ORIGINAL RESEARCH **Open access**

The Relocation of Entrepreneurial Scarcity from Idea Generation to Market Validation as Generative AI Expands the Supply of Commercial Prototypes

Marcus Lindgren[1*], Rajiv Menon[2], Aiko Nakamura[3], Nadia Benali[4]

Abstract

Generative artificial intelligence changes entrepreneurship by altering the relative cost of producing candidate solutions, value propositions, and commercial prototypes. Yet lower production cost does not imply that entrepreneurial scarcity disappears. This article reconceptualizes entrepreneurial scarcity as a stage-contingent binding constraint whose locus can move when technological change relaxes some constraints faster than others. Drawing on entrepreneurship, innovation, experimentation, and artificial-intelligence research, the article separates three phenomena that are often conflated: the ability to generate candidate commercial propositions, the ability to evaluate them internally, and the ability to obtain credible external market validation. The central argument is conditional. GenAI can reduce the relative scarcity of idea production by expanding search, recombination, and iteration, but the effect varies with task breadth, user capability, organizational readiness, and the diversity of generated outputs. Where credible market testing remains costly, rival, slow, or access-constrained, the binding entrepreneurial constraint can shift toward validation. This relocation is not universal: it weakens when validation scales with generation, when generative outputs converge, or when technical, regulatory, financing, or implementation constraints dominate earlier. The reconceptualization therefore changes what should be observed and compared in AI-enabled entrepreneurship: not simply how many ideas or prototypes can be produced, but which stage most strongly constrains credible entrepreneurial progress.

Keywords Generative artificial intelligence, Entrepreneurial scarcity, Market validation, Commercial prototypes, Opportunity formation, Entrepreneurial experimentation

*Correspondence:
Marcus Lindgren
marcus.lindgren@hhs.se
[1] Department of Entrepreneurship, Stockholm School of Economics, Stockholm, Sweden
[2] Department of Entrepreneurship, Indian Institute of Management Bangalore, Bangalore, India
[3] Department of Management, Keio University, Tokyo, Japan
[4] Department of International Business, University of Tunis El Manar, Tunis, Tunisia

Introduction

Digital technologies have progressively altered the boundaries of entrepreneurial action by making resources, interactions, and opportunity processes less tied to fixed organizational or spatial arrangements [1]. Generative artificial intelligence intensifies that change because producing plausible descriptions, designs, code, marketing assets, and other early commercial artifacts can now require substantially less specialized effort than in earlier digital environments. The theoretical problem is not simply whether AI improves entrepreneurial productivity. It is whether a construct usually discussed as if it were a stable shortage—entrepreneurial scarcity—should still be located in the same part of the entrepreneurial process once candidate solutions can be produced at much higher speed and lower marginal cost.

This is an open access article distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License (CC BY-NC-SA 4.0), which permits non-commercial use, distribution, reproduction, and adaptation in any medium or format, provided that appropriate credit is given to the original author(s) and source, a link to the license is provided, and any changes made are indicated. Adapted material must be distributed under the same license.

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

Entrepreneurship theory already provides a reason to separate creation from proof. The Lean Startup literature treats hypothesis formation, minimum viable products, experimentation, validated learning, and subsequent strategic movement as related but distinct activities [2]. A venture can therefore become more efficient at producing something testable without becoming equally efficient at establishing that the thing merits continued commitment. This distinction becomes theoretically consequential under GenAI because a technology shock can alter one stage of entrepreneurial activity more strongly than adjacent stages.

The article adopts construct reconceptualization rather than proposing another generic AI entrepreneurship framework. Conceptual engineering in management is valuable when it changes the content, boundaries, or theoretical use of a construct rather than merely supplying new terminology [3]. Applied here, the analytical task is to treat scarcity as the location of the binding constraint on entrepreneurial progress. A relocation claim is meaningful only if it changes what researchers would observe, what entrepreneurs would compare, and what evidence would count against the claim.

Digital affordances can change where opportunities arise and how dispersed actors participate in opportunity formation [4], while AI and big-data research has long emphasized that expanded information-processing capability does not remove entrepreneurial uncertainty [5]. These two points delimit the argument. GenAI may enlarge the supply of candidate commercial propositions, but it does not automatically make customers more accessible, feedback more diagnostic, experiments more credible, or market commitment easier to obtain. The article therefore asks when increased generative capacity changes the relative scarcity of entrepreneurial activities and when it does not.

Entrepreneurial Scarcity and Opportunity Formation

Entrepreneurial scarcity is often approached through familiar resource constraints: finance, knowledge, attention, legitimacy, talent, information, and access to market actors. AI can alter some of these constraints while reinforcing others. Formal work on machine learning, data access, and competition shows that data-rich incumbents and entrants can face sharply different innovation and entry conditions, so technological capability can redistribute barriers rather than simply lower them [6]. Evidence from micro-business adoption likewise indicates that the innovation benefits of AI and machine learning differ with adoption timing and organizational conditions [7]. Scarcity is therefore relational: what is scarce depends partly on which complementary resources a venture already controls.

Opportunity formation also depends on external actors. Research on lead users shows that customer characteristics, relationship history, and a firm's own R&D capacity shape whether user involvement produces more substantial opportunities [8]. Access to customers is thus not equivalent to access to useful evidence. The informational value of a market contact depends on who the contact is, what the venture can learn from the interaction, and whether the evidence bears on an uncertainty that matters for future action.

The same principle appears in entrepreneurial experimentation. A randomized controlled trial of 116 startups found that scientific-method training improved the precision of entrepreneurial decisions and affected pivoting behavior [9]. The implication is not that one experimental template is universally superior. It is that entrepreneurial progress depends on how propositions are articulated and tested, not merely on the number of ideas available. Lean Startup theory similarly separates customer discovery, minimum viable products, validated learning, and pivoting into analytically distinct components [10]. This matters for the present reconceptualization because a prototype is an instrument for learning, not evidence that learning has already occurred.

The baseline entrepreneurial process therefore contains at least two distinct forms of constraint. One limits the production and revision of candidate solutions; another limits access to credible signals about whether those solutions should be pursued. Before GenAI, these constraints could be tightly coupled because producing each new prototype consumed substantial time, expertise, and money. Once generation becomes cheaper, their relative importance can diverge.

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

Generative AI and Prototype Abundance

Recent innovation-management research portrays GenAI as more than an isolated productivity tool. Reviews and taxonomies identify applications across ideation, design, knowledge recombination, new product development, organizational innovation, and business-model change [11–13]. The relevant theoretical shift is therefore not merely faster text production. GenAI can expand the set of candidate artifacts that entrepreneurs and firms can produce, revise, compare, and present before committing to conventional development resources.

Qualitative evidence from the information-technology industry shows that GenAI can support the creation and reconfiguration of new value propositions [14]. Process research in creative organizations similarly finds that GenAI can alter innovation routines by accelerating creation and iteration [15]. These findings do not establish that any generated proposition is commercially attractive. They do establish a mechanism through which the supply of testable commercial candidates can increase: the cost of moving from an initial prompt or problem statement to a more articulated representation of a possible offering is reduced.

That mechanism remains hybrid. Formal modeling of human–GenAI creative work emphasizes that outcomes depend on how human agents elicit, select, and integrate machine-generated material [16]. A systematic review of 98 studies of AI in new product development likewise shows that AI contributions differ across front-end, development, testing, and back-end activities, with data, governance, and organizational readiness shaping what can be achieved [17]. Prototype abundance should therefore be understood as a conditional expansion in feasible candidate production, not as autonomous technological creation detached from human and organizational complements.

A large preregistered field experiment involving 791 professionals at Procter & Gamble provides a particularly useful distinction. AI assistance improved performance on real product-innovation problems and helped individuals approach the performance of human teams, yet human evaluative contribution remained consequential [18]. The study concerns innovation work rather than entrepreneurial market validation, so it should not be stretched into a claim about customers or venture success. Its theoretical value here is narrower: generative augmentation can increase solution-production capacity without collapsing generation and evaluation into the same function.

Declining Scarcity of Idea Production

Experimental evidence indicates that GenAI's creativity effects are conditional rather than uniformly expansive [19–21]. In one randomized study, access to generative AI increased individual creative performance while reducing the collective diversity of outputs [19]. A workplace field experiment found positive creativity effects that depended partly on cognitive job resources and employees' metacognitive strategies [20]. Two further randomized experiments showed that GenAI stimulated exploration in broad creative tasks but produced no significant benefit in a more constrained task [21]. Reduced production scarcity can therefore coexist with output convergence, capability dependence, and task-specific null effects.

Organizational research points in the same direction. Work on AI-enabled corporate ideation systems suggests that artificial intelligence can relieve identifiable pains in idea generation and idea processing [22]. Experimental evidence on professional writing shows that ChatGPT can substantially reduce completion time and raise assessed quality for some knowledge tasks [23]. These findings cannot be converted into a universal percentage reduction in the cost of commercial prototyping. They nevertheless support the more limited mechanism required here: some forms of candidate production can become faster and cheaper, potentially allowing more alternatives to reach a testable state.

The conceptual implication is a change in relative bindingness rather than the disappearance of ideas as an entrepreneurial problem. Declining scarcity of idea production refers to a reduction in how strongly the ability to produce and revise candidate propositions constrains entrepreneurial progress. It does not mean that originality, technical feasibility, strategic coherence, or differentiated imagination become abundant in every setting. The same technology can

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

increase output while narrowing diversity, and it can help more in open-ended tasks than in tightly constrained ones. Scarcity therefore declines only to the extent that generated candidates are sufficiently differentiated and actionable to move the venture to the next stage.

These mechanisms imply that the same GenAI-enabled increase in candidate output can relax one entrepreneurial constraint while leaving a separate requirement for decision-relevant market evidence intact; **Table 1** distinguishes the observable states produced by that separation.

Table 1. Distinguishing reduced idea-production scarcity from unresolved validation scarcity under GenAI-enabled prototype abundance

Analytical state	Candidate commercial output	Nature of remaining uncertainty	External evidence requirement	Entrepreneurial consequence	Interpretation under scarcity relocation
Generative constraint remains binding	Candidate production remains slow, specialized, or weakly improved	Whether a workable proposition can be produced	Secondary because generation itself remains limiting	Few credible alternatives reach testing	No relocation toward validation is established
Production expands but outputs converge	More candidates are produced, but alternatives are similar or weakly differentiated	Whether any candidate represents meaningfully distinct value	Market evidence remains necessary, but ideational quality is still limiting	Apparent abundance may overstate real option variety	Partial or ambiguous relocation
Production expands and alternatives become testable	Multiple differentiated candidate propositions can be produced and revised efficiently	Which candidate deserves commitment	Credible customer response, behavioral evidence, or disciplined market tests become more important	Selection pressure moves downstream	Conditions are consistent with relocation toward validation
Production and validation both scale	Candidate production and credible external testing become faster or cheaper together	Later-stage feasibility, distribution, legitimacy, regulation, or implementation	Validation ceases to be the uniquely dominant constraint	Constraint moves elsewhere or remains distributed	Focal relocation weakens or fails
Production expands faster than validation capacity	Candidate supply rises while credible external testing remains access-, time-, or attention-constrained	Which alternatives correspond to sufficiently strong market demand	Scarce access to relevant customers, contexts, experiments, and interpretable signals	More candidates compete for limited validation opportunities	Strongest condition for the proposed relocation

Increasing Scarcity of Credible Market Validation

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

The weakening of a production constraint does not make every downstream signal equally informative. A central criticism of entrepreneurial experimentation is that ventures may privilege questions for which feedback is readily observable, encouraging incremental tests while leaving deeper assumptions less examined [24]. Credible validation therefore concerns the relationship between evidence and the uncertainty being tested. A large amount of easy-to-produce feedback can remain strategically weak if it does not discriminate among consequential alternatives.

Longitudinal evidence from 152 early-stage teams reinforces this distinction. Hypothesis formulation, probing, convergence, and team composition jointly shaped how ventures learned through Lean Startup practices [25]. Validation thus requires more than exposure to feedback. It requires a sufficiently precise conjecture, an informative test, and organizational capacity to interpret the result. GenAI may help formulate hypotheses or design test materials, but those contributions do not ensure that the resulting observations come from the relevant market actors or reveal actual willingness to adopt, pay, switch, persist, or recommend.

Digital startups already operate through iterative customer-development and Lean Startup practices, yet mixed-method evidence also documents practical limitations in how these approaches are implemented [26]. Such limitations become more important when candidate production accelerates. If a venture can create many plausible variants in the time previously required to create one, the number of alternatives seeking customer attention and experimental exposure can rise without a comparable increase in the availability of high-quality external tests. Validation capacity can consequently become more selective even when prototyping capacity becomes more abundant.

Evidence from failed crowdfunding campaigns demonstrates why the distinction between market validation and other forms of approval matters. Experimental and longitudinal analyses found that market validation after failure influenced persistence and subsequent performance differently from expert validation [27]. Crowdfunding is only one institutional setting, so its signals cannot stand in for every market. The broader implication is that external market response has a distinct entrepreneurial function: it can change whether founders continue, revise, or abandon a course of action. Such evidence cannot be generated simply by producing another internally plausible prototype.

Credible market validation is therefore defined here as externally grounded, decision-relevant evidence that reduces uncertainty about whether a candidate offering merits continued entrepreneurial commitment. Its scarcity has several possible sources: access to relevant customers, the time required for real behavior to become observable, competition for attention, the cost of running discriminating experiments, the difficulty of separating curiosity from commitment, and the organizational capability needed to interpret ambiguous feedback. These sources are not assumed to intensify in every market. They become theoretically central when the supply of candidates grows faster than the venture’s capacity to obtain and interpret credible market evidence.

The relocation thesis at this stage is deliberately conditional. GenAI can loosen the constraint on candidate production while leaving validation capacity comparatively fixed, in which case entrepreneurial scarcity shifts downstream. If GenAI, digital platforms, simulation, or automated experimentation also expand credible validation at a similar or faster rate, the shift weakens or disappears. The next analytical task is therefore to identify the resources that determine who can convert prototype abundance into credible market learning and how those resources shape competitive selection.

Validation Resources and Competitive Selection

If prototype production becomes easier while credible market testing remains unevenly accessible, competitive differences increasingly depend on complementary resources. Evidence from a large deployment of generative AI to 5,172 customer-support agents illustrates the broader principle: productivity gains were heterogeneous and depended on prior skill and the kinds of problems workers encountered [28]. The transferable implication is not the study’s particular performance magnitude, which belongs to customer-support work. It is that access to a capable AI system does not equalize the complementary knowledge required to convert that system into productive action.

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

Firm-level evidence makes the same point at a different level of analysis. European SME research associates AI and robotics adoption with innovation outcomes while also showing that firms differ substantially in the conditions surrounding adoption [29]. Research combining managerial interviews with longitudinal corporate data similarly links strategic AI orientation to technological innovation [30]. These studies concern innovation more broadly rather than entrepreneurial validation specifically, but they establish that technological availability and organizational capacity are analytically separable.

Validation capacity can consequently become a source of competitive selection. Its components extend beyond technical AI capability to customer access, testing environments, contextual data, experimental skill, managerial attention, and the ability to interpret ambiguous signals. Research using large-scale corporate communication data further suggests that managerial attention to responsible AI is associated with innovation under identifiable organizational conditions [31]. Governance is not itself market validation, yet the finding reinforces the complementarity principle: organizational attention and institutionalized practices affect whether technological capacity can be converted into useful innovation activity.

The implication for entrepreneurial scarcity is comparative. When two ventures can generate similar quantities of plausible prototypes, advantage may increasingly turn on which venture can expose those alternatives to informative market situations, recognize which signals are credible, and allocate resources after receiving them. Tool access then becomes a weaker discriminator than the resources surrounding validation.

Entrepreneurial Scarcity Relocation Framework

A larger supply of information does not necessarily eliminate the scarcity relevant to entrepreneurial choice. The concept of isotropy emphasizes that decision makers may possess extensive information while remaining unable to determine which information is relevant to the decision at hand [32]. Under GenAI, this distinction becomes particularly important because entrepreneurs can obtain more generated alternatives, explanations, comparisons, and simulated responses without obtaining proportionately more evidence about actual customer behavior.

Abundance can also produce collective effects different from its individual-level benefits. Entrepreneurship theory examining AI-enabled ecosystems warns that increased individual generative productivity can coexist with reduced variation across entrepreneurial outputs [33]. Empirical evidence from corporate innovation similarly reports a double-edged pattern in which GenAI can support catch-up innovation while inhibiting leading-edge innovation under some conditions [34]. More generated material therefore cannot be treated as a monotonic expansion of economically meaningful opportunity variety.

The construct developed here defines entrepreneurial scarcity relocation as a change in the stage at which the most binding constraint on credible entrepreneurial progress is located. Three elements are necessary. First, a previously restrictive activity must become materially less binding; in the focal case, candidate idea and prototype production becomes easier. Second, an adjacent activity must remain relatively constrained; here, credible external validation does not scale at the same rate. Third, the change must alter entrepreneurial observation or choice: ventures begin to differ more strongly in their ability to secure, interpret, and act on market evidence than in their ability to generate additional candidate propositions. Relocation therefore concerns relative constraint, not an absolute declaration that one resource is scarce and another abundant.

The resulting construct can be identified only by locating the constraint that remains binding after generative capacity changes, while separating adjacent conditions that can mimic relocation.

The relationships discussed here are shown in **Figure 1**.

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

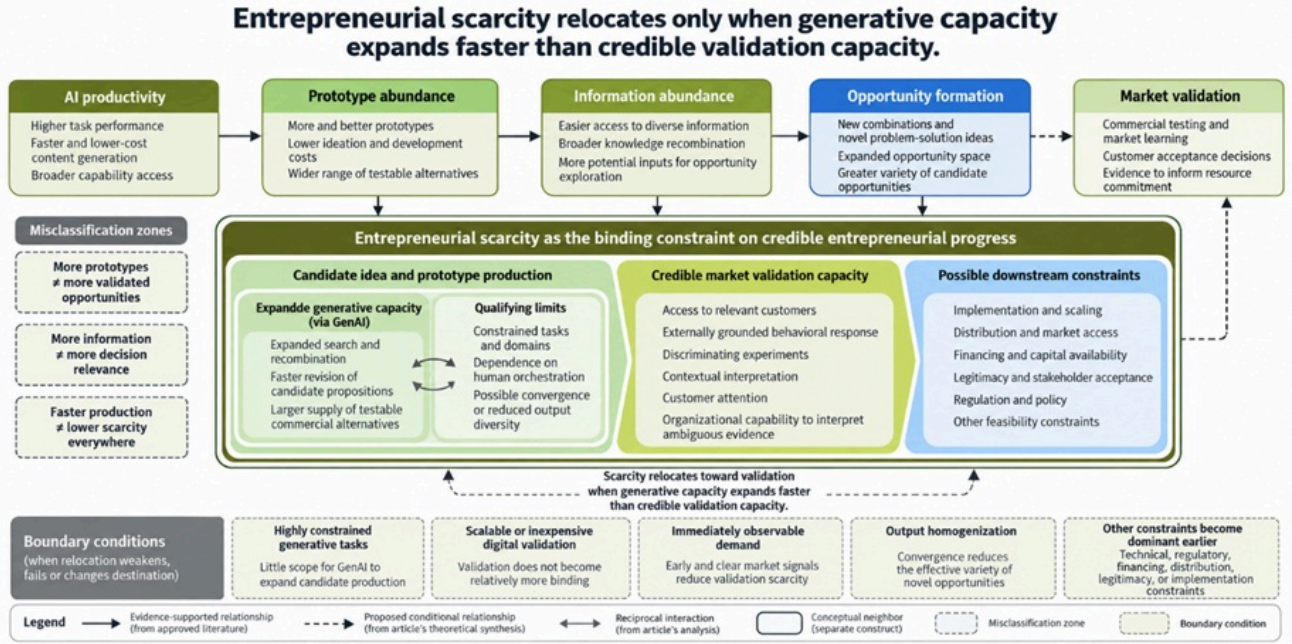

Figure 1. Entrepreneurial scarcity relocates only when generative capacity expands faster than credible validation capacity

Relocation nevertheless remains only one possible configuration. If market validation becomes nearly as scalable as generation, neither activity need become the dominant constraint. If generated alternatives converge, meaningful ideational differentiation may remain scarce despite high output volume. If technical feasibility, regulation, financing, distribution, or legitimacy becomes binding first, scarcity moves elsewhere. The same improvement in generative capability can therefore create several theoretically distinct scarcity locations.

The same increase in GenAI capability can consequently produce different entrepreneurial scarcity configurations depending on how credible validation capacity and downstream constraints respond **(Table 2).**

Table 2. Scarcity-location configurations implied by GenAI-enabled changes in candidate production

Scarcity-location configuration	Generative candidate supply	Credible market-evidence capacity	Binding entrepreneurial constraint	Distinctive observation	Predicted source of venture divergence
Generation-bound	Remains difficult, specialized, or insufficiently differentiated	Available relative to candidate supply	Producing credible alternatives	Few genuinely testable options emerge	Generative expertise and domain knowledge
Validation-bound	Expands materially	Grows more slowly or remains rival/access-constrained	Obtaining decision-relevant external evidence	Many plausible candidates compete for limited informative tests	Customer access, experimentation capability, interpretation quality

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

Jointly loosened	Expands materially	Expands at a comparable rate	Neither generation nor validation dominates	Rapid generation is matched by rapid credible testing	Later-stage execution capability
Downstream displacement	Expands	Is adequate for major uncertainties	Implementation, distribution, finance, legitimacy, regulation, or feasibility	Evidence supports an offering, yet commercialization remains blocked	Control of downstream complementary resources
Convergent-output constraint	Volume expands but meaningful differentiation does not	Potentially adequate	Distinctive opportunity formation remains limiting	Numerous outputs cluster around similar solutions	Ability to create genuinely differentiated alternatives

Propositions

The reconceptualization yields propositions about relative constraints rather than universal effects of AI.

Proposition 1. When GenAI increases the rate or lowers the cost of producing differentiated, testable commercial prototypes more strongly than it increases the capacity to obtain credible market evidence, the binding entrepreneurial constraint will shift toward market validation.

This proposition requires a relative comparison. A rise in prototype output alone is insufficient evidence of relocation because idea quality can remain poor, generated alternatives can converge, or validation capacity can expand simultaneously.

Proposition 2. The relocation of entrepreneurial scarcity toward market validation will be weaker when credible external testing is digitally scalable, inexpensive, rapidly observable, or substantially augmented by the same AI-enabled capabilities that expand prototype production.

The focal theory is therefore falsifiable. In markets where behavioral demand signals can be generated rapidly and credibly for many alternatives, validation need not become the dominant constraint.

Proposition 3. Under conditions of prototype abundance, ventures with superior access to relevant customers, discriminating experiments, contextual data, and interpretive capability will convert generative capacity into credible market learning more effectively than ventures possessing comparable GenAI generation capability but weaker validation resources.

The predicted divergence concerns learning and resource commitment, not simply the number of artifacts produced.

Proposition 4. When GenAI expands output volume while reducing meaningful differentiation among alternatives, entrepreneurial scarcity will remain partly located in opportunity formation rather than relocating cleanly to market validation.

This proposition distinguishes apparent abundance from economically meaningful option variety and prevents output counts from becoming a proxy for reduced ideational scarcity.

Entrepreneurship Implications

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

The reconceptualization changes how AI-enabled entrepreneurship should be studied. Multidisciplinary work on generative AI already identifies simultaneous productivity opportunities and problems involving credibility, transparency, bias, governance, and responsible use [35]. Entrepreneurship research can extend this insight by measuring where the binding constraint sits rather than assuming that higher generative productivity represents a proportional expansion of entrepreneurial opportunity.

Empirical studies should therefore distinguish candidate-output capacity from credible-validation capacity. Measures such as number of ideas, prototypes, prompts, or iterations capture generative throughput but do not reveal whether ventures have acquired decision-relevant market evidence. Research designs could instead compare the rate at which candidate alternatives are produced with access to relevant customers, the availability of discriminating experiments, the quality of external behavioral signals, and the speed with which uncertainty about continued commitment is reduced. The important theoretical variable is the relative bindingness of these activities.

The argument also changes the interpretation of democratization. Cheaper prototype production may widen participation in entrepreneurial experimentation while simultaneously increasing the strategic value of resources that remain difficult to scale. If customer attention, distribution access, high-quality data, trusted relationships, or credible testing environments remain concentrated, generative democratization can coexist with validation inequality. At ecosystem level, researchers should therefore test separately whether AI widens entry, changes diversity, and redistributes access to market proof.

For entrepreneurs and organizations, the implication is not to reduce investment in ideation. It is to avoid treating generative capacity as sufficient evidence of entrepreneurial progress. Where candidate production is no longer the dominant bottleneck, additional effort directed at generating more variants may produce lower learning returns than investment in customer access, experiment design, signal interpretation, and market-facing infrastructure. The relevant resource-allocation question becomes which unresolved constraint currently prevents credible movement to the next entrepreneurial commitment.

Conclusion

Generative AI can make commercial candidate production substantially less restrictive, but it does not follow that entrepreneurial scarcity disappears. The more defensible conclusion is conditional: scarcity can relocate when GenAI relaxes the constraint on producing differentiated prototypes faster than it relaxes the constraint on obtaining credible market evidence.

This reconceptualization separates prototype abundance from validated opportunity and treats entrepreneurial scarcity as the location of the binding constraint on credible progress. In some settings that constraint will move toward customer access and market experimentation; in others it will remain in idea differentiation or shift further downstream toward implementation, distribution, financing, legitimacy, regulation, or technical feasibility. The theoretical contribution therefore lies in asking where scarcity is binding after generative capacity changes, rather than assuming that increased output has removed scarcity from entrepreneurship.

Acknowledgements

None

Conflict of interest

None

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

Financial support

None

Ethics statement

None

Received: 04 Aug 2025 Revised: 09 Oct 2025 Accepted: 25 Oct 2025
Published online: 18 September 2026

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at https://creativecommons.org/licenses/by-nc-sa/4.0/.

References

1. Nambisan S. Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. Entrep Theory Pract. 2017;41(6):1029-55. https://doi.org/10.1111/etap.12254.

2. Blank S, Eckhardt JT. The Lean Startup as an actionable theory of entrepreneurship. J Manage. 2024;50(8):3012-34. https://doi.org/10.1177/01492063231168095.

3. Makowski PT. Optimizing concepts: Conceptual engineering in the field of management—the case of routines research. Acad Manage Rev. 2021;46(4):702-24. https://doi.org/10.5465/amr.2019.0252.

4. Autio E, Nambisan S, Thomas LDW, Wright M. Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. Strateg Entrep J. 2018;12(1):72-95. https://doi.org/10.1002/sej.1266.

5. Obschonka M, Audretsch DB. Artificial intelligence and big data in entrepreneurship: A new era has begun. Small Bus Econ. 2020;55(3):529-39. https://doi.org/10.1007/s11187-019-00202-4.

6. Norbäck PJ, Persson L. Why generative AI can make creative destruction more creative but less destructive. Small Bus Econ. 2024;63(1):349-77. https://doi.org/10.1007/s11187-023-00829-4.

7. Nafizah UY, Roper S, Mole K. Estimating the innovation benefits of first-mover and second-mover strategies when micro-businesses adopt artificial intelligence and machine learning. Small Bus Econ. 2024;62(1):411-34. https://doi.org/10.1007/s11187-023-00779-x.

8. de Jong JPJ, Mulhuijzen M, Merfeld K, Rigtering C, van Balen T, Boënne M. Industrial product development with lead users as a source of Schumpeterian opportunity. J Prod Innov Manag. 2024;41(6):1165-83.

https://doi.org/10.1111/jpim.12739.

9. Camuffo A, Cordova A, Gambardella A, Spina C. A scientific approach to entrepreneurial decision making: Evidence from a randomized control trial. Manage Sci. 2020;66(2):564-86. https://doi.org/10.1287/mnsc.2018.3249.

10. Shepherd DA, Gruber M. The Lean Startup framework: Closing the academic-practitioner divide. Entrep Theory Pract. 2021;45(5):967-98. https://doi.org/10.1177/1042258719899415.

11. Mariani M, Dwivedi YK. Generative artificial intelligence in innovation management: A preview of future research developments. J Bus Res. 2024;175:114542. https://doi.org/10.1016/j.jbusres.2024.114542.

12. Roberts DL, Candi M. Artificial intelligence and innovation management: Charting the evolving landscape. Technovation. 2024;136:103081. https://doi.org/10.1016/j.technovation.2024.103081.

13. Gama F, Magistretti S. Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. J Prod Innov Manag. 2025;42(1):76-111. https://doi.org/10.1111/jpim.12698.

14. Teng D, Ye C, Martinez V. Gen-AI's effects on new value propositions in business model innovation: Evidence from information technology industry. Technovation. 2025;143:103191. https://doi.org/10.1016/j.technovation.2025.103191.

15. Chu W, Baxter D, Liu Y. Exploring the impacts of generative AI on artistic innovation routines. Technovation. 2025;143:103209. https://doi.org/10.1016/j.technovation.2025.103209.

16. Pedota M, Cicala F, Basti A. Human agents, generative AI, and innovation: A formal model of hybrid creative process. Technovation. 2025;148:103323. https://doi.org/10.1016/j.technovation.2025.103323.

17. Vallé R, Seitz J, Kanbach DK, Schuhmacher MC. The use of artificial intelligence in new product development: A systematic literature review, conceptual framework, and future research agenda. Technovation. 2026;153:103541. https://doi.org/10.1016/j.technovation.2026.103541.

18. Dell'Acqua F, Ayoubi C, Lifshitz H, Sadun R, Mollick E, Mollick L, et al. The cybernetic teammate: A field experiment on generative AI and teamwork. Organ Sci. 2026;37(4):1217-42. https://doi.org/10.1287/orsc.2025.20702.

19. Doshi AR, Hauser OP. Generative AI enhances individual creativity but reduces the collective diversity of novel content. Sci Adv. 2024;10(28):eadn5290. https://doi.org/10.1126/sciadv.adn5290.

20. Sun S, Li ZA, Foo MD, Zhou J, Lu JG. How and for whom using generative AI affects creativity: A field experiment. J Appl Psychol. 2025;110(12):1561-73. https://doi.org/10.1037/apl0001296.

21. Sorin N, Pagani M. The role of task breadth and cognitive flexibility in generative AI-supported creative idea generation. Technovation. 2026;153:103540. https://doi.org/10.1016/j.technovation.2026.103540.

22. Lehmann SL, Dahlke J, Pianta V, Ebersberger B. Artificial intelligence and corporate ideation systems. J Prod Innov Manag. 2026;43(1):160-85.

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies

https://doi.org/10.1111/jpim.12782.

23. Noy S, Zhang W. Experimental evidence on the productivity effects of generative artificial intelligence. Science. 2023;381(6654):187-92. https://doi.org/10.1126/science.adh2586.

24. Felin T, Gambardella A, Stern S, Zenger T. Lean startup and the business model: Experimentation revisited. Long Range Plann. 2020;53(4):101889. https://doi.org/10.1016/j.lrp.2019.06.002.

25. Leatherbee M, Katila R. The lean startup method: Early-stage teams and hypothesis-based probing of business ideas. Strateg Entrep J. 2020;14(4):570-93. https://doi.org/10.1002/sej.1373.

26. Ghezzi A. Digital startups and the adoption and implementation of Lean Startup Approaches: Effectuation, bricolage and opportunity creation in practice. Technol Forecast Soc Change. 2019;146:945-60. https://doi.org/10.1016/j.techfore.2018.09.017.

27. Stevenson R, Allen J, Wang T. Failed but validated? The effect of market validation on persistence and performance after a crowdfunding failure. J Bus Ventur. 2022;37(2):106175. https://doi.org/10.1016/j.jbusvent.2021.106175.

28. Brynjolfsson E, Li D, Raymond LR. Generative AI at work. Q J Econ. 2025;140(2):889-942.

29. Segarra-Blasco A, Tomàs-Porres J, Teruel M. AI, robots and innovation in European SMEs. Small Bus Econ. 2025;65(1):719-45. https://doi.org/10.1007/s11187-025-01017-2.

30. Eicke AK, Sabel CA, Nüesch S. Strategic AI orientation and technological innovation: Evidence from managerial insights and panel data. J Prod Innov Manag. 2026;43(2):262-89. https://doi.org/10.1111/jpim.70001.

31. Xiong M, Xu H, Ji J, Zuo R, Wang Y, Olya H. Responsible artificial intelligence attention and firm innovation: An attention-based view. J Prod Innov Manag. 2026;43(1):186-214. https://doi.org/10.1111/jpim.70015.

32. Bhuwania A, Sarasvathy SD. Isotropy: Knowing when and how to pivot. J Bus Ventur Insights. 2026;25:e00592. https://doi.org/10.1016/j.jbvi.2026.e00592.

33. Hunt RA, Kurdoglu RS. Font of innovation or algorithmic deforestation? The ecosystem impacts of artificial intelligence in entrepreneurship. J Bus Ventur Insights. 2025;24:e00575. https://doi.org/10.1016/j.jbvi.2025.e00575.

34. Zhang X, Yang M, Hu Y, Wang Y, Wu W. The “double-edged sword” effect of generative AI applications on corporate innovation. Technovation. 2026;154:103561. https://doi.org/10.1016/j.technovation.2026.103561.

35. Dwivedi YK, Kshetri N, Hughes L, Slade EL, Jeyaraj A, Kar AK, et al. Opinion paper: “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. Int J Inf Manage. 2023;71:102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642.

© 2026 The Author(s). | Published by Institute for Management, Business, and Accounting Studies