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The Theory-Based View and Strategic Pivots: The Effects of Theorization and Experimentation on the Type and Nature of Pivots

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Abstract. We examine how formalization in cognitive processes (theorization) and evidence evaluation (experimentation) influence the type (frequency and radicalness) and nature (impetus, clarity, and coherence) of entrepreneurial pivots. We use a mixed-method research design to analyze rich data from over 1,600 interviews with 261 entrepreneurs within a randomized control trial in London. A quantitative analysis that complements human-coded and machine learning-coded measures reveals that conditional on pivoting, theorization and experimentation are complementary in their association with making single radical pivots. The extensive qualitative-case comparison further elucidates interactions between theorization and experimentation that generate differences in the nature of pivots that range from *purposeful* (clear and coherent rationale deriving from articulated theory and experimentation), *postulatory* (informed by articulated theory but not incorporating nuances or surprises generated from experimentation), and *remedial* (stemming from adjustments to preformed theories that drew on prior experiences) to *reactive* (driven by environmental stimuli absent a clear theory of value). These insights contribute to the theory-driven strategic decision-making literature and offer practical insights for entrepreneurs, incubators, and policymakers on the benefits of a scientific approach to entrepreneurship.

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Introduction

When venturing into novel contexts, entrepreneurs and strategic decision makers confront various sources of uncertainty regarding the fit of their envisioned solutions to perceived problems (Packard et al. 2017, Moeen et al. 2020). Rarely is the original solution what is finally implemented, which is why pivots are a foundational concept in strategic decision making and entrepreneurial contexts (Ries 2011, Camuffo et al. 2020, Kirtley and O'Mahony 2023). Pivots occur when decision makers learn; such learning manifests in cognitive revisiting of mental representations, in beliefs or theories of how they can create and capture value (Csaszar and Levinthal 2016, Ott et al. 2017, Zellweger and Zenger 2023), or when actions provide evidence evaluated as important enough to alter strategies (Sarasvathy 2001, Baker and Nelson 2005, Pillai et al. 2020). To help entrepreneurs learn, scholars and practitioners have developed frameworks, such as the lean start-up (Ries 2011), the theory-based view (also called the scientific approach) (Camuffo et al. 2020, 2024; Zellweger and Zenger 2023), and entrepreneurial strategy (Gans et al. 2019).

Among these, the theory-based view emphasizes a high formalization in both cognitive processes and evidence evaluation. It encourages entrepreneurs to engage in theorization—develop a formal "theory of value" that articulates underlying assumptions, cause-effect linkages, and interdependencies (Felin and Zenger 2009, 2017; Ehrig and Schmidt 2022; Zellweger and Zenger 2023)—and in experimentation—formal efforts at gathering and evaluating evidence that supports or refutes these assumptions and conjectures (Camuffo et al. 2020). In randomized control trials (RCTs) to validate its efficacy (Camuffo et al. 2020, 2024; Agarwal et al. 2024b; Coali et al. 2024; Gagliardi and Novelli 2024; Novelli and Spina 2024), the scientific approach treatment has resulted in earlier terminations of low-value ideas and higher performance outcomes of ideas taken to fruition. When examining entrepreneurial pivots, scholars have focused on frequency and radicalness (changes in core value proposition), but other aspects of their nature have remained largely unaddressed. Moreover, in examining antecedents of radical pivots, scholars utilize a composite construct of higher scientific intensity by aggregating across higher levels of theorization and experimentation. We lack insights on whether theorization and experimentation are additive, substitutive, or complementary in their effect on pivots and whether pivots are qualitatively different across higher or lower levels of theorization or experimentation. Accordingly, we ask the following question. *How do formalization in cognitive processes (theorization) and formalization in evidence evaluation (experimentation) affect the type (frequency and radicalness) and nature (impetus, clarity, and coherence) of pivots?*

To answer these questions, we adopt a mixed-method research design to examine rich data from more than 1,600 interviews with 261 entrepreneurs over a nine-month period in the context of an RCT conducted in London in 2019 and 2020. First, we use human-coded and machine learning-coded measures to quantitatively examine the effect of the scientific approach intervention on theorization and experimentation and the associations of these learning mechanisms with pivots, separately and in conjunction with each other. Second, we use inductive case comparisons to build theoretical propositions on how and why theorization and experimentation interact with the other to impact the nature of pivots. To do so, we create 15 business histories by utilizing within and across variation and by theoretically sampling cases from treatment and control groups representing high or low scores for theorization and experimentation.

The quantitative analysis reveals that theorization and experimentation exhibit strong interdependencies in their associations with focused, radical pivots (engaging in one radical pivot rather than none or multiple pivots). Although greater formalization in either mechanism (in the absence of the other) is negatively associated with focused, radical pivots, the interaction term is strongly positive and significant for both human-coded and machine-coded measures. The qualitative case comparisons dig deeper for insights about the type of pivots. *Purposeful pivots* result when the scientific treatment encouraged entrepreneurs to dynamically evolve their theory through formal articulation of a theory of value and combine it with insights gained through experiments. *Postulatory pivots* arise when treated entrepreneurs formally articulated their theories but proceeded to implementation directly; these pivots lacked the clarity and nuances observed in the presence of formal experimentation. *Remedial pivots* occur because of direct implementation of predefined theories based on past experiences by control group entrepreneurs and subsequent adjustment of strategies; regardless of whether the entrepreneurs engaged in formal evidence evaluation or not, these pivots lack the depth observed from a dynamic evolution of theories of value. *Reactive pivots* stem from an absence of theorization that guides experimentation or implementation; these entrepreneurs responded to external stimuli to engage in frequent pivots that lacked the coherence and connectedness observed in purposeful pivots.

We contribute to research on a theory-driven approach to strategic decisions by showing that engaging in the process of articulating explicit linkages rather than implicit and preformed theories stemming from prior knowledge and experience (Shane 2000, Agarwal and Shah 2014), imagination or creativity (Rindova and Courtney 2020, Rindova and Martins 2023), and vision (Schilling 2018) may better overcome bounded rationality (Simon 1956) and cognitive biases (Tversky and Kahneman 1974, Posen et al. 2018). We also uncover high complementarities between the formalization of these two learning mechanisms. Absent formal theorization, strategic decision makers may find themselves limited in evaluating evidence gathered through formal experimentation (Cohen et al. 2019), leading to a lack of coherence within the core and complementary components of their business model (Agarwal et al. 2024b). Although scholars have noted that greater theorization may substitute for experimentation (Camuffo et al. 2024), we instead find strong complementarities, inasmuch as the two in tandem enable focused radical pivots, and these pivots are purposeful and truly strategic, leveraging evidence collection to arrive at detailed insights on linkages and uncover salience of originally overlooked linkages in their initial theories.

Practically, we contribute by creating novel machine-generated measures and crossvalidating these with human-coded measures. By creating a publicly available artificial intelligence (AI)-generated dictionary of words and algorithms, we provide formal machine learning techniques to scholars so that they can utilize and build on these in future related work. Our research also has important implications for practitioners (e.g., entrepreneurs, incubators/accelerators, and business leaders) and policymakers (e.g., government agencies, such as the National Science Foundation (NSF) and the National Institutes of Health (NIH)) that sponsor entrepreneurial and strategic training programs (e.g., iCorp). Although entrepreneurial individuals are encouraged to have a "bias for action" rather than "overanalyzing" potential paths forward, we show that a balanced approach with a focus on theory articulation *and* experimentation is likely to create purposeful pivots rather than unguided, uninformed, and overly reactive changes.

Theoretical Backdrop

Pivots in Business Models: A Pivotal Concept

Strategic decision making under uncertainty is pervasive and consequential in entrepreneurial/innovative contexts; it requires judgment in seeking and sifting through myriad and often contradictory information to create a point of view regarding the best fit of an envisioned solution with a perceived problem as a superior alternative to existing products or services. Entrepreneurs are often encouraged to encapsulate this view within their business model—a conceptual tool describing how their firm will create value for specific customer segments by leveraging its core competencies and ecosystem partners and will capture profits through structuring costs and revenue flows (Amit and Zott 2001, Morris et al. 2005, Osterwalder et al. 2005). However, given that decision makers confront knowledge gaps in various dimensions—technological solutions, perceived demand, ecosystems, and institutions—affecting their business model (Moeen et al. 2020), the original business model is rarely the one that is finally implemented to achieve the envisioned solution.

This is why pivots have become a foundational concept for strategic decision making, particularly in entrepreneurial contexts. Within entrepreneurship, Ries (2011) invoked a steering wheel imagery to describe a pivot as a "sharp turn" (Ries 2011, p. 22) or a "structural course correction" (Ries 2011, p. 149) to the firm's business model as distinct from minor incremental changes that maintain a current course. Connecting it to strategy, Kirtley and O'Mahony (2023, p. 199) define a pivot as "reorient[ing] the firm's strategic direction through a reallocation or restructuring of activities, resources, and attention" accumulated across multiple strategic changes and as distinct from singular changes. Linking it to the "theory of value," Zellweger and Zenger (2023) focus on an entrepreneur's underlying beliefs to define a pivot as a "self-directed creative belief revision" (Zellweger and Zenger 2023, p. 390), distinct from persisting with the original set. Combining these descriptions, we conceptualize a pivot as *a change in the firm's strategy to achieve its vision manifested in one or more elements of its business model and based on self-directed revisions in the underlying belief system*.

Within a learning framework, scholars have highlighted the role of thinking (cognition) and doing (action) as underlying sources of pivots. Cognitive processes enable strategic decision makers to sense make and reconcile new information with existing knowledge to create or modify rules (Ott et al. 2017) and mental representations (Csaszar and Levinthal 2016) that guide new strategies. They are also critical for developing cause-effect conjectures (Camuffo et al. 2020) and updating belief systems (Zellweger and Zenger 2023) that underpin envisioned solutions. Similarly, actions—such as effectuation (Sarasvathy 2001), search (Contigiani and Levinthal 2019), bricolage (Baker and Nelson 2005), and experimentation (Ries 2011, Camuffo et al. 2020, Pillai et al. 2020)—provide evidence that informs whether strategic decision makers should stay the course or pivot.

Such learning can occur as an ex post outcome of strategic decisions or may be undertaken with an ex ante deliberate intent to address epistemic uncertainty (Agarwal et al. 2024a). Learning as an ex post outcome results in pivots because initial investments serve as economic experiments (Rosenberg 1992, Pillai et al. 2020) to endogenously address environmental uncertainty (Moeen et al. 2020) and enhance the entrepreneur's knowledge base (Bingham et al. 2007, Sarasvathy 2009). Learning as an ex ante intent includes several approaches that exhort entrepreneurs to acquire requisite information prior to making irreversible resource commitments to a strategic course, so they can winnow out ideas with low-value potential and increase value created in high-potential ideas. These include the lean start-up (Blank and Eckhardt 2023), the theory-based view/scientific approach (Camuffo et al. 2020, Zellweger and Zenger 2023), and the entrepreneurial strategy (Gans et al. 2019).[1] Although each recognizes the role of cognitive processes and evidence evaluation, they place varying emphasis on each mechanism (Agarwal et al. 2024a). Entrepreneurial strategy puts relative primacy on cognitive processes to hone viable option set, lean start-up puts relative primacy on obtaining rapid and frequent customer feedback for testing and evaluating these minimum viable products, and the scientific approach places relatively equal emphasis on both. Given our interest in examining how pivots are related to formalization in cognitive processes and evidence evaluation, we next turn to a brief overview of the latter literature stream.

Theory-Based View and the Scientific Approach to Entrepreneurship

The fundamental intuition of the theory-based view/scientific approach is that when navigating uncertain environments, decision makers can use theories as lenses or "flashlights" (Felin and Zenger 2009, 2017; Felin et al. 2017, 2023; Camuffo et al. 2020, 2023; Agarwal et al. 2024b). A theory formalizes a decision maker's cognitive processes by helping to articulate the nature of the problem at hand, identify its critical elements or "attributes," and clarify the causal links connecting attributes of the problem and envisioned solution and the beliefs they hold about them (Camuffo et al. 2023). Theorization enables decision makers to be more targeted and efficient (Felin et al. 2023). Because theories are subjective in nature and functions of economic actors' specific perspectives and circumstances (Felin et al. 2014), they are heterogeneously distributed across economic actors. This implies that a theory-based approach enables entrepreneurs to uniquely identify resources to create and capture value in ostensibly efficient factor markets (Felin et al. 2023).

The analogy to a scientist emphasizes the need for entrepreneurs to conduct formal experiments for evidence evaluation. Experimentation enables entrepreneurs to test the veracity of the hypotheses within their theory of value by gathering and evaluating evidence. Greater formalization in evidence evaluation includes attention to creating sampling frames to reduce bias (Cao et al. 2024), defining reliable metrics, and establishing clear thresholds for evaluating corroboration (Camuffo et al. 2020) Increased analytical rigor and credibility of conclusions that guide pivots reduce the likelihood that entrepreneurs go down wrong directions and not realize expected outcomes (Cao et al. 2024).

Such experimentation generates valuable insights that then feed back into the entrepreneur's theory of value and belief systems for potential modifications (Zellweger and Zenger 2023). An iteration between theorization and experimentation informs entrepreneurs' critical decisions regarding whether to terminate the project or make necessary pivots and commit resources to take the idea to market. These implications of a scientific approach on performance have been examined through randomized control trials that focus on the "intent to treat" and assess whether training entrepreneurs to use a scientific approach leads to causal effects in their decision making and performance (Agarwal et al. 2024b, Camuffo et al. 2024, Novelli and Spina 2024). Camuffo et al. (2024) also shows that the treated group has higher "scientific intensity scores," which result in a higher likelihood of termination of projects deemed to be of low-value creation potential and enhanced economic performance (higher revenues and profits) of projects taken to fruition.

Notwithstanding the clarity of the theory-based view and the empirical evidence on benefits of higher scientific intensity induced by this approach, we still have limited insights on how pivots are shaped by the underlying learning mechanisms at play. Recent research has begun to investigate these issues. For example, Camuffo et al. (2024) show that the scientific approach has a nonlinear effect on radical pivots and that it increases the likelihood of making radical pivots once (rather than none or many times), and they find that focused, radical pivots are more positively correlated with higher performance. This evidence points to the intriguing notion that entrepreneurs with a scientific approach have a better understanding of where to pivot, avoiding a trial-and-error search process involving high numbers of pivots. Also, Agarwal et al. (2024b) show that a potential mechanism underlying higher performance of the scientific approach is that it results in more coherent pivots (simultaneous changes in core and operational elements).

We join the above efforts by digging deeper in two ways. First, we parse out the underlying learning mechanisms embedded within the composite construct of scientific intensity that aggregates across theorization and experimentation. This enables us to ask and answer the question of whether these learning mechanisms are additive, compensatory, or complementary in their associations with frequency and radicalness of pivots. Second, we delve deeper into the within variation of entrepreneurs who exhibit high or low levels of theorization and experimentation while discerning among treated and control group cases. Such an examination of within variation enables us to shed light on the source of pivots—whether these stem from higher formalization in cognitive processes, in evidence evaluation, or both to generate additional insights on the nature of the pivots. Specifically, we ask the following question. *How do formalization in cognitive processes (theorization) and formalization in evidence evaluation (experimentation) affect the type (frequency and radicalness) and nature (impetus, clarity, and coherence) of pivots?*

Empirical Context and Research Methods

We use a mixed-method approach to delve into decision-making processes of 261 entrepreneurs who participated in a scientific approach RCT conducted in London from February to November 2019. We leverage the text of over 1,600 interviews collected over a nine-month period for (a) quantitative analysis based on human coding and advanced natural language processing (NLP) methods and (b) qualitative analysis based on theoretical sampling and case comparison methods of constructed business histories.

The RCT: Setting, Participants, and Allocation into Groups

The RCT consisted of a field experiment integrated into a business-support initiative for microbusinesses (firms with fewer than 10 employees) that enrolled in the training program (see Online Appendix A). This focus on microbusinesses is an ideal setting for our study's aim to study strategic decision-making processes because enrolled entrepreneurs were directly involved in making decisions with immediate consequences for economic performance. Participating firms were recruited through online (social media, blogs, and online communities) and offline (flyers) channels. Before beginning training, all participants completed an extensive survey and spoke with a data collection team member in a

30-minute phone call. This provided baseline information on their businesses and decision-making approaches prior to intervention, and it was used to verify success of the statistical software STATA's random assignment of firms to either the treatment group (139 firms) or the control group (135 firms; see balance checks) (Table A1 in Online Appendix A).

The Intervention

The program consisted of a three-month training within seven sessions (totaling 21 hours) taking place over three months (from February to April 2019). Both treatment and control groups were provided conceptual tools, such as the business model canvas (BMC) and the balanced scorecard. They were also provided training on data collection and testing adaptable to diverse entrepreneurial contexts. Both groups received the same number and types of in-class activities and assignments in highly interactive settings that incorporated hands-on activities and feedback from instructors. Entrepreneurs were assigned to smaller subgroups that were then randomly matched with six experienced instructors recruited and trained specifically for this study. This design allowed each instructor to teach both treatment and control groups, enabling us to account for instructor-related variances in our analysis through fixed effects. All instructors received identical training materials and underwent multiple "train-the-trainer" sessions to ensure consistent program delivery aligned with our research design. To minimize contamination, training sessions for the treatment and control groups were scheduled on different days of the week (Wednesday versus Thursday) or at different times of the same day (Saturday morning versus afternoon), preventing inadvertent interactions between them. Moreover, communication about the program was strictly separate for the two groups.

Table 1 shows key differences between the treatment and control groups across the seven sessions. In sessions 1 and 2, although both groups learned about the business model canvas, the two groups received

Table 1. Description of Program Content for Control and Treatment Groups

Session	Control	Treatment
Session 1	BMC. Entrepreneurs are encouraged to reflect on their business model and articulate it into choices for each of the 9 BMC boxes. They then discuss it with peers.	BMC. Entrepreneurs are encouraged to reflect on the **theory** underlying their business model and articulate **hypotheses** for each of the 9 BMC boxes. They then discuss it with peers.
Session 2	Problem formulation: customer journey and balance scorecard. Entrepreneurs are exposed to key elements of the problem formulation process and how to use the customer journey and balanced scorecard.	Problem formulation: customer journey and balance scorecard. Entrepreneurs are exposed to key elements of the problem formulation process and how to use the customer journey and balanced scorecard to reflect their theory and **elaborate hypotheses that flow logically from the theory.**
Session 3	Data sources identification and data collection. Entrepreneurs are exposed to different data gathering techniques (observation, interviews, surveys …) and encouraged to use them to collect evidence on the problem they wish to solve for their customers.	Data sources identification and data collection. Entrepreneurs are exposed to different data gathering techniques (observation, interviews, surveys …) and encouraged to use them to **test** the **hypotheses** they developed in the previous sessions, which built on their **theory.**
Session 4	Designing appropriate tests. Participants were exposed to issues concerning test design, such as sample selection and biases in test design. They were encouraged to reflect on appropriate test designs in their context.	Designing appropriate tests. Participants were exposed to issues concerning test design, such as sample selection and biases in test design. They were encouraged to reflect on **appropriate test designs to test the hypotheses previously developed.**
Session 5	Feedback on tests conducted. Measurement. Participants are exposed to the importance of collecting relevant measures and encouraged to discuss these issues in their context.	Feedback on tests conducted. Measurement. Participants are exposed to the importance of collecting relevant measures and encouraged to discuss these issues in relationship with the tests they designed **to test their hypotheses.**
Session 6	More on test evaluation. Participants are given feedback on their tests and how to assess them.	More on test evaluation. Participants are given feedback on their tests and encouraged to reflect on **whether they support their hypotheses.**
Session 7	Recap session. Participants were reminded of the key topics discussed in sessions 1–6 and how this content could be used to address challenges encountered in their business. Entrepreneurs were paired and invited to discuss their learnings and develop priorities in applying the principles for the next three months.	Recap session. Participants were reminded of the key topics discussed in sessions 1–6 and how this content could be used to address challenges encountered in their business. Entrepreneurs were paired and invited to discuss their learnings and develop priorities in applying the principles for the next three months.

Notes. BMC, business model canvas. Bold indicates the key elements of the treatment embedded in each session.

different training on its use. Entrepreneurs in the control group were taught the canvas as an input for their business model development. In contrast and consistent with high theorization, the treatment group training focused attention on ex ante theory and hypotheses development; they were instructed to *think about the theory* and use the BMC to visually represent that theory. They were then encouraged to *explicitly formulate hypotheses* deriving from it. In sessions 3 and 4, both groups were introduced to a range of data collection and testing techniques (surveys, interviews, and A/B testing). Control group entrepreneurs were encouraged to apply these techniques in tests with representative samples toward BMC elements that they deemed most relevant to challenges they encountered in their businesses. In contrast, treated entrepreneurs were explicitly guided to employ their experimentation efforts toward *testing the hypotheses that they had developed in earlier sessions*. They were also encouraged to develop tests with representative samples, measures of critical theoretical attributes, and threshold values for *critically assessing* outcomes relative to their initially formulated theory. In sessions 5 and 6, both groups engaged in evaluation. Control group entrepreneurs were provided instructions on assessing and evaluating the collected evidence and asked to make necessary adjustments to their BMC. In contrast and consistent with the synergies between theorization and experimentation, treatment group entrepreneurs were encouraged to examine whether their evidence *supported or refuted their hypotheses* and determine whether *adjustments to their theory* were necessary.

Interview Data Collection

Data on entrepreneurial theorization, experimentation, and pivots were collected from February 2019 (preintervention) through November 2019 (six months after the end of training). In addition to the preintervention data noted above, trained research assistants (RAs) gathered data in eight consecutive months of postintervention telephone interviews and surveys, the first of which was approximately eight weeks after commencement of the training program. All interviews were recorded as audio files and implemented a predefined protocol that included open-ended and closed-ended questions following recommended practices in Bloom and Van Reenen (2010) and Camuffo et al. (2020). Open-ended questions enabled entrepreneurs to report on their decision-making processes so that key themes could emerge naturally from their narratives, whereas closed-ended questions elicited self-reported performance data. The use of the predefined open-ended questions mitigated concerns of respondents biasing their answers to align with the research design, particularly because entrepreneurs were unaware that their responses would be compared with a predefined grid. To ensure interview quality and score reliability, during each interview round, an experienced member of the RA team listened to a sample of the interviews conducted by each RA and provided feedback. Some entrepreneurs left the program before the end of the observation window. See Online Appendix A for details about the attrition rate per period. We also show that attrition is not systematically related to the treatment or control condition. Altogether, these resulted in 1,637 distinct interviews, representing an average of approximately 6 interviews per entrepreneur in the RCT.

Quantitative Analysis

Abductive Quantitative Analytical Approach

We distinguish between treatment and control groups by creating an *Intervention* dummy taking a value equal to one if the entrepreneur was allocated to the treatment group (zero otherwise). We also create six *instructor dummies* for each instructor. We utilize the interview data to create quantitative measures of key variables of interest—theorization and experimentation—using both human coding and machine learning methods, as described below. We then used regression analyses to examine their differences across treated and control groups and the associations of these dimensions with the frequency and radicalness of pivots.

Human-Coded Measures of Theorization and Experimentation. For each interview, a team of research assistants analyzed and coded content according to a predefined coding scheme to create measures for formalization. Consistent with Camuffo et al. (2020, 2024), the coding scheme represents a hierarchy of components and subcomponents that are subsumed in each of the two learning mechanisms (see Table A2 in Online Appendix A). The theorization mechanism included a *theory* component with four subcomponents (clarity, detailed articulation, consideration of alternatives, and evidence based) and a *hypothesis development* component consisting of four subcomponents (explicitness, coherence, level of detail, and falsifiability). The experimentation mechanism also had two components, each comprising four subcomponents—coherence, validity, representativeness, and rigor for *testing* and data-based assessment, coherence, systematic evaluation, and explanatory power for *evaluation*.

These inputs enabled us to calculate three key variables that we employ in our analyses. *Theorization–Human* was measured by calculating the mean for each period for each firm of the theory and hypotheses components and then, calculating the mean of the aggregated component over the entire observation period. *Experimentation–Human* was measured by calculating the mean for each period for each firm of the scores for the testing and evaluation components and then, calculating the mean of this aggregated component over the entire observation period. *Scientific intensity—Human* was measured by calculating the mean for each period for each firm of the theory, hypothesis, test, and evaluation components and then, calculating the mean of this aggregated component over the entire observation period.

Machine Learning-Coded Measures of Theorization and Experimentation. We complement the human-coded scores with machine learning methods that employed natural language processing and the use of generative AI. Our reason for doing this is twofold: (1) to provide a measurement that addresses potential biases and concerns about human-coded scores (e.g., consistency, reliability, contamination because of knowledge of research design, etc.) and (2) to create crossvalidations and provide the field a more scalable methodology for measuring theorization, experimentation, and thus, overall scientific intensity. Language has long been recognized as a fundamental realization of underlying reasoning (Duncker and Lees 1945), so we have reason to believe that natural language processing techniques should be able to capture many of the nuances between scientific and nonscientific reasoning.

Online Appendix B provides detailed information on the various steps in this process, which included using (a) OpenAI's Whisper model to transcribe the recorded interviews stored as audio files; (b) ChatGPT, OpenAI's large language model, to develop independent dictionaries related to each of the four components (see Table 2); and (c) Google's BERT (Bidirectional encoder representations from transformers) and TF-IDF (term frequency-inverse document frequency) methods to vectorize and analyze the text data. We then computed cosine similarity scores for each component to measure similarity between the corpus of dictionary words obtained in step (b) and the vectorized text data from the interviews in step (c). These cosine similarity scores serve as machine-generated measures for each component for each interview.

The dictionaries reported in Table 2 are the results of an iterative interaction with ChatGPT. Throughout seven different prompts, we used various structures and perspectives to generate a diverse range of words across dictionaries and then tested the extent to which each dictionary related to the overall corpus of interviews (Mollick and Mollick 2023, Carlson and Burbano 2024). These prompts included such perspectives as the generic instructions given to RAs, instructions to use words related to entrepreneurship, and instructions to use words that a layperson would use. Our final dictionary focused on lay language as it was best related to our corpus overall. Our postprocessing methods for the machine-generated measures were identical to those that we used in postprocessing the human-coded measures. As with the human-coded measures, we accommodate sequentiality and cumulativeness in theorization and experimentation by carrying over scores from earlier interviews. Component-level scores were similarly measured by averaging the scores obtained for theory, hypotheses, test, and evaluation. Specifically, we calculate three key variables that we employ in our analyses. *Theorization–Machine* is measured by calculating the mean for each period for each firm of the scores for theory and hypotheses and then, calculating the mean of this aggregate score over the entire observation period. *Experimentation–Machine* is measured by calculating the mean for each period for each firm of the scores for testing and evaluation and then, calculating the mean of this aggregate score over the entire observation period. *Scientific intensity–Machine* is measured by calculating the mean for each period for each of the four subcomponents (theory, hypotheses, test, and evaluation) and then, calculating the

Table 2. ChatGPT-Generated Dictionaries for NLP Analysis

Component	Words
Theory	"cause," "effect," "reason," "because," "therefore," "leads to," "results in," "problem," "solution," "theory," "hypothesis," "explanation," "model," "framework," "predict," "assumption," "concept," "principle," "idea," "mechanism"
Hypothesis	"hypothesize," "assumption," "proposition," "conjecture," "postulate," "guess," "theory," "presumption," "speculation," "anticipation," "expectation," "projection," "forecast," "scenario," "supposition," "belief," "estimation," "proposal," "premise," "idea," "insight," "hypothetical," "thesis," "notion," "suggestion," "anticipate," "envision," "imagine," "predict," "project," "suggest," "theorize," "suppose," "consider," "assume," "formulate," "hypothesis," "conjecture," "proposal," "supposition," "assumption," "prediction"
Testing	"experiment," "test," "trial," "investigation," "analysis," "examination," "study," "research," "probe," "evaluation," "assessment," "measure," "procedure," "method," "protocol," "attempt," "verification," "validation," "appraisal," "review," "observation," "inquiry," "survey," "experimentation," "sample," "data," "results," "conclusion," "fieldwork," "measurement," "experiment," "test," "trial," "investigation," "study," "research," "analysis"
Evaluation	"result," "outcome," "conclusion," "analysis," "interpretation," "summary," "finding," "judgment," "assessment," "appraisal," "review," "evaluation," "examination," "insight," "understanding," "reflection," "decision," "consideration," "determination," "inference," "rating," "critique," "feedback," "comment," "report," "synthesis," "deduction," "opinion," "thought," "criticism," "estimate," "recommendation," "perception," "verdict," "analysis," "conclusion," "findings," "results," "outcome," "data"

mean of this aggregate score over the entire observation period.

Table 3 shows that the correlations between our final human-coded and machine-coded scores for theorization, experimentation, and scientific intensity range between 0.16 and 0.27. The measures are positively, but not highly, correlated, which is in line with Carlson and Burbano (2024) and Doshi et al. (2024). Low values of the positive correlations are likely because of differences between the nature of TF-IDF analysis and human-coding techniques. TF-IDF measures the frequency of dictionary terms and similar terms in the set of interviews. The dictionaries were generated with common language related to science, but many of the terms included in these dictionaries would not be commonly used by entrepreneurs (e.g., concept, experimental hypothesis, clinical trial, controlled observation, randomized control trial, and meta-analysis). Furthermore, the vectorization techniques are only able to account for one- or two-word phrases (unigrams and bigrams), so they naturally miss longer, more holistic thought sequences, such as "if … then" statements. Human coders, on the other hand, can pick up nuances and better comprehend the granular subcomponents when reading the interviews holistically and within the entrepreneurial context. Despite the low correlation, Table 3 suggests that the NLP techniques were able to detect similar patterns as those measured by the RAs. We take this as prima facie evidence that (1) human-coded scores are likely unbiased by the possibility that the coders might know who is in the treatment or control group and that (2) the machine-coded scores are reasonable and valuable substitutes for human-coded scores and may be particularly useful to other researchers when the scope or scale of their projects poses prohibitive costs for human coding.

Measures of Pivots. To measure pivots undertaken by entrepreneurs during the data collection period, we referred them to the BMC provided during training. In each interview, entrepreneurs were asked to describe any changes made to their company corresponding to any of the nine boxes of the BMC (value proposition, customers, channels, customer relationships, key activities, key partners, key resources, revenue streams, and cost structure). Consistent with Camuffo et al. (2020), we distinguish between *any* pivots (change to any of the nine boxes) and *radical* pivots (change to value proposition or customer segments rated by the entrepreneur at higher than three on a five-point scale) based on the self-reported data in the interviews. We create two dummy variables for each type of pivot to capture potential nonlinearities between zero, one, and more than one pivot. Specifically, *Any Pivot Exactly Once* is a dummy taking a value of one if the company pivoted (on any box) only once during the observation period (zero otherwise). *Any Pivot at Least Once* is

Table 3. Summary Statistics and Pair-Wise Correlations

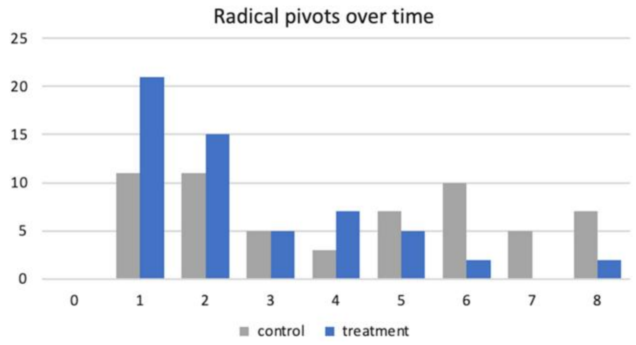
Variable	Observations	Mean	Standard deviation	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. *Intervention*	261	0.51	0.50	0.00	1.00	1.00										
2. *Theorization (Human)*	261	2.71	1.36	0.00	5.00	0.16	1.00									
3. *Evidence evaluation (Human)*	261	1.94	1.56	0.00	5.00	0.11	0.65	1.00								
4. *Scientific intensity (Human)*	261	2.33	1.33	0.00	4.75	0.15	0.89	0.92	1.00							
5. *Theorization (Machine)*	257	0.16	0.07	0.00	0.49	0.27	0.24	0.15	0.21	1.00						
6. *Evidence evaluation (Machine)*	257	0.20	0.08	0.00	0.45	0.08	0.17	0.16	0.18	0.26	1.00					
7. *Scientific intensity (Machine)*	257	0.18	0.06	0.03	0.43	0.21	0.26	0.20	0.25	0.76	0.83	1.00				
8. *Radical Pivot (At least once)*	261	0.28	0.45	0.00	1.00	0.06	0.29	0.17	0.25	0.15	0.14	0.18	1.00			
9. *Any Pivot (At least once)*	261	0.67	0.47	0.00	1.00	0.05	0.60	0.38	0.53	0.20	0.20	0.25	0.44	1.00		
10. *Radical Pivot (Exactly once)*	261	0.18	0.38	0.00	1.00	0.11	0.19	0.12	0.17	0.11	0.05	0.10	0.74	0.33	1.00	
11. *Any Pivot (Exactly once)*	261	0.13	0.33	0.00	1.00	0.10	0.07	−0.05	0.00	0.04	−0.01	0.02	−0.14	0.27	−0.05	1.00

measured as a dummy valued one if the firm has engaged in at least one pivot of any type within the observation period (zero otherwise). *Radical Pivot Exactly Once* and *Radical Pivot at Least Once* are measured as similar dummy variables for radical pivots. Table 3 reports summary statistics and pair-wise correlation for these measures.

Does the Scientific Approach Treatment Increase Theorization and Experimentation?

We begin with cross-section Ordinary Least Squares regressions (Table 4) to examine differences in the average levels of scientific intensity and each of the four components across treatment and control groups. These regressions include dummies for mentors and cluster the errors at the intervention-mentor level, such as in Camuffo et al. (2024). Table 4 shows the results using both the human-coded scores (columns (1), (3), and (5) in Table 4) and the machine-coded scores (columns (2), (4), and (6) in Table 4). Across the board, human-coded scores tend to exhibit larger effects than machine-coded scores, but also, they have larger standard errors; the machine-coded scores have tighter error margins. Both measures suggest that the treatment has a positive and precise effect on the entrepreneurs' overall scientific intensity (Models (1) and (2) in Table 4) as well as the individual *Theorization* and *Experimentation* components (Models (3) and (4) and Models (5) and (6), respectively, in Table 4). Table 4 shows consistent positive and significant effects for both the *Theorization* dimension (Models (3) and (4) in Table 4: 0.437 and 0.037 increases in the human-coded and machine-coded scores, respectively) and the *Experimentation* dimension (Models (5) and (6) in Table 4: 0.350 and 0.012 increases in the human-coded and machine-coded scores, respectively). Taken together, the human-coded and machine-coded scores suggest a consistent, positive effect of treatment on scientific intensity and on theorization and experimentation. In terms of relevance of the effect, if we look at the estimate based on the scores provided by the human coders, we see that, on average, the intervention increases the degree of theorization by 0.437. Considering that the mean of this variable is 2.71, this corresponds to an increase of 16%. On average, the intervention increases the degree of experimentation by 0.350. Considering that the mean of this variable is 1.94, this corresponds to an increase of 18%.

Figure 1. (Color online) Distribution of Pivots at the Time of the Different Interviews and by Treatment Condition



How Do Theorization and Experimentation Affect Pivoting Behaviors?

Turning to pivots, Figure 1 provides the distribution of radical pivot over the observation period. Notably, radical pivots are made early in the observation period for a declining trend for treatment firms, whereas not such clear trend is shown for the control group. Table 5 digs deeper into how theorization and experimentation (and the interaction between them) affect the frequency of pivots *conditional* on them having pivoted at least once (any or radical[2]). For *Radical Pivots Exactly Once* (Models (1) and (2) in Table 5), the coefficients for both theorization and experimentation are negative and precisely estimated for both the human- and machine-coded scores. However, the interaction of theorization and experimentation is positive and precisely estimated

Table 4. Impact of Treatment on Scientific Intensity Scores

Variables	(1) *Scientific Intensity (Human)*	(2) *Scientific Intensity (Machine)*	(3) *Theorization (Human)*	(4) *Theorization (Machine)*	(5) *Experimentation (Human)*	(6) *Experimentation (Machine)*
Intervention	0.394***	0.025***	0.437***	0.037***	0.350***	0.012***
	(0.001)	(0.000)	(0.005)	(0.000)	(0.000)	(0.001)
Constant	1.927***	0.171***	2.316***	0.141***	1.538***	0.202***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	261	257	261	257	261	257
R^2	0.046	0.046	0.039	0.082	0.043	0.008
Dummies for mentors	Yes	Yes	Yes	Yes	Yes	Yes
Clustered errors	Intervention mentor	Intervention mentor	Intervention mentor	Intervention mentor	Intervention mentor	Intervention mentor

Notes. Robust *p*-values are in parentheses. There are four fewer observations in the machine-coded analysis because of corrupt transcription files.
$^{***}p < 0.01$.

Table 5. Associations Between Frequency of Pivots (Conditional on Pivoting) and Scores

Variables	(1) *Exactly one pivot (radical) (conditional on at least one radical pivot) (Human)*	(2) *Exactly one pivot (radical) (conditional on at least one radical pivot) (Machine)*	(3) *Exactly one pivot (any) (conditional on at least one pivot) (Human)*	(4) *Exactly one pivot (any) (conditional on at least one pivot) (Machine)*
Theorization	−0.438***	−5.846**	−0.100**	0.610
	(0.009)	(0.027)	(0.033)	(0.693)
Experimentation	−0.438**	−6.202***	−0.098	−0.087
	(0.010)	(0.008)	(0.122)	(0.936)
Theorization × *Experimentation*	0.146***	28.478**	0.014	−2.148
	(0.006)	(0.015)	(0.405)	(0.691)
Constant	1.750***	1.727***	0.728***	0.327
	(0.001)	(0.002)	(0.000)	(0.261)
Observations	74	74	174	174
R^2	0.173	0.165	0.110	0.048
Dummies for mentors	Yes	Yes	Yes	Yes
Clustered errors	Intervention mentor	Intervention mentor	Intervention mentor	Intervention mentor

**$p < 0.05$; ***$p < 0.01$.

for both the human- and machine-coded measures. Although these results are purely correlational given that we do not have an instrument for each of the four subcomponents and their power is affected by the low number of observations, Table 5 suggests that theorization and experimentation learning mechanisms are complementary; both are essential, and one cannot be substituted for the other in making single radical pivots. In fact, when each one of them is present in isolation, the probability of engaging in a radical focused pivot diminishes.

Qualitative Analysis

Inductive Qualitative Analytical Approach

The above quantitative analysis highlights that radical, focused pivots are more likely to be associated with simultaneous rather than singular emphasis on theorization or formalization. We used a qualitative case comparison method (Eisenhardt 1989) to uncover additional insights regarding the nature of these pivots and how they link to these underlying learning mechanisms. To do so, we leveraged within and across variation in the treatment and control groups, and we relied on theoretical sampling to draw from four dichotomized categories constituting combinations of high and low levels of theorization and experimentation. To arrive at these dichotomized categories, we used human-coded scores of each interview for theorization and experimentation. We classified each interview as high in theorization (experimentation) for scores greater than three on a five-point scale and low otherwise. We then computed the entrepreneur-level measure for each learning mechanism as the ratio of the sum of high interviews over the sum of all interviews. We classified the entrepreneur as high if this measure was greater than the median and low otherwise. Our sampling of cases also considered the number and richness of data in the interviews. We drew two cases for each category for the treatment and control groups, with the exception of the low theorization-high experimentation control group category, which had only one case. Table 6 lists the imputed names of the 15 cases based on their business idea and categorized within a 2 × 2 of high and low theorization and experimentation and treatment or control group conditions.

We used an inductive analytical approach to uncover and investigate patterns (Glaser and Strauss 1967, Langley 1999) in an iterative process of grounding, organizing, and replicating. Guided by the theoretical backdrop and quantitative analysis, we organized the information and looked for similarities and differences in the categories to identify emerging patterns. Specifically, we examined (a) how entrepreneurs applied insights from the training to their business idea, (b) evidence of the use of theory and experiments (or lack thereof), and (c) entrepreneurs' stated rationale for making radical pivots. As patterns became apparent, we revisited the data in all cases to explore within and across variation in the dichotomized categories and treatment/control groups; here, we looked for both anomalies and replications to ascertain patterns and identify additional nuances. Following this process, we built theoretical insights linking theorization and experimentation to entrepreneurs' articulation of their rationale for radical pivots in the form of narratives for all 15 cases by drawing upon the interviews across periods. These case comparisons enable us to uncover patterns linking formalization (or lack thereof) in either or both mechanisms to the nature of the pivots. In what follows, we provide the key findings with representative quotes for one case in each category and vignettes for the other cases, whose details are included in

Table 6. Summary Description of Business Cases Based on Theoretical Case Sampling

	High experimentation	Low experimentation
High theorization	*Treatment group* NutrifyU, HHT1: Providing nutritional well-being support for university students ArtisticCare, HHT2: Providing artist (visual, music, dance, acting) babysitting services to enhance creativity and art appreciation *Control group* GlobalShield, HHC1: Providing protection bodyguard and security services executives during global travel Ecoelegance, HHC2: This company joins the program with a value proposition about offering sustainable luxury clothes and beauty products	*Treatment group* InclusionNext, HLT1: Matching "socially conscious" organizations with minority and socially disadvantaged talent pool DataPulse, HLT2: Providing data analytics services to business customers *Control group* TalentBridge, HLC1: Providing career development using psychometric assessment to refugees in for-profit and philanthropic settings and match them to firms in the financial sector MaritimeEdge, HLC2: Providing technical consultancy in commercial maritime businesses and doing asset optimization and risk management
Low theorization	*Treatment group* CharityConnect, LHT1: Providing a platform connecting potential donors to charities MindfulHub, LHT2: Creating a knowledge platform to improve mental well-being as an alternative to social media *Control group*[a] SmartStock, LHC1: Developing intelligent food packaging for automatic reordering by customers to help food retailers and grocers increase sales	*Treatment group* GeoEduConnect, LLT1: Offering geoscience information and education LifeVantage, LLT2: Offering curated media services for 45- to 70-year-old age group *Control group* MatchWrite, LLC1: Providing editorial consultancy and editorial development to writers of fiction and nonfiction DesignEdge, LLC2: Providing architecture and internal design

Notes. HHC1, High Theorization, High Experimentation Control 1; HHC2, High Theorization, High Experimentation Control 2; HHT1, High Theorization, High Experimentation Treatment 1; HHT2, High Theorization, High Experimentation Treatment 2; HLC1, High Theorization, Low Experimentation Control 1; HLC2, High Theorization, Low Experimentation Control 2; HLT1, High Theorization, Low Experimentation Treatment 1; HLT2, High Theorization, Low Experimentation Treatment 2; LHC1, Low Theorization, High Experimentation Control 1; LHT1, Low Theorization, High Experimentation Treatment 1; LHT2, Low Theorization, High Experimentation Treatment 2; LLC1, Low Theorization, Low Experimentation Control 1; LLC2, Low Theorization, Low Experimentation Control 2; LLT1, Low Theorization, Low Experimentation Treatment 1; LLT2, Low Theorization, Low Experimentation Treatment 2.

[a]Firm names are fictitious but represent business ideas as actual firm names are suppressed for anonymity There was only one case in the control group that mapped on low theorization and high experimentation. See the detailed case histories in Online Appendix C for those that are summarized in the main text.

Online Appendix C. Table 7 provides a summary of our qualitative findings and selects additional quotes from the vignette cases.

Articulation of a Theory of Value Combined with Insights Gained Through Experiments Results in Purposeful Pivots

Two treatment group firms—NutrifyU and ArtisticCare—with high scores for theorization and experimentation showed early engagement in a deliberate process of *articulating their theory of value*. Their structured theorization efforts focused on acquiring a deep understanding of their customers and their needs to identify various attributes of the value proposition and their interdependencies. This guided *insight generation* through experiments; the clearly defined components of their theoretical model enabled the entrepreneurs to identify discrepancies between the anticipated model and their experimental outcomes.

In NutrifyU (HHT1), the entrepreneur (a student) joined the program to develop the business idea of providing nutritional well-being support services for university students. In the baseline interview, the entrepreneur described the value proposition without specifying the key attributes of the theory of value.

> It's a nutrition [well-being] support service for university students … basically provide healthy eating and make it a bit more accessible to university students, because at the moment the dietary choices of first year students in particular are quite bad. —Baseline interview

The treatment condition encouraged the entrepreneur toward an articulation of the key attributes of the problem faced and the solution characteristics and their underlying beliefs in terms of cause-effect linkages. During Interview 1, the entrepreneur evolved the idea by identifying underlying problem components (e.g., budget constraints, stress, lack of resources/information) and tied them to potential solutions (e.g., pricing, nutritional planning, consultations). Also, the entrepreneur identified potential customer segments based on physical activity, articulating hypotheses connecting

Table 7. Nature of Pivots

Pivot	Nature of pivot	Type of formalization	Cases	Illustrative quotes from additional cases
Purposeful	• Structured and deliberate • Clear sense of direction and intent • Dually informed by both theory and experimental evidence	Treatment, high theorization, high experimentation	NutrifyU and ArtisticCare	Example: ArtisticCare "We're offering a creative experience that especially toddlers … And at the same time, we offer the childcare, which a lot of parents need." "[We wanted to understand] if parents actually found that having an added component to their childcare … was actually something they'd be interested in. The second one was (… how much people would be willing to pay for such a service. And the third … what people feel is the most important when somebody comes to their home to take care of their kids … the gender, the age of the babysitter, the languages they speak, the education." "It was a multiple choice survey … they just had to choose what scenarios was most appealing to them … a babysitter that simply puts their child to bed and watches TV with them … one that does creative activities with them. One was that tutors them in English or math … We asked about … whether the age group of the sitter was important … their level of education … the gender. We presented them with various price points. And which ones they would be willing to pay if their sitter was offering a little extra than just putting their child to bed." "[T]he key information we got was price point. Depending on where people were located, they were willing to pay a different amount." "We're targeting working mothers (in specific geographical areas) because they're often busier and they're the ones through our research that we found have difficulties planning both babysitting and hobbies for their children."
Postulatory	• Structured and deliberate • Clear sense of direction and intent • A function of the theoretical beliefs but disconnected from experimental insights	Treatment, high theorization, low experimentation	InclusionNext and DataPulse	Example: DataPulse "We work with customers to try and help them see where they can use data to drive change and transformation in their business." "At the minute, we get caught in these ever so slight boom and bust cycles where we get very, very busy and we all get flat out and we start generating good revenues and then we find that we go through a very fallow period because we've been so busy delivering work." "We spoke to our customers about what the value of our work was … We haven't done any proper [test] … we haven't done any proper, you know, analysis or anything like that … we haven't done it yet because we've been too busy." "The first thing we did was to benchmark where the business was in terms of our customer journey … Our revenues

Table 7. (Continued)

Pivot	Nature of pivot	Type of formalization	Cases	Illustrative quotes from additional cases
				weren't quite what we'd expected and our margins weren't quite what they'd expected … So, we looked at our customer journey to understand where those blockers were and where those gaps were." "We started adding a partner channel … we've been working with some partners in complementary industries, but who wouldn't have data and analysis skills like market research, [human relations], procurement. And we've developed … proto-partnerships in those areas with companies that we know and like … they can use our services to help their customers."
Remedial	• Guided by preformed theories based on experience • Occurs after implementation and informed by the entrepreneurs' feedback obtained during execution (as a result of deliberate efforts at gathering feedback or lack thereof)	Control, high theorization (high or low experimentation)	GlobalShield and Ecoelegance (deliberate ex post experimentation) TalentBridge and MaritimeEdge (feedback following resource commitment)	Example: Ecoelegance "[W]e're offering the conscious customer an opportunity to get quality garments that they know came from a clean supply chain … our solution will be successful because … I've had a lot of experience in the fashion industry and the industry of skincare." "So we've done polls, we've done statistics, we've been out on Carnaby Street in London. So we've been asking customers obviously for their feedback … we've revalued our products and the way it sits in the market. We've actually increased our prices by about 40% … because we realised that (what) we're giving to the market is something very, very niche and that actually our prices were making us try and compete with non-niche brands." Example: TalentBridge "Main location spectrum [is x region] and so with our largely corporate client base what we're offering is executive development based on psychometric testing and enhancement of business skills. So there are three problems being solved. One is the [gross domestic product], the economic conditions of gross domestic product. So there's a need for hard currency to come into [x region]." "I was living in [x region] for three years … I've seen anecdotally first hand … I'm a personal development trainer and … mentor … for more than 12 years … in industry." "[I]n [x region] it was going to … refugees and low income workers. So some of those low income workers would be university students … So basically what I was going to do is take a component of that and to start with I'm going to go to universities here in the [United Kingdom, in the south, and test with those university students and offer some of the training that I would have provided to their equivalents in [x region]."

Table 7. (Continued)

Pivot	Nature of pivot	Type of formalization	Cases	Illustrative quotes from additional cases
Reactive	• A function of environmental stimuli (both efforts at gathering evidence or random conversations with experts or stakeholders) • Revision of value propositions based on loose insights	Treatment or control, low theorization, (high or low experimentation)	CharityConnect, MindfulHub, SmartStock (deliberate ex post experimentation) GeoEduConnect, LifeVantage, MatchWrite, DesignEdge (feedback emerges naturally following resource commitment)	Example: SmartStock "The value proposition is we create intelligent devices that automate reordering. What that means is that we provide a physical device that allows someone to automatically reorder in the right quantity … the way most people track inventory or count inventory for themselves or for large organizations is done manually. "So our tests were predominantly in … demonstrating the product … and understand customer reactions to it … So I think conclusions from the test are that there is a fair amount of user adoption areas that we need to focus on. Two is the pricing structure has to be such that there is lower risk for the customers to try because we are a new company." "We haven't changed the value proposition … It's still the same." "Customer segment has changed, therefore the value proposition has moved slightly. So, we are now doing a [business to business] scenario where we are focusing on just inventory tracking and not necessarily looking at nutrition tracking or reorders." "In the last few weeks we've been talking to a few experts and experts in that industry, have led us to believe that it's easier to sell in a [business to business] scenario than a [business to consumer]. And therefore we've moved in that direction." Example: GeoEduConnect "[I]t's an attractive way of delivering this material which is basically geological knowledge, information, guidance … my product is actually about developing geo science information and engagement tools." "I guess my tests haven't been as rigorous … No, I can't really speak to that … because I don't have them." "I've participated in some symposium and conferences and I've actually seen that there's a need for advocacy as well as access information. So I've modified what my service I'm designing it to include the advocacy."

these segments to the components of the problem solution and already resulting in potential pivot opportunities. For instance, the entrepreneur hypothesized that providing a nutritional service to students would reduce their stress levels and food insecurity, that providing nutrition plans at different price points would address the students' lack of knowledge about what to cook and how, and that athletes would respond positively to a message emphasizing a positive relationship between their nutrition and their athletic performance.

> [S]tudents gain five and a half times more weight than the average person during their first year … suffer from tight budgets, stress from academia and food insecurity … if we teach them how to eat well, then it sets them up for a lifetime of good health. —Interview 1

Clarity in theorization informed the entrepreneur's experimentation wherein data collected through surveys were analyzed through specialized software. The survey design captured the key attributes of the customer base (e.g., age, gender, physical activity levels) and elements of the solution (e.g., price, convenience), and the analysis examined their associations. The entrepreneur recounted these efforts.

> [T]he survey … had 14 questions for the questionnaire … used the same scale for all these different factors so price, taste, convenience, simplicity of the making the food … [the questionnaire] was used on a previous scientific study so it was already validated … It wasn't regression because I didn't have normality in my data. It was a Spearman's test … to see if there's any significance. —Interview 1

The theory-informed experiments led to nuanced insights regarding the linkages between the various components (e.g., stress correlated with willingness to pay and convenience but not nutritional value).

> [T]he stress levels of students … was directly correlated to the importance of price … They preferred cheaper meal options and meals that were easier to make and tastier however … the actual nutritional value of a meal didn't really matter. —Interview 1

Moreover, the entrepreneur noted potential benefits of engaging key stakeholders, such as selling the service directly to universities and partnering with the student unions. This process led to a radical pivot that integrated across several insights uncovered through the combined learning mechanisms—the creation of a student survival kit that catered to different pricing and needs of underlying customer segments and was offered in partnership with other organizations to benefit from complementarities in consumption.

> I did a trial [membership] run … I packed it as a student survival kit for the exam season … it seemed to go down really well. —Interview 3

The entrepreneur also noted the intent for additional segmentation in the future catering to different demographics, such as athletes.

Similar patterns are observed in the detailed quotes for ArtisticCare (HHT2) included in Online Appendix C. The business idea in ArtisticCare was to provide diverse art-enhanced babysitting services. During the training, the entrepreneur (with just above a year of experience in this sector) articulated the unmet need of early exposure to various types of arts and identified component problems as awareness of this need, pricing, and safety. These were linked to potential solutions—sending different babysitters to cover a range of creative arts, with additional attention to their age, gender, and education levels. The theory of value was then tested through surveys that provided alternative scenarios to gauge importance of (various) artistic services, gender of the provider, and different price points to determine willingness to pay. The evaluation of evidence confirmed the unmet need but refuted the assumption of exposure to diverse arts given a more dominant preference for continuity (and safety) with the same babysitter. Moreover, it uncovered some "surprises" by revealing segments within their customer bases (e.g., working versus stay-at-home mothers, location, and regularity of service) and their associated willingness to pay. This resulted in a pivot to providing (focused) art-enhanced babysitting services, targeting working mothers and specific locations, and creating different payment options (per hour versus monthly fee).

The above cases reinforce the quantitative analysis that revealed strong synergies in formalization of cognitive processes and evidence evaluation in its association with focused, radical pivots. Even though in these specific cases, both entrepreneurs were young and lacked significant work experience, they responded to the treatment by developing structured representations within a formal theory of value and complemented it with experimentation to support or refute assumptions regarding core attributes of the problem, envisioned solutions, and their cause-effect linkages. Occasionally, it also led to unexpected insights or "surprises" that required more significant revisions to the theory. The evolution of their theory of value accordingly resulted in *purposeful pivots*—pivots informed by a dynamic evolution of a deeper understanding of their customers and their needs by confirming or refuting initial assumptions. As a result, they showed great clarity and coherence when developing their rationale for their pivots in terms of how they could better create and capture value through attention to market segmentation, pricing, and entry strategy. This enabled them to target superior opportunities (e.g., customer segments) for enhanced revenue models and forge important partnerships with relevant resource providers (ecosystem partners, matched babysitters) for customized solutions and cost-effective prospects for internal/external resource configuration. We summarize these insights in the following proposition.

Proposition 1. *Theorization through deeper articulation of underlying assumptions and cause-effect linkages accompanied with experimentation to assess theorized relationships enables purposeful pivots that formally link support, refutations, refinements, and surprises uncovered in this process to refined value propositions.*

Articulation of a Theory of Value Generates Novel Insights for Postulatory Pivots

Two treatment group firms—InclusionNext and DataPulse—with high theorization but low experimentation scores also showed an evolution of their business idea. Guided by the treatment prompts to articulate their theory, the entrepreneurs developed cause-effect relationships between the problems faced by their customer segments and the solutions they offered. Consequently, each *generated novel insights* for value propositions, including by expanding or narrowing customer segments. However, this theoretical diagnosis was *not* followed by formal testing of their hypotheses; trusting in their causal reasoning, each proceeded to implement these new strategic directions directly.

In InclusionNext, the entrepreneur entered the program with the intent of scaling their business idea of increasing diversity in the workforce. Initial research and implementation had provided a proof of concept and garnered interest from corporate clients. The entrepreneur was also aware of the need to provide value to both organizations and minority/low-income individuals, so the firm's initial strategy consisted of developing relationships on each side and organizing career days. Encouraged by the treatment, the entrepreneur delved deeper into the two-sided nature of the market to identify underlying barriers and bottlenecks (access, lack of skills or knowledge of success criteria) and add key additional elements into the solution (workshops, mentoring) to enable better matches.

> [F]rom an individual perspective … they don't have the networks to give them access to job opportunities … Because these companies are fishing in the small pond … so we provide opportunities for them to be mentored or to meet industry professionals at events … soft skills … We do provide a mentor who's meant to get them more rounded, be able to explain themselves more, understand how people talk within their industry. It's being missed by recruitment strategies by employers and one of the things we are doing now is we run the graduate scheme for an investment bank and we actually help employers and the talent. —Interview 8

The pivot arose because of a novel insight of identifying universities as a third organizational form in a multisided market. By the end of the observation period, universities were fully integrated in the new theory of value and reflected in the articulation of their problem solution.

> Employers, universities and individuals … for universities, our value proposition is … around wider participation funding … universities spend a lot of money to attract people from non-traditional backgrounds because that's how they can charge higher rates of tuition fees. But they found that those students haven't gone into work or they've dropped out of university a lot earlier. So we can provide those students support to reduce those dropout rates and help their students get into employment. —Interview 8

Interestingly, there was minimal effort in experimentation to examine the cause-effect linkages as revealed by answers across multiple interviews when asked specifically about what evidence was gathered.

> So in terms of the issue there has been no tests. The only tests we've done is in relation to the week five homework which was for us, the test we did was around our website and how many people we tried to get to convert into members. —Interview 1

> Not at the moment, not this month. —Interview 5

Notably, although the entrepreneur generated novel insights based on articulated theory, there was no concomitant refinement given the lack of experimentation and no additional clarity on price sensitivity, priority across preferences, willingness to pay, or relative value add of the different solution components.

DataPulse (HLT2) reveals similar patterns (see Online Appendix C). The entrepreneur—the founder of a firm engaged in providing data analytics services to corporate customers—enrolled in the program with the stated desire to reduce "booms and busts" in revenue streams because of a lack of stable customer relationships. As part of the training, the entrepreneur developed cause-effect linkages and uncovered that the business was catering to three different customer segments (small businesses, enterprise customers, and midlevel "innovative" businesses); each had different data analytical needs and associated willingness to pay. Combining these insights with in-depth discussions with employees and incorporating their preferences, the entrepreneur pivoted to a niche strategy, focusing on the "refined customer segment" and "smaller, more innovative, higher-value" work. The entrepreneur consistently reported not conducting tests across the entire observation period. Instead, the efforts honed the theory of value through direct engagement with the preferred customer segment to articulate the value proposition of protopartnerships with firms in complementary industries that outsource the data analysis in market research, human relations, and procurement.

Thus, in both cases, entrepreneurs who had ongoing enterprises and desired to develop stable revenue streams responded to the treatment by engaging in efforts at articulating their theory. They developed cause-effect linkages between the component problems of their customer segments and their current solutions, and they honed their theory of value by identifying unmet needs across multisided markets or within distinct customer segments. Consistent with Figure 1 in the quantitative analysis, these treatment group entrepreneurs engaged in radical pivots early in the observation period (as also shown in the above two cases). These *postulatory pivots* were guided by the insights from articulating their theory; indeed, the entrepreneurs were so convinced by their logic that they did not see the need to follow through with evidence evaluation. However, compared with the treated entrepreneurs who combined theorization with experimentation, those who relied solely on theorization did not demonstrate any additional refinements or report adaption because of unexpected insights before committing resources. Accordingly, we have Proposition 2.

Proposition 2. *When unaccompanied by experimentation, theorization through deeper articulation of cause-effect linkages is associated with postulatory pivots for newly developed value propositions that shape subsequent implementation.*

Predefined Theories of Value Based on Prior Experiences Inform Resource Commitment and Subsequent Remedial Pivots

All four control group cases—GlobalShield (HHC1), Ecoelegance (HHC2), TalentBridge (HLC1), and MaritimeEdge (HLC2)—that scored high on theorization had *predefined theories that were informed by extensive prior industry experience*. Moreover, there was little change in their theories during the observation period as these entrepreneurs did not evolve their articulation of cause-effect linkages for a deeper understanding of their value propositions, in stark contrast to the dynamic evolution of theories for treated entrepreneurs above. All four entrepreneurs made resource commitments consistent with their preformed theories. Interestingly, although two entrepreneurs (Globalshield and Ecoelegance) engaged in formal data collection, testing, and analysis after direct implementation of strategies, there were no discernable differences in patterns observed in the two cases (TalentBridge and MaritimeEdge) that did not do so.

The business idea in GlobalShield (HHC1) was provision of protection and security surveillance services to executives during global travel. The entrepreneur demonstrated a high degree of theorization in the baseline interview itself: a strong understanding of the general value proposition, including key attributes of the protection needs across various customer segments and customization of solutions to specific needs. The theory arose from the entrepreneur's past employment experiences and existing networks.

> I was a freelancer, just travelling around … I'd been in the military for 14 years previous to moving over to [Country X]. So I went onto a succession of security jobs —Baseline interview

> [W]e protect what you value most. So, for some people, for a corporate, that might be their reputation or their business information. For a high network family, it might be their classic car collection. For an at-risk person, it could be their actual safety. —Interview 1

The entrepreneur did not invest additional effort in an explicit articulation of cause-effect linkages to evolve the theory of value but obtained evidence ex post to committing resources to the business idea.

> We ask if we are good value for money. We provide a relevant service … Are we responsive? Would they consider referring us? Would they consider using us for the same service in other countries? —Interview 1

The entrepreneur reported making two radical pivots, both to address generation of new customers. The first relied on education and social media to increase customer awareness and gather data to examine the efficacy of this implemented strategy. The second shifted efforts from creating new leads through specific sector focus (initial strategy of attending industry association meetings) to targeting customer based on existing personal ties.

> [W]e've switched our focus to now … social media footprint across four channels … And that's driving people … to the new website. Then … there's some very clear call to actions, downloadable content, brochures, case studies. —Interview 1

> So what we've done recently is we've actually put all of our contacts into a CRM for the first time ever … We've worked out we've got 2000, some about 2080 usable contacts that either know us or are aware of us. —Interview 4

The case of Ecoelegance (HHC2) included in Online Appendix C also showcases similar patterns. In this case, the business idea—provision of organic, sustainable luxury retail clothing and skincare—stemmed from the entrepreneur's preformed theory based on prior employment in both the fashion and skincare industries. The entrepreneur stated, from the onset, how components of the problem—the desire for carbon-neutrally produced clothing and organically sourced skincare—related to their enacted solutions—sourcing from sustainable global supply chains and use of farm-fresh ingredients to create a luxury brand. Rather than delving deeper into the theory during the training, the entrepreneur focused efforts at evidence evaluation by surveying customers in high-end retail locations to assess the importance of products' features (e.g., looks), pricing, and ethical narrative, and additionally, the entrepreneur assessed associations with age. Although the initial strategy was to cater to a broad range of customer segments and be inclusive to their sensitivity to pricing, the entrepreneur pivoted later to a niche strategy, focusing efforts on the high-end, high-willingness-to-pay segment and increasing their price by 40%. As with GlobalShield, the entrepreneur did not link the pivot directly to insights from the underlying learning mechanisms; the pivot is described in general terms and lacks specificity of which linkages were tested and resulted in the changes.

In TalentBridge (HLC1), the entrepreneur had a business idea of providing psychometric assessments, skill development, and career matching services to individuals, with an emphasis on connecting them to firms in the financial sector. The entrepreneur envisioned a hybrid organization that would support philanthropic initiatives for refugees in the Middle East while leveraging for-profit operations in the United Kingdom. This dual focus was shaped by the entrepreneur's extensive experience, having lived in both regions and built a long career in the financial sector. These experiences allowed the entrepreneur to clearly identify the key challenges—such as low gross domestic product per capita, limited skill development, and inadequate banking infrastructure—and link these to the proposed solutions—providing hard currency, upskilling, and upgrading banking operations from the outset. With strong preformed beliefs, the entrepreneur engaged in minimal experimentation and moved to strategy implementation. Although interviews with bankers were reported, follow-up questions revealed that these were primarily driven by networking and resource acquisition rather than learning ("I have done interviews, but in terms of testing, I really need to do more work on the plan" (Interview 2).). A pivot occurred after initial implementation efforts failed, leading the entrepreneur to abandon international engagement and instead, target university students in the United Kingdom. This shift was based on the recognition that some of the individuals targeted in the original proposition would also be university students.

For the MaritimeEdge case (HLC2) described in detail in Online Appendix C, the entrepreneur's business idea—providing technical and business consultancy services to commercial maritime businesses—stemmed from expertise gained through two decades of increased leadership roles within different organizations. The entrepreneur clearly described the problems faced by potential customers—need to improve productivity and reduce wastage—and the business itself given a perceived lack of credibility as a small, new venture and the challenges associated with a small staff with some turnover. The entrepreneur joined the program with the intent of gaining clarity on potential positioning in terms of being a generalist/specialist and target customers (small versus large clients). The entrepreneur pivoted by adding a new value proposition—asset optimization for shipping clients through matching cargo owners in niche trades with ship owners. Although there was clear articulation of this value proposition, there were no efforts at gathering and evaluating data, nor did the entrepreneur state the source of this idea. Additionally, the entrepreneur created two working groups within the firm; one continued with the original idea of longer-term consulting projects, and the other focused on more time-sensitive projects that generated revenues through procuring cargo and vessels for shipment across destinations.

Thus, in all four cases, the entrepreneurs' theories were shaped by cognitive antecedents, such as deep industry experience, rather than cognitive diagnosis of the cause-and-effect linkages underlying the business model. As a result, they were able to link components of customer needs to their solutions from the onset (often the baseline interview itself). However, without treatment prompts to articulate underlying assumptions or cause-effect linkages, their theory of value did not evolve through a formal process of re-evaluation; as a result, the theory of value remained substantially stable over time. They invested significant resources in their business idea based on their original theory of value—resulting in both successes and failures. These outcomes translated into *remedial pivots*—pivots that either emerged from failures or those that generated additional sources of revenues through modifications/adjustments in strategy implementation. Notably, the lack of formal articulation of how cause-effect linkages affected specific components of either the problem or solution space implied that investments in evidence evaluation did not result in discernable benefits, nor did they generate a nuanced/deeper understanding or reveal surprises. These entrepreneurs were also unable to articulate the rationale for each pivot, nor link it directly to either their theorization or experimentation efforts. This leads us to the following proposition.

Proposition 3. *Theorization based on prior experiences is associated with lower deliberate articulation, and ex post learning based on resource commitment results in remedial pivots that leverage tacit knowledge or tie to general insights obtained through this process.*

A Lack of a Theory of Value Results in Reactive Pivots

The entrepreneurs who had low theorization scores—CharityConnect (LHT1), MindfulHub (LHT2), SmartStock (LHC1), GeoEduConnect (LLT1), LifeVantage (LLT2), MatchWrite (LLC1), and DesignEdge (LLC2)—engaged superficially with the treatment for theory articulation, nor were their business models informed significantly by their prior experiences. As a result, even in cases where the entrepreneurs engaged in experimentation, there were limited actionable insights generated from the process.

In CharityConnect (LHT1), the entrepreneur (with a current enterprise offering branding and website design for new/small businesses) joined the program to develop a new business idea of a platform connecting potential donors to charities. Of note, when describing the current enterprise, the entrepreneur emphasized the main advantage of being at a very low price point compared with others. The entrepreneur described the value proposition of the new idea as "marketing the charity" and even identified the two-sided nature of the platform. However, core needs of the charities were ignored as the entrepreneur largely focused on problems faced by donors (need for research, being bothered by charities) and some solutions (simplicity, good design, graphic information, guarantees for not being bothered, free service). Moreover, the business model relied on the charities covering the costs and offering the service free to donors. The entrepreneur exhibited little understanding of why these were core attributes and did not articulate underlying assumptions or cause-effect linkages. As noted,

> [t]he payments are going to be taken from charity, not from the donors or users … We give you a simple and well-constructed design … instead of the donors … doing the research, we do the research for them … our service guarantees you that you won't be bothered, unless you want a certain charity to be giving you some updates or notifications … your way of giving, that's our value proposition. —Interview 1

The entrepreneur gathered evidence on a regular and extensive basis through surveys.

> [A] survey for 340 people … How would we help, what would help them to donate or volunteer more, and how much would they be willing to pay … the results are positive which gives me like a good boost. —Interview 1

Although the results provided some insights regarding donor preferences (more charities on platform, charities not paying too much commission), the entrepreneur was unable to connect them back to the core value proposition and a revenue model that focused on charities as the paying customers. The entrepreneur's pivot—the decision to change the price point—occurred as a reaction from a conversation with friends who had sector-specific expertise rather than arising from a connection of insights gained from the interviews on why and how a change in price point would attract more charities to the platform. Moreover, such a reactive pivot was inconsistent with contrary information regarding donors' preferences.

> I had like a fixated monthly rate for charities in my mind. But now we're planning to just do like a booking.com … we'll just charge the charities 10 percent for the marketing fee. And there's less risk for them to get involved … friends who work in charities (suggested it) … That's why I changed my price point. —Interview 2

A key attribute of the business model ("*be a sustainable business*") was acknowledged later to inform an additional pivot of customizing pricing strategies based on the characteristics of the charity (e.g., size, location); yet again, there was no clear logical connection between these pivots and the underlying value proposition.

The other two cases where entrepreneurs engaged in experimentation also revealed similar patterns (see Online Appendix C). For MindfulHub (LHT2), the entrepreneur joined the program to create a knowledge platform to improve well-being for all individuals and as an alternative to social media. However, the entrepreneur did not engage in a decomposition of the problem into underlying attributes, clarify assumptions, or identify cause-effect linkages to the envisioned solution. Instead, the theorization consisted of generic hypotheses regarding overall need and willingness to pay or be a coproducer. The entrepreneur relied on a nongovernmental organization (NGO) to conduct some of the extensive tests. These tests result in multiple pivots, each reacting to iterations of results provided to the partner. The first pivot was about targeting people in the 20–35 age group, particularly in urban areas across Europe. Because the results suggested that this group experienced positive sentiments when they improved their skills and gained new knowledge. The pivot—targeting this customer segment rather than all individuals—occurred as a reaction to this evidence gathering but lacked a connection to how and why this target segment's needs are distinct from other customer segments. Moreover, the entrepreneur noted challenges in the evaluation and interpretation of feedback in terms of "doubts about our product" and how even positive attention from subscribers may translate to core features of their product or business. Later pivots revealed a similar reactivity to information provided by the NGO; the entrepreneur shifted to a focus on families first and then shifted to families with children, and moreover, the entrepreneur abandoned the focus on social media or knowledge platforms to ultimately create a WhatsApp group and meeting place for families with children.

For SmartStock (LHC1), the business idea was developing intelligent food packaging for food retailers and grocers so that they could increase sales through automated reordering by customers. The entrepreneur articulated the value proposition of the "intelligent, smart containers" in these generic terms by focusing on these attributes of the solution rather than linking the envisioned solution to attributes of the problems experienced by either the grocers or their customers or to assumptions and linkages between the product features and value proposition to these customer segments. As a result, the entrepreneur conducted extensive tests by developing prototypes and engaging in several field trials through demonstrations to gauge customer reactions in terms of perceived value and willingness to pay for the underlying product features rather than developing an understanding of their needs and priorities. These tests provided some insights—the need to derisk customers through pricing structure and increase robustness in the manufacture of the devices. However, the pivot—switch from a business to consumer to business to business with concomitant focus on inventory tracking rather than nutrition tracking and reorders—occurred in reaction to conversations with potential investors and experts, and the entrepreneur did not articulate how the evidence gathered through the extensive trials translated to a greater value proposition for business to business customers and their needs. Interestingly, postpivot, the entrepreneur began to articulate linkages between product features and focal customer needs (e.g., avoid shrinkage, food waste), but these linkages were not examined in subsequent tests that continued to focus on pricing and sales.

The final four cases consisted of entrepreneurs who received low scores in theorization and experimentation. In GeoEduConnect (LLT1), the entrepreneur joined the program to pursue the business idea of offering geoscience information and education. In follow-up interviews, the entrepreneur identified how the business intended to promote awareness (attractive packaging, use of limericks) and also, the potential need for customization for different types of customers (teachers, university versus middle and high school students). However, there was no subsequent evolution in the theorization during the training period; the entrepreneur did not delve into what the differences were and how and why these customer segments and their needs may link to potential attributes of the envisioned solutions. The entrepreneur also did not identify assumptions or cause-effect linkages in other elements of the business model in terms of value creation and capture but continued to descript the value proposition in terms of product features (geoscience information and engagement tools). Experimentation was also very limited; the entrepreneur did not respond to Interview 2 and Interview 3 calls and noted not having done any tests in Interview 4 when reporting a pivot. This pivot—the addition of an advocacy service—arose from the entrepreneur's attendance at a professional conference for a target customer group (secondary schools and teachers to early- and midcareer scientists). Through the end of the observation period, the entrepreneur did not articulate how the advocacy component was to be integrated nor how it would be a value proposition to the new target group. The entrepreneur also reported that no tests were conducted.

In LifeVantage (LLT2), the entrepreneur joined the program to develop the business idea of offering curated media services to individuals in the 45- to 70-year-old age group. The entrepreneur identified the target audience based on their age profile and their needs (travel, luxury items, beauty, dining, arts and culture) and described their product as offering these individuals written articles and video content on an online platform. There was no evidence of an evolution in the theory of value, nor did the entrepreneur report any efforts at experimentation. As a result, the pivots—creating podcasts (Interview 1); adding an emphasis on male customers (Interview 1); and then, adding an emphasis on lesbian, gay, bisexual, and transgender customers (Interview 6)—stemmed from arbitrary factors, such as random conversations, rather than systematic efforts at theorization or experimentation.

In Matchwrite (LLC1), the entrepreneur had prior employment experience as an editor in publishing companies, which shaped the business idea of provision of editorial consultancy for fiction and nonfiction writers by matching them to editors within the entrepreneur's network. The entrepreneur engaged in minimal theorization—making the connection of the prospective writer's needs (editorial assistance, agent identification) to prior experience and networks—and reported no efforts at gathering and analyzing evidence. The pivots—partnering with another business to offer editing services to their clients, offering additional services to current clients, and customizing price offerings—arose from random conversations with colleagues and experiences with clients.

In DesignEdge (LLC2), the entrepreneur enrolled in the training to develop the business idea of providing architecture and internal design to a broad range of clients—with a dominant focus on private homes but also including hotels and senior housing developers—by offering research and design services. During the observation period, the entrepreneur did not engage in theorization beyond this broad articulation of needs and solutions nor were there any systematic experimentation efforts. The pivot—dropping the private home segment to focus on businesses and honing the value proposition as designing places that "enhance people's well-being"—resulted from sensing an emerging trend based on attending conferences and through random conversations.

In all seven cases, the consistent pattern across pivots was their *reactive* nature. Without the support of theorization, pivots were frequent and in response to arbitrary environmental stimuli. For the first group of entrepreneurs (CharityConnect, MindfulHub, SmartStock), these stimuli emerged because of experimentation. However, the evidence is neither weighed nor framed by a formal theory of value. As a result, the entrepreneurs engaged in multiple efforts at evidence evaluation to assess focal customer segments, potential value proposition, and associated revenues and costs.

Absent theorization, they were unable to generate insights that can then be logically connected to their pivots (i.e., the lack of a cognitive model of the cause-and-effect linkages that may have driven the experimental outcome results in the entrepreneur being unable to envision beyond the narrow contextual information). The lack of synergies implies wasted effort because the limited ability to understand the meaning of the results that entrepreneurs obtained and used to guide subsequent action caused them to engage in frequent pivots and additional data gathering but not focus on root issues that identify and link underlying problem components to solutions. These qualitative insights are consistent with the quantitative analysis that absent theorization, experimentation is negatively associated with focused, radical pivots.

For the second group (GeoEduConnect, LifeVantage, MatchWrite, DesignEdge), the environmental stimuli consisted of random encounters or events. Similar to the first group, the absence of a cognitive model to explain the cause-and-effect linkages behind the stimuli limited their ability to see beyond the immediate context. The entrepreneurs consequently engaged in frequent pivots, which reflected the reactive nature of undirected thought and action, leading to experiences that could result in a variety of outcomes depending on the context and contingencies of outside variables. Particularly when contrasted with the other theoretically sampled cases, the absence of theorization and experimentation resulted in entrepreneurs having a limited understanding of the components of their value proposition and their cause-effect linkages to their products and services. As a result, the rationale provided by the entrepreneurs lacked specificity in terms of how and why these contribute to addressing issues in the original value proposition or improve the venture's prospects. We summarize these arguments in the following proposition.

Proposition 4. *Inattention to theorization hampers the generation of actionable insights from experimentation and results in frequent pivots that are reactive to environmental stimuli but fail to address core issues in the value proposition.*

Pivots and Formalization in Cognitive Processes and Evidence Evaluation

Prior research on the theory-based view and scientific approach to entrepreneurship has generated considerable evidence that greater formalization in cognitive processes (theorization) and evidence evaluation (experimentation) increase the likelihood of early terminations; higher performance; and making focused, radical pivots that integrate across core and operational elements of the business model (Camuffo et al. 2020, 2023; Agarwal et al. 2024b; Novelli and Spina 2024). However, this research has taken a "systems" approach to examine the combined effects of theorization and experimentation for the treated entrepreneurs (relative to control). Our quantitative, abductive analysis decomposed "scientific intensity" into the constituent mechanisms and complemented these with human-coded measures. Crossvalidations of these measures revealed that the treatment condition resulted in a consistent increase in formalization of both learning mechanisms. Moreover, theorization and experimentation are strongly complementary to each other in their associations with focused, radical pivots but not for any pivots.

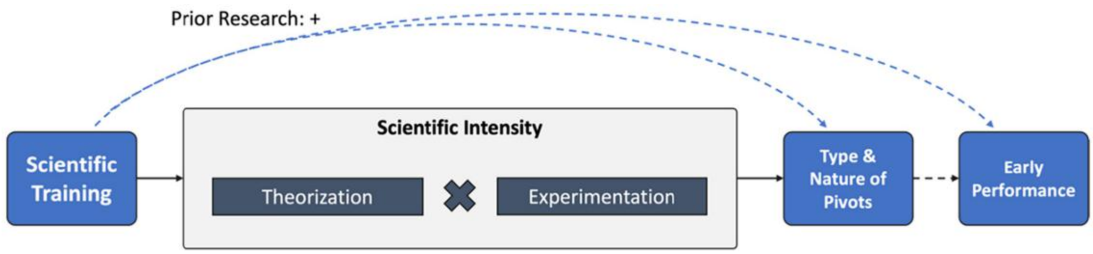
The quantitative results underscored the importance of theorization and experimentation in driving both overall scientific intensity and their relationship with the frequency and radicalness of pivots, but they did not address unresolved questions regarding how they contribute as the source of the pivots and whether they manifest in the coherence and clarity of the entrepreneur's stated rationale for why they pivoted their strategy. These questions matter because within the broader literature streams related to pivots, scholars have noted that pivots arise from intuitive or deliberate cognitive processing of the business model (Shepherd et al. 2023) or from ex post learning after committing resources within experimentation as conceptualized by search, bricolage, or effectual processes (Sarasvathy 2001, Baker and Nelson 2005, Contigiani and Levinthal 2019, Moeen et al. 2020, Pillai et al. 2020). Moreover, when new information conflicts with or expands entrepreneurs' beliefs, pivots may occur incrementally over time rather than manifest in a one-shot decision based on prior beliefs alone (Kirtley and O'Mahony 2023).

Given that our research context included both new and ongoing business operations, our inductive analysis on interview data enabled us to dig deeper into within and across variation of control and treatment groups on how entrepreneurs (re-)assessed their business ideas as informed by formalization in their cognitive processes and evidence evaluation. As we elaborate below, these analyses complement the quantitative analysis and allow us to deepen and extend the theory-based view and scientific approach by highlighting the role of complementarities in theorization and experimentation (Figure 2). Moreover, the analyses also uncover additional insights on how such formalization may occur through deliberate articulation and evolution of theories within treatment conditions or be informed by prior employment experiences and how theorization and experimentation manifest as sources of pivots and affect the clarity and coherence of their rationale (Table 7). We expand on each below.

Complementarities in Theorization and Experimentation Within the Theory-Based View

Whether undertaken informally or formally, cognition is the process by which actors understand the world

Figure 2. (Color online) Conceptual Framework of Mechanisms Underlying the Scientific Approach Training



around them and subsequently make decisions and develop strategies to achieve desired outcomes. Thus, an entrepreneur's cognitive processes will shape the entire entrepreneurial process. Informally, actors often draw from past experience to inform current beliefs (Bingham and Eisenhardt 2011) and draw on prior knowledge contexts as they engage in entrepreneurship and strategic decision making (Agarwal and Shah 2014). Such prior knowledge informs their mental models, frames, or representations (Bingham and Eisenhardt 2011, Csaszar and Laureiro-Martínez 2018). As depicted in Figure 2, the scientific approach encourages entrepreneurs to be more formal in their cognitive efforts by developing a theory of value (i.e., it recommends that entrepreneurs construct a theory to understand the problem at hand by identifying its critical assumptions, attributes, the cause-effect linkages within the envisioned solution, and their beliefs about them). The theory can then be translated into a series of hypotheses that focus on underlying assumptions and causal linkages. As cognitive processes increase in formality (i.e., they represent careful articulation and linkages between perceived problems (Baer et al. 2013), envisioned solutions (Felin et al. 2014), requisite resources (Felin et al. 2023), and potential threats or opportunities (Grégoire et al. 2010)), they increase the quality of pivots made by entrepreneurs.

Experimental actions seek to assess whether an entrepreneur's beliefs match reality. Such experiments may consist of resource commitment through search and strategy implementation (Contigiani and Levinthal 2019, Pillai et al. 2020). Moreover, observations in prior experiences and informal interviews or surveys within immediate networks of stakeholders (e.g., customers) can be the basis of casual empiricism (Gemmell et al. 2012). However, such evidence is subject to sampling biases (Clark and Wiesenfeld 2017, Cao et al. 2024) and can be very costly when gathered after resource commitment (Gans et al. 2019). The theory-based view and scientific approach nudge entrepreneurs to avoid these biases and costs by using experimentation as a predictive tool.

Notably, Figure 2 emphasizes important interaction effects from formalization in both dimensions as informed by our quantitative and qualitative analyses. Our quantitative analysis revealed that absent either theorization or experimentation, pivots are less likely to be focused or radical. Theorization guides experimentation because theories predict certain future states of the world based on envisioned solutions to perceived problems. As a result, they provide a lens for designing the evidence collection and testing and for perceiving and interpreting test results. If a theory is well articulated, then decision makers can more easily identify discrepancies between the anticipated world and the experimentally revealed world. Our qualitative analysis revealed that when the treatment was successful in nudging entrepreneurs to engage in theorization, their pivots were informed by their structured representations. Moreover, pivots arise when a priori beliefs are challenged or extended (Kirtley and O'Mahony 2023). Unclear beliefs (i.e., unclear theories) provide little to challenge or extend, whereas theories provide clarity of direction (Felin and Zenger 2017), which also extends to the interpretation of the experimental data for clarity regarding when the current direction is wrong and clarity of what the new (pivoted) direction should be.

In turn, rigor in testing and evaluation within carefully designed experiments either confirms theories of value or reveals new information and insights that have to be incorporated for deviations from the previously envisioned problem-solution nexus (Hatch and Valentine 2024). Absent experimentation, entrepreneurs and strategic decision makers may fail to ascertain the validity of their assumptions and their postulations or conjectures, rendering them vulnerable to cognitive biases or committing costly and potentially irreversible mistakes, as noted above. Furthermore, when an experiment yields surprises, theories provide a cognitive structure for re-evaluating the world with the new information in hand. This allows the entrepreneur to engage in abductive logic that leads to novel and sometimes contrarian beliefs (Zellweger and Zenger 2023) that may not be achievable without formalization in *both* cognition and action dimensions. Thus, the scientific approach enables pivots to be informed by the *synergies* in theories, and the iterative learning process creates focus and internal coherence in the pivots

(Agarwal et al. 2024b, Camuffo et al. 2024). Experimentation solidifies the scientific foundation that is laid with theorization. Trained to approach their pursuits scientifically, entrepreneurs can be more conscientious about articulating and testing their assumptions, the causal logic underlying paths from the present to their envisioned futures, and consequently, the problems they must solve to realize those futures.

Origins and Role of a Theory of Value in the Entrepreneurial Process

In addition to the above extensions to the theory-based view and scientific approach, our analyses connect to related literature streams in entrepreneurship that adopt a learning framework (Sarasvathy 2001, Bingham et al. 2007, Gans et al. 2019, Pillai et al. 2020, Blank and Eckhardt 2023), including knowledge gained because of prior employment and use contexts of entrepreneurs (Agarwal and Shah 2014). We elaborate on four fundamental insights that also constitute promising avenues for future research.

Theories of Value Can Be Based on Either Formal Articulation Processes or Prior Experiences. Our investigation utilized a treatment that encouraged entrepreneurs to articulate the underlying theory of value in their business propositions. Quantitative analysis revealed that treated entrepreneurs, on average, demonstrated higher levels of formal theorization. However, our qualitative analysis indicated that scientific treatments that encourage formal articulation of an entrepreneur's value theory is not the only route to theory-guided decision making. An alternative pathway is shaped by past experiences, which allow entrepreneurs to formulate theories of value. This connects to the extensive literature on the importance of prior knowledge contexts for entrepreneurship as they alert individuals to unmet needs or novel solutions (Agarwal and Shah 2014). Although this literature has focused on how entrepreneurs may perceive opportunities to leverage novel base principles (Shane 2000, Kim et al. 2024) to create innovative solutions or target niche applications (Shermon and Moeen 2022), it has not directly focused on how prior experiences inform entrepreneurs' theories of value. We inform this literature stream by showing how prior experiences play a *triggering* role in theory formation (Felin and Zenger 2009). As a result, entrepreneurs may be able to link seemingly disparate knowledge contexts (e.g., cross-cultural background *and* industry experience) to imagine novel possibilities. Our control group entrepreneurs were able to build on their prior knowledge contexts to inform critical elements of their venture's business model—defining critical customer segments, honing into diverse needs, leveraging existing networks, and committing resources. They also engaged in ex post learning to develop *remedial pivots* that modified their theories based on outcomes of their initial resource commitments to develop alternative value propositions.

Engagement in the Process of Formal Articulation Results in Better Theories of Value Than Those Generated from Prior Experiences Alone. Our qualitative analysis also revealed that novice entrepreneurs (e.g., students, recent graduates) who engaged in the process of formal articulation were not only able to compensate for a lack of prior experiences, but when combining their theorization with experimentation, they were able to generate *purposeful* pivots that demonstrated clarity and coherence. Moreover, for entrepreneurs using experimentation, we found material differences in pivots emerging from the process of formal articulation relative to those that build on prior experiences alone. Combining this finding with the above insight leads to a nuanced understanding of the role of the two different processes for theorization. Although entrepreneurs can build on prior knowledge to imagine possibilities, it may nonetheless be difficult for them to take the next step of using it to utilize reason and justification to develop and articulate testable theories and hypotheses (Felin and Zenger 2009). Our data and analysis suggest that the mechanism driving the step from imagination to justification is formal articulation. This lends support to the gathering body of evidence that scientific training may lead to improved entrepreneurial outcomes and highlights one of the mechanisms underlying these improvements. Across both the treatment and control groups, our entrepreneurs received similar training in the basics of entrepreneurship, including the same tools, the same trainings, the same types and numbers of activities and assignments, and the same level of interaction with feedback from instructors. What differed between the groups was the focus on articulating a theory of value and then using that theory to develop hypotheses, tests, and inferences. This finding suggests a potentially impactful role of the *act of articulating* elements of a preformed theory in moderating the influence of experience on performance. Articulating a theory—formally assessing the logical underpinnings of the idea and the assumptions that would need to be true for it to be successful—can potentially drive entrepreneurs to move beyond prior experience to utilizing reasoning and justification to develop a theory of value. This articulation process situates experience in the current and envisioned circumstances of the entrepreneurs, leading them to develop theories that are more holistic and testable than those based on prior experience alone.

Theory-Guided Experimentation Provides Better Strategic Insights Than Experimentation Alone. Comparing high-experimentation entrepreneurs across low- and high-theorization groups helps us understand how theory-guided experimentation outperforms "strong-form" learning-by-acting approaches to entrepreneurship, such as the lean start-up approach (Ries 2011, Blank 2013). In the lean start-up approach, entrepreneurs focus on experimenting to gain customer feedback without necessarily having a strong theoretical basis in place beyond the cognitive elements that constitute the hypotheses (Contigiani and Levinthal 2019, Blank and Eckhardt 2023). As we have argued, the theorization process itself is critical to the subsequent strategic decisions, including what to test, how to interpret the results of a test, and ultimately, how to act based on one's interpretation. As we showed in our qualitative analysis, it is through the complementarity of theorization and experimentation that decision makers gain insight to make *purposeful* changes to their business model. This is an important consideration for other action-oriented approaches to entrepreneurship as well, such as simple rules (Bingham et al. 2007) and effectuation (Sarasvathy 2001). In these approaches, it is often suggested that entrepreneurs should not concern themselves with attempting to predict future states of the world because the inherent uncertainty of the world implies that the future cannot be known. Although this may be true in some specific contexts, we show that the power of prediction lies not necessarily in being right about the future but in asking the right questions to understand which direction to go based on the outcomes of immediate entrepreneurial action.

Experimentation Enables Theory-Guided Entrepreneurs to Address Potential Biases and Generate More Nuanced Strategic Insights. Finally, our analysis also shows the inadequacies of theorization without experimentation or a "strong-form" theory-based approach. When entrepreneurs base their decisions purely on theory, they forfeit experimental evidence informing them whether or to what extent their theories are correct. Importantly, they also forfeit potential surprises that could not have been anticipated with cognitive processes alone. Experimentation enables entrepreneurs to overcome personal bias by providing a way for entrepreneurs to check their thinking against reality. Furthermore, experimentation creates situations that could not have been understood and would likely not have been fully anticipated by ex ante cognition alone (Rindova and Martins 2021). This is in line with the theory of creative response by Schumpeter (1947) or action that "creates situations from which there is no bridge to those situations that might have emerged in its absence." This is an important element of overcoming bias and bounded rationality. Because entrepreneurs are unable to fully predict the future state space of the world, learning must occur, to some extent, through some form of action. As Simon (1996, p. 163) wrote: "It is beside the point to ask whether the later stages of the development were consistent with the initial one. … Each step of implementation created a new situation; and the new situation provided a starting point for fresh design activity." Experimentation is a form of implementation designed to provide rapid, less expensive feedback (Gans et al. 2019) to help entrepreneurs and strategists quickly identify the extent to which their theories are true (Zellweger and Zenger 2023) and to generate novel insights and circumstances.

Discussion and Conclusion

Contributions to Research and Practice

In examining how theorization, experimentation, and their interactions affect entrepreneurial decision making related to pivoting, we provide important contributions to research and practice. We contribute to research on a theory-driven approach to strategic decisions. Scholars have noted that strategic decision makers who enact change must engage in a cognitive process of envisioning why and how their strategies help their established or entrepreneurial organizations create and capture value (Felin and Zenger 2017, Csaszar 2018, Gavetti and Porac 2018). Such a process may be implicit or explicit. Implicitly, strategic decision makers rely on prior knowledge and experience for perceptions of the potential problem-solution nexus (Shane 2000, Nickerson and Zenger 2004, Agarwal and Shah 2014), imagination (Rindova and Courtney 2020), creativeness (Rindova and Martins 2023), and vision (Schilling 2018). However, engaging in greater formalization to create explicit linkages through formal cause-effect logic (Gavetti and Levinthal 2000, Camuffo et al. 2024) enables them to better overcome bounded rationality (Simon 1956) and cognitive biases (Tversky and Kahneman 1974, Posen et al. 2018). Importantly, we uncover high complementarities between theorization and experimentation. Absent the development of formal cognitive capabilities, strategic decision makers may find themselves limited in processing information that they gather (Cohen et al. 2019). Indeed, consistent with Agarwal et al. (2024b), we find that theory-guided experimentation results in more focused and coherent pivots relative to pivots attributed to random empirical discoveries alone. Nonetheless, strategic decision makers can leverage experimentation to arrive at more detailed insights on linkages they have identified and uncover salience of originally overlooked linkages in their initial theories.

Our practical contributions are twofold. First, we utilize large language models and machine learning algorithms to provide novel machine-generated measures to validate and potentially substitute for human-coding methods and measures derived from qualitative interviews. In doing so, we also identify critical similarities and differences between the measures, which inform pros and cons for using either measure. Human coding of data may often be prohibitively costly when conducting field experiments, and it requires mitigation of concerns about biases (e.g., extent to which coders are familiar with research intent and methods) and inconsistencies (e.g., extent of interrater reliability). By creating and making our AI-generated dictionary of words and algorithms publicly available, we provide formal machine learning techniques to scholars undertaking research relying on similar measures, so they can utilize and build on these in future work. However, cons of using machine learning techniques include that they measure language according to exact rules and are relatively less capable than humans in comprehending and interpreting nuance in language and holistic conversation as well as adapting to contexts (e.g., scientists versus entrepreneurs versus laypersons) for differences in how similar concepts may be communicated using different words. Such rigidity makes the measurements of scientific intensity objective within the bounds of the dictionaries that it uses but perhaps less suitable when referent dictionaries and actual language differ across contexts of use. Our approach thus highlights the tradeoffs between human and machine coding, and it provides guidance that researchers may find helpful.

Second, our research has important implications for practitioners (entrepreneurs, incubators/accelerators, and business leaders) and policymakers (government agencies, such as NSF and NIH, that sponsor programs, such as iCorp). Across these groups, entrepreneurial individuals are often encouraged to have a "bias for action" because speed matters, and such bias results in getting things done without expending effort and time in "overanalyzing" potential paths forward.[3] By highlighting how and why interactions in formal cognitive processes and evidence evaluation result in radical rather than random pivots, we provide empirical evidence that tempers these exhortations; the solution to "paralysis by analysis" may not be moving to the other extreme but rather, adopting a more balanced approach, wherein theories inform and are, in turn, refined by experimentation within rapid cycles that yield actionable knowledge.

Limitations and Future Research

We acknowledge several limitations of our study. First among them is limited generalizability; we present results of an RCT conducted in a single location at a particular point in time and compared with a specific control training. Replications and additional studies that relax these particularities would provide a deeper understanding of which insights are generalizable and what contingencies (e.g., cultures, environmental uncertainty) are critical to observed relationships. Similarly, studies that examine a broader and more diverse set of entrepreneurs would likely add meaningful insights. Also, whereas this article investigates the implications of higher formalization in cognitive processes and evidence evaluation, an important question concerns the antecedents of higher formalization as well as of higher treatment absorption. We believe that this is an important avenue for future research.

Methodologically, we implement a novel machine-coded measures to crossvalidate and potentially substitute for human-coded metrics. In addition to the cons noted above of the measure, we also note limitations arising from the transcription process. We were limited in our ability to transcribe and postprocess all transcripts given that some interviews (less that 2%) could not be transcribed because the files were corrupted. Also, machine-based transcription still struggles to accurately transcribe conversations with high background noise or strong accents. Here, the Whisper transcription model was not able to accurately differentiate between interviewers and interviewees, so we were unable to remove the interview questions from the transcripts. Although our checks ensured that very few interviews had terse or limited responses, we acknowledge that in such cases, machine-coded scores may have overestimated the scientific intensity, creating a conservative bias in the results for scientific intensity and relationships with pivots.

Moreover, another concern regarding the machine learning analysis may relate to the limitations posed by both the relatively small sample of data and the state of technology. We believe that the size of our data is not a major limiting factor in this analysis because the NLP models that we use are state-of-the-art models that have already been trained on a significant amount of data points by their creators. For example, BERT was trained on 3.3 billion words from Wikipedia and BooksCorpus (Devlin et al. 2018). We have taken these pretrained models and fine-tuned them to our corpus. Yet, we acknowledge that although NLP technologies have improved significantly over the last decade, they are still limited by lack of clear guidelines on how to interpret unsupervised learning results (like topics and clusters) (Marchetti and Puranam 2020). Furthermore, the machine learning methods, including the use of ChatGPT, introduce elements of subjectivity and complexity into the analysis that require multiple replication attempts to verify generalizability. We are aware of these shortcomings but believe that the results are a productive—albeit imperfect—step in the direction of complementing and perhaps substituting for costlier human coding. Finally, in this study, we explore the underlying mechanisms of the scientific approach in entrepreneurial training, focusing on the distinction between formalizing cognitive processes or evidence-gathering skills and their impact on entrepreneurial performance. This highlights the need for further research to disentangle these components as well as to understand how different training methods can be optimized to enhance both cognitive processes and evidence-oriented formalization.

The insights of our study point to exciting areas for future research. There is still much to consider and learn about the nature of pivots and their relationship with theory-based view and scientific approach. True to the spirit of examining evidence within existing conceptual frameworks, our analysis provides extensions and refinements to the theory-based view and scientific approach, and it uncovers some surprises. Each of these insights needs to be formally tested and empirically evaluated. For example, we uncovered that prior experiences and treatment manifest in qualitative differences in formalization in cognitive processes. An interesting future research direction may be in examining whether prior experiences create very strong priors that are resistant to intervention or alternatively, enable expert entrepreneurs to develop even stronger cause-effect linkages relative to novice entrepreneurs. Similarly, our focus was on explicating mechanisms that resulted in differences in type and nature of pivots, and we did not examine performance. Future studies may examine how heterogeneity in the nature of pivots impacts performance. For example, how do reactive pivots affect early performance relative to postulatory pivots? Do purposeful pivots lead to higher performance for new ventures and in what performance dimensions? What happens to long-term business performance when reactive pivots are implemented? Furthermore, other factors, such as timing, resource availability, and subjective perceptions of value, will likely influence pivoting decisions and are worth careful attention. Here, our study uncovered that entrepreneurs who created explicit cause-effect linkages were able to persuade customers of their value proposition and search for/secure partnerships. More work needs to be done linking formalization in cognitive processes and evidence evaluation to persuasion and acquisition of additional resources, customers, and distribution channels.

Conclusion

By unpacking how entrepreneurs may reduce uncertainty by filling knowledge gaps through greater formalization in cognitive processes and evidence evaluation to arrive at fewer radical and purposeful pivots, we extend the theory-based view and showcase how and why the scientific approach may improve decision making by entrepreneurs as they commit their scarce resources and effort into creating novel products and services. The insights of our study elaborate and refine existing theory, and they also provide practical guidance for entrepreneurs as they conceive and manage cognitive structures and purposeful evidence evaluation throughout the entrepreneurial process. The insights also invite future research into questions deserving of additional attention that may further expound our conceptual frameworks and may develop research designs and measures that corroborate, refute, or extend the abductive and inductive insights generated in this study.

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Endnotes

[1] These entrepreneurial approaches are often embedded within academic programs (Camuffo et al. 2020, Lazar et al. 2022), accelerators and incubators (Hallen et al. 2014, 2020), and government grant programs (Howell 2017, Huang-Saad et al. 2017, Semcow and Morrison 2018).

[2] In Table B10 in Online Appendix B, we report the results of Two-Stage Least Squares estimates, which estimate pivoting as a function of scientific intensity. In line with Camuffo et al. (2024), we find that the treatment does not lead to pivots in a linear way. Although scientific intensity has a positive and precise effect with both *Any or Radical Pivots Exactly Once* in both human-coded and machine-coded measures, the relationship of scientific intensity with *Any or Radical Pivots at Least Once* in either measure reports larger standard errors.

[3] "Bias for action" is often elevated to be a key principle as in a lean start-up's focus on "fail fast" (https://theleanstartup.com/principles) and in established organizations' human resource strategy as in Amazon (https://www.amazon.jobs/content/en/our-workplace/leadership-principles).

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