DESIGNING DECISIONS IN THE UNKNOWN: TOWARDS A GENERATIVE DECISION MODEL FOR MANAGEMENT SCIENCE

Pascal Le Masson, Armand Hatchuel, Mario Le Glatin, Benoit Weil

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P. Le Masson[(1)], A. Hatchuel[(1)], Mario Le Glatin[(1)(2)], and B. Weil[(1)]

(1) Center for Management Science, i3 UMR CNRS 9217, Mines ParisTech, PSL Research University, France

(2) Zodiac Aerospace

Abstract

This study examines how design theory enables us to extend decision-making logic to the "unknown," which often appears as the strange territory beyond the rationality of the decision-maker. We contribute to the foundations of management by making the unknown an actionable notion for the decision-maker. To this end, we build on the pioneering works in "managing in the unknown" and on design theory to systematically characterize rational forms of action to structure the exploration of the unknown from a decision-making perspective. We show that action consists of designing decisions in the unknown and can be organized on the basis of the notion of a "decision-driven design path," which is not yet a decision but helps to organize the generation of a better decision-making situation. Our decision-design model allows us to identify four archetypes of decision-driven design paths. Two involve generating "wishful decisions," either by improvement or by genericity, while the other two involve generating "decision-changing states" by generating a "best-choice hacking state" or an "all-decisions hacking state." These archetypes correspond to forms of collective action characterized by a specific strategy of knowledge acquisition, a specific performance, and specific organizations. In particular, they enable us to discuss the variety of known organizational forms that managers can rely on to explore the unknown.

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Introduction

In a paper recently publish in Science (Bonnefon et al. 2016), the authors study how an algorithm should "decide" when confronted with a question such as "If the brakes have failed, should the driver of the car kill the pedestrians crossing the street or save the pedestrians by crashing the car into a wall, thereby killing the occupants of the car?" One can immediately understand the dilemma, and can be tempted to find an alternative option that is unknown to date, but would definitely surpass the two options presented.

This example underlines a basic issue in management science: rational choice is often taken as a given, but there are sometimes "unknowns" that are beyond rational choice and could deeply influence the rational choice. Hence, the general question is can one extend decision-making to the unknown to rationally support the creation of options?

This issue has largely been addressed by research in strategic management and risk management (Loch et al. 2008; Loch et al. 2006; Cunha et al. 2006; McGrath and MacMillan 1995, 2009; Pich et al. 2002; Sommer et al. 2008; Rerup 2009; Feduzi et al. 2016; Feduzi and Runde 2014; Weick and Sutcliffe 2007; Mullins 2007; Wideman 1992). The issue of the "unknown" is famous both in professional circles (Wideman 1992) and in the work of decision-theory scholars (Miller 2008). Studies have contributed to clarifying what is "unknown" in relation to decision-making: decision-makers are confronted with "the unknown" when they are *confronted with alternatives and events that were not imagined and taken into account before and still might impact them to a considerable extent by radically changing their decision situation.* More formally and more precisely, it has been shown that "the unknown" corresponds to a type of situation that cannot be handled by the theory of decision-making (Loch et al. 2006). The issue is *not* related to decision bias (a phenomenon that has largely been investigated), but to generation bias (a phenomenon that is, formally speaking, not included in decision theory).

As will be shown in the literature review, studies have described and addressed the challenge of managing the unknown: they have contributed to clarifying the goal of generating an improved decision situation and meeting the challenge of overcoming generation bias by presenting multiple ways to generate specific alternatives. However, they have failed to develop a systematic approach to the unknown and a structured map of the paths in the unknown that could contribute to improving the decision situation. Without such a formal framework, they tend to return, more or less implicitly, to "decision-making in conditions of uncertainty." Typical examples can be found in (Loch et al. 2008; Sommer and Loch 2004): in these papers, the authors explain that the issue stems from the fact that, in a decision situation, the actors cannot know all of the possible alternatives and states of the world, and explain that managing in the unknown consists of *discovering or generating* new alternatives and new states of the world. However, in the following paragraphs of the papers, the model they use is actually a *restriction* of an *ideal* set of alternatives and events, which is no longer a model of extension, but rather a model of *restriction*, which is well-known in decision theory. This restrictive approach precludes an analysis of all facets of the *generation* of alternatives and states of the world.

Hence, the aim of this study is to follow the program outlined by Loch et al. (Loch et al. 2006; Loch et al. 2008) and (Feduzi and Runde 2014) to develop normative models that can provide "the standards for comparison and evaluation that are fundamental to the progress of both descriptive and prescriptive work" (Feduzi and Runde 2014)(p. 269). We are seeking *a model for the generation of new states of the world and new decision alternatives.* That is, we propose a formal model of the *extension of decision-making theory to the unknown*, or simply a model of "decision design" in the unknown. The requirements for such a model can be listed: this extension should be formally consistent, it should contain the decision logic, it should help characterize and understand critical phenomena that occur when actors are confronted by the unknown, and it should lead to a discussion of a new organizational logic related to the unknown, making sense of the multiple forms and notions that have been identified in contemporary management of innovation and could actually be related to different types of "management in the unknown."

As will be described in the literature review, one of the key issues in such a research program is to develop a *model of generativity that is adapted to decision-making.* This is possible because of the great advances in recent years in the field of innovation management, wherein researchers must analyze situations where collective actions, organizations, and strategies consist of addressing the issue of previously unknown products, services, business models, and competences. Hence, the findings of recent studies on innovation management, and more precisely those on design theory for innovation management provide us with a model of generativity. Can it be applied to decision-making? In this study, we show how models of generativity developed for innovation management can actually be used for *decision design in the unknown*, i.e. the generation of "better" decision-making situations, and thus can enrich the field of decision-making in the unknown.

This paper follows a classical construction: literature review, methodological approach, construction of the model, results of the model, and discussion. Hence in the next part, our literature review identifies a twofold gap that should be bridged by a formal model extending decision theory to the unknown: 1) the model should formally (systematically) account for the various ways of "broadening" a decision space. and 2) the model should help characterize the performance of this process in terms of "comprehensiveness" (Feduzi et al. 2016) and "offsetting cognitive biases" (Feduzi and Runde 2014). As we will show, while decision theory helped characterize "selection bias," our model should help characterize "generation bias." In the third part, we present our method and, in particular, explain why it appears fruitful to rely on design theory to model the extension of the decision-making framework to the unknown. Research has enabled the development of a basic science, design theory, that accounts for the unique phenomenon of design, namely generativity, and is comparable in its rigor, foundations, and potential impact to decision theory, optimization, and game theory (Hatchuel et al. 2017). As a consequence, today, design theory appears to provide a promising way to model the generation of a better decision space from a given one. In the fourth part, we construct a formal model that extends decision theory to the unknown and present its main implications. In the fifth part, we present the results, i.e. we show how this model bridges our twofold gap. In Part 6 we discuss the results and present our conclusions.

Part 2- Literature review

2.1- The unknown as a limitation to classic decision theory

As noted in (Buchanan and O'Connell 2006), the history of decision-making could be considered to begin with prehistory. However, it was only after World War II that models of decision-making were progressively formalized and integrated into a general framework. Recent historians' studies have enabled us to understand the "rational choice" movement that unfolded at the end of World War II and during the Cold War (Erickson et al. 2013).

One of the greatest achievements was the formulation of a general theory of statistical decision-making under uncertainty, first by Wald (Wald 1950b, a, 1939), which was then extended to the so-called subjective expected utility theory (SEUT) by Savage (Savage 1951; Savage 1972), and also codified in management science by Raïffa and Schlaifer (1961) (Raiffa and Schlaifer 1961) (see in particular the in-depth analysis of "how homo economicus became Bayesian decision-maker" in (Giocoli 2013)).

According to this model, the decision-maker has to choose one alternative from among a set of available alternatives (actions) and each alternative will have certain consequences depending on which of the possible "states of the world" occurs. These consequences have a certain "cost" (or utility), and the decision-maker is able to assign a (subjective) degree of probability to each state of the world. In this condition, the theory predicts that there is a choice that minimizes the expected utility (i.e. minimizes the expected costs).

These studies propose a formal decision model that takes into account a certain type of "unknownness," namely, one that can be codified in probability terms. Economists have long been aware of the possibility of "unknowledge," or "unknownness," or uncertainty (Shackle 1949; Shackle 1979, 1983; Keynes 1921, 1937; Knight 1921). Uncertain events and uncertain consequences of choices were considered to be unknowns, but statistical decision theory under uncertainty integrates many of these "unknowns". This theory contributes to taming a certain type of unknown, namely, the type that can be reduced to uncertainty, i.e. to subjective probability. This progress is illustrated by a series of papers published in the 1990s on the notion of "unknowledge" in economics and in Shackle's work (Frowen 1990b): the contributors show that certain types of "unknowledge" identified by Shackle (Lachman 1990; Loasby 1990; Frowen 1990a) can be integrated into decision theory (Hey 1990). However, these works also show that one critical type remains: the "residual hypothesis," i.e. the "potential surprise," the event that cannot be formulated and taken into account in the various states of the world. This is one type of unknown that is beyond the bounds of decision theory under uncertainty.

Challenging the unknown as a research issue in decision-making

One consequence of formal statistical decision theory under uncertainty is the capacity to draw a line between uncertainty, which is manageable using decision theory, and the unknown, seen as the "new frontier" to be explored by decision-making theory builders. The problem of the unknown (or unknown unknowns (unk-unks) or black swan events) has attracted considerable attention in the management literature in recent decades (Loch et al. 2008; Loch et al. 2006; Cunha et al. 2006; McGrath and MacMillan 1995, 2009; Pich et al. 2002; Sommer et al. 2008; Rerup 2009; Feduzi et al. 2016; Feduzi and Runde 2014; Weick and Sutcliffe 2007; Mullins 2007; Wideman 1992). Of course, there are various understandings of exactly what unk-unks are, as explained by (Feduzi and Runde

2014) : authors can speak of "events" or "states," and the term unk-unk "extends variously to black swan events, unpredictable surprises, unimagined events, unexpected events, unforeseeable events, rare events" (Feduzi and Runde 2014), p. 270). Following (Feduzi and Runde 2014), we use a broad definition of the unknown that is relevant from the point of view of the decision-maker as modelled by statistical decision theory under uncertainty: i) the decision-maker actually takes into account the states of the world, which are described with the minimum of detail that enables them to compute the cost associated with the consequence of his or her actions in the states of the world. Hence, when one speaks of "unk-unks" in relation to an "isolated event" that has critical consequences, this implies, from a decision-theoretic perspective, that some states of the world are unknown; ii) moreover, when the decision-maker uncovers unk-unks, he or she will also reconsider his or her initial set of actions. Further, the innovator or creative leader is described as being capable of imagining original, previously unknown courses of action (Nutt 1993, 2000; Adner and Levinthal 2004; Mintzberg and Waters 1985). This implies, again from a decision-theoretic perspective, that some actions are unknown.

Hence, *from the decision-theorist perspective*, one can generally consider that the *unknown refers to all data relating to a decision-making problem that are not known by the decision-maker and that will impact the decision*. A decision-making problem can be "broadened" or "reframed" if one generates unknown states of the world or unknown alternatives that could change the decision. Thus, in this study, we address what we call the "*decision-challenging unknown*": self-evidently, we are not interested in an unknown that would have no impact on the decision. The issue then is to identify the relevant unknown: can we know more about this decision-challenging unknown?

2.2-Early attempts to extend decision-making theory to account for the unknown

Very early on, the theory of statistical decision-making was the subject of multiple critics that opened the way to exploring an extension of the decision-making framework. From the Carnegie School of Business perspective (represented by (Simon 1947; Simon 1955) (March and Simon 1958; Cyert and March 1963), and more recently by (Levinthal 1997; Gavetti and Levinthal 2004; Gavetti and Levinthal 2000; Gavetti et al. 2007)), Simon describes the decision-maker as a "satisficer" who cannot obtain ex ante all the detailed and well-structured information required by the theory of decision-making under uncertainty, and thus cannot act as predicted by the theory and so develops a search procedure that only leads to a "satisficing" solution, rather than the optimal one (Simon 1955). A second stream of work, involving the so-called behavioral decision theory, studied the nature of deviations that affect decision-makers ((Bazerman and Moore 2013; Edwards 1954; Edwards 1961; Kahneman and Tversky 1979; Tversky and Kahneman 1974)).

Both streams of research studied facets of the process of hypothesis *construction and generation*. The studies in behavioral decision theory uncovered biases in the generation process: being attracted by too favorable hypotheses, we fail to generate alternative hypotheses, or we generate very similar ones (Mynatt et al. 1993; Fischhoff et al. 1977). The Simonian approach goes as far as working on models of thoughts describing discovery, addressing the issue of some forms of unknown beyond the known (Simon 1977; Simon and Kulkarni 1989), challenging Karl Popper's claim that "there is no such thing as a logical method of having ideas or a logical reconstruction of this process" (Popper 1959)(pp. 31–32) (Simon 1973).

In relation to generativity, the studies opened a new pathway to overcoming one of the critical limitations in decision-making theory: how to *construct* the "residual hypothesis" (Shackle 1983), i.e. the list of alternate states of the world, and even the associated list of actions (Feduzi et al. 2016). Many of these studies were largely descriptive in nature, but also led to more prescriptive work aimed at developing techniques to assist the decision-maker to improve the quality of their decision-making. Some techniques are cognitive exercises that are recommended to enable the decision-maker to broaden the decision-making frame: "consider the opposite" (Lord et al. 1984), or "consider any plausible outcome for an event," not just the opposite (Hirt and Markman 1995), or take advantage of the variety of evaluation attributes when evaluating choices to screen alternatives and generate new ones (Larrick 2012; Miller 2008). Derived from Wason's discovery task (Wason 1960), some methods systematize a process of alternative generation, either by disconfirmation (or eliminative induction, i.e. a Popper-style falsification (Popper 1959; Farris and Revlin 1989a; Farris and Revlin 1989b)) or by counterfactual reasoning (Farris and Revlin 1989a; Feduzi et al. 2016). Some methods are more organization-intensive, relying on a combination of alternative generation and knowledge acquisition. Hence (McGrath and MacMillan 1995) examined the discovery-driven planning method, whereby decision-makers can discover alternatives and are told to keep a checklist to ensure that each assumption is flagged and tested as the process unfolds. Loch et al. studied complex learning processes involving parallel experimentation and selectionism (Loch et al. 2006), while (Schoemaker 2008) proposed a method relying on forecasting and scenario planning.

Two key issues from a decision-making perspective

These studies identify two key issues that helped us to formulate our research questions:

a) **The design of a decision space as a new model of thought.** The studies characterize actors that not only decide, but also *design* the decision space. Of course, they *will* have to decide. Further, initially they are facing a decision-making problem, but instead of "deciding," they first engage in a "generation" phase in which they switch from the initial problem to an extended one. Then, the issue becomes: how can one model this generation phase that transforms the initial decision space into a better one? The studies propose techniques to change the decision space, but there is no systematic approach to generativity. Hence, the first research question is: can one model the generation of a better decision space, i.e. can one model "decision design in the unknown," and, in particular, *how does a formal model of decision design help characterize the different directions of generativity?*

b) **Rethinking performance criteria: introducing comprehensiveness and generativity.** In examining the design of a better decision situation, the studies characterize what "better" means. Two main ways to characterize the performance of the design process emerge. Some studies tend to increase the "comprehensiveness" of the decision space, meaning "the extent to which an organization attempts to be exhaustive or inclusive in making and integrating strategic decisions" (Fredrickson and Mitchell 1984). Various empirical studies show a positive relationship between comprehensiveness and the performance of the firm (Miller 2008; Priem et al. 1995; Eisenhardt 1989). Another stream of studies considers that achieving full comprehensiveness of the decision space is less of an issue than resisting negative biases. These biases include "functional

fixedness," "satisficing," "selective perception," "concreteness," "anchoring," "availability," "confirmation bias," "predecisional distortion," "framing," "accessibility," and "focalism" (see (Larrick 2012) p. 461). More generally, we emphasize that this literature contributed to a great shift from the study of "selection bias" (a classic focus in studies on decision-making) to "generation bias" (for a synthesis, see (Cassotti 2015)). Hence, there are criteria to evaluate how the generation phase led to improved decision quality. However, there is no systematic relationship between the techniques proposed in the studies and their performance. Hence, a second research question arises: *how does a formal model of the generation of a decision space increase comprehensiveness or defixation in the generation of alternatives, i.e. how does it help to deal with generation bias?*

2.3- Learning from innovation management: extending the decision framework

To answer these questions, we rely on the results of recent studies on innovation management. The issue of the generation process has long been identified in innovation management studies. Innovation management has previously been influenced by decision theory, but also more recently by "decision-challenging unknowns." We summarize these two approaches below to show how they contribute to our twofold research question.

At the end of the 19th century, Charles S. Peirce, who was working for the US Coast Survey, proposed to undertake research on the basis of the value of uncertainty reduction (Peirce 1879) (reproduced in 1967 in Operations Research, Vol 15 n°4 pp. 643-648). This risk-reduction approach was progressively extended to other innovation skills, for example, marketing was seen as a profession that was able to increase market knowledge to reduce market uncertainty. Some researchers went as far as applying option pricing methods based on the theory of decision under uncertainty developed in finance studies to the pricing of so-called "real options" (Fredberg 2007; Perlitz et al. 1999). The decision-making framework was also used for new product development and planning (see, for instance (Clark and Fujimoto 1991; Thomke and Fujimoto 2000; Kerzner 2013)), and for the economic evaluation of projects and project portfolios with market and technology uncertainty. Assimilating a New Product Development (NPD) project to an investment, it was possible to apply the tools and techniques developed for corporate investment to NPD projects: return on investment, net present value (NPV), and expected utility.

In recent decades, building on the studies on "exploration" (March 1991), another stream of research has analyzed the logic of generativity in innovation management. The authors of these studies have proposed organizational models to enhance exploration capacity in a systematic way, using either a "modular" process model (Sanchez and Mahoney 1996; MacCormack et al. 2001), wherein exploration and creativity can occur at the level of "modular components" that are loosely coupled to the platform (Gawer 2009), or a "concept shift" process model (Seidel, 2007), whereby designers can explore a product concept not only in the fuzzy front-end phases but also later in the process, achieving a concept shift by modifying the concept's components. Numerous studies on radical and disruptive innovation have enabled researchers to characterize, analyze, describe, and prescribe the generative processes that help to deal with the unknown in a large variety of situations. They have proposed new criteria for evaluating the generation phases (see, for instance (Elmquist and Le Masson 2009)), and a large variety of new processes to deal with the unknown: new types of project management (Lenfle 2016), new forms of competence management and value management (Hooge and Dalmasso 2015), new ways to interact with the firm's environment through open innovation (Chesbrough 2003) and

open innovation in the unknown (Agogué et al. 2017), new ways to acquire knowledge through absorptive capacity (Cohen and Levinthal 1990; Lane et al. 2006) and absorptive capacity in the unknown (Kokshagina et al. 2017b; Le Masson et al. 2012a), and new types of collaboration at the ecosystem level to face the unknown (Lange et al. 2013; Le Masson et al. 2012b).

As recently synthesized by (von Hippel and von Krogh 2016), one of the critical issues addressed by studies on innovation management is related to the generation of "need–solution pairs," i.e. finding creative solutions and discovering new needs. This corresponds to the generation of alternatives and various states of the world. However, these works focus mainly on the generation phase, which is also called the "creativity" phase, and are only loosely connected with the decision-making issue. From an ambidexterity perspective, some authors even consider that they should be intentionally separated so that the decision criteria do not pollute the generation phase, i.e. creating a generation bias by focusing too much on feasibility, marketability, and, more generally, existing dominant designs (March 1991; Tushman et al. 1997; Duncan 1976; Birkinshaw and Gupta 2013; Andriopoulos and Lewis 2009). From a more interactive ambidexterity perspective, some authors suggest that there should be some form of overlap and interaction. However, questions remain, because it is not always clear how the *initial* decision space stimulates the generation process. Many studies consider an initial generation phase that ends with an evaluation phase wherein a decision occurs. Maybe the generation phase could be better *driven* by the initial decision data, and would help overcome (and not cause!) the generation bias?

Research questions

Innovation management studies have enriched our knowledge, but have failed to resolve our twofold issue:

1- Modelling decision-making with generative options: can one model the generation of a better decision space, and in particular, how does this formal model help characterize the different directions of generativity, and does it help articulate creativity and decision-making? (RQ 1)

2- Designing performance-driven strategies consistent with the unknown: how does a formal model of the generation of a decision space increase comprehensiveness or defixation in the generation of alternatives, i.e. help decrease generation bias? (RQ 2)

(von Hippel and von Krogh 2016) suggest that we should rely on formal models of generativity, such as C-K design theory (C for Concept, K for Knowledge), to better characterize generation processes, performance, and organizational facets. We follow that path in the rest of this paper.

3- Research method: integrating a model of generativity into the design of new decision spaces

As noted in the literature, there are many studies on techniques to improve decision-making situations. However, the research gap is to propose a formal model that can *systematically* characterize the different ways to improve a decision-making situation. Hence, this paper is largely formal. This formal model helps to address cognitive biases and organizational issues. One of the consequences of this is that the paper relies on some

mathematical symbols and formulae that may discourage some readers. We have tried to overcome this issue by keeping the equations to a minimal level and having one red thread example that should be considered as a simplified illustration of the general case treated formally. The technical details are presented in the Appendices. Our modelling research can be described in three steps as follows.

3.1- Step 1: from decision-making to the generation of decision spaces

The general method followed by the Carnegie School and some of the strategic decision-making literature uses the classical model of individual decision-making under uncertainty as a benchmark, and analyzes how the "real" decision-maker (or a behavioral model of the decision-maker) is often biased, and how some techniques might increase comprehensiveness or de-bias the decision-maker and help him or her to move closer to the "ideal" situation (see Figure 1). This approach tends to underestimate the fact that, in this process, the so-called "decision-maker" is actually *not* deciding, and the type of thought required from him or her during the process is *not* decision-making in the strict sense of decision theory. He or she is actually *generating* a new "decision situation," i.e. the actor is actually following *generation reasoning*, and the generation is applied to a certain object that is not a new product (product innovation process) or a new service, business model, or idea (ideation process); it is applied to a decision space. In this study, we focus on this generation process.

Our method is as follows. We consider a given decision situation, apply a formal model of generativity, and analyze how this formal model modifies the decision problem (see Figure 1).

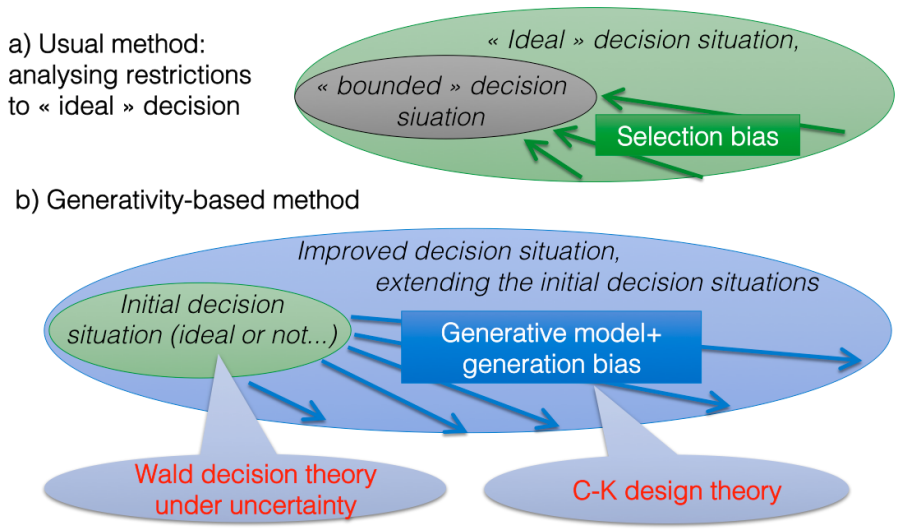

Figure 1: Method: from the study of selection bias to the study of decision-oriented generativity

Applying this method raises two methodological issues: 1), what is our generative model? Below, we justify why we rely on C-K design theory; and 2), what is our model of a decision situation? Below, we justify why we select the Wald decision model as a model for the decision situation.

3.2- Step 2: introducing a formal model of generativity: concept-knowledge (C-K) design theory

Regarding the first issue mentioned above, we rely on design theory. Research on design theory has contributed to the development of a basic science that accounts for the logic of

generativity and is comparable, in terms of its structure, foundations, and impact, to decision theory, optimization, and game theory.

Today, design theory is a powerful academic field with several competing and complementary theoretical proposals, particularly the C-K design theory that we use in this study (Hatchuel and Weil 2009). Some critical properties of design theory, in particular C-K design theory, are of particular interest in relation to our research questions.

a) Design theory considers a variety of forms of *generativity*. Formal models of design theory such as general design theory (Tomiyama and Yoshikawa 1986; Yoshikawa 1981), axiomatic design (Suh et al. 1978; Suh 1990), a coupled design process (Braha and Reich 2003), infused design (Shai and Reich 2004a, b), and C-K design theory (Hatchuel and Weil 2003; Hatchuel and Weil 2009) can all be characterized by their capacity to account for a form of generativity, as shown in (Hatchuel et al. 2011a). In particular, it has been shown that C-K design theory is more generative than Simonian approaches that aimed at modelling generativity but were "unfinished" (Hatchuel 2002). These theories have progressively evolved to become independent of professional languages and traditions. As a consequence, design theory appeals as a powerful integrative framework that can account for all activities involving generativity. In particular, studies have shown how design theory can account for generativity in engineering as well as in science (Hatchuel et al. 2013) and art (Le Masson et al. 2016b). *For our purposes, it appears that design theory is a model of generativity that is sufficiently general to be applicable to a decision problem.*

b) From a cognitive point of view, design cannot be reduced to a learning process or an experimental knowledge production process. Its departure points are the very powerful "desirable unknown" or "concept" (the "C" in C-K design theory); that is, incomplete proposals that guide us towards the emergence of new values, uses, and identities of objects (e.g., products, services, processes, and business models) and new knowledge. Applied to a decision problem, it becomes possible to consider that, given a certain decision problem, a concept is the design of an improvement to the decision situation. The theory describes the process of *formulating and structuring this concept* and designing different ways to abtain better decision situations. *Hence, C-K design theory seems to be applicable to decision problems, and can help characterize, in the C-space, the variety of unknowns related to a decision problem.*

c) Concepts emerge from multiple heterogeneous knowledge (the "K" in C-K design theory) resources, where K can be a decision problem. A design process uses C_0 and K_0 as inputs, and results in new concepts and knowledge at the end of the process, i.e. new decision problems, as well as new unknowns. This means, in particular, that a design process creates knowledge. Hence, knowledge is both an input and an output of a design process. Thus, C-K theory helps to characterize the type of knowledge that must be gained in relation to certain types of unknowns. Hence, it also helps to characterize the variety of processes that are required for exploration and knowledge creation to design new decisions.

d) Last but not least, recent works on the cognition of creativity have enabled the characterization of fixation in design situations relying on the C-K design theory framework. Hence, C-K design theory serves as a reference for the generative process, and it is possible to characterize the biases associated with this reference (Agogué et al. 2014;

Crilly 2015; Hatchuel et al. 2011b). *Hence, we have the capacity to identify generation biases.*

As a consequence, C-K design theory appears as a formal model of generativity that can be applied to a decision situation as follows: K_0 is the decision situation to be improved, while C_0 can generally be written as "design a better decision situation" (partially unknown). The design process will uncover the range of partially unknown decision situations that can be designed from the initial one (here we address research question 1). It is then possible to compare the newly created decision situations with the initial one and determine how much better they are. Fixation analysis, enables us to see not only the increase in comprehensiveness, but also the performance in term of de-biasing (here we address research question 2). Hence, we have a method that enables us to address the two research questions.

3.3- Step 3: maintaining Wald's formal model of decision-making within an extended generative perspective

To apply this method, we need a formal model of a decision situation. As noted in section 2.1, there are several candidates. Studies on strategic decision-making tend to refer to Savage's decision theory (Feduzi et al. 2016; Feduzi and Runde 2014; Dean and Sharfman 1996; Huang and Pearce 2015; Pich et al. 2002). However, in this study, we rely on Wald's model. There are several justifications for this choice.

1- Savage's model is actually a generalization of Wald's model. Thus, what do we stand to lose by relying on Wald? The main claim of Savage's decision theory is that if agents' preferences and beliefs are consistent (in the sense specified by Savage's axioms), these preferences may be represented by the expected utility formula, whereas Wald considers that the loss function and the beliefs are provided by the agent. As noted by Giocoli, the reference historian of decision theory, "Savage's theory is first and foremost a normative guide to the formation of consistent beliefs" (Giocoli 2013)(p. 74). Relying on Wald, we consider that the belief and loss functions are *given*, and do not consider how they can be revealed by the choices made by the agents. By doing this, we avoid the question of whether the consistency rules required by Savage's axiomatic can be applied effectively.

2- Wald's model not only served as the foundation for Savage's model but was also the foundation of Raiffa and Schlaifer's model (Raiffa and Schlaifer 1961), which has been widely acknowledged in the management literature (Giocoli 2013). Wald's analytical framework has been implemented in decision trees, which are still taught in many business schools and are the backbone of many studies on strategic decision-making (e.g. studies on real options). Hence, Wald's model can be considered as the operational basis of decision theory.

3- Wald developed his theory with the aim of providing an integrated framework for statistics, and in doing so he provided a model for making decisions in the face of uncertainty. For Wald, "a solution to a statistical problem must instruct the statistician about what to do, i.e. what particular action to take, not just what to say" (Giocoli 2013) p. 13). Hence, Wald's model is one of *action*, which suits our purposes.

4- We could also rely on a Simonian model of "bounded decisions." This path has already been largely explored, in particular with a view to finding ways to get closer to the optimal choice (as defined by Wald). Since the part of the path from "bounded" to "ideal" has already been widely discussed, we prefer to focus on the part between "ideal" and

"extended ideal." Using the "ideal decision" as the starting point helps us to focus the generativity process on the phase that has been least explored until now.

To conclude, we apply C-K design theory to Wald's decision-situation model (Part 4), and this formal approach provides answers to our two research questions (Part 5).

Part 4: A comprehensive and generative model for designing decisions in the unknown: properties and evaluation

In this part, we apply C-K design theory to Wald's decision-situation model. Our aim is to identify the possible extensions of decision theory using design theory. Following the C-K framework, we first identify precisely the "decision model" that is in K_0, which reminds us of the basics of Wald's statistical decision theory. Then, we describe the C-space and the expansions (see Figure 4 for an overview).

4.1- Background: Wald's statistical decision theory and K_0

Wald formulated the basic decision problem as follows (Giocoli 2013) (Ferguson 1976). There are four components: a) the available actions; b) the states of the world (also called states of nature), one of which is the true one (the parameter space); c) the loss function (also called the cost function) measuring the loss to the statistician if he or she takes a certain action when the true state of the world is given; and d) an experiment, whose goal is to help the statistician to reduce the loss and whose results (called observations) depend on the true state. A decision function is a rule associating an action with each possible experimental outcome. The available decision functions are evaluated according to the expected loss their adoption may cause under the various possible states. The statistician's task is then to choose the decision function capable of minimizing the expected loss. Wald was able to solve this problem in very general terms by adding some additional ingredients: there is a loss function defined over each pair (state of nature and action), and the experimenter may have an a priori distribution over the parameter space (belief about the states of nature, modelled with Bayesian formalism).

It is worth noting, after (Gilboa 2009), that Wald uses a Bayesian approach in the strict sense of statistics: "Anything that updates a prior to a posterior based on evidence is referred to as 'Bayesian' while in economics the term refers to a more demanding ideological position, according to which anything and everything that is not known should be modelled explicitly in a state-space model and be subject to a prior probability" (p. 40). Of course, in this study, we stick to Wald's approach and carefully avoid the economics position that hides the issue of the unknown or, said differently, codifies unknowns systematically in an a priori distribution (usually called uncertainty), which is a considerable restriction.

Wald's result (presented formally in Appendix A-1) is extraordinarily general: given the learning capacities L, the a priori belief μ about states of nature θ_j in Θ, the set D of alternatives d_i, and the cost function C (d_i, θ_j), there is always an optimal choice function to identify the optimal decision d_{opt} inside the set of all known decisions D.

Let us take a very simple example: the raincoat/hat decision problem (see Figure 2). This is actually the example given by Savage when he discussed Wald's theory in his famous

article (Savage 1951). This example was used to show how Wald's theory, which was initially thought of as a generalization of statistical problems, could be applied to simple everyday decisions.

The possible decisions are: d_1, take a raincoat on a walk; d_2, take a hat on a walk. The states of nature are: θ_1, there will be rain during the walk; θ_2, there will be sun during the walk. The beliefs are the probability of rain during the walk $\mu(\theta_1=1, \text{rain})=\mu(\theta_2=0, \text{no sun})=p$ (for instance 50%) and the probability of sun during walk $\mu(\theta_1=0, \text{no rain})=\mu(\theta_2=1, \text{sun})=1-p$. The costs are, for instance, $C(d_1, \theta_1)=C(d_2, \theta_2)=0$ and $C(d_1, \theta_2)=C(d_2, \theta_1)=C > 0$ (cost of taking a hat and it rains or cost of taking a raincoat and it is sunny).

Without sampling, the expected costs are (1-p).C for d_1 and p.C for d_2. If p>50%, then choose d_1; if p<50%, then choose d_2 (given the limited space, we do not include the sampling case (see Appendix A-3)).

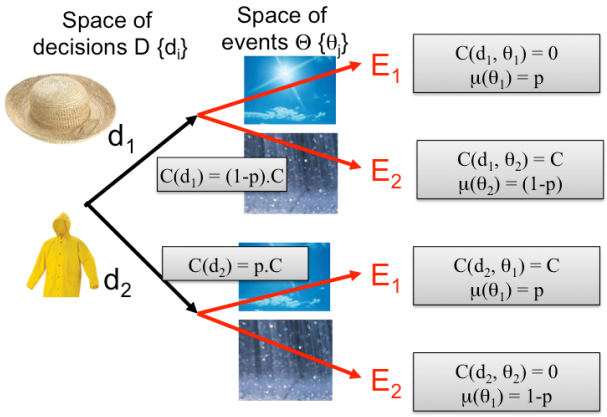

Figure 2: Decision tree for the raincoat/hat case (simplified: without sampling)

4.2- Generating new concepts of decisions (C-space): casting decision-making theory into design theory

Following the method presented in Part 3, given Wald's statistical decision problem in K_0, we actually *design a better decision situation* using C-K design theory.

In C-K design theory, the design process begins with a knowledge base K and concepts C. Knowledge K_0 is: D, the set of decisions d_i, Θ, the set of states of the world θ_i, and $C(d_i, \theta_j)$ and $\mu(\theta_i)$, which can be seen as "properties" of d_i and θ_j. There are even definitional properties, *since θ_i and d_j only "exist" in the problem through C and μ.* L(d, X) models the way to learn with X on θ_i to decide d_j, i.e. how beliefs evolve by sampling.

The concept C_0 is: *from the given problem characterized by (D, Θ, μ, C, L), design a better decision situation.*

From this initial situation, the C-K design process leads to several better decision situations. The details of the construction of these better decision situations are presented in Appendix A-1. Below, we present the main features that are deduced from this construction and illustrate them using the raincoat/hat case.

Let us begin with the illustrated case. From the initial decision situation (see Figure 2), C-K design theory leads to the graph shown in Figure 3. In C, there are several concepts of better decisions. Note that even if we added some pictures, these are only concepts of

decisions, i.e. what is designed is a decision situation (not a product) represented by a decision tree, where some branches have yet to be fully designed to become an actionable decision. Here, we briefly describe Figure 3.

1- To design a better decision situation, C-K theory prescribes that we should rely on knowledge in K_0. Hence, we can think of designing a new decision d* in D. For instance, this can be to take another accessory that is better than a hat. This can simply be "a better hat" that provides a bit of fun, even in the rain, hence the cost of having such a hat in the rain decreases (symmetrically, one could also design a better hat in the sun or a better raincoat in the sun or a better raincoat in the rain).
2- Then, C-K theory prescribes that we should use other pieces fo knowledge (from K_0) to design new options. The knowledge on belief can be used: can one design a new decision that would be good regardless of what one believes, i.e. an accessory that would be equally effective as a hat in the sun and a raincoat in the rain? We are now dreaming of something that could be called a "raincoathat" that might not yet exist, but might be able to be created! This "chimera" is represented by the illustration in Figure 3.
3- Finally, C-K theory prescribes that we should use a parameter that has not yet been used: design a better decision situation by using knowledge on the space of events, i.e. by designing a new event! Of course, it might sound strange to suggest that we "design a state of nature," but we should keep in mind that from the Bayesian perspective, the state of nature is actually the representation of nature by the decision-maker. Hence, we can proceed with this hypothesis and imagine what new states of nature can be designed. For instance, one can look for a state of nature that would increase the costs of all known decisions, i.e. hat or raincoat. Driven by this "unknown state", one can consider that there are trees all along the walk that protect us from both the rain and the sun, making the hat and the raincoat useless accessories. In this case, we have added a new state of the world that changes the decision situation (other examples are given in Appendix A-1).

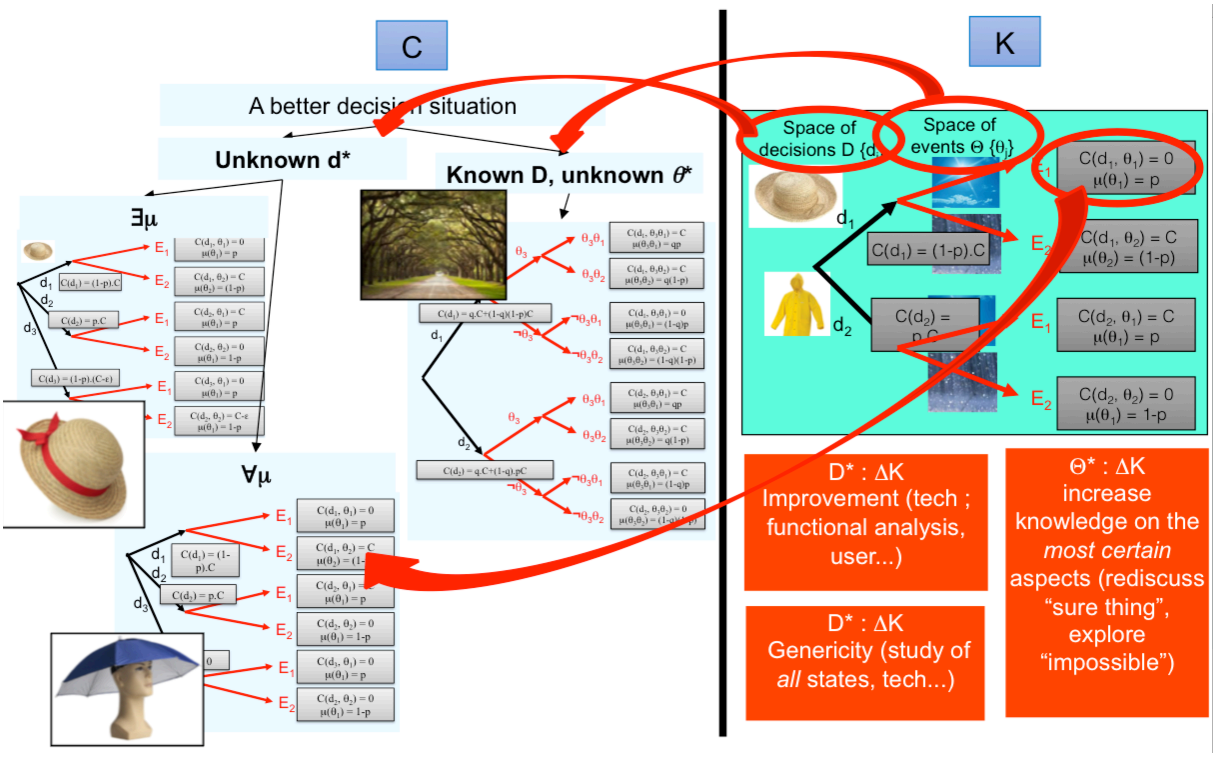

Figure 3: Extension of the raincoat/hat decision situation to the unknown – design paths toward a better decision situation are represented in the C-space; knowledge expansions appear in the K space. The red arrows represent the attributes of the initial knowledge (D, Θ, and μ) that are used to generate the new design paths.

This example illustrates the main features that appear in the formal construction of the extension of a decision situation to the unknown. Let's summarize now these features (a detailed demonstration is presented in Appendix A-1).

1.1- We systematically identify all possible ways to generate new decisions d* that improve the decision situation, while keeping unchanged the states of the world. d* is better than the known decisions d_i.

1.2- In particular, one design path generates a *generic* decision that is good for all states θ_i of Θ. d^* is different from all combinations of d_i in D and addresses all known θ_i, i.e. d^* is generic to all θ_i.

1.3- The design paths will necessarily create new knowledge, and the learning process is guided by the design path: either it is led by d_{opt}, the optimal decision in the initial decision situation, or it is led by the systematic study of all θ_i to obtain a generic solution.

2.1- The "decision designer" can also create new decision situations by designing new states of nature θ^*. This is a generalization of the Bayesian approach from a belief in the probability of the occurrence of known states of the world to a belief in new, previously unknown alternatives. The associated unknown might be either desirable (increased value) or undesirable (decreased value).

2.2- The new state θ^* is a new dimension added to Θ. One important property is that it is generated by questioning the "sure thing" or the "impossible," and not by reducing uncertainty.

2.3- θ^* increases global uncertainty and might change the initial hierarchy between decisions d_i.

Using C-K design theory, we have systematically generated an extension of a Wald decision model under uncertainty. We can now analyze how this newly constructed decision-design model answers our research questions.

Part 5: Findings and results: generating new types of decisions and revising states of nature

We obtain results in relation to our twofold research question: how to characterize the types of unknowns considered as directions of generativity (with associated value and type of knowledge to be explored) (RQ 1), and how to characterize the performance of the process of extending the decision situation to the unknown (RQ 2).

5.1- Types of unknowns corresponding to different directions for generativity (RQ 1)

Based on the model, we are able to identify, in the decision-challenging unknown, what we call decision concepts or decision-driven design paths. These are not decisions; they

are decision-driven directions for the generation of a better decision situation. A decision-driven design path is still partially unknown, but it has two critical properties:

> 1- one knows more about the value associated with it (how much it will change the initial decision situation, measured in terms of expected utility)
>
> 2- one knows about the knowledge that should be explored for the generation of the associated decision situation.

This a critical contribution: it becomes possible to *orient and stimulate* the generation process using decision-driven knowledge. In other words, knowledge about the decision situation does not necessarily restrict the generation of new decisions.

The model enables *four types of decision-driven design paths* (see the synthesis in Figure 4 and Table 1). The first two can be characterized as "wishful decisions":

1- decision-driven design path, type 1: *new wishful decision by improvement* (unknown decision d^*, exploration driven by θ_{j0}). This consists of designing a new decision d^* as a variation of decision d_{opt}, which was initially identified as the best one. The design process is driven by a desire to reduce the cost of a specific θ_{j0}, $C(d_{opt}, \theta_{j0})$. The value of the unknown is given by $C(d^*, \theta_{j0}) < C(d_{opt}, \theta_{j0})$ and knowledge creation is driven by θ_{j0}. This is the most self-evident extension.

Note that the value of knowledge is *not* in risk reduction (as in the basic model of decision under uncertainty) but in *cost* reduction associated with the new pair $(C(d^*, \theta_{j0}))$ (the probability associated with each state remains unchanged). In other words, we have a new way to value knowledge creation; decision theory under uncertainty provides a very interesting way to value knowledge creation through risk reduction. In this decision design, one can value knowledge creation in terms of the cost reduction induced by the newly generated alternative.

2- decision-driven design path, type 2: *new wishful decision by genericity* (unknown decision d^*, independent of all θ_i). This consists of designing d^* as a generic alternative that is better *whatever* the state θ_i. Knowledge creation is driven by this genericity, either independent of all θ_i or driven by features that are common to all θ_j.

Again, the value is not in risk reduction. The *value of the knowledge creation is all the higher that d^* is independent of all θ_i. The value of the knowledge lies in the new interdependence of d^* and θ_i* (in terms of costs $C(d^*, \theta_i)$). Note that this form of extension is not really examined in the literature on the unknown in strategic management; it is more common in the literature on platforms and the management of generic technology (Gawer 2009; Kokshagina et al. 2017a; Bresnahan and Trajtenberg 1995). We can see how the systematic framework unifies different types of unknowns and different types of exploration strategies.

The two other decision-driven design paths rely on the design of a new state of the world that will change the decision situation. We call them design paths toward a decision-changing state.

3- decision-driven design path, type 3: *new decision-changing state by "best-choice hacking"* (unknown state θ^*, exploration driven by having a differential effect on d_i). This consists of designing θ^* as a new dimension of the state of the world that changes the hierarchy

between decisions d_i. Knowledge creation is driven by investigating the most certain knowledge (sure thing) and by the search for the most order-changing state (heterogeneous $C(d_i, \theta^*)$). The value of knowledge relies on *new interdependencies* between d_i and θ^* (in terms of expected costs $\sum_{j=1\ldots n+1} C(\theta_j, d_i)\mu^*(\theta_j)$). This corresponds to "uncovering unk-unks" by studying the *robustness of a single solution* (for instance, the dominator, i.e. the best one). In particular, this corresponds to the try-and-learn processes described by (Loch et al. 2008). Additionally, it helps orient the exploration process: the model shows that these "best-choice hacks" can be found when looking at the most certain knowledge. The model does more than merely facilitate broad exploration; it prescribes that we should *focus on the most certain knowledge*, in other words it recommends that we look at impossible states (those that are certain not to occur) and not at the probably possible ones. Again, this underlines the fact that the issue is not in uncertainty reduction, but in unknownness exploration.

4- decision-driven design path, type 4: *new decision-changing state by "all-choice hacking"* (unknown state θ^*, exploration driven by having a systematic effect on all d_i). This consists of designing θ^* as a new dimension of the states of the world that does not change the hierarchy between decisions d_i but changes the overall value. Knowledge creation is still driven by investigating the most certain knowledge (sure thing), but it is also driven by a search of the non-order-changing states (homogenous $C(d_i, \theta^*)$). The value of knowledge relies on *new interdependencies between θ^* and existing d_i* (in terms of expected costs $\sum_{j=1\ldots n+1} C(\theta_j, d_i)\mu^*(\theta_j)$). This also corresponds to "uncovering unk-unks," this time through a parallel exploration. However, this is a parallel exploration where the generator looks for systematic conditions that will impact *all* solutions, either positively or negatively. Hence, the model leads us to focus on the hidden interdependencies that make all known states and all known decisions work together (e.g., one designs the "walk under trees" situation by trying to find a case where, regardless of the decision between a hat or a raincoat and the state of nature, i.e. rain or sun, the pair decision state will be bad).

We synthesize these four decision-driven design paths in Figure 4 and Table 1.

The model shows the four archetypes, but combinations are of course possible. In particular, the generation of a new alternative can lead to the generation of new states (at a new level in the tree, see Figure 4) and the generation of new states of the world can lead to the generation of new decisions (see Figure 4).

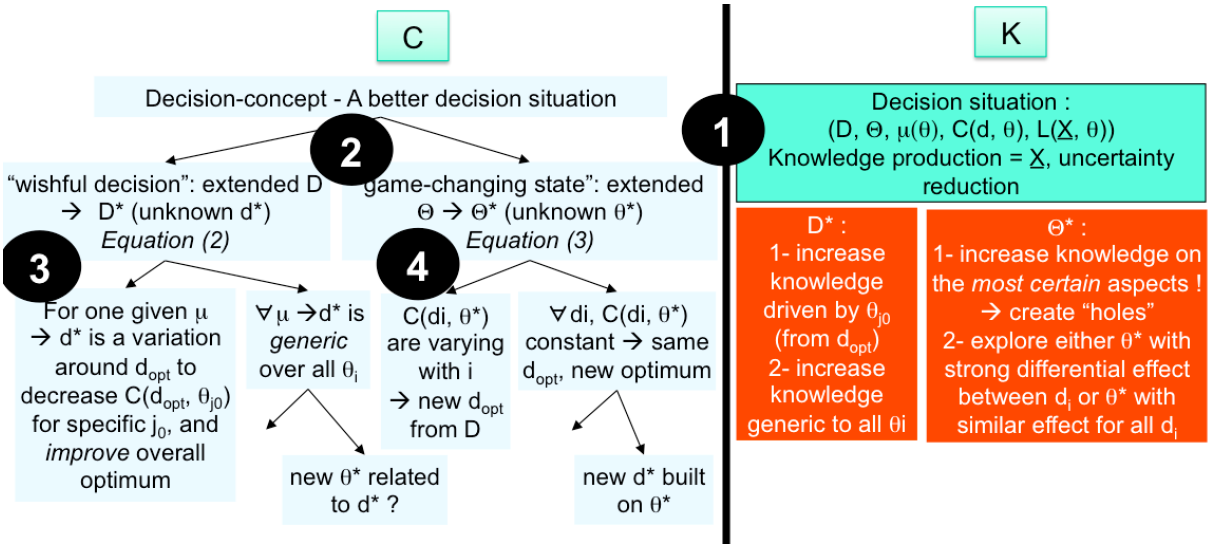

Figure 4: Decision design in the unknown. C shows the new decision-making situations after d* or θ* extension. K shows the knowledge creation strategies associated with the design of d* and θ*. Numbers 1 to 4 indicate the possible fixations (see Section 5.2).

	Reference: learning in decision theory in uncertainty	**New, wishful decision by improvement**	**New, wishful decision by genericity**	**New, decision changing state by best choice hacking**	**New, decision changing state by all choices hacking**
Unknown?	*No unknown, only uncertainty*	New decision d*	New decision d*	New state θ*	New state θ*
Driver for the exploration of the unknown	*Learning based on risk reduction (sampling to change the belief from a priori to a posteriori)*	Better than the (initially) optimal one d_{opt} on at least one state of the world θ_{j0}: $C(d^*, \theta_{j0}) < C(d_{opt}, \theta_{j0})$	Better than all decisions in all possible states $\forall i, \forall j\ C(d^*, \theta_j) < C(d_i, \theta_j)$	Explore the « most certain knowledge », the « impossibles » associated to the best decision d_{opt}.	Explore the « most certain knowledge », the « impossibles » associated (systematically) to all decision d_i
Value of knowledge	*Decrease expected costs*	Not in risk reduction, but in decision improvement	Not in risk reduction, but in genericity	Not in risk reduction but in identification of new specific risk	Not in risk reduction, but in identification of new systemic risk

Table 1: Decision design in the unknown: the main features of the four decision-driven design paths (first column: reference = reduction in decision theory)

5.2 Characterizing performance levels by types of generative biases (RQ 2)

The model underlines a general increase in comprehensiveness. In each branch, there is a gain in D and/or Θ. This is possible because the generation model retains the decision logic. It does not end with a list of "ideas," but each branch retains the decision-making formalism. In particular, this means that in each branch, it is still possible to compute the best solution according to Wald's model. One simple consequence is that the decision models that are already in place in a company are preserved and enriched by the generativity process.

However, one should note that between the initial and final states, there might be some surprising changes. For instance, the model shows that the value of the best decision might be *lower* after the generation process. This is linked to the fact that the generation process actually leads to a transformation of unknownness into uncertainty, thereby increasing uncertainty. One direct consequence of this is that the expected value of the

best alternative cannot be taken as an indicator of the increase in comprehensiveness. Thus, we should look for other indicators of performance improvement.

Another indicator of the performance of the generativity process is the capacity to map fixation and defixation areas. We now show how the model sheds light on the generation biases associated with the process of extending a decision situation to the unknown.

1- *Overcoming bias in favor of uncertainty and against the impossible:* the decision-design model helps to overcome a first-generation bias that comes from the distinction between decision under uncertainty and generation under uncertainty: individuals and teams might tend to represent themselves as *deciding* under uncertainty instead of *generating*. Technically, referring to Figure 4, it means that they tend to stay in K instead of going to C. In K, they produce knowledge for uncertainty reduction, and they are certainly not producing knowledge that enables them to rediscuss sure things. Many studies have discussed this type of bias: business plans based on optimal NPV expectations, project management dealing with uncertainty instead of unknownness (Lenfle and Loch 2010), the dangers of misleading expectations in technology development (van Merkerk and Robinson 2006; Geels and Raven 2006; Borup et al. 2006), and decisions in relation to innovation projects (Elmquist and Le Masson 2009).

2- *Overcoming bias in favor of problem solving and against environmental exploration (problem finding)*: if one supposes that a team is designing an innovative solution, a second fixation appears in relation to the alternatives D^* vs Θ^*. Some teams will be tempted to look for new decision alternatives d^* and will neglect the possibility of designing (discovering) new states of the world θ^*. This might be the case for engineering departments that design products when external conditions Θ are given by the list of requirements. Conversely, some teams might be tempted to design new θ^* for a given list of possible decisions D. For instance, this might occur when a commercial department tries to find new markets without changing the firm's technologies and products. In general, one tends to see a bias in favor of problem solving and against environmental exploration, which corresponds to problem finding. (von Hippel and von Krogh 2016) examine multiple studies that underline the risk of fixation on a problem that is not well formulated and is not regenerated (von Hippel and Tyre 1995; Sieg et al. 2010; Sieg 2012). By mapping both processes, the model contributes to overcoming fixation.

3- *Overcoming bias in favor of optimizing for one known condition and against the design of generic solutions*. Suppose a team is designing a new decision d^*: there is a possibility of fixation on designing d^* that optimizes d_{opt} on one (or a couple of) θ_j; the team will hardly consider designing a d^* that is independent of external states of the world, i.e. external demands. That is, there is a fixation on designing specific, targeted products/services instead of designing generic solutions (Le Masson et al. 2016a; Kokshagina et al. 2017a; Hooge et al. 2016).

4- *Overcoming bias in favor of increasing robustness of one known solution and against the discovery of systemic risk*. Suppose a team is now designing new states of the world θ^*: there is a possibility of fixation on testing whether d_{opt} is *robust* under alternative conditions θ^*. Hence, one is looking for specific θ^* where $C(d_i, \theta^*)$ are so different that they could change the hierarchy of decisions. Teams and individuals will less readily explore situations that *systematically* impact the overall value (and would ultimately lead to a new

d^* associated with θ^*), i.e. the investigations to uncover systemic risk are hindered by generation bias (Lenfle and Loch 2010; Loch et al. 2008).

We can see how many well-known tensions, dilemmas, or biases in innovation management can actually be mapped as generation biases in an extended decision-making framework.

Part 6. Discussion and conclusion

This study contributes to innovation management and the foundations of management science. Methodologically, it shows how progress in innovation management and design theory enables us to formally approach the question of the extension of decision-making to the unknown. Subsequently, the study proposes a model of decision design in the unknown with a clear rationality model and explicit performance. The main features are summarized in Table 2, which compares the model of decision under uncertainty with that of decision design in the unknown.

Based on the proposed model, this study contributes to the twofold issue of the unknown in decision-making: a) the paper identifies a structure of the decision-oriented unknown based on four contrasting types of actionable unknowns called decision-driven design paths and clarifies how each type relates to a particular logic of decision-oriented generativity, with a specific value and specific types of knowledge expansion (synthesized in Table 1); b) the study identifies the performance associated with the exploration strategies, this performance being assessed in terms of defixation, i.e. the capacity to overcome generation bias. We synthesize this contribution in Table 2.

	Model of decision under uncertainty	**Model of decision design in the unknown**
Rationality model	If there is: - a set D of decisions d_i, - a set Θ of probable states of nature θ_j, with a belief function μ, - and a cost function $C(d_i, \theta_j)$ (and a learning function L) → then there is an optimal decision diopt that minimizes cost function	If there is D, Q, m, C – but the optimal decision is not desirable, → Then there are four decision-based design paths to generate a better decision situation that extends the given one and this better decision situation: - New, wishful decision by improvement - New, wishful decision by genericity - New, decision-changing state by best choice hacking - New decision-changing state by all choices hacking
Performance	Overcome selection biases	Overcome generation biases

Table 2: From decision model to decision-oriented generativity model: a new rationality model and associated performance.

This raises two discussion topics that also indicate directions for further research.

1) The potential contribution to Artificial Intelligence (AI) of the new model of decision-oriented generativity

The structure of the unknown was obtained through a formal approach. Before discussing further organizational issues, it is interesting to note that a formal approach can also have intrinsic value. Today, decision theory is implemented in many algorithms (particularly in AI approaches) and leads to significant dilemmas. One example is the study we referred to in the Introduction (Bonnefon et al. 2016): how should the algorithm "decide" (*in the strict sense of a formal decision-making model*) when confronted with a dilemma such as

"If the brakes have failed, should the driver of the car kill the pedestrians crossing the street or save the pedestrians by crashing the car into a wall, thereby killing the occupants of the car?"

Formally speaking, this dilemma can be avoided by extending decision-making to the unknown, and our model indicates four design paths. This induces a question: can one implement an algorithm that corresponds to these four design paths to enable a machine to generate a new path? Interestingly, recent progress in AI (in particular on novelty searching or MAP-Elite algorithms) is enabling machines to invent new behavior when confronted with unexpected events (see (Cully et al. 2015; Lehman and Stanley 2008)). Our model of decision design in the unknown might make it possible to systematize the analysis of all the design paths that a machine might generate and/or analyze the possible generation biases in generative algorithms.

2) Revisiting organizational issues raised by the unknown

The question of managing in the unknown is one of the critical issues of management science. We frame it by revisiting its main steps. On one hand, the works of Knight (Knight 1921) taught us that 1) besides measurable uncertainty, there is unmeasurable uncertainty. In Knight's words, "It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all." Today, this second type is considered a form of unknownness, and Knight notes that 2) in this second case that is not "risk proper," the market relationship cannot work, and organization is needed. Hence, the unknown is one of the raisons d'être of the organization. Interestingly, at the same time, the grandfathers of management science, Taylor and Fayol, invented forms of organization to deal with the unknown, either at the plant level (Taylor 1895; Hatchuel 1996) or at the strategic management level (Fayol 1916; Hatchuel 2016). Hence Knight, Taylor, and Fayol were already dealing with the unknown; however, they did not provide us with a rational model of action in the unknown.

On the other hand, in the following decades, management science developed rational models of action, although these models were limited to action with uncertainty. In the 1960s, the development of the theory of decision under uncertainty provided management with "the basic disciplines that underlie the field of business administration" according to Bertrand Fow, the Director of Research at Harvard Business School in his preface to the reference book "applied statistical decision theory" of Raiffa & Schlaifer (Raiffa and Schlaifer 1961). The theory of statistical decision-making provided an integrated framework that could account for choices between known alternatives, taking into account uncertain events. Moreover, the models were able to place a clear value on uncertainty reduction endeavors (leading to option theory and later to real options), and this also led to powerful organizational models in which expertise, knowledge, and competences appear as core resources for dealing with uncertainty (see, for instance, the classical synthesis of organizational forms by Mintzberg (Mintzberg 1979, 1978)). Recent studies by historians and economists on the origins of decision-making in economics have led us to think that decision theory under uncertainty was one of the notions that was born in management before being applied to economics (Giocoli 2013).

Since the unknown is seen today as the type of situation that cannot be handled by the usual decision-making framework (Loch et al. 2006), it implies that the unknown might represent a situation in which organizations are at their limit. When organization theory

is at its limits, should one rely on the market when facing the unknown? This would be contrary to Knight's assumption. However, some studies, particularly in economics, follow this track and analyze open innovation, contests, crowdsourcing, start-up development, or ecosystems strategies as ways to deal with the unknown (e.g., (Terwiesch and Xu 2008)). Following Knight's intuition, other works (e.g. (Loch et al. 2008; Loch et al. 2006; Cunha et al. 2006; McGrath and MacMillan 1995, 2009; Pich et al. 2002; Sommer et al. 2008; Rerup 2009; Feduzi et al. 2016; Feduzi and Runde 2014; Weick and Sutcliffe 2007; Mullins 2007; Wideman 1992)) suggest that managing in the unknown leads to the development of *new formal models of rationality* that take into account the unknown and that are related to new forms of organizations. In that sense, managing in the unknown is the new frontier of management science.

This study has followed the latter approach by presenting a formal model of rationality to generate a structured mapping of exploration trajectories in the unknown (four decision-driven design paths); however, it is beyond the scope of this study to analyze all of the implications for organizations. Nevertheless, it is important to identify some consequences related to organizational capacity that are associated with the formal framework (see Table 3).

- Decision theory leads us to characterize and qualify decision capacities at a collective level: there is a clear managerial goal, namely, to select the best decision by overcoming selection biases, which leads us to identify decision-makers and experts, the latter making systematic preliminary investigations to prepare the ground for rigorous, objective decision-making by the former. There are techniques and instruments for evaluating alternatives (such as expected NPV) and there is a value ascribed to knowledge resources: knowledge reduces risks (e.g. R&D and marketing studies) and reduces selection bias, enabling a decision that is as close as possible to the optimal choice for a given actor.
- The extension of the model of decision under uncertainty to a model of decision design in the unknown leads to a discussion of the related generativity capacities. These capacities echo well-known notions in the literature such as dynamic capabilities (Eisenhardt and Martin 2000; Teece et al. 1997), ambidexterity (Birkinshaw and Gupta 2013; Tushman and O'Reilly III 1996; Duncan 1976), agile and flexible development (MacCormack et al. 2001), and parallel/sequential learning (Loch et al. 2006). Similar to the decision model for decision capacities, the generativity model induces quality criteria in relation to generativity capacities. There is a clear managerial goal of generating a better decision situation by overcoming generation bias, which leads us to distinguish the capacity to generate a new path and the capacity to manage multiple coordinated explorations. The former should enable a systematic exploration of new decisions *and* new states of the world, while the latter should organize and control generation biases, in particular by covering the four archetypal decision-oriented design paths. There is a value ascribed to knowledge resources: knowledge reduces generation biases and generates improved choices. This analytical framework, deduced from the generativity model, might help us to characterize the quality of generativity capacities and provide formal grounds and criteria for analyzing the notions evoked above: dynamic capabilities, ambidexterity, agile and flexible development, and parallel/sequential learning.

	Model of decision under uncertainty	Model of decision design in the unknown
Management (leadership, processes, competences, organizations…)	**Principle**: organize to select the optimal decision by overcoming selection biases **Organization and capacities**: *decision makers & experts* – experts gather relevant data to check D, Θ, μ, C and learn in order to reduce risk (R&D, marketing, etc.); **Quality process and techniques**: systematic preliminary investigation + decision based on rational criteria (rely on techniques to evaluate cost function: NPV, etc.) **Value of knowledge**: risk reduction and selection bias reduction (as close as possible of the optimal choice)	**Principle**: organize to generate a better decision situation by overcoming generation biases **Organization and capacities**: *capacity to generate pathes*: « exploration », « dynamic capabilities », « ambidexterity », « innovation function »,… *manage multiple coordinated explorations*: « agile », « flexible », « open », « co- », « platform based », « flexible », « parallel / sequential »,… **Quality process and techniques**: systematic actions to generate new decisions and new representation of states of the world + governance of the explorations. Requires a mix of valuation techniques and generation techniques. **Value of knowledge**: improved optimal choice *and* improved representation of states of the world – generation bias reduction

Table 3: From decision model to decision-oriented generativity model: characterizing decision capacities vs generativity capacities.

To conclude, this study aims to contribute, at least partially, to a revision of the foundations of management science by exploring the logic of the unknown in management science. The unknown is the new frontier for management and organizations. Following Knight, the unknown requires *organization*, but organizations struggle to manage the unknown, and are tempted to rely on the market to deal with situations involving too much that is unknown. Our study shows that innovation theory and design theory can provide us with formal models that help us to think about and characterize the logic of managing in the unknown. This model of decision design makes the unknown actionable via decision-driven design paths that orient the generation of better decision situations and help to overcome dilemmas and generation biases. It is interesting to note that these generation biases might actually be caused by management science itself. This means that, in a sense, these formal models also contribute to protecting management science from its own fixation![1]

More generally, this study contributes to the large body of work confirming that management is no longer limited to the decision-making paradigm, but is already in a post-decisional, generativity-based paradigm wherein models of collective action in the unknown are the new frontier. These studies contribute to making management science one of the few disciplines that is able to scientifically address the issue of the unknown, its language, its structure, and its specific logic of action. They contribute to the repositioning of management science as the discipline underlying the construction of a desirable unknown.

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