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Discussing the Use of Complexity Theory in Engineering Management: Implications for Sustainability

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Abstract: What is the state-of-the-art literature regarding the adoption of the complexity theory (CT) in engineering management (EM)? What implications can be derived for future research and practices concerning sustainability issues? In this conceptual article, we critically discuss the current status of complexity research in EM. In this regard, we use *IEEE Transactions on Engineering Management*, because it is currently considered the leading journal in EM, and is as a reliable, heuristic proxy. From this journal, we analyze 38 representative publications on the topic published since 2000, and extrapolated through a rigorous keyword-based article search. In particular, we show that: (1) the adoption of CT has been associated with a wide range of key themes in EM, such as new product development, supply chain, and project management. (2) The adoption of CT has been witnessed in an increasing amount of publications, with a focus on conceptual modeling based on fuzzy logics, stochastic, or agent-based modeling prevailing. (3) Many key features of CT seem to be quite clearly observable in our dataset, with modeling and optimizing decision making, under uncertainty, as the dominant theme. However, only a limited number of studies appear to formally adhere to CT, to explain the different EM issues investigated. Thus, we derive various implications for EM research (concerning the research in and practice on sustainability issues).

Keywords: complexity theory; engineering management; management; sustainability; conceptual

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1. Introduction

What is the state-of-the-art literature regarding the adoption of the complexity theory (CT) in engineering management (EM)? What implications can be derived for future research and practices concerning sustainability issues? In EM, addressing these questions through a critical discussion of extant findings is relevant if we consider two, intertwined aspects.

First, in general, the adoption of approaches based on CT has become, in the 21st century, increasingly popular and highly supported. Concerning sustainability related issues, in particular, this is seemingly evident, especially when research grants, funding opportunities, and/or public tenders are released on themes regarding, for example, technology management, open innovation, circular economy, green procurement, or, more generally, sustainable ecosystems [1].

Second, as also highlighted by our analysis in this article, in the 21st century, the use of complexity approaches recurs in decision-making problems, regarding how to improve the effectiveness and efficiency of new product development (NPD), project management (PM), and supply chain management (SCM), or team organization. We know that these aforementioned problems have always been considered as key themes in EM. At the same time, we are confident that, to date, they also represent key challenges towards more sustainable business models [2].

As an example, in addressing a central issue for technology management research, i.e., understanding the nature of the industry environments in which firms play, Ndofor et al. [3] argue that "if the microfoundations of industry environments are indeed strongly impacted by nonlinear relationships, then the industry environment would evolve with chaotic dynamics, as opposed to equilibrium systems" (p. 200). Relatedly, as maintained by McCarthy et al. ([4], p. 437), "early research on NPD has produced descriptive frameworks and models that view the process as a linear system with sequential and discrete stages. More recently, recursive and chaotic frameworks of NPD have been developed, both of which acknowledge that NPD progresses through a series of stages, but with overlaps, feedback loops, and resulting behaviors that resist reductionism and linear analysis."

In the same vein, as stated by Amaral and Uzzi ([5], p. 1034), "a design engineer may know about the reliability of individual parts but find it difficult to estimate how failures in one part of system are tied together or how errors might cascade through the system when apparently separate components have a low probability of failure." Likewise, as posited by Baumann and Siggelkow ([6], p. 116), "should a product design team always consider all components simultaneously, searching for designs that have high overall performance? Or should it first experiment with a subset of components and expand this set gradually in the course of the design process?"

On this premise, starting in the 1960s, several contributions to CT have arisen from various science disciplines, such as biology, mathematics, physics, chemistry, and information technology [7,8]. This is why CT is growing as a cross-disciplinary scientific perspective, offering new approaches and answers, where reductionism demonstrates limits [9,10]. In particular, according to complexity science, the assumption of Newtonian thinking, where everything can be broken down into single pieces, studied separately, and then reassembled to form the initial totality, appears too simplistic when applied to understanding situations characterized by uncertainty and unpredictability [11].

Due to the body of knowledge and continuous, massive expansion of CT, most complexity theorists currently agree on some core characteristics of complexity, and a number of intertwined definitions have been developed over time [12]. Maguire and McKelvey, for example, seminally identify a complex system as "a system (whole) comprised of numerous interacting entities (parts), each of which is behaving in its local context according to some rule(s), law(s) or force(s). In responding to their own particular local contexts, these individual parts can, despite acting in parallel without explicit inter-part coordination nor communication, cause the system as a whole to display emergent patterns—orderly phenomena and properties—at the global or collective level" ([13], p. 4). Likewise, Mitchell conjectures a complex system as a "system in which large networks of components with no central control and simple rules of operation give rise to a complex collective behavior, sophisticated information processing, and adaptation via learning or evolution" ([14], p. 13). Moreover, since complex systems show a tendency to adapt, they are often referred to as complex adaptive systems (CAS); hence, we will use the latter term in this article.

Considering the foregoing, it seems that a conceptual article that critically discusses the current status of complexity research in EM is missing. Thus, the main contribution of our research is that we conceive it as a theoretical start intended to fill this gap. To do so, in Section 2, we first provide readers with the core concepts regarding CT. In Section 3, which constitutes the core of our research, we chose the 21st century to investigate the diffusion of complexity-based accounts in EM. In this regard, we use *IEEE Transactions on Engineering Management (TEM)*, because it is considered as the leading journal in EM [15], and as a reliable, heuristic proxy to start our focus. From this journal, we analyzed 38 representative publications on the topic published since 2000, and went through a rigorous keyword-based article search. Specifically, we provide the pillars of our contribution in terms of key thematic areas investigated and authorship coverage, together with the main research methodologies and core complexity features adopted. Therefore, in Section 4, we discuss some potential (and hopefully valuable) implications of our analysis for sustainability research and practices in this EM field. Section 5 concludes our contribution and presents its limitations.

As a piece of core evidence, our analysis shows that many key features of CAS seem to be clearly observable in the dataset, with modeling and optimizing DM under uncertainty as the dominant theme. Perhaps surprisingly, however, only a limited number of studies still seem to formally adhere to CT, to explain the different EM issues under investigation. This is also why, among the various avenues presented, we suggest that more all-inclusive complexity-based research frameworks would be needed. Accordingly, formally embedding fine-tuned co-evolutionary logics in these frameworks could also add value.

2. Theoretical Background

As previously mentioned, CT represents a multi-disciplinary, modern approach that studies CAS, following its own specific set of laws, behaviors, and characteristics, such as self-organization, and emergence. In principle, CAS can be considered as open systems consisting of several agents locally interacting in a non-linear manner and forming a unique, organized, and dynamic entity; this entity is capable of adapting to, and evolving within, the environment [16]. In other words, CAS have many features in common with living systems; they adapt and evolve through learning.

As mentioned above, a first important characteristic of CAS is the concept of self-organization. The Austrian biologist Von Bertalanffy [17] seminally coins this term in reference to the growth of organisms over time. Self-organizing reflects the ability of CAS to establish an internal organization through adaptation and evolution, without central control.

Relatedly, emergence is a characteristic showed by CAS, where "the behavior of the whole is much more complex than the behavior of its parts" [18] (p. 12). The peculiarity of emergence is that its nature is not necessarily linked to that of the agents [19]. For example, in PM, it has been conjectured that the complex interactions of various parts of a project can generate a specific behavior of the project itself, which can be explained through systemic analysis.

In order to understand how CAS behave, we need to model them, i.e., identify a set of variables that operationally describe these systems. System theory helps with this operationalization [20–22]. In particular, we can define a state variable of CAS as a measurable element of the systems that describes their conditions in a given moment. The state of CAS at a given time is, thus, the set of values held, at that time, by all their state variables [11]. In this regard, there is no formal rule for choosing the appropriate number and type of state variables; however, we can assume that the greater the complexity of CAS (in terms of number of agents and level of interdependence), the greater the variety in type and number of the state variables [13]. Moreover, state variables are represented in an n-dimension space, where n = number of state variables. In this space, each point defines a precise state of the systems (such a state is the state space of CAS). Given a set of state variables, the evolution in time of CAS is a trajectory in its state space [14].

Accordingly, another important characteristic of CAS is that their trajectories in the state space can have three main types of behavior [23]:

1. Order, when the trajectory reaches a point (or an orbit) of the space and then stabilizes. This point or orbit is defined as an attractor. The systems in this regime are stable;
2. Disorder or chaos, when the trajectory shows a chaotic path. In this regime, CAS are completely unstable;
3. Complex regime (or edge of chaos), when the trajectory is attracted by a particular region of the state space. This particular region is known as a strange attractor. In this regime, the systems reach their dynamic equilibrium.

The most interesting type of trajectory appears to be the third (i.e., complex regime), since CAS in this regime show their most relevant behaviors. When CAS reach the complex regime, the conditions are set for all of its peculiarities, i.e., self-organization and emergent behavior, respectively, to be present. However, despite the tendency of the trajectory to orbit around its strange attractor, the evolution of CAS is generally unpredictable [11].

To date, CAS may be found in different contexts, such as economics (e.g., a market), sociology (e.g., a human group), biology (e.g., a cell), business (e.g., an organization), or EM (e.g., a NPD process). In this regard, approaching these contexts through the lens of complexity can, appropriately help face uncertainty and unpredictability [24,25]. In particular, complexity can help model the real world through describing its main characteristics, especially when the deterministic approach seemingly unveils its limits. To do so, to date there are many methodological tools available in the scientific arena. Agent-Based Modeling (ABM), for example, allows simulating the actions and interactions of simple agents, and capturing the emergent and usually complex behavior of the system to which they belong [26]. ABM could also generate adaptive-learning models, which assume that agents have non-linear behaviors, generally based on very simple agent rules [27]. Another tool is fuzzy modeling, which helps face the ambiguity of complexity contexts by introducing un-precise values for the selected variables [28,29]. Likewise, stochastic models countervail the inability to accurately measure well-defined parameters, assuming that an optimal representation may be indeed found within a probability distribution of such measures [30]. Finally, a contribution to help understanding and modeling of complex systems can also be provided by the system of the systems approach [31] because of its tendency to pool resources and capabilities from single systems into a more complex entity, which performs more than the sum of the systems taken separately.

3. Analysis

In order to start discussing the impact of CT on EM, since 2000, after different methodological attempts (in terms of search strings and protocols), we ultimately chose to scan only the *IEEE TEM* journal—considered as the leading journal in the field [15]—through adopting a rigorous keyword-based article search on the EBSCOhost/Business Source Complete research database. In this regard, an initial clarification about the determinants of this methodological choice seems warranted here. This choice happened for two main (intertwined) reasons:

First, at the very beginning of our research project, we attempted to adhere to a traditional systematic review protocol (e.g., [32]). In other words, we initially scanned EBSCOhost/Business Source Complete for all of the articles containing, at least, the keyword "complex*" in their abstract (as known, the asterisk at the end of "complex" allows for different, related suffixes [e.g., complex or complexity]). From a strict procedural view, we are confident that, in principle, this methodological choice would have been, perhaps, more appropriate to initially circumscribing the potentially relevant literature in the field. In practice, however, while performing it, this search produced a large amount of results. These results, in substance, would have made the subsequent steps of a traditional systematic review to be rigorously performed in terms of screening, scanning, evaluating, and selecting, substantively not feasible [33].

We then made various attempts to limit the amount of potentially relevant papers through adding more specific filters, e.g., "engineering management", as keywords in their abstract. However, after making some crash checks through looking at the papers' text, we came to the opinion that this choice would have been too risky, in that it would have probably added opacity to the article inclusion (or exclusion) process. For example, various papers focused on complexity-based innovation, PM, or SCM, thus, in line with the focus of the review, do not contain "engineering management" in their abstract. In other words, at least in our view, this choice would have probably brought the risk of biasing the accountability, rigor, and transparency that is at the core of any systematic review process [34].

Second, as a consequence of the above, we attempted to focus only on *IEEE TEM* to scan EBSCOhost/Business Source Complete for all of the articles containing, at least, the keyword "complex*" in their abstract. This initial step produced 120 results, which then became 111 after eliminating all of the articles published in *IEEE TEM* before 2000 (our focus is on the 21st century), as well as those articles that could not strictly be considered peer-reviewed (e.g., departmental notes or guest editorials). This initial amount of results, we thought, made the subsequent, needed steps for the article inclusion/exclusion, through a rigorous fit for purpose protocol [35] practically feasible.

On this premise, to ensure substantial relevance for our dataset, we scanned all 111 abstracts. Specifically, to be selected: (i) the article abstracts had to formally adopt CT and/or CAS as their theoretical framework; or (ii) if the formal adoption was absent, the presence of the most vivid characteristics of CT had to be clearly identifiable in the abstracts. In particular, as explained in our theoretical framework, this is the case for characteristics such as ABM, emergence, evolutionary dynamics, fuzzy logics, non-linear dynamics, self-organization, stochastic modeling, system of systems, and uncertainty. Overall, this phase reduced our results to 54. Additionally, to ensure conclusive substantial relevance, we repeated this fit for purpose criterion through reading the article texts of all 54 abstracts selected; 38 articles (2000–September 2019) relevant to our research scope finally emerged. In general, this size is consistent with that of many past (e.g., [36]) and recent (e.g., [37]) more traditional systematic reviews, published in the management arena.

In sum, given the exploratory aims of this conceptual article, we believe that, due to the combined mix between the consistency of our dataset and the *IEEE TEM* leading reputation in the EM field [15], an *IEEE TEM*-based initial discussion about the topic coverage can represent: (1) not only a reliable, internationally recognizable, heuristic proxy about the state-of-the-art literature regarding the topic; (2) a (hopefully) challenging starting point to inspire future research efforts in what, as our results show, demonstrates to be a fast-growing, although still not totally conceptually consolidated, area in EM. In this regard, Table 1 synthesizes various, significant items of analysis emerging from our sampled publications. We adapted the thematic areas used in the column "Main Area(s) of Interest" from those present in the ABS 2018 Journal List.

Table 1. An overview of the dataset (in decreasing chronological order per publication year).

N.	Year	(First) Author	Title	Vol., Issue, Pages	Main Area(s) of Interest	Methodology	Industry	Complexity Characteristics	Main Content
1	2019	De	Multiobjective approach for sustainable ship routing and scheduling with draft restrictions	66, 1, 35–51	Operations	Non-dominated Sorting Genetic Algorithm	Maritime Transportation	Evolutionary, Non-linear	Through considering different variables relevant in maritime transportation, the work provides a genetic algorithm to support complex decisional processes in this industry.
2	2019	Li	Optimizing the labor strategy of a professional service firm	66, 3, 443–458	Human Resource Management	Labor Strategy Optimization	Global Professional Services	Stochastic, Non-linear, Uncertainty	Through non-linear analysis and uncertainty modeling, the work designs the Labor Strategy Optimization framework to strategically optimize the use of workforce at firm level.
3	2019	Yu	A complex negotiation model for multi-echelon supply chain networks	66, 2, 266–278	Operations	Simultaneous Multi-attribute Multi-item Modeling	-	ABM	Through using ABM, the work proposes a framework to support complex negotiation problems in supply chain networks.
4	2018	Ndofor	Chaos in industry environments	65, 2, 191–203	Strategy	BDS Test, Correlation Dimension Test, Lyapunov Exponent	Various	CAS, Non-linear	The work uses the nonlinear dynamical system methods from CT to study how different industry environments evolve over time.
5	2017	Liu	Novel two-phase approach for process optimization of customer collaborative design based on fuzzy-QFD and DSM	64, 2, 193–207	Innovation	Design Structure Matrix, Quality Function Deployment	Automotive	Fuzzy, Uncertainty	In the context of NPD, the work uses design structure matrix and quality function deployment to propose a two-stage model focused on customer satisfaction and cooperation.
6	2016	Geng	A new fuzzy process capability estimation method based on Kernel function and FAHP	63, 2, 177–188	Operations	Process Capability Indicators/Kernel Function	Process	Fuzzy, Non-linear, Uncertainty	Through a simulation in the Tennessee Eastman process, the work proposes a new method to estimate the production process capability, together with a new criterion for the evaluation of capabilities and performance.

Table 1. *Cont.*

N.	Year	(First) Author	Title	Vol., Issue, Pages	Main Area(s) of Interest	Methodology	Industry	Complexity Characteristics	Main Content
7	2016	Giannoccaro	Examining the roles of product complexity and manager behavior on product design decisions: An agent-based study using NK simulation	63, 2, 237–247	Innovation	NK Model	-	ABM, CAS, Evolutionary	Through a methodology drawn from complexity science, the work studies what behavioral factors can influence project managers in their choice regarding the degree of centralization of decisions about product design.
8	2016	Sarker	Internal visibility of external supplier risks and the dynamics of risk management silos	63, 4, 451–461	Operations	Bounded Rationality, Contingency Theory	Manufacturing	Non-linear, Uncertainty	The work uses bounded rationality and contingency theory to explain non-linear and non-deterministic perception of risks associated with the SCM process.
9	2016	Zhang	A stochastic ANP-GCE approach for vulnerability assessment in the water supply system with uncertainties	63, 1, 78–90	Operations	Analytical Network Process, Game Cross Evaluation	Water Supply	Fuzzy, Non-linear, Stochastic, Uncertainty	Through the case study of the Shanghai water supply system, the work proposes a stochastic multi-criteria approach for the vulnerability assessment of each component in the system.
10	2015	Herrmann	Predicting the performance of a design team using a Markov chain model	62, 4, 507–516	Innovation, Human Resource Management	Markov Chain	Motors	ABM, Stochastic	Proposing a Markov chain model, the work studies when it is convenient for bounded rational problem solvers/agents in search for an optimal solution, to decompose complex problems of product development in different, less complex sub-problems.
11	2015	Jiang	Optimizing cooperative advertising, profit sharing, and inventory policies in a VMI supply chain: A Nash bargaining model and hybrid algorithm	62, 4, 449–461	Operations	Non Linear Nash Bargaining Model/Hybrid Algorithm	Retail	Evolutionary, Non-linear, Stochastic	The work develops a Nash bargaining and hybrid algorithm model to optimize the complex joint DM regarding vendor managed inventory supply chains.

Table 1. *Cont.*

N.	Year	(First) Author	Title	Vol., Issue, Pages	Main Area(s) of Interest	Methodology	Industry	Complexity Characteristics	Main Content
12	2015	Parraguez	Information flow through stages of complex engineering design projects: A dynamic network analysis approach	62, 4, 604–617	Information Management, Innovation	Dynamic Network Analysis	Renewable (bio-mass) Energy	Emergence, Evolutionary	Through the dynamic network model developed, the work offers a tool to dynamically quantify and analyze the information flows among the activities of complex engineering design projects.
13	2015	Tsilipanos	Modeling complex telecom investments: A system of systems approach	62, 4, 631–642	Strategy	Genetic Algorithm	Telecom	Emergence, Evolutionary, Stochastic, System of Systems, Uncertainty	Focusing on telecommunications, and adopting the system of systems method from CT, the work models a genetic algorithm useful to study optimal DM and budget allocation.
14	2015	Villalba-Diez	Improving manufacturing performance by standardization of interprocess communication	62, 3, 351–360	Operations, Information Management	Interprocess Communication Holon	Engine Manufacturing	CAS	Studying the standardization of interprocess communication in complex supply chain networks, the work proposes a holistic model from which the manufacturing performance can increase.
15	2014	Kaki	Scenario-based modeling of interdependent demand and supply uncertainties	61, 1, 101–113	Operations	Scenario Based Modeling	Manufacturing	Non-linear, Stochastic, Uncertainty	Through the case of a manufacturing company, the work develops a scenario-based framework for modeling the interdependence between demand and supply uncertainties.
16	2014	van de Kaa	Supporting decision making in technology standards battles based on a fuzzy analytic hierarchy process	61, 2, 336–348	Strategy	Analytic Hierarchic Process	Technology Standards	Fuzzy, Emergence, Uncertainty	The study uses a fuzzy analytic hierarchic process to model the emergence, selection, and survival of technological standards over time.

Table 1. *Cont.*

N.	Year	(First) Author	Title	Vol., Issue, Pages	Main Area(s) of Interest	Methodology	Industry	Complexity Characteristics	Main Content
17	2012	Muller	Relationships between leadership and success in different types of project complexities	59, 1, 77–90	Management Science, Human Resource Management	Leadership Dimensions Questionnaire	Project Management Institute/ International Project Management Association	CAS, Uncertainty	The work studies whether project complexity moderates the relationship between the leadership competences of project managers and project success.
18	2012	Shafiei-Monfared	Fuzzy complexity model for enterprise maintenance projects	59, 2, 293–298	Management Science	Graph Complexity Model	Aircraft Engines	Fuzzy, Uncertainty	Through fuzzy modeling, the work defines different levels of project (managerial and/or technical) complexity, with the model useful for budgeting, planning, and resource allocation.
19	2012	Stryker	Creating collaboration opportunity: Designing the physical workplace to promote high-tech team communication	59, 4, 609–620	Information Management, Human Resource Management	Hierarchical Regression Analysis	Pharmaceutical	Uncertainty	The work studies how the probability to achieve complex team tasks is impacted by the relationship between the physical design of the workplace and the face-to-face communication among team members.
20	2012	Van der Vooren	Managing the diffusion of low emission vehicles	59, 4, 728–740	Strategy	Modeling based on vehicle technologies, infrastructures, and consumers	Automotive	ABM, Non-linear, Stochastic	Through using ABM, the work studies the competition for technological standards between a number of low emission vehicle technologies and the dominant fossil fuel based.
21	2011	Mikaelian	Real options in enterprise architecture: A holistic mapping of mechanisms and types for uncertainty management	58, 3, 457–470	Management Science	Real option analysis	Surveillance	Emergence, Evolutionary, Uncertainty,	The work develops a holistic approach based on real option analysis to manage flexibility and DM under uncertainty in complex engineered systems.

Table 1. *Cont.*

N.	Year	(First) Author	Title	Vol., Issue, Pages	Main Area(s) of Interest	Methodology	Industry	Complexity Characteristics	Main Content
22	2011	Revie	Supporting reliability decisions during defense procurement using a Bayes linear methodology	58, 4, 662–673	Operations, Management Science	Bayes Linear Modeling	Defense	Uncertainty	Through an industrial application in a defense procurement project setting, the work proposes a Bayes linear methodology to support the reliability of DM.
23	2011	Tripathy	Organizing global product development for complex engineered systems	58, 3, 510–529	Innovation, International Business	Design Structure Matrix	Various	CAS	Adopting the perspective of complex engineered systems, the work models the offshoring and onshoring of the activities associated with NPD at global level.
24	2010	Goh	Uncertainty in Through-Life costing—Review and perspectives	57, 4, 689–701	Management Science	Through-Life Cost	-	Fuzzy, Uncertainty	The work reviews how uncertainty is classified in the engineering literature and how it is conceived in the through-life cost estimation methodology.
25	2010	Zhang	An optimal-control-based decision-making model and consulting methodology for service enterprises	57, 4, 607–619	Management Science	Approximate Dynamic Programming Algorithm	Service	Fuzzy	In the context of service management, the work proposes a DM model based on an approximate dynamic programming algorithm, which can be useful to manage the planning and evaluation of complex projects.
26	2009	Levardy	An adaptive process model to support product development project management	56, 4, 600–620	Innovation, Management Science	Adaptive Product Development Process Modeling	Packaging	ABM, CAS, Evolutionary Fuzzy, Stochastic, Uncertainty	The study conjectures the process of product development as a CAS, featured by a general class of self-organizing activities/rules, able to adapt to the changing state of the process.
27	2008	Jun	A modeling framework for product development process considering its characteristics	55, 1, 103–119	Innovation	Modeling based on product development characteristics	Automotive, Electronics	CAS, Evolutionary, Uncertainty	The work provides modeling patterns for the product development process based on its iterative, evolutionary, uncertain, and cooperative characteristics.

Table 1. *Cont.*

N.	Year	(First) Author	Title	Vol., Issue, Pages	Main Area(s) of Interest	Methodology	Industry	Complexity Characteristics	Main Content
28	2007	Pathak	On the evolutionary dynamics of supply network topologies	54, 4, 662–672	Operations	Modeling based on supply network topologies	Automotive	ABM, CAS, Emergence, Evolutionary, Stochastic, Uncertainty	Through combining CAS with industrial growth, network, market structure, and game theories, the work investigates how supply network structures evolve and survive over time.
29	2007	Raisinghani	Strategic e-business decision analysis using the analytic network process	54, 4, 673–686	Strategy	Analytic Network Process	E-Business	Non-linear	In the context of e-business, the work uses the analytic network process to model optimal DM when decision complexity increases.
30	2006	Batallas	Information leaders in product development organizational networks: Social network analysis of the Design Structure matrix	53, 4, 570–582	Information Management, Human Resource Management, Innovation	Social Network Analysis/Design Structure Matrix	Aircraft Engines	CAS, Non-linear	In settings featured by the complexity of product development projects, the work uses social network analysis to model and evaluate the information flow, with a focus on the identification of information leaders.
31	2005	Cho	A simulation-based process model for managing complex design projects	52, 3, 316–328	Innovation, Management Science	Design Structure Matrix Simulation Modeling	Aerospace	Stochastic, Uncertainty	Through an industrial application in the aerospace industry, the work uses the design structure matrix modeling to propose an approach for managing complex product design projects.
32	2005	Jun	On identifying and estimating the cycle time of product development process	52, 3, 336–349	Innovation	Modeling based on product development characteristics	Automotive	Evolutionary, Stochastic	The work provides modeling patterns for the product development process based on its characteristics of interaction, evolution, and uncertainty.
33	2005	Williams	Assessing and moving on from the dominant project management discourse in the light of project overruns	52, 4, 497–508	Management Science	Systemic Modeling	-	CAS, Emergence, Stochastic, Uncertainty	Through reviewing PM theories, the work proposes systemic modeling as a useful, learning based approach to manage the uncertainty and emergence characteristics associated with complex projects.

Table 1. *Cont.*

N.	Year	(First) Author	Title	Vol., Issue, Pages	Main Area(s) of Interest	Methodology	Industry	Complexity Characteristics	Main Content
34	2004	Lin	New product go/No-go evaluation at the front end: A fuzzy linguistic approach	51, 2, 197–207	Innovation	Logic-Based Screening Model/Linguistic Multi-criteria Decision	Machinery	Fuzzy, Uncertainty	Through an industrial application on a new machining center, the work proposes a new screening model based on fuzzy logics and linguistic approximation to assess the design of new products.
35	2004	Sia	Effects of environmental uncertainty on organizational intention to adopt distributed work arrangements	51, 3, 253–267	Human Resource Management	Partial Least Square	Various	Uncertainty	The work is an exploratory study about the convenience of using distributed working arrangements as an organizational innovation to face environmental uncertainty.
36	2004	Xirogiannis	Fuzzy cognitive maps in business analysis and performance-driven change	51, 3, 334–351	Management Science	Cognitive Mapping	Financial Sector	Evolutionary, Fuzzy, Non-linear	Positioned in the business process reengineering area, the work uses fuzzy cognitive mapping to analyze performance-driven reengineering processes.
37	2003	Huntley	Organizational learning in open-source software projects: An analysis of debugging data	50, 4, 485–493	Information Management	Adaptive Learning, Debugging	Open Source Software	Non-linear, Uncertainty	The work studies open-source debugging as a form of organizational learning, with a focus on the open source approach as a hedge against system complexity.
38	2002	Vachon	An exploratory investigation of the effects of supply chain complexity on delivery performance	49, 3, 218–230	Operations	Modeling based on supply chain characteristics	Textile, Machinery	Stochastic, Uncertainty	The work provides a conceptual model characterizing the complexity features of a supply chain, which is useful to understand the linkage between SCM and delivery performance.

Source: own elaboration.

In the four sub-sections below, we analyze these items per key content lines.

3.1. Themes

In terms of fields, as a premise, we can consider about two-thirds of our sampled publications as falling into traditional EM, one-third into technology management, and substantially none in emerging technologies (Figure 1).

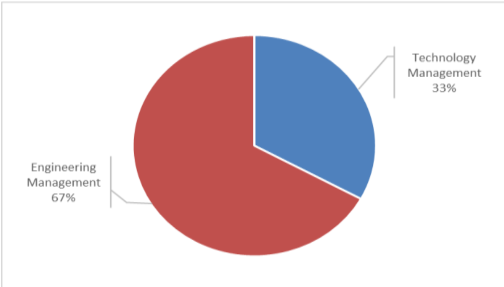

Figure 1. Publication coverage per field. Source: own elaboration.

In more detail, as Figure 2 shows, since 2000 CT has been associated with a wide spectrum of topics and themes associated with the fields above.

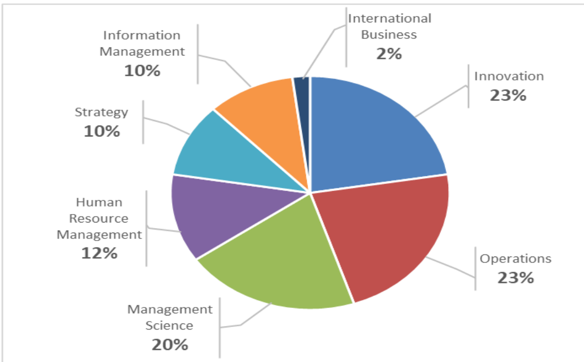

Figure 2. Publication coverage per key thematic areas. Source: own elaboration.

In particular, as Figure 2 shows, innovation, operations, and management science represent, as we could somehow expect, the most investigated areas. In this respect, works on the use of CT in DM processes, regarding NPD, procurement, and supply chain, or PM, specifically prevail. Interestingly, at the same time, considerable (although minor) amounts of observations fall into the areas of human resource management, strategy, and information management. In this instance, for example, the focus is on the use of CT to increase team productivity, competitive capabilities in (technological) environments, or the efficiency/effectiveness of intraorganizational communication.

3.2. Timely Distribution and Authorship

As Figure 3 illustrates, the time distribution of the publications witnesses an increase, especially if we separate the articles published in the years between 2000 and 2010 from those published between 2011 and 2019.

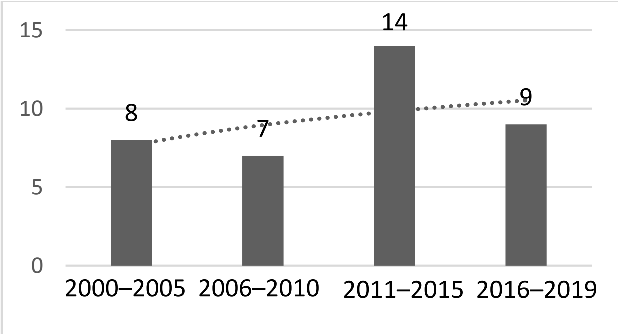

Figure 3. Evolving trend of the publications. Source: own elaboration.

On this premise, interesting evidence seemingly emerges if we focus on various features regarding the authorship coverage of our sampled publications (Figures 4 and 5).

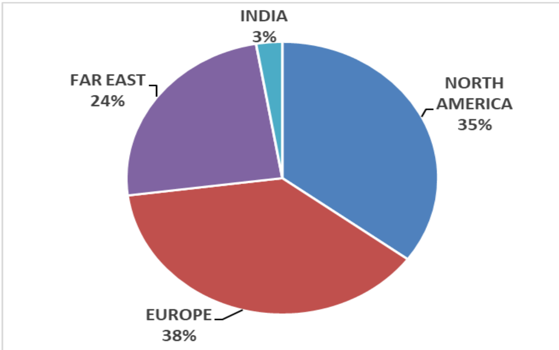

Figure 4. Publication coverage per geographical source. Source: own elaboration.

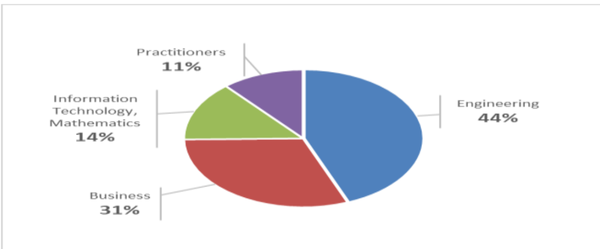

Figure 5. Publication coverage per author affiliation. Source: own elaboration.

Figure 4 substantially shows what we could consider the geographical source of our sampled publications. In particular, we developed this data-driven figure by contemporaneously considering: (1) the first author (N = 37, net of duplicates) of each publication; (2) the country in which s/he was awarded her/his PhD. In this regard, we chose to specifically focus on first authors because of the internationally acknowledged leadership role, which, in general, any first author has in terms of the research design of a publication. At the same time, we preferred to focus on the country in which the first authors were awarded their PhD rather than on their strict nationality because we thought the former could represent a more reliable proxy for the cultural orientation (and associated approach) towards the topic.

Having clarified the above, as shown in Figure 4, the geographical source of our dataset appears substantially balanced between Europe and North America, followed, at the same time, by a significant presence of Far East countries (e.g., China, Japan, Taiwan, Hong Kong, Singapore, and South Korea).

Correspondingly, Figure 5 shows the publications' coverage by author affiliation. In this case, we developed this data-driven figure by considering all of the authors (N = 107, net of duplicates) in our dataset. Interestingly, as shown in the figure, engineering schools/departments prevail, but business schools/departments also occupy a significant portion. at the same time, although in minor percentages, Figure 5 also evidences the presence of scholars from other schools/departments, such as information technology or mathematics, and practitioners as well. We could argue that this evidence can be interpreted as consistent, as explained in our theoretical framework, with the multidisciplinary nature of the approaches to CT.

3.3. Methodologies, Settings, and Complexity Features

Almost all of the studies are based on conceptual, mathematical modeling, with the vast majority also tested through industrial applications, relying, for the largest part, on quantitative methods. Interestingly, on the one hand, the conceptual modeling is featured by a wide range of techniques, these varying, for example, from genetic algorithms to design structure matrices, or analytical hierarchical/network processes. At the same time, on the other hand, many of these techniques share the common feature of grounding on fuzzy logics, stochastic modeling, or ABM as their basis. From more than one aspect, similar highlighting can also regard the context of the industrial applications. In fact, the general settings are heterogeneous ranging, for example, from aerospace, to automotive, manufacturing, or services. However, almost all of these settings share a strong hi-tech component in what is specifically observed.

Figure 6 expands on Table 1, offering statistics about the presence of the inner complexity characteristics in our dataset. In particular, we built this figure through the assumption that more than one characteristic can be simultaneously present in the observed publications.

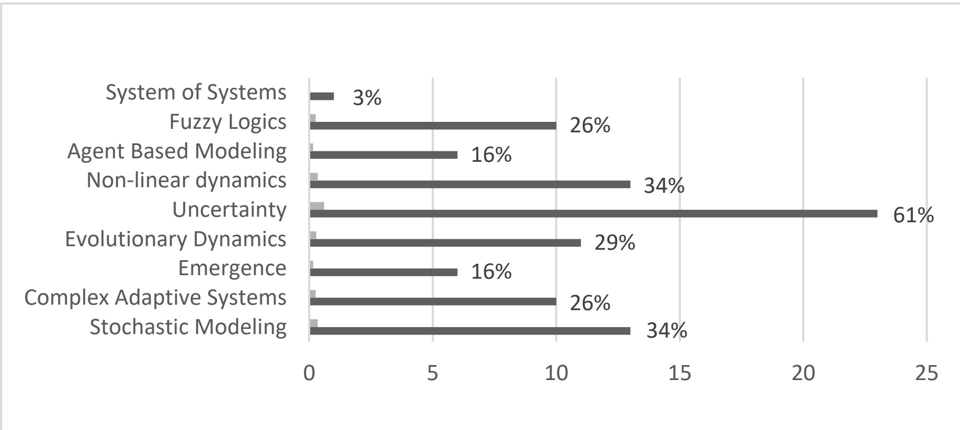

Figure 6. Presence of the complexity characteristics in the dataset. Source: own elaboration.

As evidenced in Figure 6, the study of DM and problem solving under uncertainty (and how to manage it) largely prevails, and generally serves as the ground basis for various lines of inquiry, with one or more complexity characteristic often contemporaneously present with uncertainty itself. In particular, as evidenced in the figure, uncertainty is frequently associated with non-linear dynamics and/or, as previously mentioned, stochastic modeling. The former, for example, is interestingly highlighted by Xirogiannis and Glykas [38] in their study on how performance-driven business reengineering processes work and how they could eventually work better. The latter, in parallel, is used more than once to provide insight on how to model the complexity, towards efficiency and effectiveness, regarding NPD, PM practices, or SCM.

An interesting number of observations also include the use of fuzzy logics in conjunction with uncertainty. In the area of management science, for example, and with a focus on PM, Shafie-Monfared and Jenab [39] use fuzzy modeling to identify different degrees of project complexity, based on the differentiation of managerial and technical features. Their framework can usefully provide support to budgeting, planning, and resource allocation. Similarly, through the case study of a new machining center, Lin and Chen [40] propose a new method to evaluate new product design, based on fuzzy logics in general, and linguistic approximation in particular.

Finally, in our dataset, uncertainty is also repeatedly associated with evolutionary dynamics. For example, Mikaelian et al. [41] develop a holistic, evolutionary approach, based on real option analysis, to manage flexibility and DM under uncertainty. In a similar vein, Giannoccaro and Nair [42] heavily rely on complexity science and evolutionary mechanisms to study what (and how) behavioral traits of project managers can shape their decisions regarding product design.

3.4. Complexity-Based Evidences

In relation to the third issue analyzed above, however, it seems that only a limited number of studies still formally adhere to the lenses of CT, and/or CAS, to explain the different EM issues under investigation. For example, in the innovation area, Tripathy and Eppinger [43] focus on complex engineered systems, with particular regard to the offshoring and onshoring activities associated with NPD at a global level. In detail, they use five case studies from electronics, equipment, and aerospace to study the complexity of the interactions between the product and process structures, and the strategies planned and implemented at firm level. On the basis of their findings, these scholars then propose theoretical trajectories aimed at improving the DM configuration regarding global product development in complex engineered systems. As their core idea, the modularity in design and development should be separated from that in manufacturing; furthermore, the development of the system architecture, which is a core capability, should not be offshored.

In a similar vein, Levardy and Browning [44] conjecture the processes of NPD as CAS. These scholars oppose linear, time-based vertical scheduling, in that they theorize these processes as featured by a general class of activities/rules, which can self-organize and adapt to their changing state. The implications of their modeling for DM in EM are interesting; in fact, their adaptive model considers product development as a DM process, in which each decision is potentially able to maximize the expected value of the overall project based on the particular state, in any given moment, of its internal and external variables.

Again, in the context of NPD, the work by Jun and Suh [45] appears particularly worth of explanation. They also provide a theoretical framework for the process, composed not only of iterative but also evolutionary, uncertain, and cooperative characteristics. Through an industrial application in the automotive, electronics, and environmental settings, their modeling demonstrates its potential utility to engineers and project managers involved in planning, organizing, and monitoring the design and implementation of new product initiatives.

Following the above evidences about innovation, in the strategy area, Ndofor et al. [3] use the nonlinear, dynamical system methods from CT to study how different industry environments evolve over time. In particular, adopting three operationalizations, classically utilized to discover nonlinear variable dynamisms, these scholars evidence that many industries evolve in a chaotic regime, where uncertainty increases proportionally to hypercompetitive settings. Similarly, Tsilipanos et al. [30] analyze investments in the telecommunication industry through using a methodological approach typical of CT. Specifically, these scholars model this industry as a system of systems, and use the MATLAB software to create a genetic algorithm able to provide results based on stochastic, emergent modeling. Tested through an industrial application, the more general value of their modeling, also in terms of implications for EM, mainly consist of the possibility to provide prospective investors with theoretical support to efficient DM and budget allocation.

Finally, in the operations and supply chain area, the research by Pathak et al. [46] seemingly deserves attention. Through combining the CAS approach with industrial growth, networks, market structure, and game theories, these scholars investigate how supply network structures can evolve and survive over time. The observations from their agent-based study in the U.S. automotive industry can be of particular appeal to engineers. Specifically, they find that the type of environment and the speed of adaptability both affect the survival chances of supply networks; in peaceful settings, on the one hand, the topological evolution of the networks is relatively stable, with centralized or linear network structures, often able to guarantee survival over the long term. In more competitive settings, however, only the hierarchical structure seems able to provide networks with adequate long-term survival chances.

4. Discussion and Implications

In this conceptual article, we have focused on the adoption of CT in EM since 2000. At the beginning, we introduced the key conceptual pillars of CT (and CAS). Subsequently, because of its status of being a leading journal in the field, we chose *IEEE-TEM* as a reliable, heuristic proxy to analyze and discuss those publications formally, and/or substantially, referring to complexity approaches. Therefore, we can synthesize the results from our analysis into the following three main evidences.

First, from 2000, the adoption of CT in EM has been associated with a wide range of key themes in the field. NPD, SCM, and PM prevail. At the same time, a considerable number of observations also regards team productivity, competitive capabilities in (technological) environments, and intraorganizational communication.

Second, this adoption was seen in an increasing amount of publications, especially if we consider the years 2011 to 2019. Conceptual modeling developed through a wide-range of techniques largely prevails in our dataset, then quantitatively tested in various (almost hi-tech based) industrial settings. This, again, also appears in line with the plurality and heterogeneity of analytical tools and (high-tech) settings traditionally employed in EM [47]. At the same time, the common feature among these techniques is that they are mostly based on fuzzy logics, stochastic modeling, or ABM.

Third, many key ingredients of CT seem to be quite clearly observable in the analyzed publications. Accordingly, modeling and optimizing DM under uncertainty results as the dominant theme; this theme, at the same time, is not only often associated with the mentioned fuzzy logics, stochastic modeling, and ABM, but also with non-linear and/or evolutionary dynamics. Perhaps surprisingly, however, only a limited number of studies still seems to formally adhere to CT to explain the various EM issues under investigation.

From what is summarized above, some implications for EM (concerning the research in and practice on sustainability issues) can also be derived. These implications are exposed below, sequentially ordered per item of focus.

4.1. Areas of Investigation and Leadership

Regarding the areas of investigation, on the one hand, as previously written, our results show good coverage of complexity-based approaches in key EM areas. On the other hand, we think that additional areas could also become objects of research in this field. For example, the emerging technologies/technology intelligence area could be expanded through complexity-based observations concerning artificial intelligence or Internet of Things. In fact, on both of these topics, we could not find any evidence in our analysis. Moreover, further studies could also look into how to develop, from engineers to leaders; correspondingly, we could find good coverage of human resource management in general, but, apart from scant exceptions, we could not find sizeable evidence about complexity-based leadership [48] in our analysis.

Regarding the above, for instance, and with a focus on the potential impact of complexity-based leadership on the effectiveness and efficiency of innovation (e.g., NPD) and change, the recent work by Burnes [49] appears remarkable. In particular, according to this scholar (p. 84), "unless employees have the freedom to act as they see fit, self-organization will be blocked, and organizations will die because they will not be able to achieve continuous and beneficial innovation." Furthermore, he states (p. 84), "neither small-scale incremental change nor radical transformational change works: instead, innovative activity can only be successfully generated through the third kind of change, such as new product and process development brought about by self-organizing teams."

Relatedly (p. 84), "because organizations are complex systems, which are radically unpredictable and where even small changes can have massive and unanticipated effects, top-down change cannot deliver the continuous innovation which organizations need in order to survive and prosper. Instead, it is argued that organizations can only achieve continuous innovation if they position themselves at the edge of chaos". According to Burnes, self-organization is the only way to reach and keep this position, and is itself based on rules that are order-generating. The key point here is that, if the latter (i.e., rules) result in no longer fitting the organizational context, they can be re-created exactly because of the existence of the former (i.e., self-organization).

Having explained the above, a noteworthy example of complexity-based leadership can be offered by a recent case study considering a military organization as a CAS [50], with a focus on its inner complex dynamics, as an enabler to increase organizational effectiveness. As the case demonstrates, despite the traditionally hierarchical and linear characteristics of military organizations, in order to face the surrounding complexity, the rapidly changing defense environment has substantially proved to need a more adaptable and flexible structure.

On this basis, the military leader willing to adopt a complex approach to the commanding action will seek to foster those dynamics typical of CT (such as non-linear relationships and feedback) in order to increase adaptability and organizational learning. This also implies the need to drive the organization from hierarchical to network-centered dynamics, thus assuring governance cohesion throughout the organization, thanks to the development of a shared vision across the top management team. In principle, this perspective can also be considered as presenting similarities with many conceptual underpinnings featuring the notion of socio-technical systems (e.g., [51]).

4.2. Settings of Observation and Research Methodologies

Concerning the settings of observation, in a similar vein as above, we could argue that, together with the key high-tech contexts in EM already emerging from our analysis, other central contexts in the sustainability field, such as energy, healthcare, and construction, could become the basis of complexity-based observations. Regarding these contexts, in fact, apart from a few exceptions our analysis could not evidence any specific focus.

Relatedly, with respect to research methodologies, on the one hand, our findings have shown that conceptual modeling tested through quantitative techniques has largely prevailed in the complexity-based observations in EM. On the other hand, however, we maintain that designing and conducting in-depth qualitative case studies [52] should also be important in the field. In this regard, (a) we are substantially in line with those scholars [53,54] who have, for a long time, generally argued that case studies are highly appropriate in complementing computational methods to understand the distinctive features of CAS; and (b) we are particularly in line with those scholars who have used the properties of case studies to develop complexity-based observations in key EM fields, such as NPD.

Taking the above into account, for example, McCarthy et al. [4] used a comparative analysis of three cases to examine how the CAS features of non-linearity, self-organization, and emergence can occur in NPD processes. In particular, these scholars conceive a model of NPD processes, as CAS, featured by three levels of DM, in stage, review, and strategic, respectively. Taking a middle ground between stage gate, chain linked, and chaotic models of NPD, their analysis produces interesting results. In their view, NPD is not necessarily a fixed process; it can adapt and switch from linear to chaotic (and vice versa), thus producing corresponding degrees of incremental or radical innovation. In the practice of EM, their model would be very helpful to avoid the DM traps, potentially regarding the search for fit between (new) product, (new) process, and market demand.

4.3. Conceptual Frameworks

Our analysis has shown that, among the many key ingredients of CT quite clearly observable in the analyzed publications, modeling and optimizing DM under uncertainty appears to prevail. Accordingly, we support the recent argument by Baumann and Siggelkow [6] that, in conditions of rationally bounded problem solving, understanding whether integrated (i.e., entirely and simultaneously performed) or chunky (i.e., incrementally expanded) search processes are the most appropriate could also add value. Again, in a technology innovation context of NPD, these scholars focused on this issue through the application of a simulation model. Their analysis has evidenced interesting results: incremental should be preferred to integrated patterns of search when time pressure is not a variable under consideration; moreover, the larger the chunks added at the beginning of the search process, the less the need of a totally incremental search.

According to our results for EM, complexity-based observations have often associated the uncertainty variable with fuzzy logics, stochastic modeling, and ABM, but also with non-linear and/or evolutionary dynamics. As this association has mostly happened on a separate basis (see Table 1), we argue that all-inclusive, complexity-based frameworks could be developed further. Again, this claim corresponds with other key evidence from our analysis: as previously stated, we have shown that, in EM, only a limited number of studies still seem to formally adhere to CT to explain the EM issues under investigation.

The more comprehensive frameworks elicited above could then be tested in different EM settings to assess their reliability. For example, a recent, remarkable attempt of this kind has been the Generalized Complexity Index developed by Jacobs [55]. Based on the three dimensions of multiplicity, diversity, and interconnectedness, this index can be used as an analytical decision tool to evaluate the pros and cons of potential portfolio diversification and/or product differentiation. Furthermore, especially in these learning-based, innovation contexts, distinguishing between complex adaptive and complex generative systems [56] could also be valuable. While the former systems are able to adapt without the need for radical changes, the latter can witness changes which largely modify their inner features and even generate new entities.

4.4. Co-Evolutionary Dynamics in Complexity-Based Research Designs

The issue of the interconnectedness brings us to the last item to be discussed in terms of potential implications for sustainability, which is a direct call to embed more fine-tuned co-evolutionary perspectives in complexity-based research designs [57,58]. Specifically, we argue, this call appears to have particular momentum if (and when) hypercompetitive technology environments are under investigation. In fact, recalling what was recently demonstrated by Ndofor et al. [3] on the basis of their 36-year observations of 19 industry sectors, these environments are often chaotic, i.e., featured by a significant degree of a non-linear relationship among elements, together with inter and path dependence. As a fast growing meta-theoretical perspective in social sciences [59–62], and being generally conceived as the joint and dynamic outcome between industry, managerial, and environmental forces [63–65], co-evolution demonstrated effectiveness in capturing all three distinctive features surrounding complexity [66].

In the context of technological entrepreneurship, for example, as maintained by McKelvey ([67], p. 67), "An entrepreneur could have co-evolutionary dynamics going on in his/her firm; a change in one part of a product leads to a change in another part, which then leads to further change in the part showing the initial change; these changes could affect marketing, production, supply chains, and so on. Finally, it could happen that an entirely new product appears. For example, think of all of the coevolving changes in computer, cell-phone, battery, and touch-screen technologies, computer programming, cell towers, the Internet, and the development of apps that led to current smart-phone products."

Similarly, in the context of technological ecosystems, Phillips and Ritala [68] interestingly build (and apply) a specific complexity-based, co-evolutionary framework. In particular, they suggest that three intertwined dimensions, i.e., conceptual (boundary and perspectives), structural (hierarchies and relationships), and temporal (dynamics and co-evolution) should be taken into account to understand (and predict) the behavior of complex ecosystems, especially in the case of an innovation (e.g., NPD) context.

Relatedly (and finally), as far as understanding the institutional complexity [69] of co-evolutionary ecosystems is specifically concerned, we are also in line with those scholars [70] who have recently claimed the increasing adoption of a neo-configurational perspective based on qualitative comparative analysis (QCA). Hence, for example, Misangyi [71] recently offered remarkable evidence regarding 28 business facilities projecting and implementing an environmental management system.

More generally, the claim towards the use of QCA is also in line with our claim above (please see Section 4.2.) that more qualitative research methodologies should be adopted to understand the complex nature of innovation-based settings. In this regard, for example, in a novel case study regarding innovation and change in organizational culture, Schlaile et al. [72] used a meme-based approach [73] to investigate the complexity-based interdependencies occurring in a German automotive consultancy firm.

5. Limitations and Conclusions

Through the results (and proposed implications) of this conceptual article, we do not aim to propose CT as the solution to all of the current EM sustainability-related issues. We also agree with those scholars who, seminally [74,75] or more recently [76,77], have identified the risks of transforming CT, when (even more generally) applied to management, as the fad of modern times. Specifically, we do not believe that this fast-growing approach will totally overwrite all of those theories based on positivism and reductionism [10,78].

Relatedly, we are also conscious that, from a methodological point of view, the results from our analysis present some limits, in that they are, at present, strictly focused on the leading journal in the EM field and on a static explanation. At this stage, in other words, our analysis of the 38 articles should be considered through the lens of a (hopefully useful) initial qualitative assessment, rather than the lens of a quantitative research, which has statistics and trends also aimed at being predictive. In this regard, however, we believe that our results could serve as a heuristic proxy, i.e., a conceptual start to be expanded through more journal-based searches and/or dynamic analyses.

In sum, although aware of the limitations above, and through discussing the implications of our findings, we attempted to explain how CT can contribute to govern many current issues associated with the EM research (concerning the research in, and practice of, sustainability issues). If firms are modeled as CAS, through the identification of agents, their interactions, feedback, and emergent phenomena, CT can then help find novel ways of working to foster a supposed desired emergent behavior (e.g., improved efficiency and effectiveness in NPD, team organization, technology management, or PM); thus, providing engineers and managers with new tools for improving decision-making and performance [79–81]. In this regard, for example, Bianchi et al. [82] innovatively deal with complexity management in a recent NPD context through a study of the interaction between stage-gate and agile models (and their associated principles to reduce uncertainty).

Of course, scholars and practitioners argue that, in order to be more than a metaphorical device, a relevant CT framework will need to always be more rigorous from the theoretical, mathematical, and computational modeling points of view [83,84]. We also believe that this modeling will need to be tested in different industry settings to ensure appropriate comparisons between models and real world structures [85–87]. In this way, CT may also be taken as a useful approach, for engineers and managers, to test the reliability and consistency of more conventional methods intended to improve sustainability.

In conclusion, firms, clusters, networks, and industries, may be seen, from some aspects, as similar to living organisms [88,89], which grow, evolve, and die [90,91]. They can be healthy or sick [92–94] and their behavior emerges from their internal qualities and dynamics, which provide complexity to the system, and from their interactions with the environment [95–97]. A firm's behavior is both affected by linear control, such as that imposed by bureaucracy or top-down management decisions, and natural, uncontrolled dynamics. If enterprise complexity fits the complexity of the environment, then desired behaviors, such as high performance and synergy, emerge [98,99].

To date, complexity represents one of the main problems surrounding sustainable business. While we think that the application of CT to business cannot eliminate this problem, we believe that it can help reduce it to a satisfying level.

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