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AI-Augmented Entrepreneurship: Governance and the Automate–Augment Logic Across Ideation, Discovery, Design, and Learning

EMPRENDIMIENTO POTENCIADO POR IA: GOBERNANZA Y LA LÓGICA DE AUTOMATIZACIÓN-AUMENTO A LO LARGO DE LA IDEACIÓN, EL DESCUBRIMIENTO, EL DISEÑO Y EL APRENDIZAJE

Nicolás Márquez-Álvarez[*1]
Universidad Santo Tomás

Víctor Cancino Cancino[1]
Universidad Santo Tomás

* Autor corresponsal.

1 Escuela de Ingeniería Comercial, Facultad de Economía y Negocios, Universidad Santo Tomás, Avda. Carlos Schorr 255, Talca, Chile.

Abstract

Purpose: This conceptual article reinterprets entrepreneurship as a governed socio-technical system in which artificial intelligence (AI) links ideation, customer discovery, design, and learning into continuous algorithmic loops. The objective is to explain how AI alters the speed, scale, and locus of entrepreneurial judgment, and to identify when these shifts generate value and legitimacy.
Methodology: Using an integrative literature review, the article synthesizes research on human–AI symbiosis, external enablement, creativity, and uncertainty. It proposes a stage-contingent automate–augment architecture: automating search, simulation, and initial filtering, and augmenting human judgment in problem framing, success criteria, ethical assessment, and strategic decisions. The model is structured around key techno-organizational mechanisms such as prediction, generation, and simulations alongside governance safeguards, including human-in-the-loop oversight, traceability, and bias audits.
Results: Eight propositions link AI to higher idea diversity and novelty, fairer and denser feedback, improved personalization and design quality, earlier pivots, non-linear automation effects, enhanced socio-technical learning, and stronger dynamic capabilities with integrated data and models. Boundary conditions include data quality, concept drift, domain criticality, resources, and governance maturity.
Implications: The article offers theoretical extensions, methodological guidance, and practical recommendations for responsible AI adoption in entrepreneurial processes.
Originality: The study advances a socio-technical model of entrepreneurship and introduces a structured automate–augment logic that clarifies how, when, and under what constraints AI creates value in entrepreneurial settings.

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Resumen

Propósito: Este artículo conceptual reinterpreta el emprendimiento como un sistema socio-técnico gobernado, en el cual la inteligencia artificial (IA) conecta la ideación, el descubrimiento de clientes, el diseño y el aprendizaje en bucles algorítmicos continuos. El objetivo es explicar cómo la IA transforma la velocidad, la escala y el locus del juicio emprendedor, e identificar cuándo estos cambios generan valor y legitimidad.
Metodología: A través de una revisión integrativa de la literatura, el artículo sintetiza investigaciones sobre la simbiosis humano-IA, el habilitamiento externo, la creatividad y la incertidumbre. Propone una arquitectura automatizar-aumentar contingente a la etapa: automatizando la búsqueda, la simulación y el filtrado inicial, y aumentando el juicio humano en la formulación del problema, los criterios de éxito, la evaluación ética y las decisiones estratégicas. Mecanismos tecno-organizacionales (predicción, generación, clasificación, simulación, personalización, coordinación) y salvaguardas de gobernanza (humano-en-el-bucle, trazabilidad, auditorías de sesgo, seguridad) estructuran el modelo.
Resultados: Ocho proposiciones vinculan la IA con mayor diversidad y novedad de ideas, retroalimentación más justa y densa, mejor personalización y calidad de diseño, pivotes más tempranos, efectos no lineales de la automatización, aprendizaje socio-técnico reforzado y capacidades dinámicas fortalecidas mediante integración de datos y modelos. Las condiciones limitantes incluyen calidad de datos, deriva conceptual, criticidad del dominio, recursos y madurez de gobernanza.
Implicaciones: El artículo ofrece extensiones teóricas, orientaciones metodológicas y recomendaciones prácticas para la adopción responsable de IA en procesos emprendedores.
Originalidad: El estudio avanza un modelo socio-técnico de emprendimiento e introduce una lógica estructurada automatizar-aumentar que clarifica cómo, cuándo y bajo qué restricciones la IA crea valor en contextos emprendedores.

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INTRODUCTION

Recent advances in artificial intelligence (AI) are reshaping the entrepreneurial process end-to-end. Far from a peripheral tool, AI places data and algorithms at the core of how new solutions are conceived, validated, designed, and learned from, challenging long-standing assumptions about creativity, uncertainty, iteration, and design (Gupta et al., 2024). Evidence shows a cross-cutting role of AI in new venture creation—from search to exploitation—through mechanisms that lower costs, expand networks, and restructure process phases into data-mediated iterative loops (Roberts & Candi, 2024; Schiavone et al., 2023; Usman et al., 2024). Recent reviews also highlight that AI influences entrepreneurial activity across multiple dimensions, including opportunity identification, decision-making quality, venture performance, and entrepreneurial learning processes (Giuggioli & Pellegrini, 2023).

This shift is both operational and cognitive. In decision-making, AI complements (rather than replaces) human judgment: it expands analytic capacity in the face of complexity while people contribute intuition, normative reasoning, and ambiguity management (Charles et al., 2025). This principle of augmentation relocates the locus of judgment and coordination across the process (Jarrahi, 2018; Raisch & Krakowski, 2021; Shepherd & Majchrzak, 2022). In innovation and design, the focus moves from problem-solving to problem-finding/sensemaking: instead of manually resolving static problems, entrepreneurs design AI-supported resolution loops that iterate, personalize, and learn throughout the solution's life cycle (Verganti et al., 2020). In practice, organizations report higher intensity of AI use in development (optimization, prototyping, simulated tests) and a still exploratory adoption at the front end (Roberts & Candi, 2024).

These transformations strain core theoretical assumptions. First, uncertainty: the Knightian tradition delineates epistemic limits to prediction; however, AI renders some futures partially computable. This reconfigures mechanisms of action and learning without eliminating zones of irreducibility (Packard et al., 2017; Townsend et al., 2025). Second, creativity and judgment: AI can expand the possibility space while potentially shifting creative agency if idea generation and evaluation over-rely on models. Value arises from orchestrating human and artificial intelligences to sustain originality, variety, and decision quality (Shepherd & Majchrzak, 2022; Townsend & Hunt, 2019). Third, process dynamics: AI promotes porous and fluid processes in which ideation, discovery, design, and learning are coupled into continuous algorithmic loops that raise learning density per unit of time, yet require governance to contain model dependence, opacity, bias, premature convergence, and erosion of tacit knowledge (Schiavone et al., 2023; Shepherd & Majchrzak, 2022).

This article addresses this tension with the following central question: How are AI systems transforming the core dynamics of the entrepreneurial process, and what are the implications for traditional theoretical assumptions about ideation, discovery, design, and learning? To answer this, we propose a conceptual framework of the AI-augmented entrepreneurial process that integrates transformation mechanisms across four nodes—(1) ideation (co-generation and algorithmic evaluation), (2) customer discovery (predictive inference, dynamic segmentation, preference simulation), (3) design (generative prototyping, virtual testing, individual-level personalization), and (4) learning (real-time analytics, continuous adjustment, traceability). Furthermore, we discuss scope conditions (data, concept drift, risk, regulation) and governance arrangements (human-in-the-loop, bias audits, model cards) needed to balance automation and augmentation (Jarrahi, 2018; Roberts & Candi, 2024; Verganti et al., 2020).

Despite the rapid diffusion of AI technologies, most existing entrepreneurship process models were developed under assumptions where computational systems played only a supporting role (Cristofaro et al., 2026). Frameworks such as effectuation, lean startup, and discovery-driven planning conceptualize venture creation as sequential cycles of experimentation primarily driven by human cognition and learning (Burnell et al., 2026).

While these perspectives remain influential, they face limitations in AI-mediated environments. First, they largely treat creativity and judgment as exclusively human capacities, overlooking how generative systems increasingly participate in idea generation, evaluation, and experimentation. Second, they conceptualize uncertainty mainly as a human cognitive constraint, whereas predictive systems render portions of the future partially computable. Third, they represent entrepreneurial processes as relatively sequential cycles rather than continuously coupled socio-technical systems supported by data and algorithms. Addressing these limitations, this article proposes an AI-augmented entrepreneurial process model structured around an automate–augment architecture and governed socio-technical learning loops that integrate ideation, discovery, design, and learning.

Contributions. This article makes three contributions. First, it offers an integrative review that links human–AI symbiosis to changes in the speed, scale, and cognitive locus of control within entrepreneurial processes (Jarrahi, 2018; Raisch & Krakowski, 2021). Second, it proposes a process model that formalizes the transition from sequential cycles to continuous algorithmic loops while preserving the entrepreneur as an orchestrator of human and artificial intelligences (Schiavone et al., 2023; Verganti et al., 2020). Third, it develops a research agenda articulated through propositions P1–P8 that re-examine creativity, discovery, and learning under regimes of prediction and the computational limits of AI (Roberts & Candi, 2024; Townsend et al., 2025).

The remainder of the article is structured as follows. Section 2 presents the theoretical foundations and the integrative literature review. Section 3 examines how AI reshapes the dynamics of ideation, discovery, design, and learning within entrepreneurial processes. Section 4 introduces the automate–augment architecture and governance mechanisms guiding human–AI collaboration. Section 5 revisits core theoretical assumptions of entrepreneurship under AI-mediated conditions. Section 6 presents the conceptual model, followed by Section 7, which clarifies key constructs and mechanisms. Section 8 develops the theoretical propositions, and Sections 9–12 discuss the implications for theory, methodology, and practice.

THEORETICAL FRAMEWORK

Literature Review Approach

Following an integrative review approach (Snyder, 2019), this study synthesizes emerging research on artificial intelligence and entrepreneurial processes. Searches were conducted in major academic databases including Scopus, Web of Science, and Google Scholar using combinations of keywords such as "AI entrepreneurship", "human–AI collaboration", "AI innovation", "algorithmic decision-making", and "AI venture creation".

The review focused primarily on peer-reviewed articles published between 2017 and 2025, reflecting the rapid development of generative and predictive AI technologies in entrepreneurial contexts. Articles were screened based on conceptual relevance to the stages of the entrepreneurial process (ideation, discovery, design, and learning) and to governance mechanisms associated with human–AI interaction.

Through iterative reading and comparison, the literature was synthesized to identify recurring mechanisms, theoretical themes, and governance considerations that inform the proposed conceptual model.

AI as an External Enabler of the Entrepreneurial Process

AI operates not merely as a tactical tool but as an external enabler that alters the environmental conditions—technological, temporal, regulatory, and organizational—under which new ventures are conceived and executed (Davidsson & Sufyan, 2023). This perspective explains why AI changes not only efficiency but also process structure: it reduces exploration costs, expands the search space, and shortens validation cycles, thereby reconfiguring incentives and sequences of action (Chalmers et al., 2021). In process architecture terms, this translates into transversality: AI permeates ideation, discovery, design/development, and learning, connecting stages through data and models that circulate with less friction and weakening previously sharp boundaries between phases (Roberts & Candi, 2024).

Recent research documents that AI contributes across the entire entrepreneurial process through concrete mechanisms: lowering resource requirements, introducing new organizational processes, and expanding networks—from prospecting to exploitation (Schiavone et al., 2023). In parallel, scoping reviews show AI strategies that accelerate market analysis, hypothesis prioritization, and automation of repetitive tasks, albeit with substantial heterogeneity by industry, data, and organizational maturity (Usman et al., 2024). The relevant question is no longer whether AI enables entrepreneurship, but how it does so and under what conditions its effects are positive and sustainable.

From Problem-Solving to Problem-Finding: Human–AI Orchestration

In innovation and design, AI shifts the focus from manually solving problems to defining problems and designing resolution loops that learn continuously from real-use data (Sreenivasan & Suresh, 2024). This transition reinforces design-thinking principles—human-centeredness, abductive reasoning, iteration—but introduces a qualitative difference: extreme personalization and life-cycle learning become structural features (Verganti et al., 2020). Entrepreneurial work thus moves from "doing to learn" to "orchestrating to learn," managing objectives, constraints, metrics, and risks over time.

This transition creates value when conceptualized as augmentation—not substitution—of human judgment. Human–AI symbiosis underscores that systems expand analytic reach and exploration speed, while humans retain advantages in intuition, moral reasoning, and ambiguity management (Jarrahi, 2018). Consequently, the entrepreneur's role shifts toward orchestrating intelligences: deciding what to automate and what to augment, with explicit governance to contain bias, opacity, and premature convergence (Shepherd & Majchrzak, 2022; Raisch & Krakowski, 2021).

Uncertainty, Prediction, and "Computable Futures"

The Knightian tradition emphasizes that certain economic phenomena are not probabilizable; however, AI renders some futures partially computable through predictive capabilities, simulation, and synthetic prototyping (Miller, 2023). This computability recomposes the mix of uncertainties entrepreneurs face, accelerating transitions—for example, from ignorance to estimable risk—without eliminating irreducible zones (agentic novelty, practical indeterminism, competitive recursion) (Townsend et al., 2025). Theoretically, this compels a reassessment of action logics: when is it preferable to plan (causation) with algorithmic support, and when is it better to sustain effectual logics of experimentation and stakeholder co-creation?

Viewed as a process, uncertainty is a sequence of transitions; entrepreneurs navigate uncertainty types that evolve as they progress and learn (Packard et al., 2017). AI accelerates these transitions and reorders their temporality: more ex-ante diagnosis, real-time feedback, and earlier pivots. Still, the challenge remains to determine what uncertainty endures and how organizations translate algorithmic signals into learning that is valid, reliable, and aligned with purpose (Amaya & Holweg, 2024).

PROCESS DYNAMICS

Ideation

Generative AI expands the idea space by recombining distant concepts and rapidly producing alternative solutions, offering semantic and visual scaffolding for abductive reasoning (Chen et al., 2019; Yu, 2025). When well governed, such co-creation increases diversity and originality; when poorly governed, it can induce premature convergence or shift the locus of creativity if generation and evaluation over-rely on models (Townsend & Hunt, 2019). The challenge is not whether AI "creates," but how to combine generative power with human criteria of value, feasibility, and novelty.

At the empirical frontier, AI supports idea elaboration (e.g., structured prompting, low-fidelity prototyping) and enables blind, traceable evaluation that mitigates bias against "atypical" proposals, improving feedback quality (Nevo, 2025). This opens an agenda on equity and access; in entrepreneurship education, these tools enable new pedagogies for training creativity and problem framing in human–AI hybrid teams.

Customer Discovery

AI enables dynamic segmentation, large-scale signal analysis, and preference simulation, reducing validation costs and improving hypothesis prioritization (Li et al., 2022). Its value depends on data quality/ representativeness, reasonable explainability, and the team's interpretive capacity (Fu et al., 2024). With more ex-ante inference, decisions tend to drift toward more causal logics; however, non-computable domains persist, justifying effectual experiments and in-the-field learning.

As an evaluative process, pitching and post-pitch learning can be redesigned with AI to shorten learning loops (e.g., interest scoring, AI-assisted Q&A, automatic synthesis of feedback), reordering the sequence pre-pitch → pitch → post-pitch → evaluation and shifting pivots earlier (McSweeney et al., 2025). Again, the key is to govern algorithmic mediation to avoid bias, model dependence, and overconfidence in non-causal correlations.

Product/Service Design

Generative algorithms explore large, constraint-bound solution spaces, enable virtual prototyping, and raise learning density (Verganti et al., 2020; Roberts & Candi, 2024). This shifts entrepreneurial work toward defining valuable problems, setting quality/safety thresholds, and preserving exploratory diversity. In technical, engineering-intensive domains, AI is embedded in design software to generate parameterized variants and evaluate design trade-offs (Okafor & Murphy, 2025).

Acceleration carries risks: premature convergence, myopic optimization of local metrics, and erosion of craft if traceability and human review are absent. Hence, a stage-contingent "automate vs. augment" matrix is recommended, with human-in-the-loop as a design principle, plus bias audits and model cards for decision governance (Shepherd & Majchrzak, 2022; Raisch & Krakowski, 2021).

Learning

With AI, entrepreneurial learning moves from experiential/episodic to algorithmic/continuous: experiment–measurement–adjustment cycles shorten, with real-time feedback and iterative updating of assumptions (Enholm et al., 2021). This acceleration increases speed and scope but can erode tacit knowledge and judgment if practices of reflection, documentation, and traceability are lacking (Plekhanov et al., 2023).

A solution is to design socio-technical loops: AI detects patterns and suggests adjustments; humans explain, reframe, and prioritize with strategic and normative criteria (Shepherd & Majchrzak, 2022). In terms of dynamic capabilities, AI adoption strengthens sensing–seizing–transforming provided there is organizational integration and robust data/model governance (Gao et al., 2025). In short, learning faster does not equal learning better without structures that preserve judgment, ethics, and sensemaking.

"Automate vs. Augment" Architecture and Governance of the Hybrid Process

The performance of AI-intensive processes depends on what to automate (e.g., classification, synthesis, low-fidelity prototyping) and what to augment (e.g., problem framing, ethical judgment, prioritization). Evidence indicates higher AI intensity in development and more exploratory use in front-end ideation, suggesting stage-contingent designs (Roberts & Candi, 2024). Maintaining human-in-the-loop not only improves performance but also mitigates risks—algorithmic bias, opacity, model dependence, or "myopic optimization" (Shepherd & Majchrzak, 2022).

Governance becomes a condition of possibility: decision traceability (model cards, version histories), bias audits, quality/safety thresholds, and escalation protocols under residual uncertainty (Raisch & Krakowski, 2021). At the ecosystem level, access to complementary assets (data, talent, compute) and rules for interoperability/competition shape the viability of AI-intensive startups (Chalmers et al., 2021). Without these safeguards, the promise of speed and scale can strain equity, creativity, and legitimacy.

REVISITING FOUNDATIONAL ASSUMPTIONS

Entrepreneurship theory has long rested on three interrelated assumptions—creativity, uncertainty, and agency—each grounded in a humanist understanding of cognition and intentionality. The rise of artificial intelligence invites these assumptions to be revisited not through technological enthusiasm, but through epistemic critique. AI does not replace entrepreneurial capabilities; it transforms the very conditions under which they emerge, redistributing knowledge, judgment, and moral responsibility across socio-technical systems.

First, the notion of creativity as an inherently human act of imagination (Schumpeter, 2021) is challenged by generative AI's capacity to externalize the mechanisms of variation and recombination. Algorithms can now simulate novelty, design artefacts, and generate ideas autonomously (Verganti et al., 2020; Weber et al., 2022). Yet, as Shepherd and Majchrzak (2022) note, such systems do not replace human ingenuity—they transform it into a process of hybrid co-creation. The entrepreneur becomes a curator of intelligences, orchestrating feedback between human interpretation and machine generation (Raisch & Krakowski, 2021; Miller, 2023). Creativity shifts from invention to epistemic design, where originality lies in how meaning and legitimacy are governed within algorithmic environments.

Importantly, this discussion should not be interpreted as implying that AI systems "invent" or "create" in the legal sense of the term. Concepts such as invention, originality, and authorship carry specific legal meanings that differ from their analytical use in organizational research. In this article, these terms are used to describe processes of idea generation and recombination within socio-technical systems rather than to attribute legal or intellectual ownership to algorithmic agents.

Recent developments in generative and agentic AI systems further intensify this transformation. Contemporary AI architectures increasingly exhibit autonomous planning and tool-use capabilities, expanding the scope of algorithmic participation in creative and design processes (Mariani & Dwivedi, 2024). These developments suggest that the boundaries between human creativity and machine-assisted generation are likely to evolve further, reinforcing the importance of governance and human oversight in entrepreneurial contexts (Krakowski, 2025).

Second, uncertainty, once defined by Knight (2014) as the unknowable domain of entrepreneurial judgment, becomes partially computable through predictive analytics and simulation (Packard et al., 2017; Townsend et al., 2025). However, the reduction of uncertainty produces its own paradox: algorithmic opacity and bias introduce new forms of ignorance (Cowgill et al., 2026; Uriarte et al., 2025). Entrepreneurs must therefore learn to govern rather than eliminate uncertainty—deciding what to compute, what to question, and what should remain indeterminate to preserve exploration and moral reflection (Roberts, 2024; Gao et al., 2025). In this sense, uncertainty becomes reflexive: a condition that demands epistemic and ethical awareness rather than technical mastery.

Finally, agency, traditionally associated with autonomy and intentionality, becomes distributed across humans, algorithms, and institutions (Nzembayie & Urbano, 2026; Weber et al., 2022). This shift resonates with broader transformations in organizational knowledge systems, where automation and information architectures—such as enterprise resource planning—restructure how professional judgment and administrative reasoning are produced and legitimized (Hoffmann, 2023). Decision-making unfolds within infrastructures that suggest, filter, and even justify actions. This calls for a reconceptualization of agency as governed judgment (Raisch & Krakowski, 2021; Roberts & Candi, 2024): the capacity to align computational logic with human purpose. Entrepreneurs no longer act alone but within reflexive systems of accountability that integrate ethical oversight, transparency, and interpretability (Fox, 2024; Nevo, 2025).

Taken together, these shifts signal a profound theoretical reorientation. Creativity becomes hybrid, uncertainty becomes computable, and agency becomes governed. Entrepreneurship thus emerges as an epistemic system of governed judgment, where value is created through the negotiation between human intention, algorithmic reasoning, and moral responsibility. The task for future theory is to understand how cognition and governance co-evolve—and how entrepreneurs cultivate the reflexive literacy required to navigate this new epistemic terrain.

CONCEPTUAL MODEL OF THE AI-AUGMENTED ENTREPRENEURIAL PROCESS

We argue that AI couples ideation, discovery, design, and learning into continuous algorithmic loops, shifting entrepreneurial work from "manual problem solving" toward problem-finding and orchestration of intelligences (human and artificial; see Figure 1). This coupling operates through techno-organizational mechanisms—prediction, generation, simulation, classification, personalization, and coordination. In turn, these mechanisms transform three fundamental process properties: speed (shorter iterations), scale (more alternatives/users in parallel), and the cognitive locus of control (reallocation of judgment between human and system). However, AI yields advantages only under scope conditions. These include data availability/quality, environmental stability (e.g., concept drift), governance (traceability, bias, safety), and human–AI orchestration capabilities (deciding what to automate and what to augment at each stage).

An AI-augmented entrepreneurial process is a socio-technical architecture that (a) defines objectives/criteria, (b) allocates tasks between humans and systems (an automate-vs-augment matrix), (c) executes ideation → discovery → design → learning loops in near real time, and (d) governs risk/legitimacy (human-in-the-loop, bias audits, model cards). Value arises from coupling algorithmic mechanisms with human judgment to avoid premature convergence, model dependence, and loss of tacit knowledge.

The model does not assume universal benefits. It performs better when: (a) data are adequate (representative, up-to-date, traceable), (b) the domain is relatively stable (low concept drift), (c) complementary resources are available (talent, compute, integration), (d) governance is effective (human-in-the-loop, audits), and (e) problem complexity is sufficient for AI to add advantage in search/simulation. Outside these conditions, automation may degrade creativity, decision quality, and legitimacy. These conditions are crucial for falsification: they predict when the model should fail to produce the expected effects.

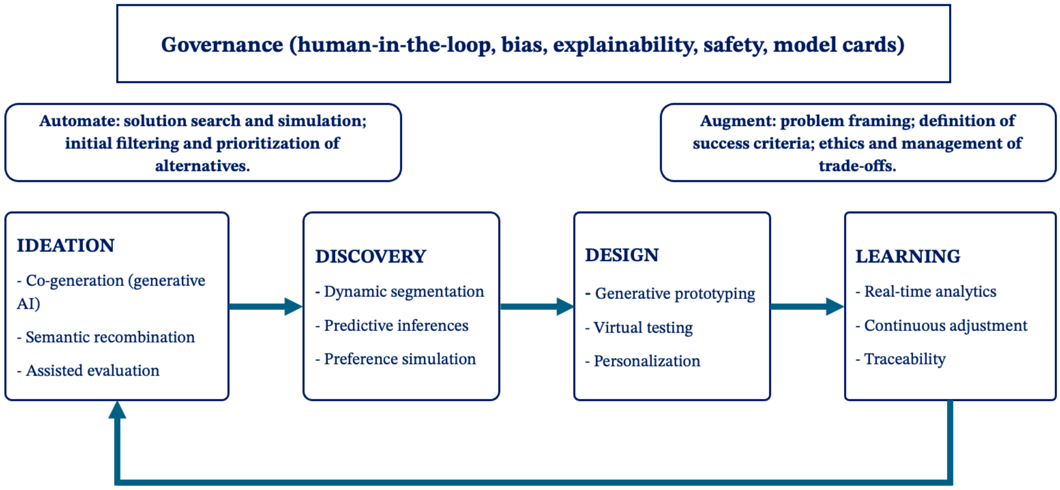

Figure 1. AI-Augmented Entrepreneurial Process: Governance and the Automate–Augment Logic Across Ideation, Discovery, Design, and Learning.
Notes: The model depicts continuous algorithmic loops (Ideation → Discovery → Design → Learning) under human-in-the-loop governance. "Automate" covers search/simulation and initial filtering; "Augment" preserves human framing, success criteria, and ethical trade-offs. Source: Own elaboration.

CONSTRUCTS AND MECHANISMS: EXPLANATION AND ARTICULATION

This section clarifies the core constructs and mechanisms underlying the proposed framework, thereby establishing these conceptual foundations improves analytical precision and facilitates the empirical operationalization of the model in future research.

Continuous socio-technical (algorithmic) loops. We define continuous socio-technical loops as iterative connections linking ideation, discovery, design, and learning through AI-mediated feedback while remaining embedded in human judgment and governance. Rather than purely computational cycles, these loops represent hybrid processes in which algorithmic inference and human interpretation jointly shape entrepreneurial action. The core mechanism is information-friction reduction: by synchronizing generation, measurement, and adjustment, the process increases iterations per unit of time (speed) and broadens the portfolio of alternatives (scale), shifting sequential processes toward near–real-time coupling (Verganti et al., 2020; Roberts & Candi, 2024).

To improve conceptual clarity and facilitate future empirical research, Table 1 summarizes the key constructs of the framework, their definitions, underlying mechanisms, and potential empirical indicators.

Table 1. Key constructs and potential operationalization.

Construct	Definition	Mechanism	Possible empirical indicators
Uncertainty mix	Coexistence of computable and irreducible uncertainty in entrepreneurial decisions	Predictive inference combined with experimentation	Share of assumptions validated ex ante; pivot frequency
Governed judgment	Human oversight over algorithmically mediated decisions	Human-in-the-loop governance	Traceability of decisions; override frequency
Continuous socio-technical loops	Iterative cycles linking ideation, discovery, design, and learning through AI-mediated feedback	Rapid generation–evaluation–adjustment cycles	Iteration speed; feedback density; pivot timing

Source: Own elaboration.

Grounded on these loops, the framework relies on four complementary mechanisms that structure AI-augmented entrepreneurial processes: human–AI orchestration, partial computability, stage-specific automate–augment design, and process governance.

Human–AI orchestration. We conceive orchestration as the explicit allocation of tasks between people and systems, together with rules of interaction (who decides, with what thresholds, under which safeguards). The mechanism is complementarity: AI assumes search/simulation and initial filtering, while humans preserve the locus of judgment for problem framing, value assessment, and ethical/strategic trade-offs (Jarrahi, 2018; Shepherd & Majchrzak, 2022).

Partial computability. We posit that part of the entrepreneurial future is predictable/estimable (computable) and coexists with irreducible zones due to agentic novelty or competitive recursion. The mechanism is a recomposition of the uncertainty mix: more ex-ante diagnosis and earlier pivots where prediction is reliable, without eliminating experimentation where it is not (Townsend et al., 2024; Packard et al., 2017).

Stage-specific "automate vs. augment" matrix. We propose a process-design rule: automate where AI is strong (e.g., content generation, initial filtering, simulation) and augment where humans are irreplaceable (framing, judgment, governance). The mechanism is task–technology fit; we anticipate inverted-U relationships between overall automation and performance when judgment, variety, or safety is eroded (Raisch & Krakowski, 2021; Roberts & Candi, 2024).

Process governance. Governance provides performance and legitimacy safeguards: traceability, sufficient explainability, bias controls, quality and safety thresholds, and escalation protocols under residual uncertainty. Its mechanism is to limit risks (model dependence, premature convergence, opacity) without throttling system speed (Shepherd & Majchrzak, 2022).

Linkage to the Four Stages

Ideation. AI expands the idea space through generation and recombination, while humans set value and novelty criteria and prevent premature convergence during evaluation (Chen et al., 2019; Yu, 2025; Townsend & Hunt, 2019).

Discovery. AI densifies signals (dynamic segmentation, preference simulation); humans validate assumptions with users and balance causation/effectuation when non-computable domains persist (Li et al., 2022; McSweeney et al., 2025).

Design. AI accelerates prototyping and virtual tests; humans define valuable problems and govern design trade-offs and risks of myopic optimization (Verganti et al., 2020; Okafor & Murphy, 2025; Roberts & Candi, 2024).

Learning. AI enables continuous adjustment with real-time analytics; humans institutionalize reflection (post-mortems, traceability) to retain tacit knowledge and judgment (Enholm et al., 2021; Gao et al., 2025).

THEORETICAL PROPOSITIONS

Across all propositions, AI is conceptualized as augmenting rather than replacing entrepreneurial agency. Human actors remain responsible for framing problems, interpreting outputs, and governing the use of algorithmic systems.

This section advances eight propositions (P1–P8) that translate the conceptual model into testable claims. Organized around the four stages of the entrepreneurial process, they specify how the automate–augment logic, under explicit governance, reshapes speed, scale, and the locus of judgment. For each proposition we detail the claim, underlying mechanism, boundary conditions, and observable implications, delineating measures and study designs for empirical evaluation while offering guidance for practice. Collectively, these propositions provide a structured lens to assess where AI-augmented entrepreneurship is likely to excel, where it may fall short, and how its benefits can be realized responsibly.

Ideation

P1 — Ideation (diversity and novelty).

Statement. Human–AI co-ideation (human framing + algorithmic generation) increases the diversity and novelty of the idea portfolio compared to purely human or purely automated ideation; the effect follows an inverted-U when evaluation is over-automated.

Mechanism. Large-scale algorithmic recombination broadens the search space, and human judgment averts premature convergence.

Boundary conditions. Data coverage/heterogeneity; prompting quality; time available for iteration.

Observable implications. Portfolio entropy; novelty scores; share of "viable–novel" ideas.

P2 — Ideation (feedback equity).

Statement. AI-mediated evaluation may improve fairness by anonymizing attributes and standardizing evaluation criteria. However, these improvements depend on the absence of bias in training data and model architecture, since algorithmic systems may reproduce biases embedded in datasets and development processes (Hanna et al., 2025). Therefore, governance mechanisms such as bias audits and transparent evaluation protocols remain essential.

Mechanism. Attribute blindness plus consistent criteria reduce bias and improve the information signal.

Boundary conditions. Interface design; rubric robustness; model bias.

Observable implications. Distribution of feedback types by group; improvement in quality/clarity across subsequent iterations.

Customer Discovery

P3 — Discovery (uncertainty mix).

Statement. Predictive analytics recomposes the uncertainty mix: it shifts part of ignorance toward estimable risk and favors more causal decisions, without eliminating the need for effectual experiments where prediction is weak.

Mechanism. Dense signals enable ex ante diagnosis and better-grounded hypothesis prioritization.

Boundary conditions. Data representativeness and freshness; sufficient explainability; market volatility.

Observable implications. Higher share of assumptions validated ex ante; reduced time-to-pivot; lower false-positive rates.

P4 — Discovery (sequencing and speed).

Statement. Integrating AI into pre-pitch → pitch → post-pitch → evaluation shortens learning loops and pulls pivots earlier; performance improves in data-rich contexts and falls with overfitting and weak proxy metrics.

Mechanism. Scoring, AI-assisted Q&A, and automatic feedback synthesis concentrate early signal.

Boundary conditions. Clarity of objectives; metric stability; concept drift.

Observable implications. Shorter time to PMF; more early pivots with better unit economics; fewer "empty" iterations.

Product/Service Design

P5 — Design (problem-finding and orchestration).

Statement. Shifting work from "solving" to "framing and orchestrating AI loops" increases design quality/speed/personalization; the effect strengthens with explicit governance (criteria, thresholds, safeguards).

Mechanism. AI automates resolution/simulation while humans set objectives, constraints, and trade-offs.

Boundary conditions. Clarity of success metrics; regulated risks; minimum exploratory diversity.

Observable implications. Higher satisfaction/retention; effective personalization; less late-stage rework.

P6 — Design (automate/augment matrix).

Statement. Task–technology fit that automates search/simulation and augments framing/safety maximizes performance; overall automation follows an inverted-U (very low = inefficiency; very high = loss of judgment/ethics/variety).

Mechanism. Complementarity: AI explores, humans impose limits and meaning.

Boundary conditions. Domain criticality; consequences of error; expert availability.

Observable implications. Nonlinear curve between % automation and quality/development time; incidents avoided via human intervention.

Learning

P7 — Learning (socio-technical).

Statement. Pairing continuous algorithmic learning with structured reflection (post-mortems, traceability, model cards) preserves tacit knowledge and outperforms approaches that rely only on AI or only on experience.

Mechanism. Reflection converts signals into transferable knowledge and slows the erosion of judgment.

Boundary conditions. Learning culture; documentation tools; team bandwidth.

Observable implications. Greater lesson reuse; fewer repeated errors; better generalization across products/teams.

P8 — Learning (dynamic capabilities).

Statement. AI integration strengthens sensing–seizing–transforming when data integration and governance are in place; without these capabilities, performance variability increases (fast successes vs. failures due to model dependence).

Mechanism. Higher signal sensitivity + rapid adjustment + resource reconfiguration.

Boundary conditions. Data-pipeline quality; access to compute/talent; regulatory stability.

Observable implications. Outcome heterogeneity explained by capabilities and governance; lower variance under good practices.

Beyond enumerating effects, P1–P8 provide a diagnostic: if data, governance, and task–technology fit hold, AI-augmented entrepreneurship should accelerate learning without sacrificing judgment; if they do not, the same mechanisms invite premature convergence, bias, and fragile performance. This duality motivates the Discussion that follows, which consolidates the propositions into a coherent account of tensions, boundary conditions, and design rules—and repositions the entrepreneur as architect of a governed socio-technical system.

DISCUSSION

Taken together, P1–P8 show that AI does not "add" stages to the entrepreneurial cycle; rather, it couples ideation, discovery, design, and learning into continuous algorithmic loops. This coupling operates through three levers—speed (shorter iterations), scale (more alternatives/users in parallel), and the locus of judgment (reallocation of cognitive tasks between human and system). When the process is designed with an automate–augment logic and governance (such as human-in-the-loop, traceability, bias controls, safety), AI increases the diversity and novelty of ideas (P1), makes feedback denser and more useful (P2), recomposes the uncertainty mix toward estimable risk (P3), and shortens time-to-pivot/PMF (P4). In design and learning, orchestrating work—automating search/simulation and augmenting problem framing, metrics, and ethics—improves quality, personalization, and retention of tacit knowledge (P5–P7), translating into stronger dynamic capabilities (P8).

At its core, the framework revolves around two fundamental tensions that structure AI-augmented entrepreneurship: (1) automation versus human judgment, and (2) prediction versus exploration under conditions of partial computability. Framing the model around these tensions improves conceptual parsimony while preserving the richness of the socio-technical dynamics described.

The propositions also surface structural tensions that the model makes explicit. First, speed vs. sensemaking: acceleration can erode judgment and induce early convergence if evaluation is over-automated (inverted-U patterns in P1 and P6). Second, prediction vs. exploration: partial computability nudges decisions toward more causal logics (P3) yet leaves non-computable zones that require effectual experimentation (P3, P4). Third, performance vs. legitimacy: optimizing local metrics without governance can introduce bias or opacity (P2, P6–P7). The framework's contribution is translating these tensions into design decisions: what to automate, what to augment, with which thresholds and safeguards, and how to document the reasoning of both system and team.

At the same time, it is important to acknowledge that AI adoption may also generate unintended negative consequences. Overreliance on algorithmic recommendations may narrow entrepreneurial search processes, reduce cognitive diversity, and lead to premature convergence around solutions suggested by dominant models (Jorzik et al., 2024). In addition, increasing dependence on proprietary AI infrastructures may concentrate technological and informational power in large platforms, potentially shaping which opportunities become visible or viable for entrepreneurs (Fossen et al., 2024). These dynamics suggest that AI-enabled entrepreneurship should be analyzed not only in terms of performance gains but also in terms of structural dependencies and governance challenges.

Our argument also repositions the entrepreneur's role: from task executor to architect of a socio-technical system. Distinctive competence is no longer only "solving," but framing problems, orchestrating intelligences, and governing the process. This requires complementary assets (data, compute, talent), traceability practices (e.g., model cards, version histories), and reflection routines that convert signals into transferable learning (P7). It also specifies scope conditions—data representativeness, concept drift, domain criticality, and regulation—under which the model's effects should (or should not) be expected (P3–P6, P8).

Importantly, AI should not be interpreted as displacing human judgment. Rather, it reshapes the conditions under which judgment is exercised. Predictive systems alter information availability, speed of feedback, and the structure of decision environments, but responsibility for judgment remains with human actors. Entrepreneurs therefore retain accountability for interpreting algorithmic outputs, framing problems, and making final decisions under uncertainty.

AI expands the computable portion of entrepreneurial environments but does not eliminate uncertainty. Novelty, competitive dynamics, and social interpretation preserve irreducible zones of uncertainty that cannot be predicted algorithmically. As a result, entrepreneurial judgment remains necessary to interpret signals, frame opportunities, and navigate ambiguity.

Finally, P1–P8 invite a revisit of core assumptions: (i) from the process as sequence to a data- and model-coupled system; (ii) from exclusively human creativity to hybrid orchestration; (iii) from "non-probabilizable" uncertainty to mixed regimes with partial computability and irreducible zones; and (iv) from "neutral" processes to governed architectures. This shift opens new units of analysis (human–AI networks, process traces) and a programmable empirical agenda to test the model.

Beyond performance considerations, the framework also highlights potential systemic risks associated with AI-augmented entrepreneurship. The increasing reliance on shared models and data infrastructures may generate forms of opportunity homogenization, where entrepreneurs converge toward similar solution spaces suggested by dominant AI systems. In addition, dependence on large AI platforms may concentrate technological and data power in a small number of actors, potentially shaping the boundaries of entrepreneurial experimentation. Recognizing these risks reinforces the importance of governance mechanisms, critical reflection, and human oversight to ensure that AI-mediated entrepreneurial processes remain diverse, responsible, and socially legitimate.

THEORETICAL IMPLICATIONS

Our model repositions the entrepreneurial process as a governed socio-technical architecture, not a neutral sequence of tasks. In process theory terms, it specifies mechanisms (prediction, generation, simulation, coordination) that couple ideation–discovery–design–learning into continuous algorithmic loops and shift the locus of judgment toward human–AI orchestration. In creativity, it replaces the assumption of exclusively human agency with a hybrid ensemble: variety stems from algorithmic exploration, while quality and legitimacy depend on human judgment and governance. In uncertainty, it proposes mixed regimes of partial computability: some portion of the future is inferable and feeds into causal decisions; another remains irreducible, preserving the value of effectuation and field learning. The core contribution is to translate these intuitions into design rules (a stage-specific automate–augment matrix) and scope conditions that predict when the expected effects should emerge—or fail.

METHODOLOGICAL IMPLICATIONS

The framework suggests operationalizations and study designs to test P1–P8. In terms of measures, we propose: (i) diversity and novelty of the idea portfolio (entropy; novelty scores); (ii) uncertainty mix (share of assumptions validated ex ante; time-to-pivot); (iii) design performance (perceived quality, late rework, effective personalization); (iv) degree of automation and its nonlinear relation to outcomes; (v) socio-technical learning (traceability, lesson reuse, error repetition); and (vi) dynamic capabilities (sensing–seizing–transforming). For study designs, we prioritize controlled experiments (manipulating automation in ideation/ evaluation), process traces and A/B tests in incubators/accelerators, longitudinal panels of AI-intensive startups, and quasi-experiments around process changes (e.g., adoption of AI-assisted blind evaluation). For unstable domains, we recommend simulations with concept drift to probe robustness.

PRACTICAL AND POLICY IMPLICATIONS

For entrepreneurs and teams, the actionable result is a stage-wise decision matrix: automate search/simulation/initial filtering; augment problem framing, success criteria, and ethical trade-off management. Governance (human-in-the-loop, bias audits, model cards, escalation protocols) mitigates risks of model dependence, opacity, and premature convergence. For incubators and venture studios, we recommend redesigning pitching and post-pitch learning with AI-assisted analytics and synthesis while maintaining explainability and anonymization where appropriate. In public policy, we prioritize access to complementary assets (quality data, compute, talent) and interoperability rules that lower entry barriers and prevent concentration that could stifle innovation.

CONCLUSION

We reconceptualize the entrepreneurial process as a governed socio-technical system in which AI couples ideation, discovery, design, and learning into continuous algorithmic loops. Rather than automating everything, superior performance stems from designing the automate–augment logic: automate search, simulation, and initial filtering; augment problem framing, success criteria, and ethical trade-offs via human judgment and human-in-the-loop governance. The eight propositions (P1–P8) specify how this architecture raises idea diversity/novelty, densifies and fair-balances feedback, recomposes the uncertainty mix toward estimable risk, brings earlier pivots, improves design quality/personalization with non-linear automation effects, and strengthens dynamic capabilities when data/model integration is in place.

Limitations and scope. Our model does not assume universal gains. Its effects hinge on data quality/representativeness, concept drift, domain criticality (costs of error), and the availability of complementary assets (talent, compute, integration). Over-attribution to "AI effects" is possible when managerial discipline (e.g., metric rigor) drives outcomes. Several measures (e.g., novelty and judgment traceability) are still maturing; thus, mixed-method triangulation and external validation are essential. These scope conditions also falsify the model: when they are absent, automation may degrade creativity, decision quality, or legitimacy.

Furthermore, the performance improvements discussed throughout the model should be interpreted with caution. Outcomes attributed to AI-augmented processes may also reflect complementary factors such as managerial discipline, team capabilities, or resource endowment. The framework therefore aims to identify mechanisms and conditions under which AI may influence entrepreneurial processes, rather than assuming universal performance gains.

Outlook. By translating human–AI symbiosis into design rules and testable propositions, we offer a programmatic agenda for theory and practice. The payoff is not just speed and scale, but legitimacy—creativity, equity, and explainability—achieved through explicit governance and a disciplined orchestration of human and artificial intelligences.

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