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The Agentic Artificial Intelligence Venture Co-Founder (AIVC): An AI Operating System for Lean Experimentation, Strategic Decisioning, and Responsible Scaling in Technology Startups

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Abstract

Artificial intelligence (AI) is increasingly embedded in startup operations, yet is often treated as fragmented productivity tools rather than an integrated operating system. This paper introduces the Agentic Artificial Intelligence Venture Co-Founder (AIVC), a conceptual multi-agent system that senses markets and regulatory signals, designs and executes lean experiments, maintains causal traction models, allocates resources, and enforces governance-by-design. The framework defines five capability bundles: sensing, experimentation, decisioning, governance, and venture memory, shaping outcomes through four mediating mechanisms. A conceptual architecture specifies model classes, application programming interfaces (APIs), and latency budgets across three deployment tiers for resource-constrained environments. AIVC is distinguished from the build-measure-predict-learn (BMPL) model, and supported by a structured literature protocol, four testable propositions, and explicit boundary conditions. As a theory-building contribution, all propositions are hypotheses for future validation. The paper advances entrepreneurship, strategy, and machine learning systems research by shifting focus from AI adoption to the quality of the founder–AI decision loop under Knightian uncertainty.

Keywords: agentic AI, multi-agent systems, lean startup, responsible AI, human-AI teaming, venture operating systems, governance-by-design, machine learning systems, resource-constrained environments

1. Introduction

Technology startups operate under extreme uncertainty, constrained resources, and intense time pressure. Entrepreneurial theory positions hypothesis-driven experimentation and validated learning as the fundamental unit of progress (Ries, 2011; Raneri et al., 2022). Yet in most ventures, experimentation loops remain manually orchestrated: AI is deployed as a fragmented toolkit with separate analytics dashboards, coding assistants, and generative content tools that leave the most consequential activities largely un-augmented. Similar architectural gaps have been documented in low-resource open and distance learning environments, where agentic multi-agent designs offer promising remedies (Adewale and Sambo-Magaji, 2026b).

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Recent advances in large language models (LLMs), multi-agent orchestration, and agentic AI architectures make it technically feasible to move beyond this paradigm. Prior work suggests that AI may accelerate hypothesis testing (Raneri et al., 2022; Chalmers et al., 2020), augment opportunity search (Ramoglou et al., 2025; Giuggioli and Pellegrini, 2022), and support strategic decision-making at quality levels approaching those of human experts (Csaszar et al., 2024; López-Solis et al., 2025; Camuffo et al., 2026).

This paper introduces the Agentic Artificial Intelligence Venture Co-Founder (AIVC): a conceptual framework recasting AI as a persistent, goal-directed startup operating system that augments founder cognition across sensing, experimentation, decisioning, and governance under Knightian uncertainty. It (1) synthesises four literature streams; (2) conceptualises five capability bundles shaping four mediating mechanisms and venture outcomes; (3) specifies a technical architecture with model classes, APIs, and latency budgets; and (4) advances testable propositions and an AIVC Maturity Model. AIVC supports incremental adoption: early-stage teams begin at Levels 2–3 under Tier 1 constraints and add governance and memory as capacity grows.

2. Literature Review and Gaps

2.1. AI in Entrepreneurship

Chalmers et al. (2020) argue that AI reshapes venture creation by reducing search costs whilst introducing liabilities of technological leverage. Giuggioli and Pellegrini (2022) synthesise an AI-enabled entrepreneurial process across prospecting, design, and exploitation, and Schiavone et al. (2022) identify six AI-enabled mechanisms across venture phases. Aziz et al. (2025) report that AI may improve decision precision and opportunity recognition whilst exposing governance gaps in resource-constrained startups.

2.2. AI in Lean Experimentation

Raneri et al. (2022) propose a build-measure-predict-learn (BMPL) model, embedding an active-learning algorithm into the lean startup loop to select product design decisions and signal prediction uncertainty. Csaszar et al. (2024) provide experimental evidence that LLMs may generate and evaluate strategies at quality levels comparable to accelerator participants and investors, and propose a virtual strategy simulations as a complement to field experimentation. Mac Cord et al. (2026) examine how facilitated AI access is beginning to reconfigure startup decision architectures empirically. This aligns with prior work showing how machine learning can reshape effectual and causal decision logics in entrepreneurial settings (Lupp, 2023).

2.3. Human-AI Teaming

Shepherd and Majchrzak (2022) map opportunities and threats at the AI–entrepreneurship nexus. Murtinu and De Massis (2025) propose that AI may function as a relational nonhuman actor managing cognitive diversity in entrepreneurial teams. Ramoglou et al. (2025) posit a symbiotic epistemic division of labour in which machine creativity expands ideation whilst human judgement contracts it through curation. López-Solis et al. (2025) conclude that human judgement remains critical in high-uncertainty contexts even as generative AI improves efficiency.

2.4. Responsible AI Governance

Raneri et al. (2022) warn of a prediction paradox in which AI over-reliance erodes founders' capacity to handle contingencies. Yun (2025) identifies data provenance, evaluation discipline, and multi-agent orchestration as conditions for trustworthy AI in regulated domains, whilst Chinnaraju (2025) proposes resource-efficient governance guardrails for sustainable scaling. Camuffo et al. (2026) provide RCT evidence that agentic AI system design may itself be a source of competitive advantage.

2.5. AIVC vs. BMPL: Precise Differentiation

The AIVC extends BMPL in four ways. First, BMPL is a single-agent, product-scoped algorithm; AIVC is a multi-agent, venture-scoped operating system. Second, BMPL has no governance layer, enforcing neither data minimisation nor audit logging. Third, BMPL has no venture memory: no experiment registry, concept graph, or decision log persists across pivots. Fourth, BMPL's uncertainty handling is purely statistical; AIVC additionally addresses strategic and epistemic uncertainty through causal traction modelling and human-override protocols. BMPL is best understood as a component instantiated inside AIVC's experimentation layer; AIVC is the surrounding architecture that governs, contextualises, and remembers.

2.6. Critical Gaps

Three gaps across these literatures motivate the AIVC construct.

- **Fragmented capability views.** Existing work treats AI capabilities as discrete and does not integrate them into a coherent, agentic venture operating system architecture.
- **Governance and venture memory marginalised.** Governance appears as a principle or risk list, not as an operational capability embedded in lean experimentation loops; venture memory is absent from existing frameworks.
- **Under-specified boundary conditions.** Data sparsity, founder AI literacy, regulatory intensity, organisational maturity, and market volatility are acknowledged but rarely operationalised as moderators.

3. Methodology

Because the AIVC is a novel theoretical construct and an emerging design space, this paper adopts a conceptual theory-building and design-science methodology (Gregor and Hevner, 2013). This is an established approach for developing foundational constructs in information systems and entrepreneurship research. We outline a four-phase programme to guide future empirical work.

3.1. Literature Selection Protocol

A structured search across Scopus, WoS, Google Scholar, and Semantic Scholar (2018–2025, with backward tracing for seminal earlier works) used four Boolean strings targeting: (S1) AI and startups; (S2) lean startup and ML; (S3) human-AI teaming and entrepreneurial decision-making; (S4) responsible AI governance and SMEs. After deduplication: 177 records. Five inclusion criteria (peer-reviewed or DOI-registered; English; on-stream; attributable contribution; 2018–2025) yielded 114 after Stage 1 screening, 63 full texts after Stage 2, and 19 papers after Stage 3 eligibility. Figure 1 presents the PRISMA-style screening flow.

3.2. Research Design

Because the AIVC is a novel theoretical construct with no existing empirical base, this paper adopts a conceptual theory-building and design-science methodology (Gregor and Hevner, 2013). Consistent with this approach, no prototype has been implemented and no field data have been collected at this stage; Sections 4 and 5 constitute design-layer contributions, and all propositions in Section 4.4 are explicitly hypotheses awaiting Phase 2–4 validation.

Four phases are proposed. **Phase 1** (this paper): integrative theory building across lean experimentation (Raneri et al., 2022; Csaszar et al., 2024), dynamic capabilities (Chalmers et al., 2020; Schiavone et al., 2022), human-AI teaming (Shepherd and Majchrzak, 2022; Murtinu and De Massis, 2025; Ramoglou et al., 2025), and responsible AI governance (Yun, 2025; Chinnaraju, 2025; Aziz et al., 2025). **Phase 2**: design-science prototyping guided by the architecture in Section 5. **Phase 3**: comparative case studies tracing learning loops in ventures using fragmented AI tools versus AIVC-like systems. **Phase 4**: simulation in synthetic market environments to stress-test governance thresholds and experimental policies.

4. The AIVC Conceptual Framework

4.1. Capability Bundles

Five interlocking AIVC capability bundles are proposed to constitute the venture's AI operating system.

Sensing agents continuously monitor market signals, competitor moves, internal product telemetry, and regulatory shifts, pre-structuring signals for downstream agents (Chalmers et al., 2020; Giuggioli and Pellegrini, 2022).

Experimentation agents implement an experiment autopilot, translating founder hypotheses into experiment briefs, suggesting multi-armed bandit portfolios, automating instrumentation, and triggering pivot-or-persevere recommendations based on pre-defined risk thresholds (Raneri et al., 2022).

Decision agents aggregate evidence from experiments, telemetry, and synthetic rehearsals around explicit human-override policies (Murtinu and De Massis, 2025; Ramoglou et al., 2025; Camuffo et al., 2026). Overrides must be single-action triggers, not multi-step dialogs, since complex protocols are routinely bypassed under time pressure. Automation bias — habitual acceptance of recommendations without critical review — is the principal risk, moderated by founder AI literacy (Section 4.3).

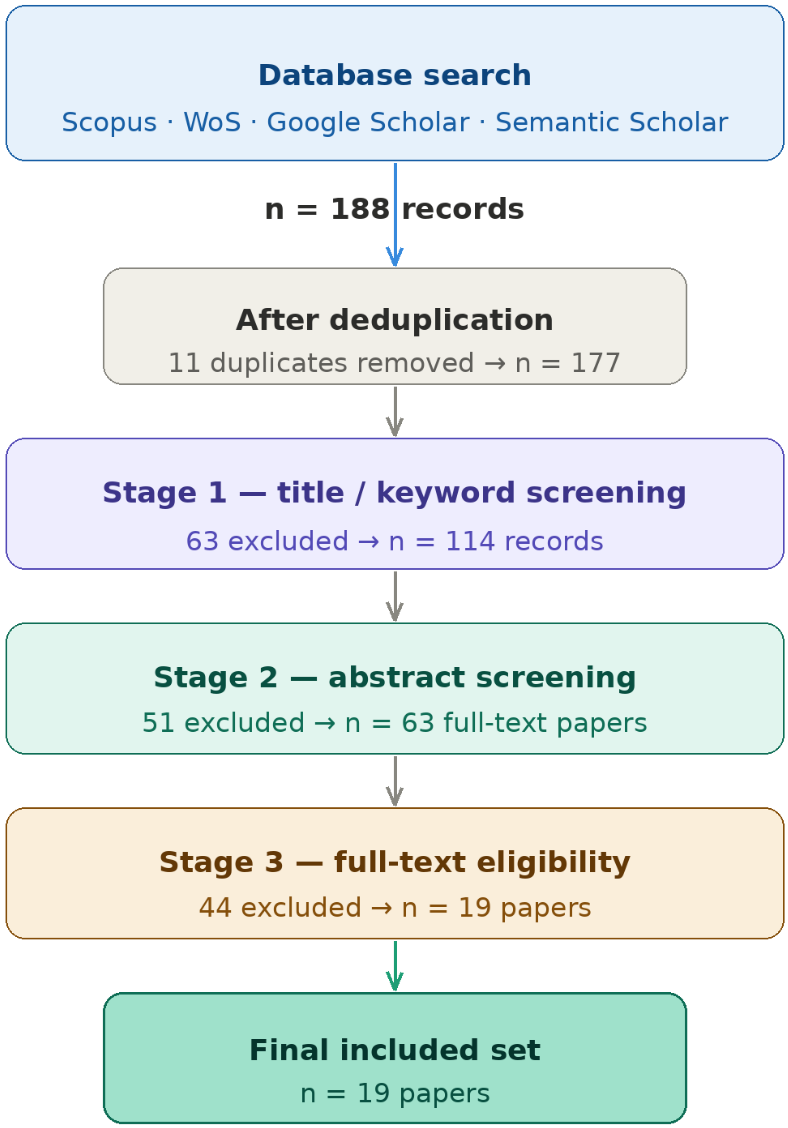

Figure 1: Screening flow from the initial yield to the final included set.

Governance agents embody governance-by-design: enforcing data minimisation, consent checks, and audit logging in line with every agent call, rather than as a post-hoc function (Chinnaraju, 2025; Yun, 2025).

Venture memory provides a structured, persistent knowledge base comprising an experiment registry, concept graph, and decision log, proposed to reduce organisational amnesia across pivots (Aziz et al., 2025; Yun, 2025).

4.2. Mediating Mechanisms and Outcome Variables

The five bundles are hypothesised to influence startup outcomes through four mediating mechanisms detailed in Table 1. Four outcome variables are proposed as directly measurable: (i) time-to- product-market-fit (PMF) in weeks from founding to first revenue-positive cohort; (ii) learning efficiency measured as validated hypotheses per USD 10,000 of burn; (iii) traction yield measured as the percentage of experiments producing statistically significant positive effects; and (iv) compliance incident rate measured as regulatory or reputational incidents per 100 experiments deployed.

Table 1: AIVC Mediating Mechanisms

Mechanism	**Proposed Definition and Operationalisation**	**Primary Bundle(s)**
Learning Velocity	Speed and quality of validated learning per unit burn. Operationalised as validated hypotheses per USD 10,000 burn per quarter.	Sensing + Experimentation + Venture Memory
Decision Quality Under Uncertainty	Degree to which decisions avoid systematic errors via causal validation. Operationalised as proportion of resource allocation decisions with ex-post positive ROI within 6 months.	Decision + Experimentation (+ human override)
Execution Reliability	Consistency with which growth processes meet pre-specified stopping rules and standards. Operationalised as percentage of experiments reaching pre-registered stopping criteria without protocol deviation.	Experimentation + Decision + Governance
Trust and Legitimacy	Confidence of investors, customers, and regulators in the venture. Operationalised as ethics debt count (unresolved compliance issues) at Series A and investor due diligence pass rate.	Governance + Venture Memory

4.3. Boundary Conditions

Five boundary conditions are proposed to moderate AIVC impact: (1) **data sparsity** (fewer than 500 monthly active users) constrains predictive accuracy and requires increased human oversight; (2) **founder AI literacy** (measured via scales such as AILS) moderates override decision quality; (3) **regulatory intensity** (number of applicable compliance frameworks) may require stricter governance policies, trading learning velocity for safety; (4) **team maturity** (age in months and headcount) determines the appropriate AIVC maturity level; and (5) **market volatility** (monthly churn rate variance over 12 months) may accelerate model obsolescence, making distributional drift governance critical.

4.4. Research Questions and Propositions

Four research questions guide future empirical investigation:

RQ1 How may agentic AI be designed as a venture co-founder to operationalise lean startup learning loops?

RQ2 Which AIVC capability bundles are expected to most strongly predict learning velocity and decision quality in early-stage startups?

RQ3 What governance-by-design mechanisms may convert AI use from a productivity tool into a scalable strategic capability?

RQ4 Under what boundary conditions is AIVC expected to accelerate traction, and when may it amplify risk through hallucinations, over-automation, or ethics debt?

Four testable propositions are derived from the framework and prior literature.

P1 (Experiment Automation and Learning Velocity) Startups with more mature experimentation agents are expected to achieve higher validated-hypothesis rates per unit burn than those using AI only for content generation or coding assistance. This is grounded in the BMPL active-learning result (Raneri et al., 2022) and in experimental evidence that AI-evaluated strategies may reach expert quality (Csaszar et al., 2024; Camuffo et al., 2026).

P2 (Human Override and Decision Quality) AIVC is hypothesised to improve decision quality under uncertainty only when paired with explicit human-override rules and causal validation; predictive dashboards without such routines may not improve and could degrade decision quality. Grounded in the prediction paradox warning (Raneri et al., 2022) and the finding that human judgement likely remains critical in high-uncertainty contexts (López-Solis et al., 2025).

P3 (Governance-by-Design and Ethics Debt) Ventures deploying governance agents are expected to accumulate lower ethics debt—operationalised as the count of unresolved data, bias, or consent violations at the time of first institutional funding round—than those relying on ad hoc compliance, improving investor readiness (Chalmers et al., 2020; Aziz et al., 2025).

P4 (Venture Memory and Pivot Effectiveness) Ventures with structured venture memory are hypothesised to achieve faster PMF after a pivot—operationalised as fewer weeks to positive-cohort revenue following a declared pivot—than those without (Aziz et al., 2025; Yun, 2025).

It bears reiterating that all four propositions above are hypotheses derived from prior theory and the AIVC's design logic; no empirical evidence for or against them is reported in this paper, and readers should interpret the framework accordingly.

5. Conceptual Technical Architecture

This section specifies the model classes, API boundaries, latency budgets, and orchestration patterns proposed for a production AIVC system, grounding the framework for the ML audience. Figure 2 presents the reference architecture as a layered system diagram.

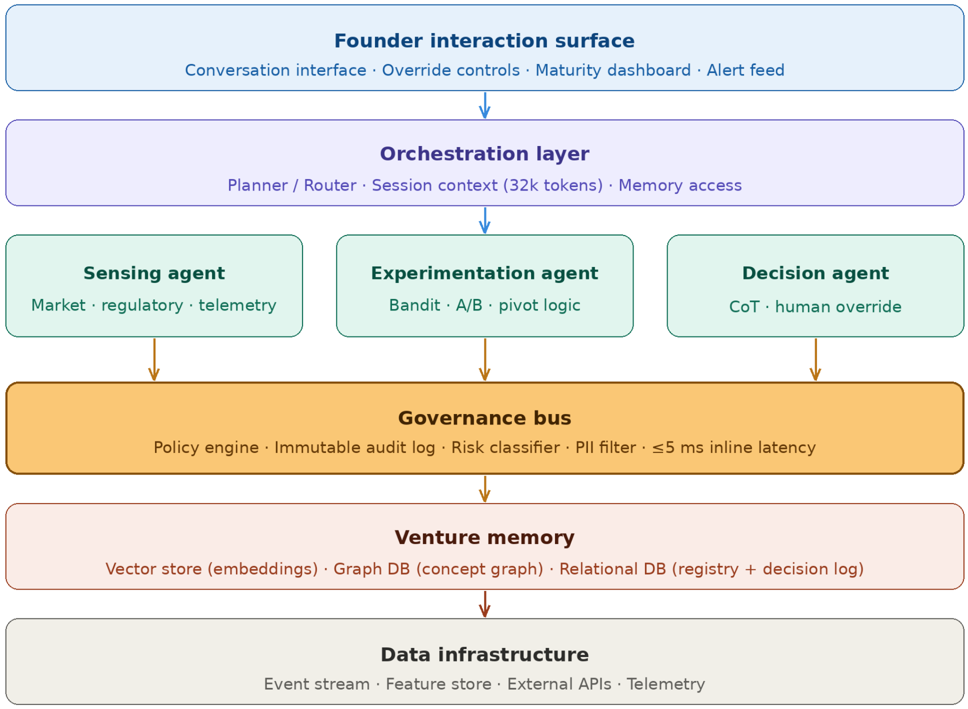

Figure 2: AIVC layered reference architecture. The governance bus (amber, centre) intercepts all inter-agent messages inline; latency overhead is estimated at ≤ 5 ms per call under co-located deployment conditions (see Section 5.2).

5.1. Agent Layer Specifications

Table 2 specifies each agent's model class, primary APIs, latency budget, and primary failure mode. The orchestration layer maintains a session context window of approximately 32,000 tokens for active experiment state and recent decisions, issuing retrieval calls to venture memory for a longer-horizon context. Collectively, Table 2 constitutes a concrete ML systems design contribution: each agent layer specifies a distinct model class, defines primary APIs, latency budgets, and principal failure modes, providing a reproducible specification that grounds the framework for an ML systems audience and enables Phase 2 design-science prototyping.

The governance bus is synchronous middleware applying three inline checks per inter-agent message: a data classification check (blocking PII egress without consent), a risk classification check (flagging sensitive-population experiments for human review), and an immutable audit write. Venture memory is implemented across three coordinated stores: a vector database for dense embeddings, a property graph for the concept graph, and a relational database for the structured experiment registry and decision log.

Table 2: AIVC Agent Layer Specifications

Agent	Model Class	Primary APIs	Latency	Failure Mode
Sensing	RAG over live feeds with a fine-tuned classifier	Web search; app reviews; internal telemetry; regulatory feeds	Async 2–5 min/cycle	Missed weak signals; noise amplification
Experimentation	LLM planner with Bayesian multi-armed bandit engine	A/B testing APIs; feature flags; survey intercepts; statistical libraries	<30 s plan Continuous monitoring	Premature stopping; underpowered experimental design
Decision	LLM reasoning with structured output parsing	Roadmap API; causal model store; human escalation webhook	<60 s per recommendation	Hallucinated causal claims; ignored override
Governance	Rule engine with LLM policy interpreter and audit writer	Data classification API; consent ledger; audit logging system	<5 s inline <10 min async audit	Policy gaps; stale rules; audit failure
Venture Memory	Embedding model with graph and relational storage layers	Vector search API; graph queries; experiment registry; decision logs	<2 s read Async write <30 s	Stale embeddings; schema drift

5.2. Orchestration and Governance Bus

Orchestration layer. A central planner/router agent decomposes founder intents into subtasks, routes them to specialist agents, and assembles responses. The planner maintains a session context window of approximately 32,000 tokens, sufficient for active experiment state, recent decision history, and the current hypothesis backlog. For a longer-horizon context (past pivots, historical traction data), the planner issues retrieval calls to the venture memory layer. Recommended model class: a frontier LLM with function-calling capability (for example, a GPT-4-class or Gemini-class model), constrained by a system prompt encoding the founder's current priorities and active risk thresholds (Adewale and Sambo-Magaji, 2026a).

Governance bus. The governance bus is synchronous middleware intercepting all inter-agent messages and data writes. It applies three inline checks: (1) a PII classification check blocking data egress without consent; (2) a risk classification check flagging sensitive-population experiments for human review; and (3) an immutable audit write logging every agent action, input, output, and timestamp. Inline latency is at most 3–5 ms under co-located deployment; distributed deployments with network hops or external consent-ledger queries may incur materially higher overhead, an open question prioritised in Phase 4.

Venture memory. Implemented as three coordinated stores: a vector database (such as Pinecone or pgvector) holding dense embeddings of all experiment briefs, post-mortems, and customer conversation summaries; a property graph database (such as Neo4j) holding the concept graph; and a relational database holding the structured experiment registry and decision log. Retrieval calls query all three stores in parallel with a timeout of 2 seconds.

5.3. Resource Footprint for Resource-Constrained Environments

AIVC is designed for deployability across three resource tiers. **Tier 1** (under USD 200/month): sensing and experimentation agents only, using a mid-tier LLM API, a managed vector store free tier, and a SQLite-based experiment registry; governance is a static rule engine, and the concept graph is approximated by a JSON-serialised adjacency list. **Tier 2** (USD 200–800/month): all five bundles with a frontier LLM API, managed graph database, and hosted audit log. **Tier 3** (over USD 800/month): all bundles with fine-tuned or private LLMs and formal compliance management integration. This tiered approach aligns with the IndabaX Nigeria 2026 theme of efficient AI for resource-constrained contexts, and complements parallel work deploying edge-based agentic architectures under fragile connectivity in ODL settings (Adewale and Sambo-Magaji, 2026b).

5.4. Deployment Tiers and AIVC Maturity Model

Three deployment tiers are proposed to accommodate resource-constrained environments. Table 3 maps these tiers to the proposed six-level AIVC Maturity Model.

Table 3: AIVC Maturity Model (Levels 0–5)

Level	Label	Description and Deployment Tier
0	No AI	No AI in venture operations.
1	Productivity Hacks	Siloed tools only (code copilots, copywriting). No link to experimentation or decisions.
2	AI-Enhanced Analytics	Dashboards and basic prediction; manual experimentation; weak governance. Tier 1 with sensing only.
3	Semi-Integrated AIVC	Sensing and experimentation agents support lean loops; governance and memory are ad hoc. Tier 1 or early Tier 2.
4	Integrated AIVC	All five bundles functional; governance-by-design and memory support most decisions. Tier 2.
5	Audited AIVC OS	Full OS with explicit policies, external assurance on governance, autonomy, and performance. Tier 3.

5.5. Evaluation (Illustrative)

Because this paper is design- and theory-building, we provide a lightweight evaluation to demonstrate how AIVC operationalises the venture decision loop and produces auditable artefacts. This evaluation is illustrative and does not report empirical effect sizes.

Walkthrough (one loop). A seed-stage venture observes a retention drop. AIVC (i) retrieves prior experiments from venture memory, (ii) generates competing hypotheses (connectivity-driven onboarding failure vs. value mismatch), (iii) prioritises a low-cost offline-first onboarding experiment by expected information gain, and (iv) logs the decision rationale and risk controls as an auditable impact receipt.

Example impact receipt (illustrative, abbreviated). Table Table 4 shows a sample impact receipt

Table 4: Example impact receipt (illustrative, abbreviated)

Field	**Value**
ID	`AIVC-R-001`
Context	Retention drop + access issues
Signals	Retention metrics; support tickets; connectivity proxy
Hypothesis H_1	Connectivity-driven onboarding failure ($c = 0.62$)
Hypothesis H_2	Value mismatch ($c = 0.41$)
Action	7-day offline-first onboarding experiment (low-connectivity cohorts)
Controls	Data minimisation; pre-registered stopping criteria
Owner	Founder
Override	`false`

Mini vignettes (hypothetical). In regulated enterprise pilots, AIVC decision logs support traceability and reduce compliance friction. In data-sparse markets, venture memory reduces repeated mistakes. These vignettes illustrate operationalisation feasibility; formal field evaluation is left to future work. Testability links to propositions: P1 uses decision-cycle time and validated-hypothesis ratio; P2 uses calibration error and override appropriateness rate; P3 uses experiment integrity failures and incident rate; P4 uses audit-log completeness and policy-violation rate.

6. Discussion

The AIVC recasts AI in entrepreneurship from discrete tools to a coherent agentic operating system, centring the founder–AI decision loop as the unit of analysis and advancing research on human–AI collaboration, trust calibration, and epistemic division of labour. Governance-by-design becomes a strategic capability: the governance bus adds negligible latency (3–5 ms) while reducing ethics debt at fundraising. Synthetic market rehearsal enables low-cost stress-testing but risks miscalibration if simulations diverge from real markets. The framework also surfaces failure conditions, including idea flooding, prediction paradox effects, and over-automated deployments extrapolating from sparse or biased data, meaning AIVC's net effect is contingent on alignment between system design and venture context.

7. Contributions, Limitations, and Conclusion

7.1. Contributions

Conceptual: introduces AIVC as an integrated five-bundle venture operating system, specifying the internal architecture through which AI shapes dynamic capabilities (Chalmers et al., 2020; Giuggioli and Pellegrini, 2022). **Technical:** provides model classes, APIs, latency budgets, and three deployment tiers for ML systems audiences. **Empirical:** derives four operationalised propositions with concrete metrics (learning efficiency per USD 10k burn, PMF weeks, compliance incident rate, ethics debt count). **Practical:** proposes an AIVC Maturity Model and Tier 1–3 roadmap aligned with the IndabaX Nigeria 2026 resource-constrained deployment theme.

7.2. Limitations

As a conceptual contribution, AIVC remains untested; all propositions require empirical validation. The architecture abstracts over model drift, infrastructure complexity, and security risks, and broader societal impacts (labour displacement, capability concentration, systemic bias) are only briefly addressed. Four failure modes warrant attention. First, incomplete governance rulesets may yield false negatives, silently passing harmful data operations. Second, LLM hallucinations may propagate through orchestration and be stored as validated causal claims, compounding across retrieval cycles; confidence thresholds and mandatory human review for high-stakes decisions are essential. Third, automation bias may reduce human override to a rubber stamp, a risk moderated by AI literacy and central to Phase 3 investigation. Fourth, poorly governed deployments that over-automate or extrapolate from sparse data may accelerate illusory product–market fit and amplify ethics debt.

7.3. Conclusion

This paper has proposed the Agentic Artificial Intelligence Venture Co-Founder (AIVC) as a new conceptual lens for understanding and designing AI-enabled startups. By specifying five capability bundles (sensing, experimentation, decisioning, governance, and venture memory), four mediating mechanisms (learning velocity, decision quality, execution reliability, and trust/legitimacy), a conceptual technical architecture, key outcome variables (PMF speed, burn efficiency, traction per experiment, safe scaling), and contextually contingent boundary conditions, the AIVC framework provides a basis for systematic theory development and empirical inquiry. The proposed research questions, propositions, and methodological roadmap invite scholars to rigorously investigate when, how, and under what conditions AIVC-like systems enhance or undermine entrepreneurial performance. For practitioners, the tiered deployment architecture (Tier 1 at under USD 200 per month), AIVC Maturity Model, and governance-by-design blueprint point towards a future in which startups, whether in Lagos, London, or Lima, treat AI not as a set of siloed tools but as an auditable, configurable co-founder that helps them learn faster, decide better, and scale more responsibly.

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References

M. D. Adewale and A. Sambo-Magaji. Foundation models as strategic infrastructure: Control points, orchestration, and build–buy–ally choices. In *Strategic Innovation in the Digital Era: Aligning Technology, Culture, and Leadership*. Productivity Press, 2026a.

M. D. Adewale and A. Sambo-Magaji. Agentic AI orchestrators for real-time learner support in low-resource open and distance learning: A framework grounded in multi-agent and edge AI literature. In *Innovations and Challenges of Agentic AI and Intelligent Agents in Education*. IGI-Global, 2026b.

M. F. Aziz, I. Ali, N. O. Alshaghdali, D. Galgotia, R. I. Dell'Aversano, and M. Grimaldi. The role of artificial intelligence as an amplifier of intellectual capital in improving entrepreneurial decision-making: A systematic exploration. *Journal of Intellectual Capital*, 2025. doi: 10.1108/jic-04-2025-0130.

A. Camuffo, A. Gambardella, S. Kazemi, and A. Pandey. Beyond black boxes: Designing and testing agentic AI systems for strategy. *Strategy Science*, 2026. doi: 10.1287/stsc.2025.0432.

D. Chalmers, N. G. MacKenzie, and S. Carter. Artificial intelligence and entrepreneurship: Implications for venture creation in the fourth industrial revolution. *Entrepreneurship Theory and Practice*, 45(5):1028–1053, 2020. doi: 10.1177/1042258720934581.

A. Chinnaraju. AI-driven strategic decision-making on innovation: Scalable, ethical approaches and AI agents for startups. *World Journal of Advanced Research and Reviews*, 2025. doi: 10.30574/wjarr.2025.25.2.0575.

F. A. Csaszar, H. Ketkar, and H. Kim. Artificial intelligence and strategic decision-making: Evidence from entrepreneurs and investors. arXiv preprint, 2024.

G. Giuggioli and M. Pellegrini. Artificial intelligence as an enabler for entrepreneurs: A systematic literature review and an agenda for future research. *International Journal of Entrepreneurial Behaviour and Research*, 28(2):498–528, 2022. doi: 10.1108/ijebr-05-2021-0426.

S. Gregor and A. R. Hevner. Positioning and presenting design science research for maximum impact. *MIS Quarterly*, 37(2):337–355, 2013.

O. López-Solis, A. Luzuriaga-Jaramillo, M. Bedoya-Jara, J. Naranjo-Santamaria, D. Bonilla-Jurado, and P. Acosta-Vargas. Effect of generative artificial intelligence on strategic decision making in entrepreneurial business initiatives: A systematic literature review. *Administrative Sciences*, 15(1):22, 2025. doi: 10.3390/admsci15020066.

D. Lupp. Effectuation, causation, and machine learning in co-creating entrepreneurial opportunities. *Journal of Business Venturing Insights*, 18:e00334, 2023. doi: 10.1016/j.jbvi.2022.e00355.

D. Mac Cord, C. Ramos, and G. F. A. Monteiro. Hybrid decision architectures: Exploring how facilitated AI access reconfigures startups' organisational structures and decision-making. *International Journal of Entrepreneurial Behavior and Research*, 2026. doi: 10.1108/ijebr-11-2024-1316.

S. Murtinu and A. De Massis. Artificial intelligence machines as relational nonhuman actors in entrepreneurial teams. *Journal of Small Business Management*, 2025. doi: 10.1080/00472778.2025.2461031.

S. Ramoglou, Y. Chandra, and Q. Jin. Opportunity search in the era of GenAI: Navigating uncertainty in an expanding universe of imaginable but unknowable futures. *Journal of Management Studies*, 2025. doi: 10.1111/joms.70011.

S. Raneri, F. Lecron, J. Hermans, and F. Fouss. Predictions through lean startup? Harnessing AI-based predictions under uncertainty. *International Journal of Entrepreneurial Behavior and Research*, 2022. doi: 10.1108/ijebr-07-2021-0566.

E. Ries. *The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses*. Crown Business, 2011.

F. Schiavone, M. Pietronudo, A. Sabetta, and F. Bernhard. Designing AI implications in the venture creation process. *International Journal of Entrepreneurial Behavior and Research*, 28(5):1136–1157, 2022. doi: 10.1108/ijebr-06-2021-0483.

D. Shepherd and A. Majchrzak. Machines augmenting entrepreneurs: Opportunities (and threats) at the nexus of artificial intelligence and entrepreneurship. *Journal of Business Venturing*, 37(4):106227, 2022. doi: 10.1016/j.jbusvent.2022.106227.

H. J. Yun. The influence of artificial intelligence on paradigms of entrepreneurship and innovative product development. *The American Journal of Interdisciplinary Innovations and Research*, 7(1):1–24, 2025. doi: 10.37547/tajiir/volume07issue11-02.