A SCIENTIFIC APPROACH TO ENTREPRENEURIAL DECISION-MAKING AS BAYESIAN LEARNING

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INTRODUCTION

Recent academic work has advanced the concept of Bayesian entrepreneurship (Agrawal, Ajay et al., n.d.; Chavda et al., 2024; Ehrig & Schmidt, 2022; Zellweger & Zenger, 2022). This concept refers to how entrepreneurs make decisions. Central to Bayesian entrepreneurship is the idea that entrepreneurs face choices characterized by high degrees of uncertainty. Bayesian entrepreneurs address this uncertainty by learning about their environment and the cause-effect linkages associated with their actions, and by acting in ways that maximize their subjective utility. Specifically, they develop subjective beliefs (or prior distributions) regarding the probabilities of various opportunities or scenarios they might encounter and select those they deem most likely to be conducive to the desired outcomes. Aware of the uncertainty in their prior distributions, Bayesian entrepreneurs collect signals from the environment in a deliberate attempt to learn about the entrepreneurial opportunities they envision. These signals function similarly to a likelihood distribution, allowing them to update their prior probability distributions and develop posterior distributions, which then inform subsequent entrepreneurial actions.

The notion that entrepreneurs can learn in a Bayesian manner adds a significant perspective to the lenses through which entrepreneurial decision-making can be interpreted, potentially leading to valuable insights. To advance our understanding of whether, to what extent, and how this approach can offer value to entrepreneurs, three fundamental questions arise. First, while the key elements of a Bayesian learning-based decision-making approach are clear (prior formation, testing, and updating), it is not obvious how such an approach works in practice. Second, there is a lack of evidence on the implications of Bayesian decision-making approaches in entrepreneurship. Finally, a relevant question concerns the extent to which a Bayesian approach to entrepreneurship can be effectively taught, as this could affect the phenomenon's magnitude under investigation.

This chapter aims to begin addressing these questions by building on insights from recent research that has promoted a scientific approach to decision-making in entrepreneurship (Agarwal et al., 2023; Camuffo et al., 2020; Camuffo, Gambardella, Messinese, et al., 2024; Zellweger & Zenger, 2022). This scientific approach involves theory development, hypothesis formation, testing, and evaluation, applying the principles of the scientific learning process to the context of entrepreneurship. Notably, a scientific decision-making approach shares important similarities with Bayesian learning, particularly in how decision-makers rely on prior beliefs and engage in a deliberate process of evidence collection to update these beliefs and guide their actions. The purpose of this chapter is to present the most recent

empirical results on a scientific approach to decision-making and, by highlighting the similarities with Bayesian entrepreneurship, to offer insights that might inform and support future research in this area. In doing so, we also hope to contribute to filling a broader empirical gap: existing field evidence on Bayesian learning is limited, with current evidence mostly derived from environments where true probabilities are known or can be reliably estimated, such as gambling, lotteries, and sports (Benjamin, 2019).

To this end, the chapter is structured as follows: First, we provide an overview of the scientific approach to entrepreneurial decision-making, highlighting its similarities to the process of Bayesian learning. Next, we describe the methodology employed in the recent research program on this scientific approach. Following this, we present the key findings from this body of research and discuss their implications for the study of Bayesian entrepreneurship. Finally, we conclude by identifying open questions in this area that could guide future research in Bayesian entrepreneurship.

A SCIENTIFIC APPROACH TO DECISION MAKING AS BAYESIAN LEARNING

Recent research has conceptually advanced and empirically explored the implications of a scientific approach to decision making (Agarwal et al., 2023; Camuffo et al., 2020; Camuffo, Gambardella, Messinese, et al., 2024; Zellweger & Zenger, 2022). In contrast with the idea that entrepreneurs make decisions following their gut feelings (Bennett & Chatterji, 2023) the approach advocates that entrepreneurs can benefit when informing their decisions with a deliberate and structured approach to learning, which follows the same structured approach used by scientists when learning about phenomena. Specifically, scientific entrepreneurs follow four fundamental steps: (1) the formulation of a theory of value; (2) the derivation of hypotheses from this theory; (3) the acquisition of evidence to support or challenge these hypotheses; and (4) the rigorous evaluation of the collected evidence.

The study of a scientific approach to decision making represents a potential opportunity for the advancement of research on Bayesian entrepreneurship because these four steps essentially reflect important elements of Bayesian learning. The process of theory and hypotheses development can be equated to a process of prior distribution formation; the process of evidence gathering resembles a process of likelihood estimation; the disciplined evaluation of the evidence collected can be reconnected to a process of posterior development (Figure 1).

[Insert Figure 1 about here]

Theory and hypotheses development as prior formation

Entrepreneurs using this scientific approach start by defining the problem with a theory of value, which serves as a conceptual framework for understanding how their business generates value (Felin & Zenger, 2017; Zellweger & Zenger, 2022). This framework involves linking the core elements of their business idea with relevant environmental contingencies. Using the language of Camuffo, Gambardella, & Pignataro (2024) these core elements can be referred to as attributes. These attributes are interconnected through causal links. As part of the theory development process, entrepreneurs articulate their prior beliefs or subjective probabilities concerning the accuracy of the proposed causal structure. This cognitive

process enables entrepreneurs to identify the fundamental principles underlying their business idea's value creation and uncover the mechanisms that could potentially lead to the startup's success (Agarwal et al., 2023; Camuffo, Gambardella, Messinese, et al., 2024; Felin et al., 2020, 2024).

The theory development process is further refined by breaking down the theory into hypotheses, which are specific, testable, discrete predictions (Agarwal et al., 2023; Felin & Zenger, 2017). This approach benefits entrepreneurs by allowing them to decompose the problem into manageable components, thereby reducing causal ambiguity (Felin et al., 2020; Leatherbee & Katila, 2020). Together, the process of developing theories and hypotheses shares similarities with prior formation in Bayesian learning. In Bayesian learning, forming priors involves establishing initial beliefs about the likelihood of various outcomes based on existing knowledge, thereby creating a baseline understanding from which decisions are made. The definition of attributes, causal linkages, and beliefs in the entrepreneurial theory parallels the definition of parameters and structure in a Bayesian model and the allocation of prior probabilities.

Evidence gathering as prior testing

In the context of the scientific approach to decision-making, defining a research design and collecting relevant data to test hypotheses provide critical feedback that can be used as a signal on the validity of the theory of value. This process is similar to that of prior testing in Bayesian learning, where both processes involve a feedback loop in which new data are collected to refine initial assumptions. In both Bayesian learning and the scientific approach, the data or evidence collected acts as a signal about the accuracy of the initial beliefs or hypotheses. This signal informs whether the entrepreneur's current understanding is likely accurate or requires revision.

Evidence evaluation as prior updating

Finally, in the scientific approach the methodical and critical evaluation of the gathered evidence enables entrepreneurs to compare the results against the original theory and determine whether the evidence collected either supports it, refines it or refutes it. This is similar to the process of prior testing in Bayesian learning, where initial beliefs (priors) are assessed against new data. In Bayesian learning, after collecting new evidence, the prior beliefs are updated to form posterior beliefs. If the evidence supports the prior, the belief is strengthened; if it refutes it, the belief is adjusted.

SCIENTIFIC DECISION MAKING IN ENTREPRENEURSHIP: A RESEARCH PROGRAM

The scientific approach to decision-making has been empirically studied through a large-scale research program involving approximately 4,000 entrepreneurs. This program began with an initial study in Milan (Camuffo et al., 2020) and has since expanded to include a series of international randomized controlled trials (RCTs) in various locations: London, Turin, Hyderabad, Shanghai, Dar-Es-Salaam, Rotterdam, Bogotá, Barcelona, and Chennai. Although the specific design and treatments varied across the different

RCTs, reflecting the unique research questions each aimed to address, the program maintained a common methodology: entrepreneurs were randomly assigned to different treatment conditions and monitored for at least 10 months. This period was used to observe the impact of the treatments on their decisions and performance across a range of locations. The rationale for conducting multiple RCTs was to ensure reproducibility across different settings and to enhance statistical power. This approach is consistent with the research design implemented in other large-scale RCTs across various contexts (Banerjee et al., 2015; Bowers et al., 2017; Davis et al., 2023).

The RCTs were conducted in the context of business support programs were promoted nationally through both offline and online channels and were marketed as business support initiatives, offered free of charge to entrepreneurs from any industry. The involvement of leading institutions in each hosting country attracted a large number of applicants. Participants were required to complete an online survey and a telephone interview as part of the application process and had to commit to the procedures for the program's duration. To reduce bias, participants were randomly assigned to either a treatment or control group. Additionally, each instructor taught both treatment and control groups and was kept blind to the researchers' expectations to minimize instructor-related bias.

Intervention Details

Experimental groups participated in an entrepreneurship business support program consisting of approximately 20 hours of training over a three-month period. The sessions were experiential, with small class sizes ensuring personalized feedback. In the first batch of RCTs (RCTs 1-4), the program aimed to compare the effectiveness of a structured scientific approach against traditional entrepreneurship training methods. Participants were divided into a treatment group and a control group. Both groups received training that included elements of cognitive-based decision-making, such as strategy frameworks and tools (e.g., the Business Model Canvas or Balanced Scorecard), and evidence-based decision-making, incorporating various data collection and testing techniques like surveys, qualitative interviews, and A/B testing to suit different entrepreneurial contexts. However, the control group was not explicitly encouraged to integrate these approaches.

In contrast, the treatment group was explicitly encouraged to do so, adopting a scientific approach to decision-making. Specifically, the treatment group was instructed to use the strategy frameworks introduced in the training to develop a theory of the problem they were facing, derive hypotheses from this theory, and subsequently use data-gathering and analysis techniques to test these hypotheses. Specifically, the treatment group was instructed to use the strategy frameworks introduced in the training to develop a theory of value, derive hypotheses from this theory, and subsequently use data-gathering and analysis techniques to test these hypotheses. Coali, Novelli, et al., (2024) provide more insights on the characteristics of the andragogical tools that can support the delivery of these types of interventions.

Data Collection Process

Entrepreneurs provided data on their decision-making processes and business performance throughout the training program via monthly telephone interviews conducted by research assistants (RAs). RAs were rigorously trained to ensure consistency in data collection and coding. Interviews included closed- and open-ended questions on various aspects of business development, with data recorded and stored securely. Several measures were implemented to minimize attrition, such as offering the program free-of charge through prestigious universities and organizing monthly events (identical but run separately for treatment and control) to encourage ongoing participation.

KEY FINDINGS

The current available empirical evidence on a scientific approach refers to three key entrepreneurial outcomes: project termination, pivoting, and economic performance. Results from this stream of research provide insights that can be used to understand more about the implications of Bayesian entrepreneurship.

Project Termination

Bayesian entrepreneurship and termination

One important entrepreneurial outcome is project termination. As ventures progress, entrepreneurs naturally or deliberately gather data and receive signals about the market, customer interest, competition, and overall feasibility. This new information serves as evidence that can be used to update the prior probability into a "posterior probability"—a refined estimate of the venture's success prospects. For example, if an entrepreneur initially believes that a new product has a high probability of success but then encounters consistent market feedback indicating a lack of interest, Bayesian reasoning would involve adjusting this belief (or probability estimate) downward.

Conversely, a scenario where entrepreneurs escalate their commitment to a failing project despite negative signals can be seen as a failure in the Bayesian updating process. Entrepreneurs might suffer from cognitive biases, such as overconfidence or the sunk cost fallacy, leading them to ignore or misinterpret new evidence (Chen et al., 2018). Instead of adjusting their beliefs in response to negative data, they might irrationally maintain the original high probability of success. This behavior can result in continued investment until external constraints, like running out of funds, force termination (Artinger & Powell, 2016)

A scientific approach and termination: Empirical evidence

The research program on the scientific approach provides evidence relevant to the dynamics discussed above. In a large-scale study involving 759 entrepreneurs observed for up to 18 months following the

start of their training, Camuffo et al. (2024) demonstrate that a scientific approach to decision-making is associated with more frequent and timely project terminations. Specifically, entrepreneurs trained in the scientific method are 9.8 percentage points more likely to terminate their projects than traditional entrepreneurs and do so 2.7 weeks earlier. This aligns with the patterns observed in Bayesian entrepreneurship, wherein scientifically trained entrepreneurs are better able to identify unpromising ideas more quickly.

However, firms may choose to terminate projects or ventures for a variety of reasons, each with different implications (Wennberg & DeTienne, 2014). To distinguish between these scenarios and understand the underlying mechanisms, (Coali, Gambardella, et al., 2024) go beyond merely examining the termination decision itself. They explore the entrepreneurs' own estimates of the value of their projects throughout the observation period, particularly before the decision to terminate. Their findings indicate a general disconnect between termination decisions and entrepreneurs' expectations prior to the termination event, suggesting that entrepreneurs do not always anticipate termination. However, this disconnect is less pronounced among entrepreneurs trained to think and act like scientists. Notably, these trained entrepreneurs tend to lower their expectations about the value of their ideas and anticipate project termination earlier than those in the control group. This behavior supports the notion that scientifically trained entrepreneurs act as Bayesian decision-makers, adjusting their initial beliefs as they gather new data.

This intuition is further supported by the analysis of the longer-term implications of the scientific approach. While entrepreneurs in the treatment group showed a higher probability of terminating their projects in the short term (up to 18 months after the start of the program), the long-term results (up to 5 years after the start of the program) indicate that the proportion of projects terminated by treated and control groups is not significantly different. Over time, the initial discrepancy in termination rates between the two groups leveled out. By 2023, the termination rate was 75.8% for treated entrepreneurs compared to 81.8% for the control group. Interestingly, the results also show that after termination, treated entrepreneurs initiated more new projects compared to their control group counterparts, with an average of 0.805 new projects per treated entrepreneur versus 0.484 for those in the control group. This suggests the possibility, which should be tested by further research, that treated entrepreneurs who terminated projects earlier were able to redirect resources more effectively in line with Felin et al.'s (2020) intuition. This finding is significant as it demonstrates that over time, all entrepreneurs, regardless of whether they adopt a deliberate learning process, adjust their expectations downward, likely due to natural market feedback. However, the deliberate process followed by scientific entrepreneurs, combined with their willingness to base decisions on learned insights, enables them to update their expectations more quickly in line with Bayesian updating.

Finally, Coali et al. (2024) address whether the downward adjustment made by scientific decision-makers accurately reflects an update of their priors based on environmental signals, or if they might react too negatively, potentially increasing false negatives while reducing false positives. To determine which of

these two possible interpretations is more likely they make the following assumption: if the second interpretation was correct, and the treatment made entrepreneurs excessively critical, one should observe that the projects that are discarded by treated entrepreneurs are of higher quality compared to those discarded by the control group. To investigate this, they used two relatively "objective" indicators of the value of entrepreneurial projects: (1) the successful acquisition of external funding (blind to the treatment) and (2) expert assessments of projects at the baseline. Their examination of the terminated projects reveals that the proportion of terminated projects securing external funding did not significantly differ between treated and control groups, nor were the expert assessments at the baseline superior for projects terminated by treated entrepreneurs. This suggests that the scientific approach does not lead to an overcorrection in the idea selection process.

Pivoting

Bayesian Entrepreneurship and Pivoting

Another important entrepreneurial outcome is pivoting, which refers to a change in a firm's strategy that reorients its strategic direction (Kirtley & O'Mahony, 2023, p. 199; see also; Gans et al., 2019; Pillai et al., 2020). Given the uncertainty faced by entrepreneurs, their ideas are subject to change over time. For entrepreneurs using a Bayesian approach, pivots are a natural outcome of the learning process. Their ideas and specific configurations of their value propositions are based on prior beliefs (Felin & Zenger, 2017; Zellweger & Zenger, 2022). As they update these priors with new information from the environment, their value propositions also evolve, leading to pivots. However, Bayesian entrepreneurs, guided by a theoretical framework and structured prior beliefs, are more likely to conduct a highly targeted search process (Felin et al., 2023). This suggests that while Bayesian entrepreneurs may pivot more frequently, their pivots are more focused: when they pivot, they do so based on signals obtained through their structured learning process, with a clear and well-reasoned configuration in mind, rather than pivoting indefinitely in a trial-and-error manner.

In the context of a scientific approach to decision-making, Camuffo, Gambardella, Messinese, et al., 2024 identify two core mechanisms: methodic doubt and efficient search. They suggest that the mechanism of efficient search underscores the superior efficiency of scientific entrepreneurs in exploring potential solutions to business challenges. This efficiency stems from their enhanced ability to prioritize ideas that are more likely to succeed. Conversely, the mechanism of methodic doubt increases their awareness of factors that could diminish the likelihood of an idea's success. Entrepreneurial ideas are considered valuable only when supported by thorough reasoning, strong arguments, and consistent evidence.

A scientific approach and pivoting: Empirical evidence

In line with the above, Camuffo, Gambardella, Messinese, et al., 2024 findings reveal that the relationship between scientific intensity (i.e. the extent to which an entrepreneur decision making adheres to the

principles of a scientific approach to decision making) and pivoting is not linear. Instead, scientific decision-makers are more likely to engage in fewer but more focused pivots, rather than not pivoting at all or pivoting multiple times. Specifically, the scientific treatment increases the probability of executing a radical pivot once (versus not pivoting or pivoting many times) by 8.3 percentage points.

Valentine et al. (2024) expand on this by exploring the synergies between theorization and evidence evaluation—the two key components of a scientific approach to decision-making, which closely mirror the processes of prior formation, testing, and updating. Their qualitative analysis, supported by quantitative associations, suggests that entrepreneurs who engage in high levels of theorization and evidence-gathering are more likely to undergo exactly one pivot during the observation period, as opposed to multiple pivots.

Through a series of case studies, they demonstrate that when the process of theorization guides subsequent evidence-gathering, the latter becomes more focused and targeted. This leads to four possible outcomes regarding updates to the entrepreneurs' original priors, which eventually inform their pivots. First, the evidence-gathering process might support the prior beliefs, in which case the entrepreneur typically does not pivot but instead increases their confidence in their value proposition and acts accordingly. Second, the process might reveal that the prior beliefs are completely refuted. Third, the process can confirm the general validity of the priors but also lead to a refinement of these beliefs. Finally, the process might uncover unexpected "surprises," i.e., new relevant attributes that were not initially considered in their priors.

Economic performance

Bayesian Entrepreneurship and economic performance

An important question in research on Bayesian entrepreneurship concerns whether making decisions based on this approach ultimately leads to superior economic performance. In principle, if Bayesian learning results in a more accurate assessment of the key attributes in the entrepreneur's environment and the causal linkages between them, it could be argued that this should enhance the entrepreneur's ability to optimize actions and, consequently, maximize utility. Therefore, it is rational to assume that improved economic performance would be a desirable outcome of this approach.

A scientific approach and economic performance: Empirical evidence

Camuffo et al. (2024) demonstrate that entrepreneurs who adopt a scientific approach generally achieve superior economic performance, generating more revenue compared to control firms, conditional on remaining active. In the top 25% of cases, startups using the scientific method generated an average of €28,000 more than control companies over the course of the experiment. For the top 5%, these startups earned an average of €492,000 more.

Additional insights are provided by a study conducted by Agarwal et al. (2024), which underscores the importance of theory-based prior formation over an approach focused solely on evidence

gathering. In their RCT, they compared a treatment that combined theorization and evidence evaluation as the basis for decision-making with a treatment that emphasized evidence evaluation without theorization. The results indicate that entrepreneurs who developed their priors through a comprehensive articulation of their theory were able to make coordinated changes in both the core and operational elements of their business models. This comprehensive approach led to superior performance.

Novelli and Spina (2024) examine the contingencies that influence prior formation and theory development. They particularly note that the utility of a scientific approach in supporting decisions varies significantly throughout the entrepreneurial journey. Early in the process of business model development, entrepreneurs have made only a low degree of strategic commitment to key business model choices. Radical changes are still possible, and the decision-making process has many degrees of freedom. In contrast, later in the process of business model development, strategic commitments have been made, and decisions involve more granular refinements.

Their study reveals that entrepreneurs exposed to a scientific approach early in their business model development experience a "*back to the drawing board*" effect. They begin to question their macro choices, increasing their epistemic uncertainty about the value of the business model. As a result, they delay action to reconsider their choices with the intention of making changes that will position them on a better trajectory later. Consequently, their economic performance is lower compared to non-scientific entrepreneurs who continue with business as usual. This finding aligns with Gans et al. (2019), who show that feedback early in the search process can induce further exploration.

Conversely, when entrepreneurs are exposed to a scientific approach later in their business model development, after making strategic commitments on core business model choices, they undergo a process of fine-tuning the existing model and quickly refine and improve it. As a result, their economic performance increases rapidly. Treated firms that were at an average degree of business model development at the program's start experienced revenues that were 13% lower than those of the control group by the end of the program. However, treated firms that were one standard deviation above the mean in their degree of business model development at the program's start reported revenues that were 38% higher than the control group at the end of the program.

DISCUSSION AND OPEN QUESTIONS FOR FUTURE RESEARCH ON BAYESIAN ENTREPRENEURSHIP

Overall, the insights from research on a scientific approach suggest that entrepreneurs who base their decision-making on a clear articulation of their prior beliefs, and actively update those beliefs with evidence, tend to engage in earlier project selection, more focused pivots, and achieve superior economic performance. The findings also indicate that such decision-making approaches can be effectively taught to entrepreneurs. These insights raise important questions that could inform future research on Bayesian entrepreneurship.

One key area for further exploration is the process of *forming prior beliefs*. The research on scientific decision-making shows that entrepreneurs can be encouraged to articulate their prior beliefs into a coherent theory of value through dedicated interventions. However, evidence also indicates that some entrepreneurs in the control group demonstrated high levels of theorization without such interventions (Valentine et al., 2024). Therefore, it would be valuable to investigate alternative mechanisms that enable entrepreneurs to develop articulated priors. Valentine et al. (2024) provide qualitative evidence suggesting that entrepreneurial experience is a significant factor for high theorization among control entrepreneurs. Similarly, Frosi et al. (2023) highlight that an entrepreneur's educational background and domain expertise also influence the development of priors. Jannace and Camuffo (2023) further show that the priors developed by scientific decision-makers differ in their level of parsimony compared to others. Future research should delve deeper into these aspects to understand the role of environmental and behavioural contingencies in shaping these important cognitive processes.

A second line of inquiry concerns the process of *evidence gathering*. Qualitative evidence on the scientific approaches to decision-making has revealed that entrepreneurs employ a wide range of methods to collect evidence supporting their prior beliefs. These methods include conducting surveys, detailed customer interviews, A/B testing, as well as conceptual experiments or the observation of comparative case studies of competitors (Camuffo, Gambardella & Pignataro, 2024; Novelli & Spina; Valentine et al., 2024). Future research could benefit from developing a comprehensive rubric of all approaches used by entrepreneurs in the process of prior testing under different contingencies and analyzing the implications of different approaches on the development of effective signals.

A third important area for future research involves a closer investigation into the process of *updating prior beliefs*. Qualitative data collected in the context of a scientific approach to decision-making has revealed that some entrepreneurs exhibit resistance to updating their beliefs. This finding aligns with existing experimental work on Bayesian learning, which has documented various systematic learning biases, such as under- or overreaction to information, overconfidence, and correlation neglect (Benjamin, 2019). Understanding the characteristics that make entrepreneurs more receptive to Bayesian decision-making would be crucial. Finally, future research would benefit from a closer analysis comparing the Bayesian approach to decision-making with other structured approaches. This comparison could help assess the effectiveness of each approach in guiding entrepreneurial decisions, particularly under various types of environmental contingencies.

In conclusion, the findings from research on a scientific approach to decision-making offer valuable insights, suggesting that by fostering a systematic theory-and-evidence-based methodology, Bayesian entrepreneurship can enhance entrepreneurs' ability to make informed and adaptive decisions. As the field of entrepreneurship continues to evolve in an increasingly complex and uncertain world, adopting Bayesian principles could provide a promising pathway to more effective and successful entrepreneurial endeavors.

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FIGURES

Figure 1. Bayesian Entrepreneurship and a Scientific Approach to Entrepreneurial Decision Making