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How AI Helps to Increase Organizations' Capacity to Manage Complexity – A Research Perspective and Solution Approach Bridging Different Disciplines

Abstract:

A major challenge for organizations and their strategic management today is the increasingly complex internal and external information and knowledge environment. To tackle this problem, we want to provide a fresh perspective on how to construct a modern AI-based socio-technical support system for strategic management. Methodologically, we provide a deep problem analysis and use the resulting insights to provide a solution approach drawing on different disciplines and bridging the gap between social science and computer science. Starting from challenges for strategic analysis in the age of information-overload, we analyze organizations as social communication systems. This yields a deeper understanding of the organization processing strategic information and its complex information environment. Based on the resulting insights we propose our framework design by building on text mining and knowledge graph technology and give some guidance for its implementation. The novel system generates strategic intelligence by tapping into qualitative data: defining constantly changing information needs, interpreting information in its context as well as in reflection to the organization and making new knowledge promptly available to the right people. Throughout, we give illustrating examples from the domain of strategic research management.

Managerial relevance statement:

Artificial intelligence has found its way into a broad variety of commercial applications throughout many different sectors. At the same time, until now, it has hardly taken root in the process of strategic decision making on management level. Strategists face the challenge of supporting management to make the right

decisions while overlooking the organization in its full complexity as well as the interconnections to and reverberations with various complex surrounding fields like science, technology, economy, politics or ecology. In this article we introduce a solution approach which bridges the gap between insights from systems theory, strategic management and cutting-edge AI methods. By incorporating the logic of social communication systems and building on text mining and knowledge graph technology we propose a framework design to generate a highly automated interface connecting the inside to the outside view of an organization and thus reduce the complexity to a level which creates a picture for the analyst amenable to drawing the right strategic conclusions. With the proposed framework, analysts have the capabilities to bring the idea of networked thinking to operational life. Building on a sound theoretical background and by providing technical details, the article presents our vision of a 21st century strategic analytics system, by bridging the gap between a number of existing theories and methods from different disciplines.

I. Introduction

The problem is as old as the mere concept of organizations. Human organizations face the challenge of understanding their immediate and further environment in order to detect risks or challenges and act strategically upon these insights. Often the abundancy of information is in stark contrast to the available certain knowledge.[1] Not surprisingly, strategic thinkers from different ages and disciplines like Thucydides, Clausewitz, Drucker or Luhmann have come up with solutions to tackle this problem [7–10]. How can relevant information be extracted from complex environments? How can the signal be traced in the noise? How can we provide "[…] the right information in the hands of the right people at the right time so that those people are able to make informed business decisions about the future of the business"? [11, p. 1].

This matter of strategic intelligence[2] is a question of timely acquiring and efficiently managing relevant information which poses severe problems of volume and complexity. *Volume* because with modern communication technology enormous amounts of unstructured and qualitative data have to be screened continuously for strategic relevance. *Complexity* because this data may come from very different interacting fields that can all be characterized as complex in their system's behavior: like politics, science or markets regarding external sources and the organization itself regarding internal sources. In addition, this high-volume data from strategically relevant fields is often not provided in an easily monitorable or interpretable numerical and structured way. It is rather of qualitative nature and is provided in an unstructured manner in the form of natural language or even multimodal communications, i.e. news or scientific articles, white papers, patents, etc. Therefore, this form of data highly depends on the context and needs thorough and individual interpretation.

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[1] A "sign" becomes "data" by adding syntax. "Data" becomes "information" by adding the semantic context. "information" becomes "knowledge" by pragmatic linkage (authors' translations) [1, pp. 1-5], [2], [3, pp. 53-82]. Other authors add "wisdom" to this list to imply an even higher order of "knowledge" like "evaluated understanding" or "know-why" [4–6].
[2] Here we consider strategic intelligence as the „[…] convergence of knowledge management, business intelligence and competitive intelligence" [12] to obtain „[…] strategically significant information from a company's internal and external environment […]" [13].

This leads to tough issues when it comes to efficiently generating and managing a comprehensive knowledge base for strategic management. First of all, the environment as well as the managed organization itself are both subject to constant change. This makes defining the qualitative information needs to filter for the right information an enduring task. Secondly, any piece of information not only needs interpretation in the context of its source but also in reflection to the organization in its full complexity. This also means that the newly gathered information needs to be evaluated against and linked to the already available information within the organization to create an integral knowledge base. Thirdly, the new state of knowledge must be made available promptly to the right people in order to draw conclusions with regard to strategic measures and act near term.

Artificial intelligence technology offers extremely promising avenues to tackle these strategic challenges. Hence, the question of how to apply AI methods to strategic management has increasingly become of interest [14–18], for a comprehensive and systematical review on research in this field see [15]. With the established field of business intelligence, we do see great advances when it comes to processing numerical and structured data with a focus on the internal environment for decision-making in corporate management. However, tapping into the tremendous amount of qualitative and unstructured data as a source of knowledge for strategic decision-making using AI is still in its infancy.

Hitherto existing practical approaches in this area focus on different specific aspects. In distinction, the perspective presented in this paper aims at generating strategic intelligence by using AI to link the internal and external information environment. We add to the existing literature by analyzing and discussing the role AI can play when addressing the issues described above: defining constantly changing information needs, interpreting information in its context and in reflection to the organization in its full complexity and making a new state of knowledge promptly available to the right people within the organization.

We argue that to fully appreciate the challenges at hand an unconventional interdisciplinary approach is necessary bridging a gap between social science and computer science. By taking a bird's eye view and analyzing this real-life managerial problem with social systems theory we generate the conceptual foundation for a practical AI-based solution approach.

In *section II* we start from classical approaches to strategic analysis and their nowadays challenges. We later shed a fresh light on the matter by putting it in the context of social systems theory. Doing this allows us to scrutinize the underlying social structures and processes organizations use to generate knowledge from their highly complex environment of different functional subsystems of society (e.g. politics, economy). As we will show, this deep problem analysis produces the necessary theoretical foundation, hints and criteria to propose the solution approach in *section III*. Based on recent advances in AI technology the conceptual framework of a modern socio-technical support system for strategic management is presented. By building on text mining and knowledge graph technology we propose a highly automated interface linking the internal and external information environment to generate a comprehensive knowledge base for strategic management. Consequently, the interplay of artificial intelligence and human workforce as well as target oriented organizational and operational changes are also discussed as part of the approach. Finally, in *section IV*, we draw conclusions, discuss further technical advances and give an outlook on the implications of our approach for potential future development.

Strategic analysis is of course a critical approach to numerous challenges in all kinds of fields – ranging from the military and politics to civil organizations and economic actors. Even though, all these areas of application face similar analytical challenges we developed our approach along the example of strategic research management. It is a challenging example, as typically (think of large state-funded and program-oriented research institutions) the internal organizational structure as well as the relevant environment can be quite broad and complex. Therefore, in future developments our approach can most likely be adapted to other domains with possibly more manageable internal and external environments. With the proposed framework, analysts have the capabilities to bring the idea of networked thinking to operational life. Building on a sound theoretical background and by providing technical details, the article presents our vision of a 21st century strategic analytics system.

II. Deep Problem Analysis

A. Classical approaches to strategic analysis

Strategic analysis as a process is about collecting, analyzing and evaluating information about the organization itself[3] [19] and its relevant environment (e.g. competitors, politics) – framed *environmental analysis* [20]. Methods for environmental analysis such as STEEP[4] or Porter's Five Forces are critical elements of any SWOT-analysis [21]. Ansoff has contributed the idea of detecting *weak or early signals* for environmental discontinuities in order to avoid surprise or to exploit chances in a very early stage [22]. The goal of strategic analysis is to extract knowledge from the collected information in order to inform strategy formulation or strategic actions.[5] This goal can be achieved e.g. by making prognoses for relevant (upcoming) trends and developments and by deriving strategic chances and risks. In that way strategic analysis supports management and paves the way for strategic decision-making and is essential for the strategy development process.

What does this mean in practice for strategic research management? To give an example, take, a large state-funded and program-oriented research organization. Here, the task of a strategy analyst[6] is to inform the top management in a timely manner on strategic chances and risks resulting from changes outside of or within the organization together with fact-based advice on possible strategic (i.e. high-level) courses of action. This could be delving into a new promising research area, loss of significance of existing research

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[3] The insight that the internal view on the organization is crucial is championed by Porter who uses the concept of the "value chain" to describe this view [19].
[4] STEEP stands for the social, technological, economic, ecologic and political fields.
[5] Strategic actions are usually based on decisions by the top management and relate to courses of actions for large parts or even the whole organization.
[6] In our understanding a strategy analyst performs the tasks related to strategic analysis.

infrastructure or communicating certain related own research results to a broader public. Strategy analyst here face the task of monitoring sometimes quickly changing societal and political demands, legal frameworks, funding opportunities or the actions of competitors relevant to the organization. Information on these questions may be found inside a myriad of freely available sources like political documents, law texts, press statements, publications of funding organizations or even scientific publications. One difficulty lies in assessing the relevancy of a particular piece of information for a complex research organization with an equally complex portfolio of research topics, fields and related infrastructure. Another problem is the identification of trends and developments, that is, of connecting different related pieces of information. Still another problem is to interpret the findings and generate as well as communicate possible courses of action including estimations of effects and side-effects to top management.

B. Challenges for classical approaches to strategic analysis

To stay with the above example of a large state-funded and program-oriented research organization: Why should research managers here bother at all about strategic analyses? Are their organizations not placed in relatively stable environments with a steady growth perspective and flow of resources? Truth is, that in many fields competition between research organizations has become fierce and often globalized [23]. Public money is in short supply (and might be in even shorter supply for some fields because of global anti-pandemic measures) [24]. At the same time tax payers have more possibilities to scrutinize performance, e.g. by greater transparency through public data and media. The expectations by politics and society are generally high. Furthermore, innovation is the ultimate goal in many research fields which makes strategic considerations (e.g. knowledge about the market situation) necessary. Therefore, chances and risks for the organization have to be identified in an early stage in order to enable management to define resilient strategies. This insight has led to a tendency to implement strategic management approaches and tools in research organizations and public organizations world-wide [25].

What are the concrete challenges for research organizations concerning strategic analysis? Today, *in general* there is exponential growth in available data [26]. At the same time, it gets more and more difficult to make sense of this growing amount of data, i.e. to extract knowledge from the data.

As for *internal data* of organizations, with ongoing digitization of processes potentially much more data becomes available. However, in large and often complex organizations, i.e. for example many departments and hierarchy levels or local integration in many locations and markets, it is nevertheless difficult to obtain an adequate and up-to-date picture of the situation. This holds true especially in hierarchical organizational forms (which often remain in place) since they often lead to so-called information siloes thus making the data unavailable to usually centralized strategy departments [27]. Another problem is that organizations often lack clear data governance and do not have a data strategy in place. Both are very helpful elements in order to draw on organizational data for strategic management. Examples of internal data necessary for strategic analysis are: project data; publication data; business data; data on the structure of the organization itself (such as departments and the communication interfaces and levels of cooperation between them).

Concerning *data from organizations' environment,* the amount of potentially relevant data has grown enormously in the last years, e. g. scientific publications, political documents, patent descriptions, news articles, social media. Again, getting an adequate and up-to-date picture of the relevant environment of the organization is a very hard task. The problem often starts by not knowing what exactly is the relevant information strategic management needs to be aware of and understand; more often than not the information needs are simply unclear. Furthermore, the environment of organizations has become notoriously difficult to understand. This phenomenon has been characterized by the abbreviation term VUCA,[7] which stands for volatility, uncertainty, complexity and ambiguity [28]. That is, changes occur

[7] At the same time, the suggested answer to the environment being VUCA was again VUCA, this time standing for vision, understanding, clarity and analysis. However, this still leaves open the question how these certainly correct goals can be attained.

quicker and the information situation is generally characterized by too little sound knowledge (in spite of the growth in data!) as the phenomena that organizations try to understand tend to be highly complex (see fn. 1 for the juxtaposition of data and knowledge).

Even if the information demands are more or less known, a number of technical issues arise. Often, relevant information is, though publicly available, multimodal and often in unstructured form, e.g. texts, documents or even pictures and videos. Furthermore, the sources of information, like websites or data bases, are wide-spread over the internet. Sometimes information is only available for a short period of time before being put into sometimes restrictedly accessible internal archives (think of blogs, news or press releases, etc.). However, in a lot of cases it only retrospectively becomes clear that a certain kind of information is highly relevant.

At the same time many organizations need to scan or monitor quite a lot of fields. As for our example of research organizations, in order to formulate holistic strategies, it is necessary to know what are the developments in all of the STEEP areas. The reputation of the organization in society is as important as what is happening in the political realm, for instance, due to public funding. However, it is a special challenge to monitor and predict political and social changes.

A further more general problem lies in the nature of processing and understanding social information. This problem was articulated already in the 1960s by social systems theory [10, 29] and since then empirically confirmed many times (e.g. [30]): different subsystems of society use different communication "codes" making it hard to fully understand communication from a standpoint outside of the subsystem in question. This poses practical problems for a strategy analyst trying to understand cross-system phenomena as they will be very differently treated in the subsystems of society. E.g. the topic of climate change is treated as a problem of "truth-finding" in the system of science, however, the same topic in the system of politics will be treated as a "power-problem" which has to be transformed in a way susceptible to political decision-making [30].

If strategy departments of research organizations try to address all these challenges with classical means a very high manual effort results for collecting and monitoring the relevant data and to derive information and knowledge for decision-making processes. Furthermore, manual intelligence processes run the risk of introducing severe levels of cognitive biases, e.g. groupthink [31], additive bias [32], confirmation bias [33], leading to potentially strategically dangerous blind spots etc. Of course, AI-based methods introduce other "machine biases" [34], which are as dangerous. However, if correctly implemented AI-based methods of intelligence can be used to minimize human bias [35], e.g. by timely scanning vast amounts of literature in an ongoing debate to overcome conformation bias. In any case, social machines as the combined approach of human judgment and computer-based performance seems quite promising to address the issue [36].[8] This does not only hold true for the risk of bias but for a larger risk surface (cyber, legal, etc.) when it comes to AI-based data processing and decision making. A finding that seems to apply to any modern complex technological system such as cyber physical systems (CPS) or industrial internet of things (IIoT). For a review article in this context see [38].

C. Strategic analysis in the light of social systems theory

Strategic analysis heavily involves *strategic thinking* [39, 40].[9] "Strategic thinking", in turn, is an individual or group thought process involving rationality, psychological factors, creativity and foresight and is about generating and applying unique business insights to be more competitive [39]. The concepts of strategic analysis and strategic thinking complement each other – the former constitutes the process view and the latter the cognitive view. From a systems perspective [42] strategic thinking is an approach to cope with

[8] An in-depth discussion of bias in Artificial Intelligence and resulting ethical and social questions, however, is not within the scope of this paper. For a recent general discussion of the topic see [37].
[9] For the differentiation between "strategic thinking" and "strategic planning", see [41].

highly complex systems, that is, to cope with a situation characterized by a fundamental lack of information and, following from that, a lack of knowledge. Complex systems do not behave in easily foreseeable linear ways but are characterized by nonlinearity, emergence, and phase transitions, among others [42]. These properties make complex systems hard to model and predict. A strategic thinker has the ability to take those effects into account, or at least, to make statements about insurmountable levels of uncertainty or indeterminacy. In the context of futures studies, it has been shown that the ability to think in terms of complexity does not come natural to people but has to be trained specifically ([43], see also [44]). In sum, from a systems perspective strategic thinking means extracting knowledge about the present and the future from incomplete data in highly complex situations and draw conclusions for strategic decision-making.

The solution approach we propose here can be thought of as a powerful technological augmentation to help and support strategy analysts in the art of strategic thinking. As discussed, probably the most critical challenge for strategy analysts is coping with information abundance and the entailed consequences. In this respect, Luhmann's systems theory as a theory of communication in social complexity [10] can make an important contribution in setting out the rationale for the development of the framework (for newer work on complexity theory and organizations see [45], [46]). In fact, it provides the theoretical explanation for the question: Why do organizations not simply adapt to the changing information environment outlined above? Answers to this question give critical hints on how modern AI-based technologies can help overcoming some of the central problems.

According to Luhmann, *organizations* are a type of social system [47], [48]. Organizations as all social systems distinguish themselves against their environment by performing autopoietic self-referential *communication* operations, here especially decision communications [10].[10] The function of these inter-

[10] We can only give a very short outline of Luhmann's theory focusing on one detail of it, namely organizations and their information processing. An accessible introduction to the full theory of social systems is [49]. The complete theory in every

connected communication operations is to reduce complexity by filtering relevant information from the overwhelming complexity of entire society's communications. *Complexity*, in turn, "is a measure for indeterminacy or lack of information. Viewed in this way, it is the information that the system lacks fully to grasp and to describe its environment (environmental complexity) or itself (system complexity)" [10, pp. 27-28]. By using structural and procedural devices like communication codes, symbolically generalized media of communication,[11] or programs, goals and hierarchies, social systems increase their internal complexity in order to reduce the far greater external complexity of their information environment [10]. By communicating about it, new information is interpreted in the light of these devices and by linkage to already processed information – if it does not resonate within the system, it cannot be considered and is thus filtered out. The resulting reduction of complexity allows to extract social meaning, that is meaning for the system, from overwhelming data input. Importantly, organization's complex social environment consists of modern society's functional subsystems like politics, economy, science and law. These are by themselves social communication systems serving the purpose of problem solving for society by reducing complexity of information [10]. At the same time organizations are essential parts of one or more of these functional subsystems.

What does this mean in practice? According to social systems theory, a research organization is above all part of society's subsystem of science. As research organizations are, however, also strongly affected by, say, political or economic decisions (e.g. on research resources or the build-up of relevant industries), they must also be aware of relevant social communications within these subsystems. Accordingly, if a research organization is e.g. interested in trends in research politics, it declares this area of social communication as a relevant part of its environment. When e.g. new political documents in this area are published, they must inevitably be processed according to existing contextual knowledge and methods of interpretation to make

detail is contained in [10]. A concise account on the function system of politics is [50]. The information processing problems of social systems, illustrated by the example of ecologic problems, become very clear in [51].

[11] E.g. "truth, love, property/money, power/law […]" [10, p. 161].

sense to the organization. Furthermore, to draw connections or linkages between a number of political documents these must be classified as being somehow equivalent, e.g. containing political information on one topic. Only when these conditions are being met, signals (for political trends in this example) can be traced from the complexity of social communication (on research politics in this example).

Luhmann's perspective implies that organizations pose severe problems and barriers to networked strategic thinking as described above. New data are inevitably processed along existing structures leading to difficulties in drawing novel connections between information and thus creating truly knew knowledge. Information siloes in this perspective are a necessary function of internal differentiation and division of work. As mentioned above organizations situated in their specific function system (in our example science) are unable to interpret political, economic or ecologic information as such but will unavoidably process them along their predominant internal "code" (in our example: as a problem of "truth-finding").[12] Being autopoietic communication systems, organizations in general have problems with "newness" of information as they can only process information that connects to the existing information within the system. Taken together, systems theory implies a (empirically often observed) "institutional stickiness" [52], that is, their inherent difficulty to structurally adapt to new circumstances.

Conceiving of organizations as *communication systems* therefore implies a very distinct concept of *strategy* [53]. The function of strategy is then what Luhmann calls "second-order observation" [49]. The logic behind this term is that systems observe themselves, thereby constructing their perception of the world as outlined above (*level*). Strategists, in turn, observe this observation (*meta-level*) [53].

To give an example: Research organizations will, according to this theory, inevitably construct perceived problems, e.g. climate change, as research problems like "what are the main drivers of climate change?". Being aware of this construction process, a strategist in the research organization, may intentionally reflect

[12] For a still highly relevant account of society's severe difficulties to adapt to ecological threats see [51].

on the same problem of climate change, say, from the perspective of politics. For politics the problem of climate change must be transformed into a problem which can be solved by political decisions, e.g. on new research funding programs, laws or taxes. This change of perspective allows the organization to better adapt to political needs and demands.

Strategic problems in this perspective become problems of social information processing, more precisely, the question becomes: How can the system's information processing capabilities be supported or even improved? How can actionable knowledge and insights be created for the system? As information for social systems is always conveyed in the form of communications connected to each other, strategic analysis has to cope with large amounts of text data while considering their underlying network structure. That means, that e.g. communications on one and the same topic but in different social subsystems must be recognized and interpreted as belonging together.

The following findings for the rationale of the framework development are emphasized by this perspective. *First*, as there is no objective environment of social systems but this environment is constructed from within, strategic analysis has to start within the system and take an inside-out perspective – which, at the same time, has to be projected outside-in appreciating "the self-referential circularity between organizations and their environments" [54, p. 363]. In the best cases, it can fully grasp the internal complexity of the organization in terms of structure, processes and decision communications. Only from this position, a meaningful analysis of external data sources can be performed. Importantly, strategists have to take care that they not simply reproduce the internal complexity but take measures to open-up the possibility for drawing new connections between information and thus create truly new knowledge. To give an example, to detect opportunities for successful new research programs a research organization must first be fully aware of its own research portfolio, experts and infrastructure. Only on the basis of this knowledge, changes, say, in the scientific community, politics, industry or public opinion, may be correctly interpreted as chances for the organization. If it is noticed early-on that a lot of stakeholders are e.g.

pushing towards climate friendly energy sources and it is known to the organization that is has competencies in the field of aerodynamics and aeroelasticity and that these competencies are an important capacity in the development of efficient wind turbine design, management can proactively allocate resources accordingly.

Taking up this thought, *secondly*, strategic analysis has to scrutinize the devices the system uses for reducing complexity. Are communication codes, programs, goals and means, hierarchies, roles or topics still correctly chosen in the light of an ever-changing environment? How can they be adapted? Systems theory insofar especially highlights the necessity to accompany technological systems of information processing with adequate organizational change [55]. To give an example: If strategy analysts detect a new highly important scientific topic for a research organization, they may e.g. advice management to create a new role in the organization to drive the new topic forward.

Following from that, *thirdly*, strategic analysis has to ask the question about blind spots in the environment. Is there relevant information in the environment which could not be spotted due to current structures, processes and devices for reducing complexity? If so, how can these be adapted in order to erase blind spots. If strategy analysts in a research organization observe that information on, say, a promising research opportunity was systematically overlooked in the past, they may either advice management to take organizational measures (compare the second point) or update their own technical search strategies (compare the next section).

Fourthly, the question arises how strategic information has to be presented in order to be useful for the decision communication operations within the system. It will only be useful if it resonates within the system, that is, if it somehow connects to former communications within the system. Practically spoken, strategy analysts in a research organization may generate the best strategic intelligence for management. However, if this information is not conveyed in the right manner it might easily be ignored. Take the given example on climate friendly energy sources. Management might be much more open to a suggestion reallocating existing research capacity in the field of aerodynamics toward wind turbine design than to enter the field of research on renewable energies.

But how can the logic of social systems theory be translated into a technical concept? As outlined organizations understood as social systems construct their own reality by socially communicating about this reality in a specific way. Depending on the functional subsystem of society they belong to, they will use a specific “vocabulary” in describing the organization’s reality. Enshrined within this vocabulary is how the system describes itself, how it distinguishes itself from its more complex social environment and what it considers as relevant parts of this environment. For example, financial organizations will describe their reality predominantly in the form of numbers (e.g. prices) and indicators, thereby indicating the subsystem of the economy as their most relevant environment. Research organizations, however, will describe their reality predominantly in the “language of science”, i.e. research topics, research questions, experiments and so forth, marking the subsystem of science as most relevant environment. Of course, large organizations need to understand what happens in other subsystems as well (like politics or law), so this interest will also be reflected in its internal vocabulary. From this point of view, technical approaches to strategic analysis need to tackle the problem of unlocking the organization’s internal construction of social reality in order to improve awareness of crucially important strategic intelligence in the environment.

As will be shown below, our framework approach allows to operationalize this system logic of organization and strategy. It unlocks its potential even in large scale data sets, especially by making use of text mining methods and knowledge representation.

III. Solution approach: an AI-based socio-technical support system for strategic management

A. Strategic analysis in the 21st century: the state-of-the-art

How can strategy analysts in research organizations tackle the challenges described? A possible answer: "simply" put an emphasis on *networked thinking* in strategic thinking. Indeed, there is broad agreement in social science that in order to formulate successful strategies for all kinds of organizations it is important to use networked strategic thinking (e.g. [44]). As far back as the 19th century theoreticians wondered about the factors which made up the "strategic genius" able to correctly take into account different kinds of data from different domains, e.g. on politics, economics, law, culture, as well as their complex interactions, while making strategic decisions [8, pp. 100-112]. However, it is unclear how networked strategic thinking can be achieved, apart from training approaches in which practitioners are confronted with simulated complex problems and by getting feedback to their actions ([44]; for future studies see also [43]). While being certainly worthwhile, even this approach quickly reaches its limits when massive amounts of data need to be considered as outlined above.

In this paper we present an approach to address the outlined problems which is inspired by social systems theory and makes use of technological and scientific developments in the fields of text mining and knowledge representation. This concept fundamentally and very practically supports strategy analysts in the art of *networked strategic thinking* even in highly complex environments.

In the following, we first analyze existing literature, which is in accordance with our approach inspired by social-systems theory outlined in section II. The goal is to identify preliminary work as well as knowledge gaps. Both insights help to design a new solution approach later in this section.

As Keding [15] shows in an extensive systematic literature review on the interplay of AI and *strategic management,* research in the field can be structured into antecedent conditions and consequences. As for antecedent conditions or implementation, research highlights that AI is not a "plug-and-play technology" [15, p. 18] but needs accompanying factors like managerial willingness, interdisciplinarity and organizational alignment. As for consequences, AI technology has the "potential to transform how to generate competitive advantages" [15, p. 19], especially by enhancing cognitive abilities of decision-makers, reduce data overload and thereby create new ways to use knowledge. It is seen as a technology that augments managers rather than replacing them, freeing up time and energy for more creative tasks. While these insights support our framework approach, "there is still very limited theoretically grounded research aiming at understanding the utility of the latest generation of AI from a technology-application perspective." [15, p. 23][13]

The literature on *business analytics* has recently also dived deeper into the possibilities of AI (e.g. [58–60]), for a critical view see [61]). While it certainly corresponds to our conception of extracting knowledge from big data, it essentially differs by its focus on quantitative data, mainly internal business data. The opposite is true for contributions in the field of AI-supported *competitive intelligence*: the concepts developed there lack the interconnected focus on the internal vocabulary, structure and processes of organizations and tend to be rather technical approaches (e.g. [62–64]).

In a recent McKinsey publication, a conceptual bridge between business analytics and strategic environmental analysis has been proposed in talking about *strategy analytics* [14].[14] In their practitioner-style contribution the authors give four use cases applying AI methods to strategic problems: benchmarking internal strategic plans against historical similar cases and their outcomes; identifying areas of potential business growth by clustering large amounts of unstructured text data; tracking of emerging trends; and applying simulation and modelling methods to strategic choices in complex situations [14]. The merit of this publication is certainly its application orientation and hands-on focus on specific analytical tasks, unfortunately, it lacks a clear theoretical foundation and does not fully explicate its approach.

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[13] Concepts for the use of AI to enhance innovation management, as opposed to the broader perspective of strategic management, are put forward by [56] and [57].

[14] For an overview of the term strategy analytics see [65]. While going along the same lines, in this work the focus is less on the practical application of the latest big data analytics on strategic questions but rather on the theoretical and conceptual integration into management science and strategic management.

However, none of the literature really focusses on tapping into the tremendous amount of qualitative and unstructured data as a systematic global approach to generate strategic intelligence by coupling text mining and knowledge graph[15] technology. Organizations in crucial subsystems of society like politics, science or law predominantly describe their social reality in natural language vocabulary, in other words qualitative data. If communications of those organizations cannot be monitored systematically, important parts of strategic intelligence will be missing. While data driven knowledge graphs are asserting as powerful tools to exploit „diverse, dynamic, large-scale collections of data“ [66, p. 2] the topic of enterprise knowledge graphs still has great potential for development. Especially its capacity to support strategic thinking is still rather untapped and to our knowledge not yet part of a broader scientific discourse. Knowledge graph technology has been used on the one hand to make large knowledge repositories accessible like the internet or scientific publications ([67]; for an overview on Knowledge Graphs see [68]). On the other hand, quite recently, the same technology has been applied on the level of entities. Thus, it is used to organize the knowledge of individual persons [69], laboratories [70], enterprises [71, 72], cities [73] or even nations [74]. Especially relevant in the context of strategic management is the scientific discussion about the "enterprise knowledge graph" (for an overview see [72]). In this literature, the knowledge graph is seen as a way of integrating heterogenous data sources within organizations. As such, the technology is discussed as a way to enhance business analytics (e.g. [75]). The knowledge graph is predominantly seen as a powerful search mechanism allowing to ask semantic questions which are then answered by deductive inference methods (see e.g. [76]). Of course, business analytics also encompasses external data sources like information on customers. However, the existing literature does not focus on the broader information environment of organizations. By this we mean the social communications within society's "natural language-driven" subsystems which basically compare to the social, political, economic and ecologic environment ("STEEP"). Challenges for strategic analysis here lie in the detection of discourses, trends or

[15] Put simply, a knowledge graph can be conceived as a data model, that allows linking entities and their attributes in a networked structure.

early signals respectively (for an application of topic modeling methods to detect emerging trends and technologies see [77]). As outlined above these factors are, however, crucial for systemic strategic thinking. They are less susceptible to direct deductive inference methods, but need a “human-in-the-loop” as described below. While enterprise knowledge graphs are definitely a powerful application for management purposes, in this paper we want to put knowledge graph technology to a slightly different use. In the following, we propose a rather simple form of knowledge graph that does not aim at inference but at modelling internal knowledge complexity. By text-mining a document corpus that is representative for the organization’s description of itself and its relevant social environment, a sort of “informational digital twin” of the organization is created. This is than used to reduce the even higher knowledge complexity in the organizational environment by identifying and filtering for relevant information in the vast amount of qualitative data coming from external sources. The obtained information is evaluated against and then linked to the already available information within the organization to create an integral knowledge base to support strategic management. This approach is detailed in the following section.

In this sense, our conceptual framework and solution approach builds on the outlined literature and contributes to an important research gap. In order to solve the problem of reducing high external complexity of organizations to strategically gain competitive advantage we see a key in this theoretically-grounded and viable approach combining insights from social systems theory, strategic management and AI research.

B. A new approach on how to construct a modern AI-based socio-technical support system for strategic management

Firstly, in the following we will depict which roles modern text mining technology and knowledge representation play and how to employ them. Secondly, we will describe how to combine this approach with networked strategic thinking toward AI-supported strategic analysis. Thirdly, the overall integrated framework is derived.

1) Modern text mining technology and knowledge representation as a technological foundation

As mentioned, a basic challenge for strategy analysts lies in the exponential growth of available data that needs to be considered in a VUCA environment especially in terms of uncertainty [28, 78]. Issues in this context such as workload or bias have been described above especially when there is severe data overabundance. So how can we maintain efficiency when it comes to handling internal and external data, add semantic context to retrieve relevant information and interlinking it to create knowledge?

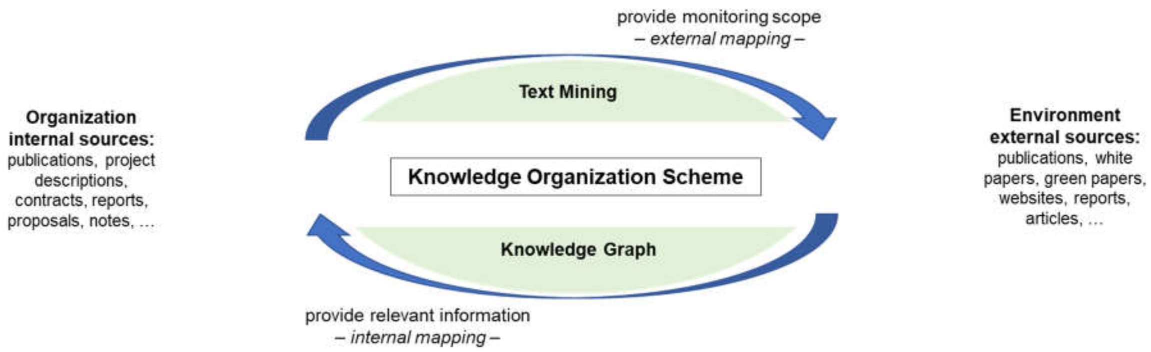

Fig. 1: Knowledge Organization Scheme

The first step is to create a Knowledge Organization Scheme as depicted in Fig. 1. The Knowledge Organization Scheme that is needed for this approach is more than a mere thesaurus simply listing important concepts and their synonyms but less than a clear-cut taxonomy which comprises important concepts in linear relationships. Instead, it can be described as a much more flexible or fuzzy self-learning taxonomy, that is automatically generated by the analysis of the internal databases. Text mining and knowledge representation technologies provide a promising solution to this problem. Take the example of a large national research institution. The general idea here is that a text corpus based on internal documents of the organization such as scientific publications, patents or project plans is representative for the fields of interest of that research organization. Therefore, this corpus (if representative) contains all the necessary information to generate a thematic map of the organization to serve as a monitoring scope for environmental scanning. It allows to fully grasp what we should be looking for when searching through external sources – therefore externally mapping the internal topics of interest. In our practical example this would primarily include research topics, significant scientists and collaboration partners or competing institutions in the field of science.

Text mining technology allows to unlock the contained information from the corpus and create the monitoring scope in an automated manner. Different levels of automation are applicable here. The approach spans from the creation of search queries based on a simple term vector model such as the bag-of-words approach to a highly sophisticated approach where the monitoring scope is created using contextual word embeddings that draw on transformer-based machine learning techniques such as Google's BERT language model (see [79]). These more sophisticated algorithms not only allow for synonyms to be recognized, but they can also cope with words that have different meanings in different contexts.[16] Practically spoken, an extremely simple approach would lead to a long list of Keywords that frame the topics of interest to the organization. A sophisticated approach, however, would create a high-dimensional topical representation of the content within the corpus.

This same text mining technology that yields the environmental monitoring scope of an organization can then also be used to search through the abundance of documents from external sources. In the very simple approach these documents would be scanned for the keywords of interest to decide if the document is of relevancy. In the sophisticated approach every document would be transformed into the high-dimensional space and compared to the topical representation of the organization's corpus. Obviously, this leads to a much higher precision because the algorithm can consider the context of words with multiple meanings. In addition, it would improve recall because even documents that use a slightly different language or more

[16] For further reading on basic text mining technologies see [80].

modern vocabulary could be identified because it rather looks for equivalency of information instead of certain terms. To give a simplified example from the field of informatics: A simple keyword list might look for publications on the topic of “CNN” meaning “convolutional neural networks” but might return papers from media research with respect to the “cable news network” leading to a bad performance regarding precision. And in terms of recall a sophisticated approach would increase performance by identifying a scientific paper on a rather new field like quantum reservoir computing because the paper has content proximity to papers in the field of machine learning.

As a result, and depending on the degree of precision, the described approach allows to identify which of the documents and contained information found in external sources might be relevant to the organization’s strategic orientation. It furthermore allows to extract that information and to map it to internal structures. In the given example this means that the term “quantum reservoir computing” would be identified as a new and unknown term that seems relevant for the organization. In addition, the knowledge organization scheme would automatically connect the identified document with its respective piece of information to the informatics department and the topic of machine learning because of the close content proximity to existing documents in this field. In order to do so information and knowledge have to be extracted from the text data by using advanced text mining methods for topic analysis, keyword extraction or named-entity recognition and linking. These are used to enrich the documents with annotations and to interconnect the entities through unique identifiers, e.g. to identify that different papers belong to the same author.

The result of this process is a graph structure that contains interconnected entities with their according attributes linked to richly annotated documents in the background. In order to store and work with this representation of knowledge, we propose to put the results into a graph-based model, here a *knowledge graph*. Basically, it consists of nodes and links between the nodes where the nodes describe entities and the links describe different relations between the entities. Technically speaking, we propose to use a modern multi-model database to implement the knowledge graph, which allows to cope with documents but also benefits from property graph style queries (along these lines: [81]). In a knowledge graph very different types of information can be linked flexibly, enabling efficient analyses on different levels of information. This knowledge graph is different from e.g. Google's knowledge graph in its application and it is much simpler: Google's product is used for semantic searches on the internet and therefore builds on a very sophisticated semantic in its core. The organizational knowledge graph is far more tailored to organizational needs and gets by with fairly simple semantics. Its central function is to project external information onto internal information through a graph structure which allows to analyze interconnections between the two spheres. In this way not only can we automatically detect relevant pieces of information or knowledge but we can also assign these findings to people or groups within the organization or to stakeholders in the vicinity.

To illustrate how such a graph would look like, let us draw on the simplified example from above. There would be a node that represents machine learning as a research field and this node would be connected to several nodes representing topics in this field such as CNN. Every topic would again be linked to nodes representing individual authors and the respective richly annotated publications would again be linked to topics and authors. However, it does not end there. Along the process of building the knowledge base more and more entities would be enriching the graph and these could include locations, research-programs, institutions and test facilities, departments, years, etc. So, along this graph the topic of quantum reservoir computing and the according publication would not only be linked to CNN and other research topics by a certain degree of separation. It would also be linked to governmental strategies on AI, norms on ethics in AI, institutions and scientists in the field, relevant research programs, research calls, patents, etc. And this holds true not only for the information coming from within the organization but also from any data source that has been monitored and processed outside of the organization. Put simple, the system transforms data into information or even preliminary stages of knowledge by creating links in between.

And it does all of this while being transparent of the predominant internal “code” and the organizations internal structure. As such, the system creates a kind of self-reflective view on the organization and can point to missing links. These could be a research topic that is not accounted for in a research program or a missing competency in a large-scale project team and so on.

At its core, this approach aims at an automatically generated but manually curated representation of the existing documented knowledge about and within the organization as well as the representation of the existing documented knowledge outside the organization that is of strategic relevance. The presented approach therefore also accounts for the understanding that generating and managing a comprehensive knowledge base is extremely valuable for strategic decision-making [82].

2) Toward an AI-supported strategic analysis

Now how can we combine this approach with networked strategic thinking to evolve toward AI-supported strategic analysis? The general idea can be seen in Fig. 2. With the resources that are spared due to automation in gathering and processing information, strategy analysts can focus on identifying the relevant sources and deriving strategic output based on the provided information and knowledge.

In terms of identifying sources an essential step is to create a corpus representative of the organization and curating the monitoring scope.

Fig. 2: AI-supported strategic analysis

First, a data strategy is needed. It has to be decided which are the most promising internal and external data sources to be scanned and monitored in order to provide information relevant to the cause.

As a starting point, internal fields of interest have to be defined. In public research organizations a good starting point might be to analyze internal strategy documents and research program documentation, project databases and all sorts of publications as these usually allow to derive the core fields of interest, core competencies and research topics. Other promising data sources may include internal development plans, descriptions of competencies and facilities, organizational databases etc.

Similarly, to the inside view, the results of stakeholder and competitor analyses can be used to identify relevant external data sources, given the specific organizational environment. Taking public research organizations as an example this will roughly return entities from politics, social movements, science, and science-related parts of the economy as these constitute relevant stakeholders as well as other research organizations in similar fields as they are direct competitors. Promising data sources are then e.g. certain political documents or press releases, (social) media, scientific publications, blogs and reports of competitors – to name a few. In order to obtain a structured 360° outside view, the organizational environment can additionally be segmented into fields of interest, e.g. according to the STEEP-logic. Then, the data sources identified can be segmented according to this logic – yielding the basis of a future radar chart visualization.

Once internal and external sources have been decided on the data pipeline is established based on the data strategy. In order to set up the data pipeline the different kinds of internal and external data-sources need to be made machine-readable. Also, the Knowledge Organization Scheme is established as described above drawing on text mining and knowledge representation technology.

With the growing need for future-oriented strategic intelligence the presented approach heavily supports collective intelligence, engaging strategic thinkers within the organization and connecting them. The strategy analysis team needs to be interdisciplinary in order to understand cross-system phenomena, i.e.

apply strategic network thinking. The organization-wide *Network of Strategic Thinkers*[17] is even more interdisciplinary in nature and will help the core team answer strategic questions on the basis of preliminary data analyses. Their tasks are, among others, to inform and be informed, generate feedback, curate AI-generated knowledge graph updates, mitigating AI-induced risks, put information further into context, evaluate information and to support the decision-making processes. Now, how can the Network of Strategic Thinkers access the information and knowledge that is stored in the knowledge graph to perform strategic analyses? Put simple, a user interface is needed. This interface can best be described as a Strategic Information Cockpit (SIC). The Information Cockpit not only provides easy access to the knowledge graph through queries but also allows to perform strategic analyses building upon the structured knowledge. The SIC serves as the central communication and collaboration platform for the core team of strategy analysts and the organization's community of strategic thinkers. Its purpose is to provide information to the strategic thinkers of the organization and include them in the process.

The overall framework that is depicted in Fig. 3, leads to a new level of strategy work providing a strong competitive advantage to the organization. To argue this advantage some of the potential applications shall be discussed in the following.

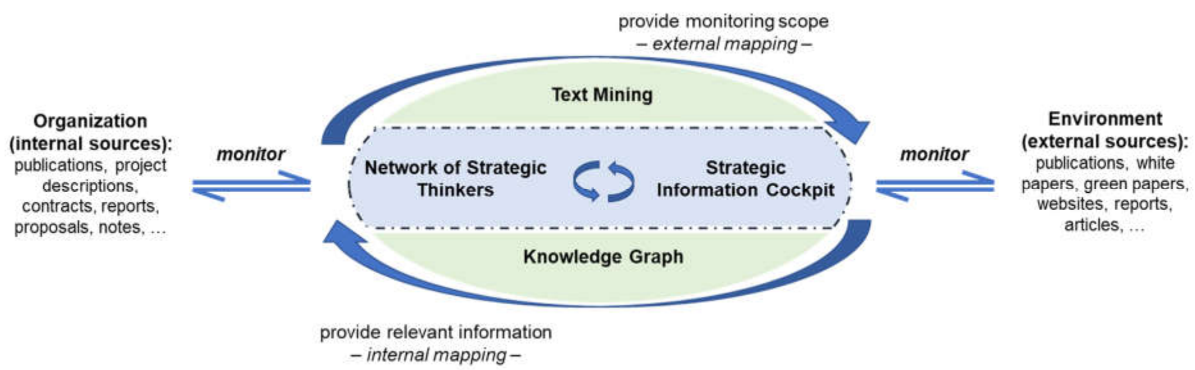

Fig 3: Overall framework

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[17] This could be a group of experts supporting the team of strategy analysts in a small organization or a foresight network in a large organization or any other kind of structure. However, the approach benefits of a group covering the full topical span of the organization and taking on this task.

To give an example, think about a typical analyst's tasks such as putting together a dossier on an upcoming research and development field such as quantum computing. The capabilities of the SIC would incorporate structuring the broad term of quantum computing into relevant subcomponents on the hardware as well as software side or the different scientific disciplines involved like computer science or physics. So, it might structure the analysis into subtopics like "superconducting quantum computing" or "trapped ion quantum computer". Due to the nature of the knowledge graph, the SIC would also return information on research organizations in the field and which institutes spear head in a certain topic, including the identification of leading scientists in the field internally and externally. Furthermore, it allows to give an overview on internally allocated program budgets, publicity work, identify governmental strategy including funding programs, relevant patents and potential collaboration partners in the industry, public perception, recent and future events and conferences, etc. When putting together the dossier, the analyst would benefit from tapping into the broad information base relieving him during his research and increasing situational awareness to create in depth strategic intelligence. However, it does not end there, the SIC incorporates different analytical tools that analysts can apply to the data in order to detect trends through time series analysis, cross-system patterns or visualize information networks. In sum, the SIC provides analysts with the capability to handle enormous internal and external system complexity and, at the same time, reduce it to levels amenable for humans to "connect the dots" and draw the right strategic conclusions.

Moreover, the networked nature of the knowledge representation and the additional layer of the SIC allows to personalize access to the system and thus spares the user from information overflow. Over time the system can learn what type of information might be interesting to the organizational user by processing any text-data the user provides to the system or any information accessed by the user. At the same time, it allows to share any piece of knowledge created between strategic thinkers to gain a truly interdisciplinary perspective. Hence, the concept can be described as a fuzzy publish-subscribe pattern, where every user "subscribes" to that subgraph of the knowledge graph that is of individual interest. In this way, the SIC provides a thoroughly tailored automated information feed to the user considering the individual field of competence and organizational environment and any newly available information. It can also serve as an early warning system which first-of-all ensures that no important information is missed by the experts in the organization. From a foresight perspective it also supports the analysts detecting early signals for e.g. upcoming research trends, new technologies or even trends in policy formulation or societal developments [83]. By using certain types of graph analysis combined with unsupervised text mining methods like topic modeling it opens up the possibility to even find so-called “unknown unknowns” (new knowledge no one expected). Think of publications that use newly coined terms or concepts and fall within the monitoring scope. This information would be identified as potentially interesting and automatically fed to the right user. Technically speaking an unknown entity extracted from a published document would automatically be linked to any existing entity in the knowledge graph if they bear resemblance given the context they both appear in. And an analyst subscribing to this part of the graph would then be in informed about the update. Table 1 gives an overview of several further tasks and problems in strategy work and how the proposed framework addresses these.

In a highly volatile world of information abundance having an AI-based support system that filters for individual user relevancy and timely pushes the latest information is a huge competitive advantage allowing to act agile and stay efficient.

Table 1: Strategic challenges and proposed solutions made possible by the presented framework

Strategic Challenge		**Proposed Framework Solution**
Information overflow; heterogeneity of data	-	AI-based monitoring of databases representing organization’s environment; automatic and inductive identification of interested groups within the organization for new documents and providing the information to them (e.g. publications)

Obtaining situational awareness within complex organizations with many departments and hierarchy levels spread among many locations	-	AI-based analysis and monitoring of databases representing organization's internal activities; networked knowledge representation within the Strategic Information Cockpit
Strategic information needs unclear	-	Knowledge Organization Scheme provides full scope of relevant information and is updated automatically based on an organizational document corpus
Find and extract knowledge from multi-modal and unstructured data	-	Advanced information retrieval methods and networked knowledge representation
Extract knowledge from social information	-	Interdisciplinary team of analysts connected through the Strategic Information Cockpit and are timely provided with any relevant information that is published
Identify experts within the organization	-	Query the Knowledge Graph to identify any expert on a topic based on internal documents, e.g. project descriptions or scientific publications
Existence of highly relevant unknown unknowns	-	Identify unknown unknowns by seeing if new terms are coined/pop up within fields or in different context; outcome of the graph network evolution in terms of new vertices or edges

Information and knowledge loss by employee turnover	- Evolved internal knowledge management by partial automation and improved continuity based on the Knowledge Graph as well as individual SIC user profile that is created and stored with respect to an individual job profile or responsibility for a specific subject
Early detection of relevant weak signals and upcoming trends	- Analysis of signal distribution within Knowledge Graph
Being aware of public opinion	- Monitoring public debate on certain critical fields; matching external view of organization to internal capacity; monitoring public relations activities
Knowledge about funding opportunities	- Monitor funding opportunities and targeted information of potential applicants
Knowledge about competitors	- Monitoring competitor behavior and fields of activity including new actors in a field; monitoring issuing of relevant publications and patents
Knowledge about industry opportunities	- Support by automated market exploration and evaluation
KPIs in a complex world: Knowledge about strategic performance	- Support by automated qualitative monitoring of strategic goals in terms of output

IV. Conclusion and implications

Digital transformation in all areas of life is going on with ever increasing speed. However, in the field of strategy there are still only first signs of operational applications of AI-based methods when it comes to tapping into unstructured qualitative date. This can be considered a puzzle as the field of strategy, being characterized by severe complexity and information abundancy challenges, might benefit especially from the digital transformation. Above, we started from a system perspective on organizations. Seeing them as communications systems, the challenge of strategy lies in “connecting the dots” between highly complex networks of internal and external communications using an inside-out perspective. Strategists face the challenge of supporting management to make the right-decisions while overlooking the organization in its full complexity as well as the interconnections to and reverberations with various complex surrounding fields like science, technology, politics or ecology. Also, the question whether an organization-as-a-system uses the “right” model of itself and its environment to reduce complexity in an ever-changing world at least becomes accessible to discussion and analysis. The solution approach and concept framework introduced here, may be thought of as an operationalization of the logic of social communication systems. AI-based methods are able to absorb enormous levels of internal and external information complexity, also in the form of text-data, and are able to carve out underlying network structures. The idea of the organizational knowledge scheme works as the highly automated interface connecting the inside to the outside view of the organization and thus reduces the complexity to a level which creates a picture for the analyst amenable to drawing the right strategic conclusions. The Strategic Information Cockpit is key here, as it serves as the main user-AI-interface augmenting analysts with the capabilities to bring the idea of networked thinking to operational life. As the knowledge representation behind the SIC comprises the information and knowledge about the organization itself and important environmental systems and is updated automatically and continuously it can be conceived of as a digital twin of the organization. This “static” digital twin of the organization can be made into a “dynamic” digital twin of the organization in the long run. Future research and development are necessary here. However, we can build on recent studies [74] and substantial knowledge and therefore rather see the challenge of combining and integrating different pieces. By introducing the capability of applying complex systems simulations creating a dynamic networked system model, questions can be addressed like the probable effects of e.g. changes to the organizational structure, procedures or changes in the environment of the organization (e. g. think of increased funding vs. budgetary cuts). System effects like nonlinearity, emergence or phase transitions can be considered by the simulation. As part of the presented approach, changes to the team culture and structure of strategy analysts like interdisciplinarity, flat hierarchies and an intensified exchange with strategic thinkers throughout the organization yield a massive competitive advantage. Heterogenous teams may be suited best for tackling the problem of different communication structures in different fields of society, which have to be analyzed holistically. We argued by drawing on the example of strategic research management. Research organizations face the challenge of coping with the explosion of world-wide research activities also fired by advances in digital technologies while at the same time having to track and consider changes in politics, society and the economy in their strategic decision making. Using this rather complex example hopefully allows managers to apply these thoughts successfully on different kinds of organization as well. Concluding, in this article we presented our vision of a 21st century strategy analytics system, by bridging the gap between a number of existing theories and methods from different disciplines.

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