Towards a general framework for innovation shaped with AI to create and transform market offerings

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TOWARDS A GENERAL FRAMEWORK FOR (EARLY-STAGE OF) INNOVATION SHAPED WITH A.I. TO CREATE AND TRANSFORM MARKET OFFERINGS

Abstract: Our research focuses on early-stages of innovation, especially at the Biotech and Pharmaceutical industry, where the business research is still hit-and-miss, mainly based on trial and error and experimentation. We leverage the story of a high-growth startup, building and expanding on behavioral economics that examines the relationships between science and innovation, especially dynamic capabilities and related problemistic search, organizational learning and strategic options generation. A general framework for innovation shaped with both Narrow and General A.I. (advanced data analytics, intelligent algorithms, etc.) is proposed to create and transform market offerings, hybridize domains heretofore dissociated, together with knowledge spillovers and build organizational fit with prior and novel core elements. For firms, it can be exploitable as a competitive advantage, making it possible to efficiently anticipate, hence adapt to the most general types of change in representation or taking place in the environment.

Keywords: framework for innovation, strategic options generation, problemistic search, A.I., creation of market offerings, decision-making, organizational learning

Introduction

Spectacular advances in many scientific disciplines, both theoretical and technological, have occurred over the past several years, making it possible to understand very complex problems, along with impressive progress in A.I. This evolution is encouraging the diffusion of a new approach to industrial research (Gambardella 2004). However, the nature of business research is still pretty hit-and-miss, based on highly empirical experiments in the hope of having more direct effects on innovation, and shorter application lags. But to find what may work and to scale up or transfer experimental results requires a body of knowledge in general forms (including representations, theories, models, etc.) about some class of things, objects, or phenomena, about characteristics and properties that they have, about how they behave and interact with each other. This defines a science (Simon 1996 p. 1). And the latter "*has rarely offered more than a general and indirect framework for innovation*" (Gambardella 2004 p. 1). In turn, such framework for innovation requires greater reliance on trial and error and experimentation. Behavioral economics literature examines the relationships between science and innovation. If only because this input of science for organizations, generally under the form of external knowledge rather than in-house knowledge, implies learnings and performance. A fairly great framework for innovation, certainly and efficiently influences the "*creation of (and consequent change in) market offerings, business processes, or models that result from the use of digital technologies*" (Nambisan and al. 2017 p. 224). This defines digital innovation management. Valuable theoretical advancements should be realized in this direction with A.I. (Bharadwaj and al. 2013) to achieve a competitive advantage in the future (Lichtenthaler 2019). Also, the search for innovation gains at being focused on early-stages, especially at the Biotech & Pharmaceutical industry where the development of new drugs faces related problemistic search, organizational learning (Cyert and March 1963) and strategic options generation (Garbuio and al. 2015). "*Most human decision making, whether individual or organizational, is concerned with the discovery and selection of satisfactory alternatives*" (March and Simon 1958 pp. 140-141). This is not to argue that other stages of innovation are unimportant.

A.I. aims to understand and mimick human cognition. It determines our capacity to organize knowledge, to give it meaning, to increase our decision-making capacities and to master systems in a tech-driven and ever-changing business landscape (Villani 2018). As value chains, especially in the digital sector, are now global, the leaders in the field of A.I. can capture a large part of the value of the systems they transform and control. In 2021 the market size is valued at USD 58,3 billion. Investments in research and in industry reached record breaking sums. In 2020, "*Drugs, Cancer, Molecular, Drug Discovery*" received the greatest amount of private A.I. investment, with more than USD 13.8 billion, 4.5 times higher than 2019 (Zhang and al. 2021). The transformative potential of A.I., such as Deep Learning for high data volumes or Machine Learning in healthcare and biology, is widely recognized (Stone and al. 2016, Chen and al. 2012, Wuebker and al. 2018). Many firms from diverse sectors increasingly apply A.I. in terms of advanced data analytics and intelligent algorithms (Lichtenthaler 2019). We have entered in what some call the "*Age of With - Humans working with AI*" (Deloitte AI Institute). Though, there are at least two types of AI (Samoili and al. 2020) (i) Artificial General Intelligence relating to hypothetical intelligent machines indistinguishable from the human mind (i.e. Turing capable) or possessing an essential property of human intelligence (Fjelland 2020) (ii) contemporary Narrow AI (Fleming 2018) restricted to specific areas or tasks performed autonomously using human-like capabilities. This type of A.I. which represents all the existing A.I. is not creative and cannot come up with original ideas. As yet, there are no approved A.I.-developed drugs (Ibid). This means the way innovation is organized and coupled with A.I. needs to gain a clear understanding of when to replace and/or augment human interventions (Lanzolla and al. 2018) and how to overcome A.I. limitations especially in early-stage of exploration (Haefner and al. 2021). "(…) *human innovation management will be expected to work side by side with AI and machine learning algorithms in identifying and selecting opportunities as well as investigating what could be the organization's next competitive advantage (…) However, our knowledge of AI's limitations in the context of innovation is still quite sparse*." (Ibid, p2). This is probably the major obstacle to shape with A.I. and a proper framework for innovation, great strategies pertaining to the creation and the transformation of markets offerings. It is the subject of this research, grounded on an interactive and constructivist approach (Glaser and Strauss 1967) and in line with Cyert and March's (Ibid p. 3) call for an "[*e*]*mpirically relevant, process-oriented, general theory of economic decision making by a business firm*". The paper (i) starts with theoretical constructs we are building on and expanding (ii) then details empirical material and findings at the Biotech & Pharmaceutical industry (especially through the story of a high-growth startup) (iii) finally opens a discussion on our research, accomplishments and the attainment of objectives.

1. Theoretical constructs

In this section, we develop three theoretical constructs we're building on and expanding. The first subsection outlines a theoretical working basis of AI and more widely of scientific models proposed in economics, statistical theory of decision-making or management science, namely a preexisting *universe of possibles*, well axiomatized, wherein the problem space and the solution space cannot be redefined. The second subsection explains a theoretical framework for *extending* scientific representations while redefining the *universe of possible*s on a proper augmented axiomatic basis and for overcoming AI limitations. The third subsection highlights the expected theoretical change the *extension* framework involves in behavioral economics, especially for strategic options generation, organizational learning and for problemistic search concerned with innovations.

1.1. A theoretical working basis of AI: a preexisting *universe of possibles* wherein the problem space and the solution space cannot be redefined

"*Dating the beginning of any movement is difficult, but the Dartmouth Summer Research Project of 1956 is often taken as the event that initiated AI as a research discipline (…) The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it.*" (Moor 2006 p.87). AI was launched just for this purpose without any agreement on methodology or choice of problems or general theory. Though, a theoretical working basis of AI is a *universe of possibles* given beforehand and well axiomatized wherein to exploit and explore. Other scientific models proposed in statistical theory of decision-making, management science, design science, or economics, use similar assumptions with related concepts of *the universe*, *the world*, *the state of nature*, *the state of the world*, or *a true state of the world*, etc. (Savage 1954, Simon 1996, Aumann 1999, Samuelson 2004). In such *universe of possibles*, since E. Galois (Liouville 1846) and also according to H. Simon (1996 p. 116), the way of defining problems (exploring the problem space representing the 'outer' environment) and the way of addressing problems (exploring the solution space representing the 'inner' environment such as alternatives of action) cannot be redefined. This would imply laying novel knowledge foundations, meaning a novel axiomatization. Indeed, although the mapping of knowledge may change overtime, somewhere within a given *universe of possibles*, knowledge lies waiting to be partitioned in one part or another. To illustrate, the well-known Euclidian geometry applied on a flat surface like a plane wherein the shortest route is a straight line and the non-Euclidian geometry applied to map on a curved surface the shortest route (Riemann 1898), such as a great-circle arc on a sphere, are two different ways of defining and addressing such problem of a shortest route search (See Figure 1: *defining the problem of the shortest route search on the Euclidian's plane versus on the Riemann's sphere*).

Representations of the world or certain aspects of the world, including theories, models, etc., are definable as "*conceptual structures in individuals' minds that encapsulate a simplified understanding of the reality these individuals face (Thagard 2005)*" (Puranam 2018 p. 81). They play a key role to design A.I.-based organizational learning – "*the process through which organizations change or modify their mental models, rules, processes or knowledge, maintaining or improving their performance*" (Chiva and al. 2014 p. 689, Argyris and Schon 1978). Many formal languages may be used to shape scientific representations of a real problem, accepting that semiformal (in reference to specified branches of mathematics) and even informal (as in the typical axiomatic presentation of Euclidean geometry) languages are possible (Suppe 2017). In computer languages we encounter such statements as "J = J + 1" which everybody seems to understand (Jaynes, 2003). In conventional mathematics or in formal logic, the formalization starts by laying identities (equalities, equivalences, similarities, common domain of reference, etc.) and dependencies (constraints, objective functions, etc.) between known entities with certainty or only in terms of a probability distribution and unknown ones (Simon 1996), which are subsequently processed to facilitate its resolution when possible. This structure of relationships (such as a system of equations or an objective function for instance) is assumed to be the same for both known and unknown entities, while they are relative to the creation of the problem (problem space structure) or to its solution respectively (solution space structure). Major problems are unsolved because of this confinement as A. Einstein explained: "*Problems cannot be solved by the level of awareness that created them*".

On the whole, research using A.I. and adaptive learning (such as metaheuristics, hybridmetaheuristics and hyper-heuristics, etc.), with underlying deterministic models or stochastic ones, taking an empirical approach, with or without prior knowledge, works exploring and exploiting a specific pre-defined *universe of possibles* so-called research space. "*Development in the field of metaheuristics largely stems from the importance of complex optimization problems to the industrial and scientific world (…) According to the no free lunch (NFL) theorem, the averaged performance for all possible problems is the same for all algorithms.*" (Gogna 2013 p. 2). On a cyclical basis, they collect information, and often stochastically, with a view to enhancing understanding of the problem (based on different phases that can be classified in exploration phases or diversification phases), storing it in a myriad of possible forms, whether collectively (considering the problem as a whole) or inter-individually (considering one solution in relation to another), then sorting through it so as to reduce dispersion (in the phase called exploitation or intensification). Same working assumptions are true for scientific models applied in Data science to discover meaningful and useful structures within dataset (Kotu and Deshpande 2018), such as Knowledge Discovery in Databases, defined as "*the non-trivial process of identifying valid, novel, potentially useful and ultimately understandable patterns in data.*" (Fayyad and al. 1996 p. 40). The assumption of a preexisting *universe of possibles* is also true in the subfield of Deep

Learning concerned with understanding of human learning, for the most promising pioneering researches so-called Deep Reinforcement Learning (i.e. combining representation learning with reward-driven behavior) and Meta-Reinforcement Learning (i.e. reflexive learning) (Botvinick and al. 2019, Gupta and al. 2018, Mnih and al. 2015). All of them are framed as Markov Decision Processes (MDP), a mathematical framework used for modeling decision-making problems under uncertainty (Ibid) and predicting (in probability) a possible future that only depends on the current state, not the history. MDP build on the powerful theory of dynamic programming, an algorithmic technique for solving an optimization problem by breaking it down into simpler subproblems and utilizing the fact that the optimal solution to the overall problem depends upon the optimal solution to its subproblems (Ibid).

1.2. A theoretical framework for *extending* scientific representations and overcoming AI limitations

While, understandably, to stabilize an order of human activities, scientific representations of the world or certain aspects of the world meet the assumption of a preexisting *universe of possibles* (Johnson-Laird 1983, Simon 1996), the process of shaping new representations doesn't. "*One doesn't come equipped with a* "*space*" *of representations, or even a generator of possible representations (…) The process of discovering new representations is a major missing link in our theories of thinking and is currently a major area of research in cognitive psychology and artificial intelligence*." (Ibid p. 109). And since representations are not perfect, shaping a "preferred one" whose value is unknown in the current representation, can be useful (March 1991). Devising so, as a designer would (Simon 1969 p. 111, Rumelt 2011, Garbuio and al. 2015), may provide a design cognition approach for developing a theoretical and foundational framework, all in accordance with the behavioral economics (like cognitive science in general) that underline the impact of change in representation on human behaviors and decision-making (Gavetti 2012). One such framework, first formalized in mathematics (Liouville 1846, Cohen 2002), extends a scientific representation to a novel and more general one, such as a geometrization of space deemed acceptable in a *scale dependent manner* (i.e. in an observer dependent metric, just as with any GPS), Euclid's one on a flat surface or Riemann's one on a sphere, if we refer to our previous illustration (See Figure 2: *an extended geometrization of space to define the problem of the shortest route search in a scale dependent manner acceptable both on the Euclidian's plane subspace and on the non-Euclidian Riemann's sphere subspace*).

In the original sense (Ibid), the term *extension* means that the outcome of the framework is a novel *universe of possibles*, more general in this sense that it includes any prior ones as sub-ones, namely the Euclidian space and the non-Euclidian space, without introducing any contradiction. Only a novel appropriate axiomatization can make it possible, for example, first redefining a shortest route as a *geodesic* generalizing the notion of a straight line to curved spaces including great-circles. Moreover, memory being the substratum, whether human or artificial, wherein everything stands, especially wherein the *universe of possibles* is stored, the novel one must be stored including a copy of itself (as it was initially) while generalizing it. To date, only humans have such reflexivity, imagination and abstraction levels to perform this operation. It is clearly not a matter of generating a more creative and innovative idea or opportunity, by "extending" search – then understandable as a "narrow" *extension* in a very restricted sense – beyond existing knowledge domains to new fields that are more exploratory in nature (Haefner and al. 2021, Amabile 2019, Von Krogh 2018), while staying in the same *universe of possibles*. Since knowledge domains are based on a common axiomatic basis tailored for them all, the *universe of possibles* then remains the same. Otherwise, an *extension* framework as originally defined and that might be called "general *extension*" (to make the difference) must be engaged. The same difference is found between "Narrow AI" and "General AI". Thus, the *extension* framework, now understood as general *extension* framework, provides an opportunity to overcome AI limitations and also meet the conditions of an inventive test if reference is made to the World Intellectual Property Organization (WIPO) which requires to *extend* search ["*to show an element of novelty*"] beyond existing *universe of known possibles* ["*body of existing knowledge in its technical field*"] so-called "prior art"[1], to unrelated ones.

The machinery through which the *extension* framework is fulfilled remains to be seen carefully. The key is the extension of structures understandable as the creation of an overall structure (e.g. a meta-structure) exposing unknown entities, whether or not combined with known ones, to a meta-identity, such that the prior structure attached to known entities may become a sub-structure of this novel meta-structure. At this stage, that may be called 'prepared mind' (to mean that mind has learned to see from the outside also), unknown entities may result in entities of a heretofore unknown kind (e.g. novel entities). And by building relationships between relationships, with strategic new knowledge, the meta-structure shapes meta-identities between the various identities and thus becomes more general. To illustrate, according to the US Food & Drug Administration, vaccines work by mimicking the infectious bacteria or viruses that cause disease, and vaccination stimulates the body's immune system to build up defenses against the infectious bacteria or virus (organism) without causing the disease. Until the new mRNA-based technique was discovered, vaccines contained weakened versions of a bacteria or virus, or only part of the bacteria or virus. Now, they can contain only the genetic material for a specific protein and direct the body to produce a small amount of that protein to trigger an immune response if the real virus enters the body. As outlined here, the *extension* framework, like a chrysalis, changes the identity of things (e.g. their definition) and their meta-structure of relationships. It fundamentally differs from frameworks operating within a *universe of possibles* given beforehand, such as the well-known Bayesian inference process, identified because – as an optimal processing of incomplete information (Jaynes 2003 p. xix) – more than other models, it better captures the way in which any decision maker learns and updates his degree of rational beliefs about a possible *state of nature θ* among all enumerated ones whether in human or artificial memory (a theory, a hypothesis, an event, an observation, or an occurrence), in order to make a better judgment, while taking into account new *evidences E*

[1] Website

(new knowledge, new measurement, new sampling data, or other standpoints) (Seongmin and al. 2017). This way, by reference to probabilities[2], when feasible, the decision maker weighs his trust in his own choice and his perceived credibility in information received from outside (others, A.I., etc.), before he begins updating his judgment. While the *extension* framework has become of great importance in the Natural Sciences (Weyl 1952-1984), it has not received all the attention it deserves in the Human Sciences, albeit in a very limited extent via the concept of "*expandable rationality*" (Hatchuel, 2002).

1.3. The *extension* framework underpinning strategic options generation in behavioral economics

Except a relatively recent and significant piece of work done by Garbuio and al. (2015) that proposed a unifying framework built on dynamic capabilities theory to highlight how to add to traditional strategy (constrained by existing principles) to explain strategic options generation, the field of strategic management remains relatively distant from a clear theoretical or even empirical understanding of how to shape a great strategy (Ibid, Gavetti and Rivkin 2007). A definition for Dynamic capabilities is "*the capacity of an organization to purposefully create, extend or modify its resource base*" (Helfat and al. 2007 p. 83). And a great strategy is definable as "*one that yields exceptional benefits to customers while also creating a profitable and defensible position for the firm*" (Schilling 2018 p. 335). According to the authors Garbuio and al. (2015), although it is unachieved, their framework has the potential to serve as a guide for understanding knowledge representations associated with a design cognition approach in strategy formulation (Visser, 2009): "*One limitation of our work is that, as we propose cognitive acts that can shed light on the "magic" that happens at the end of the analysis, it would be premature to discuss what a strategy-by-design process looks like*" (Ibid p. 462).

The origin of great strategies is known to be fundamental to the study of decision making and organizational behavior (Calabretta and al. 2017, Whittington 2018, Argote and Greve 2007). Everyone agrees that great strategies emerge from status quo that can be technological

[2] $p(\theta|E).p(E)=p(\theta).p(E|\theta)$

(materialization), cognitive (representations) or economic (value systems), which stabilize a market or a competitive order of human activities. One's approach depends on the foundational assumptions made about the world, the reality, the rationality, the agency, etc., which are as numerous as the variants of the strategic management itself. Cognitive representations have long been of paramount importance in the conceptions of strategy (Simon 1947, Gavetti 2012, Jardat 2015, Gavetti and Ocasio 2015, Gavetti and Porac 2018). Given that the preponderance of cognitive representations is also found in the field of A.I. (Kaplan and Simon 1990; Pomerol 1997), there is a non-void intersection wherein to address the issue of the origin of great strategies, especially when they are shaped with A.I. By the way, the behavioral theory of the firm (Cyert and March 1963) has, since its inception, been intimately linked to A.I. (Augier and Prietula, 2007). As great strategies are assumed to come from theories (Felin and Zenger 2017), provided the *extension* framework is applicable to representations (including theories, models, etc.), it is also applicable to strategies. This is reasonably assumable in so far as strategies are definable formally as theories, in line with what Simon (1947) explicitly did when refering to game theory (Van de Steen 2016): "*Decision, or choice, [...] is the process by which one of [the] alternatives for each moment's behavior is selected to be carried out. The series of such decisions which determines behavior over some stretch of time may be called a strategy*" (Simon 1976 p. 67). The *extension* framework leads neither to a new theory which is created alongside the old one (Penrose 1959) nor to a new theory which replaces the old one [creative destruction] (Schumpeter 1951). It leads to a novel theory that includes the old one while generalizing it. In a more formal language, it can be conceptualized as a change in theory - e.g. a consistent set of statements as a stable and comprehensive knowledge (defined concepts and assumptions such as system of axioms) controlling all of its consequences (derived causal predictions such as theorems) (Argote and Greve 2007 p.337) and pertaining to the identity of things, objects or phenomena (such as their equality) - that have no universal value but only a relative (local and temporary) one. It is thus consistent with a business world in which humans continue to think and to invent and it provides an adequate answer to the question of designing a great strategy. The *extension* framework is understandable as an adaptive framework through which it is possible to efficiently anticipate, and hence adapt to the most general types of change taking place in the environment and also to the most general types of change in representation (Heylighen 1990). Interestingly enough, the framework of Garbuio and al. (2015) is based on five cognitive acts – *imitation*, *framing*, *analogical reasoning*, *abductive reasoning*, and *mental simulation* – that are at play in the *extension* framework: (i) the act of *imitating* – when refering to any intentional replication such as a formal representation or self-representation (e.g. reflexivity) (ii) the act of *framing* – when producing a schema (e.g. a *frame*work) for the interpretation of the facts of a situation, their assumptions, and precedents by drawing associations and dissociations among them (iii) the act of *analogy* which always relies on the extension to new situations of solutions based on ancient representations: "*analogy between two decision problems is a mapping that transforms one problem into the other while preserving the problem's structure.*" (Amarante 2015 p. 797) (iv) the act of *abductive reasoning*, defined as the form of logical reasoning that is essential in the creation of desired futures (for example a better explanatory hypothesis or the best possible guess in order to take an action or a suitable overall structure/meta-structure) (i) the act of *mental simulation* – when modifying a given representation of a situation by projecting the situation into future sequences of events. E. Schilling merely formulated the process another way: "*Great strategists use abstraction to identify the most important dimensions of a given technology or market, and they then seek the larger pattern of which those dimensions are a part. (…) abstracting away from the details of a situation to its more fundamental structural elements also facilitates an individual's ability to solve a problem through analogical transfer (…) an individual utilizes the structural similarity between an unsolved problem and a problem that has been solved, and applies the logic of the solved problem to yield a solution to the unsolved problem.*" (Schilling 2018 p. 336 p. 338).

Also, problemistic search (Cyert and March 1963) that is, a process whereby decision makers seek to identify possible solutions to the problem at hand, has much to gain considering the general *extension* framework over the narrow one depending on whether or not the search should continue within the same *universe of possibles*, so long as the problem is unsolved. As the authors point out "*When an organization discovers a solution to a problem by searching in a particular way, it will be more likely to search in that way in future problems of the same type; when an organization fails to find a solution by searching in a particular way, it will be less likely to search in that way in future problems of the same type.*" (Ibid p. 174). This highlights a reason why "*decision-making theory examines how organizations solve the opposition between innovations and organizational stability, legitimacy and risk aversion* (Greve 2003a p. 685). "*Developing innovations is a form of organizational search*'' well suited to redefining problems (Ibid). And thus, the *extension* framework is part of the solution to "one persistent problem in the development of a theory of the firm [that] is the problem of innovations" (Cyert and March 1963 p. 178). This latter issue will be explored more fully in examining the empirical cases at hand.

2. Field investigations and findings: A.I.-based research for expanding market offerings at the Biotech/Pharmaceutical industries

This section examines the empirical cases at hand and outlines the findings to enable a better understanding of the theoretical constructs that are made. The Biotech & Pharmaceutical industry is unique in terms of front-end innovation (Aagaard and Gertsen, 2011). And innovation is defined as a dynamic process leading to the conception of an idea, a behavior or a new object, bringing about its assimilation and widespread application, whereby knowledge accumulates through learning and interaction (Oslo Manual 2005, de Beaune 2008). In this early-stage of innovation characterized by numerous uncertainties, exploration comes up against the glass ceiling of AI limitations to the point where scientific discoveries are regarded as serendipitous. How this industry works and deals with A.I. to provide relevant applications, explanations, interpretations and predictions, to further expand the pipeline in areas of high unmet medical need and open new markets, is investigated through the story of a high-growth startup facing change in representation and in A.I.-based strategy: from serendipity (chance discovery) to drug repositioning (old drugs for new uses) while staying in the same *universe of possibles*, then to *extension* framework in a changing *universe of possibles*. This way, we leverage the case of MedDay while remaining focused on our research question.

2.1. Before the change in representation: Drug development strategy based on A.I. and serendipity in a given universe of possibles

MedDay is an international pharmaceutical company targeting brain metabolism to treat nervous system disorder. This high-growth startup was founded in 2011 by a leading neurologist and neuroscientist with 90 publications focused on inborn errors of metabolism and his co-founder who had more than 25 years' experience in drug development in rare and orphan diseases. At the origin, while they conducted clinical trials in the hospital environment, one of the patients tested who was suffering from a neurodegenerative disease showed surprising signs of improvement. The result was quite unexpected double title. First, the treatment had not been planned for this purpose and second, no known treatment had ever made it possible to obtain such a result. The experiment has been subsequently confirmed and the complete results of clinical studies have been shown to be effective in reversing disease progression never previously demonstrated by another drug (Tourbah and al. 2016). The development of this new therapeutic use cost a hundred times less than usual in the pharmaceutical field ($10 million euros instead of $1 billion euros) (Deotarse and al. 2015). The founders thought all this was a fortunate coincidence and a rather unique history. Such phenomenon falls under the definition of serendipity: "(…) *making discoveries, by accidents and sagacity, of things which they were not in quest of*" (Remer 1965 p. 633). Louis Pasteur said: "*in fields of observation, fortune favors the prepared mind.*" (Pasteur 1854 p. 131). The neurologist and neuroscientist probably had his mind prepared to be able to see the implications of the clinical trial for aspects of the neurodegenerative disease that others might overlook and to construct theories about cause-and-effect relationships that are outside of their direct field of experience (Spelke and al. 1992, Schilling 2018). Serendipity pertains to contexts of discovery (Merton and Barber 2004): "*The serendipity pattern refers to the fairly common experience of observing an unanticipated, anomalous and strategic datum which becomes the occasion for developing a new theory or for extending an existing* *theory*." (Ibid p. 635). MedDay tried, from that, to further expand the pipeline in areas of high unmet medical need, providing serendipity to identify and develop new therapeutic targets and compounds that have the potential to enhance neuron functioning and self-regeneration capacities in patients suffering from neurodegenerative disorders. The strategy was then based on a sound expertise in accelerated development, establishing strong academic and commercial collaborations with key partners and an innovative A.I. research information-sharing platform to examine metabolomic and lipidomic signatures of the cerebrospinal fluid of patients suffering from Central Nervous System disorders. Note that this A.I.-'data-driven' strategy is used (i) for an empirical search in esston and at random in a given *universe of possibles*, (ii) in the hope of observing happenings, accidents and incidents which were unknown to the researcher before and which may become crucial for further analyses and for creating new hypotheses and theoretical constructions, (iii) in the quest for replicating MedDay's history again or finding a comparable history still in its infancy somewhere in a lab or in a startup. Such a serendipity-A.I.-based search for a competitive advantage has been widely discussed in the literature and many risks have been analyzed through resource-based theories and theories of managerial cognition (Schmidt 2015) especially: the fuzziness in the understanding of the phenomenon (McCay-Peet and Toms 2018), the subjectivity and the situationality of opportunities (Schmidt 2015), the limited role of cognition (Winter 2012), the unlikely source of strategic opportunity (Denrell and al. 2003), the lack of privileged knowledge about external resources required for identifying an opportunity and thus the important role of prior knowledge (Shane 2000), the failure of the serendipitous discovery to respond to a valuable new market opportunity (Christensen 1997), the undervalue of an unexpected advantageous position and the strong path dependencies (Barney 1986), the restriction of the search for new solutions to the neighborhood of what is already known (Nelson and Winter 1982). In part, these risks probably caused concern to MedDay. However, a first turning point is a change in representation that led to a new A.I.-based strategy.

2.2. After the first change in representation: Drug development strategy based on A.I. and drug repositioning still in a given universe of possibles

It became clear, on closer reflection we engaged in with the founder of the startup and his staff about the process of discovery, that a side effect of a molecule originally designed with a specific patient population in mind and clinically tested by a combination of circumstances on a patient suffering from a neurodegenerative disorder, had revealed an efficacy in reversing disease progression. That meant the phenomena fell under the definition of drug repurposing. "*Drug repurposing pertains to the development of new therapeutic uses or new formulations for a known drug, or the combination of two or more known drugs that were previously used separately. These drug development strategies are known as drug repositioning, drug reformulation and drug combination, respectively. Within drug repurposing, the two most frequent strategies are drug repositioning and drug reformulation.*" (Cabana and al. 2017 p. 1). A recognizable example of repositioning that generated billions of euros worldwide for Pfizer, is 'Sildenafil', mainly marketed as Viagra, for the treatment of erectile dysfunction and originally developed as an anti-hypertensive (Ghofrani and al. 2006). Pfizer's story, very similar to that of MedDay, shows that the latter is not unique. What was seen as an unusual discovery process had to be relativized. The same applies to penicillin and therefore to antibiotics. This change in representation, from serendipity to drug repositioning, raised serious awareness on the part of the startup. Notwithstanding a worldwide pressure on prices, challenges from generics and ever-increasing regulatory hurdles, drug development is so time-consuming and expensive (on average, it takes 10 years and at least $1 billion to bring a drug to market) that pharmaceutical companies have become increasingly interested in the process referred to as drug repurposing or repositioning[3]. A considerable number of new indications that have been found via this strategy, with approximately half of the target indications currently under development (Ibid)

[3] Traditional drug development strategies usually include five stages: discovery and preclinical, safety review, clinical research, FDA (Food and Drug Administration) review, and FDA post-market safety monitoring. There are four steps in drug repositioning: compound identification, compound acquisition, development, FDA post-market safety monitoring.

and 25% of annual revenue of the pharmaceutical industry (Naylor and Schonfeld 2014). "*More and more companies are scanning the existing pharmacopoeia for repositioning candidates, and the number of repositioning success stories is increasing.*" (Ashburn and Thor 2004 p. 673). Historically, drug repurposing has been largely a serendipitous process that took place when a drug was found to have an off-target effect or a previously unrecognized on-target effect that could be used for identifying a new indication. But it can be stated since many years that drug repurposing has become a common drug development strategy - old drugs for new uses - particularly in poorly addressed therapeutic areas, such as the Central Nervous System (Sleigh and Barton 2010), with public policies support and encouragement. This was largely driven by a change in the regulatory framework, creation of A.I. information-sharing platforms for potential target molecules, and development of partnerships between non-profits and government agencies, academia and companies (Murteira and al. 2014). But "*the current disease characterisation within CNS [Central Nervous System] is very much founded on clinical aspects, rather than the underlying pathophysiology*" (Aminoff and al., 2012). In other words, most of the disorders within the CNS and also the exact mode of action by which many of the currently approved CNS drugs exert their effect are still poorly understood. Unsurprisingly, the discovery and development of drugs for CNS diseases has one of the lowest success rates (Pangalos and al., 2007). The main issue in drug repositioning is the detection of novel drug-disease relationships (e.g. new indications for an approved drug) including all operations such as screening of side effects, lack of therapeutic applications, pathologies and variety of symptoms, interactions among metabolic pathways, similarities, signatures, associations, combinations, propagations, mechanisms of action, overlap and profiling of neuroreceptors or neurotransmitters affected, etc. To address this issue, a variety of A.I. computational approaches, biological experimental approaches and mixed approaches have been developed and have also decreased the time cost of the drug development process significantly (1-2 years to identify new drug targets and 8 years to develop a repositioned drug, on average) (Sertkaya and al. 2014). Many companies[4] have shaped their drug repositioning strategy on the development of A.I. with platform technologies including databases and data mining capabilities to process voluminous amounts of scientific and clinically curated data and a large number of potential drug candidates while maximising the generation of ideas through open source partnerships (Xue and al 2018). BioVista is one such company, widely regarded as a pioneer in both the USA and Europe with its so-called 'Clinical Outcome Search Space'. Another company is Theranexus (France) "*A powerful technology platform, generating a diversified portfolio of patented drugs*" (report 2018 p. 10). Also, Therametrics (Switzerland) with a robust pipeline and its 'unique bio-mathematical technology research platform'. Note that, although any of which aspire for being a 'novel strategic options generation' process useful for an empirical A.I.-based search still in a given *universe of possibles* and for creating theoretical constructions, such quest is unachievable without coupling both Human and Artificial Intelligence. The startup MedDay has to play on this international chessboard where, moreover, leading the race to intellectual property protection is key.

2.3. After another change in representation: Drug development strategy based on A.I. and on the extension framework while redefining the universe of possibles

The extension of existing theory about the A.I.-based repositioning of drugs that is matched with product pipeline expansion and new market creation, lifted the debate to the higher level of drug-disease relationships, to detect novel relationships between relationships (e.g. novel indications drug-diseases), especially ((drug--effects)-(causes--diseases)) among all others (drug-metabolic pathways, mechanisms of action, etc.): See Figure 3 - *Universe of possible* meta-relationships [[drug--effects]-[causes--diseases]]. The following first checks empirically the *extension* framework redefining the *universe of possible* 'drug-diseases relationships' (subsection 2.3.1) and next explains the way humans and A.I. gain to interact in the exploration process, especially to base problemistic search on innovation and to generate

[4] https://biopharmguy.com/links/company-by-location-ai.php
Online directory of biotech companies (8000+) and AI Focused Biotech Companies – Worldwide (71+).

novel strategic options (subsection 2.3.1).

2.3.1. Extension framework redefining the universe of possibles

Let's first consider the collection of the following sets of elements: E_1 as the set of diseases (disorders within the CNS), E_2 as the set of diseases' recognized causes, E_3 as the set of drugs, E_4 of drugs' recognized effects. Let's next consider the following structures of relationships: S_1 (E_2 x E_1) between diseases and their recognized causes, S_2 (E_3 x E_4) between drugs and their recognized effects, S_3 (E_4 x E_2) between drugs' recognized effects and diseases' recognized causes. Note that the last structure S_3 is a meta-structure drawn coupling relationships S_3 (S_2 x S_1). These structures mirror the current knowledge the subject researchers have. As most of the disorders and also the exact mode of action by which many drugs exert their effect are poorly understood (see subsection 2.2), it follows that structure S_1 and S_2 so are always incomplete. Therefore, this is equally true for the structure S_3. Note that these structures are drawn up by researchers from all operations previously mentioned (see subsection 2.2) while considering the collection of the sets E_2, E_3, E_4 as unchanged. Now to complete the structures S_1, S_2, S_3, researchers must, for a given disease, extend their knowledge by extending either or both, the set E_2 of diseases' recognized causes, the set E_3 of drugs, the set E_4 of drugs' recognized effects. This is precisely what has happened in the case at hand when researchers revealed a previously unrecognized on-target effect that could be used for a new indication. The so-called drug MD1003 is a highly concentrated formulation of biotine also known as 'vitamin B7' or 'vitamin H'. The biotine plays a key role in the conversion of proteins, glucids and lipids into substances that are absorbable by the human body. Such recommended daily intake as a food supplement to people presenting signs of deficit for this vitamin and commonly to pregnant women, highly contributes in hair or eyes or liver's health and to the correct functioning of the nervous system too. Note that the biotin is an element of the set E_3 of drugs and its effect is an element of the set E_4 of drugs' recognized effects. The dose administered in the context of the clinical tests and corresponding to this drug as a potential treatment for the progressive multiple Sclerosis and for the optic neuritis is of 300mg/day. This dose is 300 time higher than that procured by over-the-counter products. “*MD1003 at this dose has been shown to play a role in stimulating myelin production and improving nerve impulse conduction; specifically, it activates several enzymes – including acetylCo1 carboxylase – involved in energy production and the synthesis of myelin*” (Sedel and al. 2015). Note firstly that this effect of high-dose biotin is a novel element of the set E_4 (of drugs' recognized effects) which extends the structure S_2 (E_3 x E_4) between drugs and their recognized effects and, by implication, the meta-structure S_3 (E_4 x E_2) between drugs' recognized effects and diseases' recognized causes. (See Figure 4 – *Extension* framework redefining the *universe of possible* meta-relationships [[drug--effects]-[causes--diseases]]). Note secondly that the identity of biotin has to be redefined from now in a dose dependent manner, no more only as a vitamin B7 or H, but also as a potential treatment for the progressive multiple Sclerosis and for the optic neuritis. Indeed, according to the Cambridge dictionary, a vitamin is defined as follows: any of a group of natural substances that are necessary in small amounts for the growth and good health of the body. This pictures how the *extension* framework leads to a novel representation generalizing both the (meta-)structure and the identity of things and phenomena while including any prior representation as a sub-one. We can draw a close parallel here with the geometrization of space (see subsection 1.2).

2.3.2. Humans and A.I. interactions in the early-stage of exploration: innovation-based problemistic search, organizational learning and novel strategic options generation

In the first stage of exploration in the value chain, scientists use A.I. at two different points in time in the hope of repositioning drugs, just as in the case of the MD1003: (i) when leaving the collection of the sets E_2, E_3, E_4 as it is (the *universe of possibles* is then unchanged) (ii) when extending the collection of the sets E_2, E_3, E_4 (the *universe of possibles* is then changed). Both problemistic search and strategic option generation are affected.

(i) Strategic options generation based on “narrow” *extension* framework coupled with A.I. in a fixed *universe of possibles*: Since the collection of the sets E_2, E_3, E_4 is unchanged, A.I. can work well aligned with a 'data driven' A.I.-based strategy in coupling computational and biological experimental approaches while processing massive scientific and clinical data, for instance, in search for “*known drugs targeting disrupted metabolic pathways*” in what concerns MedDay and, more generally, for signatures of a specific neurological disease profile (such as cardinal behavioral signs or morphological changes in different regions of the brain or metabolic and lipidomic abnormalities) and corresponding neuronal and neurochemical alterations, potential drug candidates (activating, inhibiting or reactive, etc.), similarities between diseases (geometry, energy or structure, etc.), side effects, etc. A.I. then helps accelerate the search and improve the efficacy and safety like never before, by processing a large volume of information and scientific studies, by reducing the risk of errors, by achieving accuracy with more precision, etc.

(ii) Strategic options generation based on “general” *extension* framework coupled with A.I. in a redefined *universe of possibles*: Provided the collection of the sets E_2, E_3, E_4 is extended, yet, scientists gain at combining in a proper alternation of search with A.I. and human decision, to get strategic new knowledge, such that the ensuing change in representation takes shape as drug repositioning for novel target therapies (See Figure 5 – Strategic options generation based on “general” *extension* framework coupled with A.I. in a redefined *universe of possibles*):

⇒ Search 1

- Income 1: the search with A.I. is done in the set E_4 of drugs’ recognized effects for correcting a relevant minor disorder in the functioning of the nervous system (without necessarily belonging to the set E_1 of disease).
- Outcome 1: Biotin identifiable among candidates.

⇒ Search 2

- Income 2: the search with A.I. is done in scientific and clinical databases for relevant studies or experiments on high-dose Biotin’s effects (or any other strategic amplification mode). Note that income 2 performs on outcome 1: high-dose Biotin’s effects.
- Outcome 2: no results (or very indirect results) means possible patent deposit and extension of the set E_4 (Biotin’s novel recognized effect); some partial results such as side effects may advance the research; some other results could sound the search bears no

fruit (no novelty).

⇒ Search 3

- Income 3: together with in vivo and/or in vitro experiments, the search with A.I. is done in S_3 ($E_{4\ extended}$ x E_2) between Biotin's novel recognized effect and diseases' recognized causes (within the CNS). Note that income 3 performs on outcome 2: S_3 ($E_{4\ extended}$ x E_2)
- Outcome 3: major disorders in the functioning of the nervous system, especially progressive multiple Sclerosis and optic neuritis.

3. Discussion on great strategies shaped with A.I. and a proper framework for innovation to create and transform market offerings

Now, research results and theoretical advances must be discussed for engaging all organizations concerned with great A.I.-based strategies to shape business search in life sciences and create or transform market offerings. The empirical studies make it clear that Narrow A.I. must be coupled with Human cognition and decisions for sustaining an A.&H. Intelligence-based competitive advantage (Davenport, 2018; Lichtenthaler 2019, Rai and al. 2019). To innovate and overcome A.I. limitations, the empirical cases also show how the *extension* framework, redefining the *universe of possibles* and by the way both problem space and solution space, provides a manageable alternative to building on serendipity (or even on open innovation) that remains uncertain. Somewhat as if "*what may appear to be serendipity actually has an underlying mathematical structure that can be exploited*" (Fink and al. 2017 p. 272). Thus, it is highlighted that A.I.-based organizational learning (including Meta-Reinforcement Learning, etc.), A.I.-based problemistic search (developing innovations being a form of) and strategic options generation, gain at implementing such a powerful framework, the structure of which is mathematical in origin.

Though, it cannot escape anyone's attention that, as a strategic input of knowledge, the element of novelty (such as entities of a new kind or new knowledge) is generated in a "scale dependent manner" and it is not demonstrated that such a specific operation would be a relevant option for any problemistic search or organizational learning situations. Consequently, the organization's capability to generate such a novel element as an input of knowledge to initiate a change in axiomatized representation, is a major issue to be addressed (Colombo and al. 2010, Hohberger J. 2014, Brem and al. 2017). Fink and al. (2017) saw things this way: "*A strategic understanding of which components to adopt, and when to adopt them, is more crucial than ever.*" (p. 279).

3.1. Coupling separated (yet completive) domains to generate markets extension

A corollary primitive question is thus to clear how, building on dynamic capabilities (Helfat and al. 2007), organizations can generate a proper element of novelty. Note that, until now and according to the *extension* framework, the generation of an element of novelty is methodically processed from inside the starting axiomatized representation, making it excessively difficult from this inner position. Another is to consider that elements of novelty, could come from another domain so far taken as independent. And although conditions governing laws of invention are becoming progressively less easy to read and understand overtime, due to the accumulation of human experience, a circulation of ideas and an entanglement of influences, practically all of the great discoveries and inventions throughout human history, can be analyzed this way (Bar 2007, de Beaune 2008): "*association by the mind, things that experience so far dissociated*" (Ibid p. 50). Such was the way in our case study and in the whole area of biotechnologies and pharmaceutical industry with drug repositioning. Finally, extensions capabilities to solve outstanding problems or create new markets are related to hybridizations capabilities (e.g. to shape meta-structures and meta-identities with structures and identities originating from heretofore dissociated domains). Turning this relation around makes it possible to assess and compare hybridizations opportunities in terms of market extensions (demand-side) and feasibility (supply-side). Drawing on evolutionary economics (Nelson and Winter 1982), while "*markets emerge, collide, split, evolve and die*" (Eisenhardt and Martin 2000 p. 523), innovation may be viewed in terms of fits between an inner universe (e.g. domain or environment) which is the potential donor of elements of novelties – and an outer separated universe (e.g. domain or environment) – which is both the potential recipient of these latter regarded then as suitable for the invention (supply-side) and a new market opportunity (demand-side) that extends the original market addressed in the inner universe (e.g. domain or environment) (See Figure 5 – Coupling domains to generate markets *extension*). Not to mention that it will be even more challenging for competitors to copy such combinations. The potential negative aspect is the coupling of separated ruling frames that goes with the coupling of separated domains, entailing inherent complex and lengthy policymaking. All cases we reported properly illustrate this mechanism: *Sildenafil* (hypertension & erectile dysfunction research domains) or *mRNA* (gene therapy & vaccines research domains), *MD1003* (Central Nervous System & Vitamin research domains), etc.

Hence, the view of innovation in terms of fits between an invention and "its" environment (Steiner 2018) may be better understood this way. Also, this may highlight the evolution of 'organization toward fit' and the positive alignment with the firm´s performance (Siggelkow 2002). Anyway, note that the universe of strategic possibilities (e.g. all possible recipients for a given donor and all possible donors for a given recipient) cannot be given beforehand waiting to be explored to make the right satisfactory completive choice, what the theoretical basis of a pre-existing *universe of possibles* would require. Once a valuable hybridization is made possible, the *universe of possible* can be entirely redefined and extended (i.e. there is no preconception of what is possible).

3.2. Searching for completive domains with General A.I.

Scholars have investigated emergent behavioral and adaptive strategy, resulting over time from firms' experimentation with their internal resources, beliefs and capabilities and the external competitive environment (target users and customers, trends, new knowledge sourcing, etc.) in the hope of identifying advance findings from the R&D well aligned with new market opportunities (Mintzberg and Waters, 1985, Garbuio and al. 2015; Steiner 2018). An exploration of the coupling of previously separated domains (such as donor and recipient organisms) cannot be based on stochastic models (probability theory or Theory of Probabilistic Functionalism (Ibid), etc.) as they all assume the pre-existence of a *universe of possibles*. The issue is not to draw combinations of balls of desired colors from an urn that contains balls of different colors. Dispensing with this assumption in a vision of innovation based on the coupling of separated domains, is a precondition for being able to reflect on *inherent vulnerabilities and opportunities*, by generating experimentation and mental/artificial simulations which may be used as a basis for forecasts about the potential future events. The strategic search for compatible and complementary donors and recipients, cannot be driven by Narrow A.I. in the hope of making the right satisfactory completive choice, in line with procedural rationality. There should be no expectation of such help from Narrow A.I. Looking forward, a move to General A.I., is preferable, more closely in line with the perspective of evolutionary science. This entails novel theoretical advancements applicable now by humans, while awaiting their algorithmic implementation (if possible and if desirable). Valuable ones have been done on how knowledge spillovers stemming from environmental innovation facilitate firms' innovativeness, economic openness, as well as appropriate policy design (Aldieri and al. 2020). "*While authors define knowledge spillovers in various ways* (…) *they relate to the capture, integration and utilization of knowledge generated elsewhere into firms' (or nations', regions', industries', etc.) own innovation processes*: "*one firm's innovative activity leads to new ideas and enhances innovative activity in a second firm without the second firm having to compensate the first*" (Barry and al. 2003 p. 590)." (Ibid p. 1). Some studies have explored the impact of environmental intra-sectoral or inter-sectoral spillovers on firm's productivity and the effects of technological diversity of the firms (Ibid). Others have examined the role that geographic and technological distance play in determining spillover intensity (Orlando 2004). At a macroscopic scale, knowledge spillover state changes can be measured in terms of entropy that indicates the degree of randomness of the firm's knowledge base, which means innovation specialization or technological diversity. Somehow, ex post, it measures the increase of the accessible space of knowledge (e.g. spatial entropy of Clausius, 1868) and the space of accessible speeds of learning (e.g. kinetic entropy of Boltzman, 1902). In our view, knowledge spillovers can be formalized ex ante as (narrow or general) extensions, or similarly, as couplings of completive environments. Such vision falls without any doubt under the definition of general A.I. (intelligent machines possessing an essential property of human intelligence) but must also meet the starting conjecture of A.I.: "*every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it*" (Moor 2006). Now inspired by the sciences of nature, some scientists have begun to propose a perspectival epistemology of randomness, unpredictability, noise, space, time and state (Longo and Montévil 2014, Sarti and al. 2019). For example (Ibid), to formalize the coupling of two previously separated domains (such as two separated probability spaces, etc.) in each of which an operator (a function, differentiation, transformation, map, etc.) is defined, it is difficult to describe a deformation of one operator on the other. However, it is possible to extend both of them to the overall domain (e.g. overall space) assigning value 0 outside its domain. This can be made by multiplying each of them by a function that has value 1 in one domain and 0 outside. If we also normalize the two functions in such a way that their sum is identically 1, the couple may then be called partition of unit. Thanks to this extension, the two operators act on the same set of functions, allowing a coupling (e.g. heterogeneous assemblage), which is a deformation of an operator on the other. This process of coupling (e.g. assemblage) can be formally expressed as a linear combination of the two extended operators. Since the first function takes value 1 in the first sub-domain (that was originally the first domain) and 0 outside, the coupling (e.g. assemblage) coincides with the first operator in the first sub-domain. Analogously, since the second function takes value 1 in the second sub-domain (that was originally the second domain), the coupling (e.g. assemblage) coincides with second operator in the second sub-domain. The resulting operator is then a smooth transformation of the first operator into the second one. Note that this is just one of the many coupling possibilities.

If we seek to go further, as some would like to see, and perhaps we are some of those, we must always hope for the best, but plan for the worst. Thus, we must realize the risk that we are putting humans under. Some are visible (high-cost, safety and security, privacy, bias, unemployment, etc.), others not yet, according to procedural rationality.

Conclusion

Our research has brought together areas of great contemporary interest, especially life sciences and A.I. It was a really ambitious and difficult attempt to bridge the insights from different economics-related fields including innovation and industrial economics, strategy and behavioral economics. The subject of our research was to shape with A.I. and a proper framework for innovation, great strategies pertaining to the creation and the transformation of market offerings. To this end, the research has focused on early-stages of innovation, especially at the Biotech and Pharmaceutical industry, for improving the performance of a business research still hit-and-miss and advancing by trial and error and experimentation. The relationships between science and innovation have been examined under the light of behavioral economics, especially dynamic capabilities and related problemistic search, organizational learning and strategic options generation, we have built and expanded on. We have leveraged the story of a high-growth startup facing change in representation, from serendipity to drug repositioning while staying in a same *universe of possibles*, then to an "out-of-the-box" framework for innovation. The latter, mathematical in origin, makes it possible to "extend" the *universe of possibles*, leading to a novel representation (or theory) generalizing the structure and the identity of things and phenomena, while including any prior representation as a sub-one. It displays outstanding potentialities. It makes it possible to efficiently anticipate, hence adapt to the most general types of change in representation or taking place in the environment, thus it is exploitable by firms as a competitive advantage. It meets the conditions of an inventive test if reference is made to the World Intellectual Property Organization and thus, overcomes A.I. limitations to create and transform market offerings, hybridize domains heretofore dissociated (such as a donor and a recipient), together with knowledge spillovers and build organizational fit with prior and novel core elements. It is a relevant option for any innovations-based problemistic search requiring to redefine both problem space and solution space and for organizational learning situations shaped with A.I. It clears how cognition acts (such as imitation, framing, analogical reasoning, abductive reasoning, mental simulation) are framed in strategic options generation and interact with A.I.

Though, a fundamental issue, still opened, is *where* (given that the issue of *how* is already cleared in this paper) to travel searching for completive domains to be hybridized with the aim of “extending” market offerings, if no *universe of possibles* is pre-existing.

This issue opens novel kinds of A.I.-based problemistic search (especially without pre-existing *universe of possibles* wherein to exploit and explore), of related strategic options generation (such as a scale-dependent approach or metric used in this paper) and of related organizational learning (external knowledge from undefined *elsewhere*). Valuable theoretical advancements should be made in this direction to achieve a General A.I.-based competitive advantage in the future.

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