iEducation, 2026, 2(1), 69-79
https://doi.org/10.71204/pa99ky74

Paradigm Reconstruction of University Entrepreneurship Education in the AI Era

Zhifang Fan [1, *]

[1] Xinzhou Normal University, Xinzhou 034000, China

*** Correspondence:**

Zhifang Fan

ashlyfan@qq.com

Received: 9 February 2026 / Accepted: 5 May 2026/ Published online: 6 May 2026

Abstract

This paper proposes a conceptual framework for reconstructing university entrepreneurship education in response to the emergence of Artificial Intelligence Generated Content (AIGC). Drawing on the philosophy of technology and educational sociology, this paper argues that the displacement of routine entrepreneurial functions by AI necessitates a paradigm shift — from instrumental rationality to Symbiotic Rationality, and from generic creativity to adaptive, context-specific competencies. The proposed framework operates across three dimensions: cultivating innovation ecosystem participants rather than standalone entrepreneurs; developing situated capabilities, including critical AI literacy, value-rational decision-making, and interpersonal intelligence; and reorienting pedagogy toward real-world intervention through entrepreneurship laboratories. To assess these outcomes, this paper introduces a three-dimensional evaluation framework comprising process indicators, capability measures, and impact assessments, grounded in Whitehead's process philosophy, Dewey's pragmatism, and Value Sensitive Design. The framework centers on Adaptive Innovation Capacity (AIC) as its core construct, offering a theoretically integrated response to the pedagogical challenges of the AI era.

Keywords: Artificial Intelligence; Entrepreneurship Education; Paradigm Reconstruction; Adaptive Innovation Capacity; Symbiotic Rationality

1. Introduction

The emergence of AIGC technology challenges the existing mode of instruction in entrepreneurship education, as many business-related work can be done by current AIGCs, such as writing plans, conducting market analysis or developing innovative ideas. The technology poses challenges to the teaching methods used traditionally. The conventional model of entrepreneurship education is linear. Opportunity identification, then planning, and finally fundraising. But AI systems do the same thing today more efficiently at a lower cost. This raises questions about why there is a need for an entrepreneur education that focuses on people, rather than other approaches to business innovation.

AI not only helps automate activities but also transforms entrepreneurship by altering the ways in which entrepreneurs work with skills that were perceived to be the cornerstone of conventional courses like S. W. O. T. analysis, financial planning, and strategic decision making. Modern-day AIs are capable of producing technically adequate business plans in a very short period. Universities that keep training students in the standardized ways of entrepreneurship will see what they teach rendered obsolete by increasingly capable AIs. This paradox challenges us to rethink what should be taught. Today's reality involves substantial uncertainty, and collaboration between people and computers. It is, therefore, an urgent task to identify educational elements which are not simply imitable through technology.

This paper proposes to change the focus from teaching students how to do things to be able to create value by quickly building prototypes and gaining experience-based knowledge in complex, changing, uncertain contexts. However, AI is not as flexible compared with the human brain. Firstly, humans are able to handle uncertain scenarios which cannot be modeled with probability distributions. Furthermore, human decisions involve complex ethics depending on the context. In addition, humans can radically change the problem, or redefine it, while AI tends to be limited to specific goals.

Dell'Acqua et al. (2023) document that AI does well with highly structured problems but it fails in tasks that require deeper understanding. The result is a complex set of competencies where entrepreneurs must develop Adaptive Decision-Making Competency, which means knowing when to apply the benefits of artificial intelligence and when not to rely on it. Existing scholarship has begun to address AI's role in entrepreneurship education from several angles. Kuratko (2005) traces the historical development of entrepreneurship education, highlighting its predominantly skills-based orientation. More recently, Chalmers et al. (2021) explore how AI reshapes venture creation in the Fourth Industrial Revolution, while Dell'Acqua et al. (2023) demonstrate empirically that AI augments productivity when used critically but diminishes performance when adopted uncritically. Despite these contributions, existing frameworks largely address AI as a tool to be integrated into existing curricula rather than as a force that demands fundamental pedagogical reconstruction. The specific limitations of prevailing educational theories in responding to AIGC—particularly their inability to cultivate judgment under uncertainty, ethical reasoning in human-AI collaboration, and ecosystem-level thinking—remain insufficiently theorized.

Therefore, how should university entrepreneurship education be reconstructed in response to AIGC? More specifically, what theoretical foundations, educational objectives, curriculum content, teaching methods, and assessment approaches are required? This paper develops a conceptual framework integrating the philosophy of technology and educational sociology to address these questions.

2. Theoretical Framework

2.1. From Instrumental Rationality to Symbiotic Rationality

Conventional entrepreneurship pedagogy relies upon the notion of Instrumental Rationality, which breaks down the process of creating a company into steps that can be taught, replicated, and learned. The limitations of this approach have been brought out by the rise of artificial intelligence. Entrepreneurship depends on tacit knowledge, responds to contextual factors, and includes judgmental elements. To define them as skills which are quantifiable misses the point.

According to Heidegger (1977), technology enframes the understanding of the world, reducing beings to resources available for optimization. Applying this to AI in education, an instrumentalist approach reduces students to skill-processors and entrepreneurship to an executable algorithm. Moving beyond this enframing does not mean rejecting AI. It means cultivating what Heidegger calls *Gelassenheit*—a disposition of openness that preserves human agency and judgment. Pedagogically, this translates into designing learning environments that deliberately create space for reflection, ethical deliberation, and value-driven decision-making—capabilities that resist algorithmic substitution. This kind of theory calls for Dynamical Plasticity. The model goes beyond pure functional logic, and calls for business innovators to retain critical thinking, inspiration, and a sense of responsibility towards the use of artificial intelligence. This new mindset is empirically supported. Dell'Acqua et al. (2023) find that humans boost their productivity by almost 40% if they use artificial intelligence cleverly. On the other hand, students that used AI irresponsibly saw a significant drop in performance. As a result, the teaching goal can be reoriented, where instead of training entrepreneurs who operate AI tools, teaching how to cope in this ever more complicated world is more important. Symbiotic Rationality is introduced here. It views users not as passive consumers but rather as active partners in shaping the ways that technologies are integrated into innovative activities.

2.2. The Turn Toward Innovation as Social Practice

The change in perspective to Symbiotic Rationality affects the relationship toward technologies. However, this point of view should be completed by a sociology approach, because entrepreneurship is socially constructed in organizational contexts. Pierre Bourdieu's theory offers some useful instruments to do so. In the conceptualization of Bourdieu (1990), social systems work in a multitude of semi-autonomous fields. Instead of being individual inventors, entrepreneurs compete inside specific entrepreneurial ecosystems defined by certain rules. They choose strategies that depend on their status, as well as the resources. The advent of AI creates new forms of capital relating to data and algorithms fundamentally altering the logic of competition.

In the social scientific sense, Adaptive Innovation Capacity (AIC) is not simply a personal attribute. It entails knowing how industries evolve over time and deciding what actions to take. AIC consists of three interrelated dimensions. The first dimension is related to the analysis of industrial models. The entrepreneurs must understand how AI changes money flows. The business rules of their industry; opportunities they may pursue along with constraints. The second part is about uniqueness. It refers to identifying a sustainable niche given the resource, rather than following algorithmic recommendations. Entrepreneurs must leverage distinct human attributes that are not easily imitable by AI. Third, the practice needs to be reoriented. Entrepreneurs create new rules: new relationships, new tools or techniques. They do not follow existing standards, but aim at changing those.

This sociological approach complements the philosophical underpinning described above; together, they provide an overarching narrative. Both individual judgment and situational understanding are cultivated. Building on these philosophical and sociological foundations, AIC operates through three dimensions—field analysis, situated judgment, and iterative learning—that directly structure the educational reconstruction in the following sections.

3. Educational Framework Transformation

The incorporation of artificial intelligence into entrepreneurial settings calls for a paradigm shift. In other words, where past paradigms have focused on training managers in engineering skills, today's paradigm seeks to produce creators who can collaborate effectively with machines. The change is not only conceptual, but also relates to new meanings of entrepreneurship. Coursework built on outdated understandings of the relationship between people and technology may be training students for a world that has already passed us by. In the following, three dimensions will be discussed.

3.1. From Training Entrepreneurs to Cultivating Innovation Ecosystem Participants

Traditional entrepreneurship usually has an end goal in mind—starting new enterprises. However, AI changes what it means to be an entrepreneur. The incremental cost of invention approaches zero, starting a standalone business is only part of a larger set of options available. New forms of collaboration between humans and artificial intelligence create new types of entrepreneurship which are not easily categorized, generating so-called augmented entrepreneurial personhood patterns.

The changing environment demands cultivating so-called ecosystem participants who are able to manage complex innovation ecosystems rather than starting a business themselves. Three key attributes differentiate these ecosystem participants.

Firstly, they are sensors for useful information and possible opportunities. They can identify new demands arising from AI adoption. They see these problems as a way to drive the development of new technologies

Secondly, AI became an important production factor, fundamentally changing what is important for firm success: How one manages, coordinates dispersed resources matters far more than having those resources (Helfat & Peteraf, 2003). It resembles more like a conductor leading the symphony as creating value through coordination of human and AI agents.

Third, throughout the process of innovating, they rely on adaptive methods. The frequency of dynamic innovation practices needs to be observed.

3.2. From Knowledge Transmission to Situated Capability Generation

Driven by the shift towards symbiotic rationality, universities will have to stop teaching how to write a standardized business plan or do competitive market analysis and start teaching, building capabilities to recognize the emergence of new technology/social shifts, orchestrating distributed resources toward specific objectives, and adjusting plans based on real-world results. Traditional entrepreneurship training is based on the assumption of a known business context, teaching students how to write business plans, internal analysis using SWOT matrices, marketing planning. Those analytical skills are structured and can therefore be recorded and duplicated. Today, as these tasks are outsourced to machines, skills training should be focused on skills which are hard to automate or in which human advantages will show through. Teaching students the use of technologies such as ChatGPT is not sufficient for building technology literacy. As shown in Long & Magerko (2020), the general definition of AI covers a range of abilities such as—but not restricted to—the ability to critically analyse the application of AI: work effectively with intelligent systems, and use the technology ethically in different contexts. These ideas must be reflected in the business curriculum. Students must be taught how to evaluate issues like fairness, transparency, and accountability in computing technologies. For example, recommendation engines promote echo chambers because they repeatedly recommend similar content to people. Concrete, real-world examples are employed to enhance learners' understanding of the practical implications associated with diverse systems-level design decisions.

An important perspective here is the Social Shaping of Technology approach: technology does not develop in a neutral, inevitable manner. Instead, social factors such as authority relations, culture, or economics shape not only the technology but also its adoption practices Williams & Edge, (1996). That knowledge allows a CEO or other decision-maker to put ethics ahead of what is technically possible. Acknowledging cognitive bias adds a new layer to technological literacy, as people tend to have preferences for thinking: e.g., confirmation bias, machine learning algorithms may inherit and even amplify biases present in the data they are trained on. It is essential to equip students with how to recognize these biases within themselves as well as the technologies developed, and how to mitigate or avoid biased outcomes of technology.

With the development of intelligent algorithms, the ability to make complex decision-making and ethics will be more important. AI can rapidly generate multiple feasible solutions and predict the probability of each solution's success or failure. At this point, humans' roles change from providing solutions to making decisions. While the central challenge is no longer identifying feasible solutions but selecting the optimal one among them.

In this regard, courses need to highlight the role that values play when making decisions and choices. There are at least two forms of rationality according to Weber (1978): instrumental rationality, which aims for a specific goal with maximal efficiency, and the rationality of values, which means acting morally regardless of consequences. Education today needs to teach both kinds of rationality. In particular, future workers must learn how to weigh ethical considerations and social implications in addition to economic productivity when making decisions. Students should be able to react quickly and decisively in unprepared, emergency circumstances. Young people need to learn how to use intuition, experience, and values in making timely decisions where deferral is not possible.

Emotional intelligence and relationships with people are two aspects that AI can't currently match. Good leadership and teamwork. Innovative startups gather teams of individuals with different skills: technical specialists, designers, developers, marketing staff, product managers, and executives. Both understanding users' emotion states as well as discovering latent user needs require different skills: while analyzing behavioral data reveals patterns of what is observable, often misses the big motivations and mental processes. Ethnographic methods such as in-depth interviews and the elicitation of unstated needs which may be unknown to the user himself/herself. While AI can easily identify patterns in existing data, it may not account for those subtle feelings and emotions, which can also play a major role in influencing consumers' purchase decisions.

At every stage in the process of innovation, negotiation and conflict mediation skills are essential, as innovation contexts involve complex webs of actors with multiple viewpoints. The future demands consensus in the face of disagreement. Such difficult conversations demand advanced communication skills that acknowledge the tension, personalize the provision of information for particular constituencies, and find creative solutions that meet several goals at once.

These capabilities—particularly ethical decision-making and value-rational judgment—form the core competencies that the assessment framework in the following section is designed to measure.

3.3. From Artificial Exercise to Practice

The focus must shift toward applied learning, defined here as learning based on direct experience with the processes involved in making things and running a business.

Today's project teams are collaborative human-AI working environments. Mollick & Mollick (2023) recommend positioning AI as a teacher's assistant. Students learn how to distribute their cognitive loads effectively. It is capable of quickly coming up with a range of ideas for the solution and also simulates customers that test different aspects of proposed solutions. and additional scanning of the other papers in order to identify relevant concepts and connections. However, students retain the agency to identify problems, weigh ethical considerations, and reach conclusions.

Learning is a cyclical and iterative process that works from an affectation logic. The learning methodology supports a rapid feedback cycle of continuous building and assessment, and learning (Ries, 2011). Users build simple working models as quickly as possible. They learn through direct interaction with their users. They discover truths in the contrast between assumptions about how people will behave and what they actually do, leading to improved later generations. It is a learning loop based on experience and not just data acquisition.

This teaching strategy has its roots in well-established pedagogical theories. This strategy is rooted in experiential education (Dewey, 1997) and social constructivism (Vygotsky, 1978). Within a lab environment for entrepreneurship learning, students interact with AI agents and end-users, experts, or any number of stakeholders. Each interaction reveals different facets of a problem and different criteria for successful solutions.

For example, in a semester-long entrepreneurship laboratory, student teams might be assigned to address a real urban mobility challenge in three phases. In the first phase, like week 1 to 4, students use AI tools (e.g., ChatGPT, Perplexity) to conduct rapid market scans, while the instructor facilitates critical reflection sessions on AI output reliability. For the next phase, such as in weeks 5 to 12, students conduct ethnographic interviews with target users—a task deliberately withheld from AI—to surface latent needs. While the final phase, from weeks 13 to 16, teams iterate prototypes through build-measure-learn cycles, with AI agents simulating customer responses and faculty assessing the ethical reasoning embedded in design decisions.

4. Enhancing Curriculum Assessment Methodologies

The following approach is measured in terms of (a) ecosystem participation; (b) contextual skills acquisition and real-world applications outside the classroom environment. The proposed evaluation framework moves beyond traditional start-up metrics to assess the three capabilities central to AI-era entrepreneurship: ecosystem participation, situated competencies, and real-world intervention outcomes. Typically, entrepreneurial education has been measured by the traditional metrics of industry and manufacturing: for example, universities track start-up rates. Such quantitative measures offer simple, directly comparable information attractive to program developers. Yet such an assessment is far from complete. Traditional performance indicators capture only the most superficial and short-term learning results, ignoring indirect education effects, crucially, the complexity of human-AI interaction. Current metrics also fail to capture social outcomes and ethical dimensions. A far more fundamental weakness with end-result measurement is that it measures past achievement, i.e., it serves as a lagged indicator of observing the outcome of events without providing timely feedback for adjusting teaching practices. A paradigm shift in evaluation methodology is now warranted. It must capture multiple facets of evaluation, not just reduce achievement to numbers or simple metrics. It has to capture dynamic processes when they happen and not only evaluate the end outcome. It should also embed ethics within its design; not dealt with on the periphery. The most important thing is that such a new paradigm supports the development of what is called Adaptive Innovation Capacity. This paper presents an evaluation framework that is based on the following categories of indicators: process criteria, competence assessment, and impact assessment.

4.1. Developing a Multidimensional Assessment Framework

Traditional assessment instruments are focused on documenting what programs do, not evaluating how they adapt over time. This paper proposes a set of interrelated domains that focus on assessing AIC.

The behavioral axis captures the way in which learners deal with uncertainty and human-AI collaboration. Crucial indicators include the transition from blindly accepting AI outputs to critical interrogation. Similarly important are critical thinking skills wherein students can identify algorithmic bias, logical fallacies, and moral hazards. Project development documentation and reflection journals indicate if the student questions LLM outputs, or blindly accepts them.

Furthermore, refinement rate evaluation must be based upon learning content instead of the number of repetitions. The changes should reflect genuine evidence-based knowledge and not gut feeling posing as assessment. The focus is on whether human-AI interactions led to substantive improvements in the project's logic and viability

The developmental exam comprises several items to evaluate adaptability. Researchers can use existing instruments like the Cognitive Flexibility Scale (Dennis & Vander Wal, 2010) that tracks students' behaviors in response to uncertainty. Building on the ethical decision-making competencies introduced in Section 3.2, assessment here focuses on how students apply value-rational judgment in practice. Scenario-based tasks reveal whether students systematically deploy VSD methods — specifically, whether they can balance instrumental efficiency with ethical accountability when evaluating AI-generated recommendations. The impact dimension deals with broad impacts. Social value creation is not only about economics. Sustainability means whether the stakeholders consider long-term viability rather than ephemeral spectacle. A key metric is whether a project leads to collaboration between different stakeholders or encourages change in another stakeholder's behavior.

4.2. Integrated Utilization of Combined Research Techniques

Measurement is not possible with quantitative evidence alone; therefore, an integrated method that includes various kinds of evidence on both breadth and depth is required. While quantitative data (e.g., LMS activity logs, psychometric scales) provide baseline comparisons, they fail to explain why events happen or describe the nuances of human-AI processes.

The qualitative approach reveals dynamics, context effects etc. , which are not captured by quantitative analysis. Students must keep a log of his/her experience with the Human-AI co-innovation project. They contain information about decisions made at each step, the AI agent's communications issues faced, values, and teamwork behaviors. These stories undergo analysis using grounded theory coding, demonstrating how these adaptive innovative abilities develop in detail. Researchers are also observers who attend multiple semesters. The researcher captures real-time use cases of AI tools, detects changes due to unexpected events, and spots patterns of behaviour. To assess students' portfolios, a set of artifacts documenting students' learning journey is required. The artifacts can include questions showing increasing sophistication, participant discussion transcripts, iterative design changes based on feedback, and individual responsibility lists for ethical issues. These detailed logs create a story line for evaluators to track progress in skills through written evidence. Implementing this mixed-method approach requires faculty training in ethnographic observation and portfolio assessment to effectively measure the nuances of AI-integrated entrepreneurship.

4.3. Process Philosophy, Pragmatism, and an Ethically Aware Evolution

The proposed framework is oriented towards growth. It requires a radically new epistemology grounded in three theoretical pillars.

This model is built on Whitehead's process philosophy (1978). Process philosophy views reality as a network of dynamic events rather than static objects. In such an educational assessment paradigm, learning is a transformative experience per se. Students constantly produce themselves through interaction with AI, social networks. The idea of adaptive innovation capability is not something you can measure at the end of a programme—it's more something which emerges in doing the evaluation itself. It means that evaluation becomes the act of tracing lines of change rather than taking points in time.

Dewey's pragmatic philosophy (Dewey, 1997) emphasizes learning by doing. Assessment must occur as part of real world tasks and be formative. In teaching entrepreneurship in uncertain contexts, such formative evaluation method plays an important role.

Value Sensitive Design (Friedman et al. , 2017) ensures that ethical values form its foundation assessment. Ethical considerations should be incorporated into assessments by design, for example, when defining criteria that are to be assessed and establishing expectations at the beginning of a project or program. This encourages students to weigh ethical impact on society rather than treating ethics as an afterthought.

5. Conclusion

The impact of AI is not only a question of technology substitution, but an inflection point marking the limit of instrumental rationality. The disruptive nature of AI forces us to reevaluate education through the lens of symbiotic rationality. This model is based on three dimensions: Structural analysis situates technical innovation within social rules. Distinctiveness leverages unique human attributes, and practice redefinition fosters ethical intervention. To nurture Adaptive Innovation Capacity, universities must shift from information transmission to process-oriented assessment and real-world intervention.

However, this paper only offers a conceptual framework and does not present empirical validation. The proposed AIC construct and three-dimensional evaluation framework require empirical testing across diverse institutional and cultural contexts. Future research should examine implementation challenges, including teacher preparedness for ethnographic and portfolio-based assessment, institutional constraints on curriculum redesign, and the ethical risks of embedding AI agents within entrepreneurship laboratories. Longitudinal studies tracking the development of AIC across a full program cycle would further strengthen the evidence base for the proposed paradigm.

Author Contributions:

Conceptualization, Z.F.; methodology, Z.F.; software, Z.F.; validation, Z.F.; formal analysis, Z.F.; investigation, Z.F.; resources, Z.F.; data curation, Z.F.; writing—original draft preparation, Z.F.; writing—review and editing, Z.F.; visualization, Z.F.; supervision, Z.F.; project administration, Z.F.; funding acquisition, Z.F. All authors have read and agreed to the published version of the manuscript.

Funding:

This research received no external funding.

Institutional Review Board Statement:

Not applicable.

Informed Consent Statement:

Not applicable.

Data Availability Statement:

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments:

The author would like to thank Tingting Qiao for her support and assistance.

Conflict of Interest:

The author declares no conflict of interest.

References

Bourdieu, P. (1990). The Logic of Practice (R. Nice, Trans.). Stanford University Press.

Chalmers, D., MacKenzie, N. G., & Carter, S. (2021). Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution. Entrepreneurship Theory and Practice, 45(5), 1028-1053.

Dell'Acqua, F., McFowland, E., Mollick, E., et al. (2023). Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. Social Science Research Network, 24-013.

Dennis, J. P., & Vander Wal, J. S. (2010). The Cognitive Flexibility Inventory: Instrument Development and Estimates of Reliability and Validity. Cognitive Therapy and Research, 34(3), 241–253.

Dewey, J. (1997). Experience And Education. Kappa Delta Pi.

Dreyfus, H. L. (1992). What Computers Still Can't Do: A Critique of Artificial Reason. MIT Press.

Ellul, J. (1964). The Technological Society. Vintage.

Etzkowitz, H., & Leydesdorff, L. (2000). The Dynamics of innovation: from National Systems and “Mode 2” to a Triple Helix of University–industry–government Relations. Research Policy, 29(2), 109–123.

Friedman, B., Hendry, D. G., & Borning, A. (2017). A Survey of Value Sensitive Design Methods. Foundations and Trends® in Human–Computer Interaction, 11(2), 63–125.

Gartner, W. B. (1988). “Who Is an Entrepreneur?” Is the Wrong Question. American Journal of Small Business, 12(4), 11–32.

Habermas, J. (1971). Knowledge and Human Interests. Boston : Beacon Press.

Heidegger, M. (1977). The Question Concerning Technology (W. Lovitt, Trans. ; pp. 3–35). New York Harpercollins Publishers.

Helfat, C. E. , & Peteraf, M. A. (2003). The Dynamic resource-based view: Capability Lifecycles. Strategic Management Journal, 24(10), 997–1010.

Kuratko, D. F. (2005). The Emergence of Entrepreneurship Education: Development, Trends, and Challenges. Entrepreneurship Theory and Practice, 29(5), 577–598.

Long, D. , & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–16.

Mollick, E. R., & Mollick, L. (2023). Assigning AI: Seven Approaches for Students, with Prompts. The Wharton School Research Paper. https://doi. org/10. 2139/ssrn. 4475995

Polanyi, M. (1966). The Tacit Dimension. University of Chicago Press.

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

Sarasvathy, S. D. (2001). Causation and effectuation: Toward a theoretical shift from economic inevitability to entrepreneurial contingency. Academy of Management Review, 26(2), 243–263.

Schumpeter, J. A. (1934). The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle. New Brunswick (U.S.A.) London (U.K.) Transaction Publishers.

Shane, S. , & Venkataraman, S. (2000). The Promise of Entrepreneurship as a Field of Research. The Academy of Management Review, 25(1), 217–226.

Simon, H. A. (1996). The sciences of the artificial. The Mit Press.

Teece, D. J. (2007). Explicating Dynamic Capabilities: the Nature and Microfoundations of (Sustainable) Enterprise Performance. Strategic Management Journal, 28(13), 1319–1350.

Vesper, K. H. (1980). New Venture Strategies. Prentice Hall.

Vygotsky, L. S. (1978). Mind in Society: the Development of Higher Psychological Processes. Harvard University Press. https://w. pauldowling. me/rtf/2021. 1/readings/LSVygotsky_1978_MindinSocietyDevelopmentofHigherPsycholo. pdf

Weber, M. (1978). Economy and society: an Outline of Interpretive Sociology. University of California Press.

Whitehead, A. N. , Griffin, D. R. , & Sherburne, D. W. (1978). Process and reality : an essay in cosmology. Free Press.

Williams, R. , & Edge, D. (1996). The Social Shaping of Technology. Research Policy, 25(6), 865–899.