `2*AE` and `datA-Inno` frameworks, the study employed a multi-sited, multi-phased qualitative approach across diverse innovation environments, including a five-month immersion in a fintech fostering program in Luxembourg and interactions with digital entrepreneurs in Senegal, which revealed infrastructural constraints and highlighted the need to model affordance evolution across contexts.

V. Formalizing `datA-Inno` through `2*AE`

In this light, we reconceptualize `datA-Inno` as a reflexive infrastructure model grounded in the `2*AE` framework. Below, we then outline each of its phases.

A. *Phase 1: Data-scarce context*

The current setting demonstrates affordances enabled by integrated AI components, primarily Large Language Models (LLMs), operating within a data-scarce environment while preparing for transition to data-rich industrial deployment.

AI Technology: Pretrained foundation models (e.g., LLaMA, GPT, Gemini, Mistral) provide advanced language understanding without proprietary data. Meaningful functionality is achieved through prompt engineering techniques [7].

Affordances

Using LLMs to synthesize complex venture project descriptions, extract key entities from unstructured text, and identify qualitative strengths and weaknesses. These affordances emerge through systematic experimentation by system designers.

Experimentations

The main constraints and optimization challenges include:

- LLM outputs demonstrate sensitivity to prompt structure, model selection, and generation parameters (temperature, top-p)
- Limited real-world feedback constrains ground-truth evaluation, requiring robust internal validation mechanisms

To overcome these constraints, designers employ mitigation and optimization strategies, such as:

- Role-based prompt engineering: prompts are crafted to simulate domain-specific roles to steer LLM behavior towards task-relevant output, domain informed prompt can be experimented, but also inclusion of examples (few shot) or no example (zero shot) to check most accurate prompting techniques.
- Evaluation of different combination of LLMs models and prompt design to determine optimal configurations without relying on sensitive data.
- Human-in-the-loop evaluation: expert assessments are conducted to validate the relevance and coherence of generated content. Techniques such as LLM-as-judge [8] enable enable simulation of evaluation criteria, providing preliminary scoring that is subsequently compared and calibrated against human judgments using metrics like the Interclass Correlation Coefficient (ICC) and Spearman correlation coefficients [9].

Actualization

Actions: Decision-makers or innovators submit project descriptions. Actualized Outcomes: Decision-makers gain strategic project understanding through AI-generated thematic summaries and qualitative assessments while project owners improve documentation quality, coherence, and persuasiveness through LLM-assisted editing and feedback.

Evolution

This phase represents the AI system's transition from exploratory, data-limited environments toward operational industrial deployment, establishing conditions for domain-specific fine-tuning.

Candidate Context: The evolution targets established organizations that will internally fine-tune LLMs using proprietary, domain-specific data. This transition addresses the performance limitations of generic LLMs while aligning with specific operational objectives.

Transition Preconditions: Successful evolution requires preparation across three dimensions. Technical feasibility assessment evaluates dataset availability, computational requirements, and regulatory constraints while verifying system compatibility and identifying data gaps. Infrastructure development establishes secure data pipelines, scalable fine-tuning environments, and robust deployment mechanisms. Documentation requirements specify fine-tuning procedures, resource allocations, and integration protocols aligned with industrial constraints and training schedules.

Added Value: Industry-specific deployment delivers four interconnected advantages. Enhanced performance emerges as fine-tuned models master domain-specific nuances and terminology, producing more accurate outputs than generic alternatives. Improved security provides greater control over sensitive information through internal processing, reducing external dependencies and mitigating data exposure risks. Better governance ensures AI alignment with organizational values and ethical guidelines, which is essential for regulated industries. Stakeholder alignment tailors systems to specific use cases, driving higher adoption rates and measurable business impact.

This systematic transformation from data-scarce environment to industry-specific solution supports long-term AI system success and sustainability.

B. Phase 2: Industrial Context

Technology Retrieval-Augmented Generation (RAG) and Fine-Tuning (FT) are two key strategies for adapting LLM to domain-specific tasks [10]. This stage refines LLMs via these techniques by using proprietary, domain-specific data. It focuses on making LLMs experts in tasks critical to the industry by leveraging their datasets.

Affordances

Readapting the previous version with their own expectation, getting the model closer to their methodologies and their context as it learns from their own data.

Experimentation

Depending on the available data, a suitable fine-tuning technique is applied. For example, if demonstration data consisting of input samples and their expected outputs are available, supervised fine-tuning (SFT) can be performed. If the organization has labelers who can rank the AI system outputs according to human preference from best to worst, reward model (RM) training can be conducted. If both approaches are feasible, SFT followed by RM can be implemented following Ouyang et al. [11]. As recommended by Balaguer *et al.* . in an agricultural context, RAG is effective in cases where data is contextually relevant, such as in the interpretation of venture data [10].

Actualization

Decision-makers operationalize domain-specific AI insights for strategic analysis, while designers integrate fine-tuned models into specialized workflows.

Evolution

At this point, the organization has a clear understanding of the model strengths, limitations, and of the specific data requirements for further improvement. Internal success will demonstrate the tangible benefits of domain-specific AI, making the system an attractive upgradable system for collaborative initiatives.

Candidate Context: This system can evolve to a collaborative system to leverage various data and model specific from industries to enhance the model. It requires the presence of multiple organizations that are aligned in objectives but constrained in sharing data directly due to privacy, regulatory, or competitive concerns.

Transition Preconditions: Cross-organizational collaborative network contexts operate within fundamentally distributed environments where multiple entities share AI development responsibilities while maintaining data sovereignty.

Added Value: : Access diverse, larger datasets, collectively drive faster AI innovation, tackling complex industry challenges that no single entity could solve in isolation.

C. Phase 3: Blockchain-based federated learning version

Cross-Organizations collaboration for enhancing their models. Local models serve as inputs and the global model as the output for each global iteration [12].

Technology Overview. This phase leverages federated learning to enable decentralized model training across organizations, preserving data privacy by avoiding raw data sharing. Blockchain infrastructure complements this setup by ensuring coordination, accountability, and transparent record-keeping among all participants.

Affordances

This configuration enables organizations to collaboratively develop high-performance AI models without relinquishing control over their data. It supports cross-organizational knowledge sharing while maintaining confidentiality and regulatory compliance. The arrangement fosters trust among participants, promotes data-driven innovation across sectoral boundaries, and reduces barriers to collaborative AI development.

Experimentations

Technical experimentation focuses on designing and validating Blockchain-empowered federated learning [13]. This includes benchmarking aggregation algorithms across heterogeneous data sources, implementing privacy-preserving methods, and investigating blockchain design choices such as the type of blockchain, the consensus mechanisms, to ensure synchronization and auditability. Experiments also simulate adversarial behaviors to assess system robustness, evaluate communication efficiency under varying network conditions, and verify the alignment between local training pipelines and global model update schedules.

Actualization

Industry actors deploy local training environments, connect to the blockchain coordinated federation, and contribute model updates while preserving data privacy. Through repeated training rounds, organizations collaboratively shape a shared model that integrates sector-specific knowledge without disclosing sensitive datasets. As a result, the ecosystem produces a functioning federated AI model, validated across partners, along with an operational governance layer that ensures trust, auditability, and compliance.

Evolution

Candidate Context: This phase may evolve into a distributed AI ecosystem, where independent actors operate autonomously yet remain interoperable through common standards and interfaces.

Transition Preconditions: Advancing to a distributed ecosystem context demands the establishment of interoperable standards, decentralized coordination mechanisms, and governance frameworks that facilitate autonomous actors participation, including onboarding of new stakeholders, while ensuring transparency, trust, and security.

Added Value: This evolution expands innovation capacity, reduces the dependency on centralized coordination, and enables broader participation in the ecosystem. It also supports organic scaling while maintaining coherence and shared purpose.

D. Phase 4: DAO-Based Governance for the federated learning version

Decentralized Autonomous Organizations (DAOs) [14] are digital entities comparable to traditional companies, but they empower members to propose and vote on governance decisions that are typically reserved for boards or executives. *Technology*: a smart contract-based framework that leverages the power of DAOs to address these federated learning (FL) challenges such as lack of transparency and security in traditional FL systems attributed to the centralized validation of local model and global model updates [12]

Affordances

Key affordances include community-driven, transparent and tamper-resistant governance processes, incentive alignment through token economies, and automated, rule-based management of AI development and deployment.

Experimentation

This involves the design and testing of smart contracts that encode governance logic, ensuring they are secure, auditable, and scalable for decentralized AI coordination. Token-based incentive mechanisms are also developed to align stakeholder motivations and support sustained engagement in decision-making processes.

Given the immutability of smart contracts, experimentation must also address significant technical constraints. Advanced mitigation strategies are required, including the use of static analysis tools for early vulnerability detection, and gas optimization frameworks to reduce execution costs.

Actualization

Actors engage in concrete governance activities, such as proposing, voting, and executing decisions through smart contracts. The outcomes include transparent governance records, aligned incentives among stakeholders, improved collective management of AI resources, and increased trust and participation within the ecosystem.

Evolution

This model can evolve toward an incentive-based DAO, enabling participants to commercialize the use of their model. The governance foundation established in this Phase can evolve toward a more mature, incentive-aligned ecosystem where the DAO not only coordinates development but also enables economic valorization of AI outputs. This transformation marks a shift from governance to market-enabling infrastructure.

Candidate Context: Organizations lacking proprietary data or the infrastructure to participate in federated learning, yet requiring advanced AI-driven decision support.

Transition Preconditions: Separation between governance rights and service access must be operationalized. This includes the deployment of usage-based access mechanisms and smart contract-based incentive models to ensure fairness between contributors and consumers.

Added Value: This evolution extends the model's impact beyond its initial contributors by enabling monetized access to its capabilities. By introducing usage-based service access and incentive-compatible mechanisms, the system attracts new stakeholders without altering its core architecture. This commercial layer not only ensures the sustainability of decentralized innovation but also mitigates known risks of inefficiency and low engagement often associated with decentralized AI governance [15]. It thereby enables extensible value creation, balancing openness with operational viability.

`datA-Inno` concludes at the decision point in the `2*AE` framework, where after completing key phases, the system either evolves through another cycle or stops. In this study, `datA-Inno` represents a stable AI infrastructure at this final stage, with no further evolution planned.

E. Findings

`2*AE` proves more effective than the AEA model in formalizing `datA-Inno` by consolidating the importance of the experimentation phase introduced by AEA. As demonstrated by Du *et al.* and Keller *et al.* [4], [6], this phase is essential for translating affordances into concrete outcomes. Our modeling shows that these experiments vary significantly across contexts, which justifies the need for a more explicit and adaptive structuring precisely what `2*AE` provides.

By facilitating the recontextualization of experimentation, `2*AE` strengthens the actualization of affordances while enabling more rigorous preparation for phase transitions. The evolutionary dimension of `2*AE` thus supports better alignment with the specific dynamics of each context.

For example, in the evolutionary trajectory of Phase 4, affordances expand such as through the commercialization of AI-generated outputs without altering the core actors or the broader domain, which remains focused on innovation support.

Finally, `2*AE` introduces a reflexive and non-linear logic: a process may begin in Phase 2 (industrial deployment), evolve into Phase 3 (federated collaboration), or even allow an organization to enter directly at a later phase before returning to refine its model in an earlier one.

VI. Discussion and Related works

A. Theoretical Contributions

This research makes several significant contributions to affordance theory and technology adoption scholarship:

Temporal and Spatial Extensions: The `2*AE` framework extends affordance theory beyond its traditional focus on single-context, single-time implementations to encompass the complex temporal and spatial dynamics of multi-contextual deployments. This extension provides new theoretical tools for understanding contemporary technology adoption processes.

Relational Complexity: Our framework incorporates relational complexity by modeling how affordances emerge from interactions between multiple contexts, not just between technology and a single organizational setting. This insight reveals new dimensions of affordance dynamics that have been overlooked in previous research.

Experimentation as an Evolutionary Lever: Unlike static models, `2*AE` embraces experimentation not merely as a validation step but as a dynamic mechanism for evolving affordance realization across phases and organizational shifts. It consolidates the role of experimentation introduced in AEA [4] and extends prior work by Keller et al., who proposed enriching the experimentation phase with 'conceptual exploration' to better address AI-enabled systems [6]. Our framework further formalizes and structures experimentation across multiple contexts, emphasizing adaptive recontextualization and evolution throughout the deployment process.

Practical Applicability: The integration of theoretical development with practical implementation demonstrates the value of combining abstract theoretical insights with concrete technological solutions. This approach provides a model for future research that seeks to bridge theory and practice in technology studies.

The evolutionary dimension of `2*AE` refers to its capacity to support shifting configurations of affordances over time, enabling flexible transitions between deployment phases while maintaining coherence within the broader system architecture.

B. Practical Contributions

The `datA-Inno` architecture provides several practical contributions to AI infrastructure design:

Multi-Contextual Deployment Strategies: `datA-Inno` demonstrates how AI systems can be designed to support multiple operational contexts simultaneously while maintaining performance, security, and stakeholder value. This approach provides a blueprint for future AI infrastructure development in complex environments.

Governance Innovation: The platform's approach to evolving governance structures provides practical insights for managing complex stakeholder networks in AI deployments. These insights are particularly valuable for innovation ecosystems where traditional governance approaches prove inadequate.

Scalability Solutions: `datA-Inno`'s modular architecture and phase-based deployment approach offer solutions to the scalability challenges that plague many AI infrastructure projects. These solutions are applicable beyond innovation ecosystems to other complex, multi-stakeholder environments.

VII. Limitations and Future Research

Our validation is limited to innovation ecosystem contexts, which may not fully represent the diversity of multi-contextual environments where the `2*AE` framework might apply. Future research should test the framework across broader contextual domains.

`datA-Inno` can evolve or be repurposed across fragmented data contexts and shifting actor needs, as demonstrated in the evolutionary phase of Phase 4. This work supports the development of an industrial product by a startup focused on designing infrastructures that foster innovation. Future research will explore additional business models that leverage `datA-Inno` in decentralized settings.

Although this study prioritizes decentralized approaches over centralized approaches, we recognize the trade-offs between breadth and depth [15]. To mitigate limitations of decentralization, the evolutionary step in our framework guides transitions toward more incentive-aligned contexts.

VIII. Conclusion

This research bridges gaps in affordance theory and AI infrastructure design through an integrated framework that unites theoretical advancement with practical application. The `2*AE` framework extends affordance theory to multi-contextual deployments, while `datA-Inno` illustrates its application in designing adaptive AI infrastructures for AI-based support of innovation.

Our findings contribute theoretically by expanding affordance theory beyond single-context assumptions, and practically by guiding the development of AI systems that balance stakeholder diversity with system coherence. This dual contribution offers a model for aligning theoretical insight with technological implementation.

Future work should test this approach across broader contexts and technologies to assess its generalizability.

IX. Acknowledgments

This work is supported by the Luxembourg Ministry of Foreign and European Affairs through their Digital4Development (D4D) portfolio under the project LuxWAyS (Luxembourg/West-Africa Lab for Higher Education Capacity Building in CyberSecurity and Emerging Topics in ICT4Dev). We would like to thank LHoFT of Luxembourg and the LuxWAyS/LITA Summer School on Cybersecurity (Senegal), which allowed us to access various projects and explore applications of AI systems.

References

[1] S. Narne, T. Adedoja, M. Mohan, and T. Ayyalasomayajula, "Ai-driven decision support systems in management: Enhancing strategic planning and execution," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 12, no. 1, pp. 268–276, 2024.

[2] S. Sachan, F. Almaghrabi, J.-B. Yang, and D.-L. Xu, "Human-ai collaboration to mitigate decision noise in financial underwriting: A study on fintech innovation in a lending firm," *International Review of Financial Analysis*, vol. 93, p. 103149, 2024.

[3] E. Prem, "Artificial intelligence for innovation in austria," *Technology Innovation Management Review*, vol. 9, no. 12, 2019.

[4] W. D. Du, S. L. Pan, D. E. Leidner, and W. Ying, "Affordances, experimentation and actualization of fintech: A blockchain implementation study," *The Journal of Strategic Information Systems*, vol. 28, no. 1, pp. 50–65, 2019.

[5] R. R. Golani, "Llm fine-tuning vs prompt engineering for consumer products," *IJSAT-International Journal on Science and Technology*, vol. 16, no. 2.

[6] R. Keller, A. Stohr, G. Fridgen, J. Lockl, and A. Rieger, "Affordance-experimentation-actualization theory in artificial intelligence research: a predictive maintenance story," in *Affordance-Experimentation-Actualization Theory in Artificial Intelligence Research: a Predictive Maintenance Story*, 2019.

[7] G. Marvin, N. Hellen, D. Jjingo, and J. Nakatumba-Nabende, "Prompt engineering in large language models," in *International conference on data intelligence and cognitive informatics*. Springer, 2023, pp. 387–402.

[8] J. Gu, X. Jiang, Z. Shi, H. Tan, X. Zhai, C. Xu, W. Li, Y. Shen, S. Ma, H. Liu *et al.*, "A survey on llm-as-a-judge," *arXiv preprint arXiv:2411.15594*, 2024.

[9] P. Sedgwick, "Intraclass correlation coefficient," *Bmj*, vol. 346, 2013.

[10] A. Balaguer, V. Benara, R. L. d. F. Cunha, T. Hendry, D. Holstein, J. Marsman, N. Mecklenburg, S. Malvar, L. O. Nunes, R. Padilha *et al.*, "Rag vs fine-tuning: pipelines, tradeoffs, and a case study on agriculture," *arXiv preprint arXiv:2401.08406*, 2024.

[11] L. Ouyang, J. Wu, X. Jiang, D. Almeida, C. Wainwright, P. Mishkin, C. Zhang, S. Agarwal, K. Slama, A. Ray *et al.*, "Training language models to follow instructions with human feedback," *Advances in neural information processing systems*, vol. 35, pp. 27 730–27 744, 2022.

[12] U. Majeed, S. S. Hassan, Z. Han, and C. S. Hong, "Dao-fl: Enabling decentralized input and output verification in federated learning with decentralized autonomous organizations," *Authorea Preprints*, 2023.

[13] J. Zhu, J. Cao, D. Saxena, S. Jiang, and H. Ferradi, "Blockchain-empowered federated learning: Challenges, solutions, and future directions," *ACM Computing Surveys*, vol. 55, no. 11, pp. 1–31, 2023.

[14] W. Ding, J. Hou, J. Li, C. Guo, J. Qin, R. Kozma, and F.-Y. Wang, "Desci based on web3 and dao: A comprehensive overview and reference model," *IEEE Transactions on Computational Social Systems*, vol. 9, no. 5, pp. 1563–1573, 2022.

[15] P. Cihon, M. M. Maas, and L. Kemp, "Fragmentation and the future: Investigating architectures for international ai governance," *Global Policy*, vol. 11, no. 5, pp. 545–556, 2020.