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Article — Published Version

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Management Review Quarterly

Provided in Cooperation with:

Springer Nature

Suggested Citation: Mundlos, Philip (2024) : The impact of artificial intelligence on managerial attention allocation for discontinuous change: a conceptual framework, Management Review Quarterly, ISSN 2198-1639, Springer International Publishing, Cham, Vol. 75, Iss. 2, pp. 1-45, <https://doi.org/10.1007/s11301-024-00409-0>

This Version is available at:

<https://hdl.handle.net/10419/323494>

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The impact of artificial intelligence on managerial attention allocation for discontinuous change: a conceptual framework

Philip Mundlos¹ 

Received: 3 March 2023 / Accepted: 12 January 2024 / Published online: 17 February 2024
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Abstract

The early detection of discontinuous change plays a decisive role in the performance and competitiveness of organizations. Whether and how top managers perceive change is mostly determined by their attention. However, research has shown that many top managers are often unable to allocate their attention properly and may therefore react with inertia or not at all to relevant changes. This raises the question of how managerial attention can be influenced to make top managers more receptive to discontinuous changes. A promising approach to this problem may come from the growing research field on the impact of AI on strategic decision-making. In this paper, I provide a conceptual framework of how the use of AI might help top managers better focus their attention on discontinuous change. Based on a systematic literature review and an attentional model, I highlight factors that influence top managers' attention allocation and likely enhance or inhibit it through the use of AI. This allows me to derive propositions for the application of AI in discontinuous change detection that can serve as a starting point for future empirical research. My paper contributes to broadening the research field of AI in the area of managerial attention.

Keywords Managerial attention · Discontinuous change · Artificial intelligence · Strategic management

Zusammenfassung

Das frühzeitige Erkennen von diskontinuierlichen Veränderungen spielt eine entscheidende Rolle für die Leistungs- und Wettbewerbsfähigkeit von Organisationen. Ob und wie Topmanager Veränderungen wahrnehmen, hängt wesentlich von ihrer Aufmerksamkeit ab. Die Forschung hat jedoch gezeigt, dass viele Topmanager ihre Aufmerksamkeit oft nicht richtig zuordnen können und deshalb mit Trägheit oder gar nicht auf relevante Veränderungen reagieren. Dies wirft die Frage auf, wie die Auf-

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merksamkeit von Führungskräften beeinflusst werden kann, um sie für diskontinuierliche Veränderungen empfänglicher zu machen. Ein vielversprechender Ansatz zur Lösung dieses Problems könnte sich aus dem wachsenden Forschungsfeld der Auswirkungen von KI auf die strategische Entscheidungsfindung ergeben. In diesem Beitrag stelle ich ein konzeptionelles Modell vor, wie der Einsatz von KI Topmanagern helfen könnte, ihre Aufmerksamkeit besser auf diskontinuierliche Veränderungen zu richten. Basierend auf einer systematischen Literaturrecherche und einem Aufmerksamkeitsmodell zeige ich Faktoren auf, die die Aufmerksamkeitsallokation von Topmanagern beeinflussen und die wahrscheinlich durch den Einsatz von KI verbessert oder beeinträchtigt werden. Daraus leite ich Thesen für den Einsatz von KI zur Erkennung diskontinuierlicher Veränderungen ab, die als Ausgangspunkt für zukünftige empirische Forschung dienen können. Meine Arbeit trägt dazu bei, das Forschungsfeld der KI im Bereich der Aufmerksamkeit von Managern zu erweitern.

1 Introduction

For many decades, researchers tried to understand why organizations drop out of competition. Here, discontinuous change is seen as an important reason for organizational failure. It differs from conventional change as it massively deviates from existing assumptions about norms, processes, and concepts (Christensen and Bower 1996) by not only providing entirely new market information (Luger et al. 2018; Teece 2014) but also by devaluing existing knowledge within organizations by radically changing the market paradigm (Posen and Levinthal 2012). Previous research has found organizational inertia (Eggers and Park 2018), existing divergent patterns of experience (Nadkarni and Barr 2008), and inattentional blindness (Mack 2003) to be important drivers for the insufficient recognition of discontinuous change, which in turn can have costly consequences for organizations (Tripsas and Gavetti 2000). Over the last years, research on managerial and organizational cognition (MOC) (Eggers and Kaplan 2013; Gerstner et al. 2013; König et al. 2021) has identified managerial attention as another central concept explaining heterogeneous perceptions of discontinuous environmental change (Kammerlander and Ganter 2015; Maula et al. 2013; Ocasio 1997). Studies have shown that managers' attention plays an important role in effectively detecting and dealing with discontinuous environmental change (Eggers and Kaplan 2009) by allocating attention to those stimuli that appear most relevant (Ocasio 1997), thereby significantly influencing the strategic agenda (Ocasio and Joseph 2005). Surprisingly, however, the question of how to influence managers' attention to be more receptive to discontinuous change remains unanswered.

A promising approach to this problem may come from research on the impact of artificial intelligence (AI) on strategic decision-making in organizations, which has gained much interest in the past (Keding 2021). Here, AI expresses "*a system's capability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption*" (A. Kaplan and Haenlein 2019, p. 3). While AI-based systems are already actively shaping decision-making in many other fields, such as healthcare (McKinney et al.

2020) or transportation (Grigorescu et al. 2020), applications in strategic decision-making are still in their infancy. Only recently have management scholars begun to examine the impact of AI on strategic decision-making in more detail (Keding 2021; Krogh 2018). While at the individual level, research has primarily focused on managerial cognition concerning AI's potential to improve strategic decision-making (Ghasemaghaei et al. 2018; Merendino et al. 2018) and the associated trust in it (Logg et al. 2019; Schneider and Leyer 2019), research at the organizational level increasingly investigated the degree to which AI can independently substitute humans in strategic management tasks (Agrawal et al. 2017; Jarrahi 2018). These recent findings on AI in a management context combined with technological developments (Agrawal et al. 2019; Intezari and Gressel 2017) give reason to believe that AI-based decision support systems can influence managers' attention to discontinuous changes (Mühlroth and Grottke 2020; Robinson et al. 2020) and thus contribute to improved strategic decisions.

Therefore, I combine results from a systematic literature review (SLR) on managerial attention with recent studies of AI in management decisions to examine how the use of AI might help top managers direct their attention to discontinuous change. I argue, based on Shepherd and colleagues' (2017) attentional model, that AI affects the perception of discontinuous change by increasing the complexity of the top manager's knowledge structures, a *"kind of mental template that individuals impose on an information environment to give it form a meaning"* (Walsh 1995, p. 281), and reducing the situational level of task demands, i.e., the demands required to achieve a given level of performance (Hambrick et al. 2005). This allows manager's attention allocation to be more bottom-up (stimulus-driven; exogenous) than top-down (schema-driven; endogenous) (Mcmullen and Shepherd 2006).

The paper contributes to the research in three ways. First, I contribute to research by connecting the Attention-based View of the Firm (ABV) with AI. Thereby, I integrate AI into management research beyond the known research streams such as trust and acceptance (Lichtenthaler 2020; Schneider and Leyer 2019). Second, I contribute to research on discontinuous change by illustrating how technologies can help managers detect discontinuous change. These findings can serve as a starting point for future empirical studies. By providing frameworks to consider when using AI, this paper also contributes to practice.

2 Discontinuous change and the attention-based view

Discontinuous change radically challenges existing norms, processes and concepts (Christensen and Bower 1996; König et al. 2012) which makes it a widely-studied phenomenon to explain organizational failure. For example, according to an extensive field study by Tripsas, (2009), organizations facing discontinuous change are often unable to successfully adapt to new market conditions, because their organizational identity prevents them from perceiving identity-critical changes, i.e., discontinuous ones. Moreover, organizations often even lack the incentive to adapt to environmental changes (Christensen and Bower 1996), especially when their capabilities and resources are aligned with the current market standard (Anand et al.

2010), because they deviate from existing organizational structures and processes (Abernathy and Clark 1985; Gerstner et al. 2013). Therefore, they often react with a variety of inertial forces (Danneels 2004), such as resource dependence or incumbent position reinvestment (Gilbert 2005; König et al. 2021), which can result in the loss of competitive advantage of companies such as Polaroid, that failed to notice the shift from analogue to digital imaging (Tripsas and Gavetti 2000) and ultimately market position (Henderson and Clark 1990; Hill and Rothaermel 2003).

Some scholars have analyzed drivers for the recognition and adaptation to discontinuous change on the organizational level. For example Garud and Karunakaran (2018) find that integrating participatory experimentation into an organizational design can promote the internal management of change. Birkinshaw and colleagues (2016) find evidence that different environmental changes require different modes of adaptation, which are closely linked to the dynamic capabilities of an organization. In addition, research indicates that resource commitment (Christensen 1997) and insufficient routine rigidity (Gilbert 2005) are drivers for divergent recognition of discontinuous change.

Research on the individual level has increasingly focused on the link to managerial and organizational cognition (MOC) (Eggers and Kaplan 2013; Gerstner et al. 2013; König et al. 2021). Gerstner and colleagues (2013), for example, show that narcissism leads to a more aggressive adaptation of technological discontinuities, while Kammerlander and Ganter (2015) find that specific noneconomic goals of family firm CEOs, such as “family power and control”, foster their adaption to technological discontinuities. Within the MOC research field, managerial attention is considered one of the central concepts explaining heterogeneous perceptions of discontinuous environmental change (Maula et al. 2013; Ocasio 1997).

Managerial attention has received increasing research attention over the last decades (Ocasio 2011). For example, research has analyzed attention in the context of routines and bounded rationality (Cyert and March 1963; March and Simon 1958), ambiguity (March and Olsen 1976), or enactment processes (Weick 1979). Drawing on these findings, Ocasio, (1997) formulates the Attention-Based View of the Firm (ABV), a metatheory in which he defines attention as “*the noticing, encoding, interpreting, and focusing of time and effort by organizational decision makers on both (a) issues: the available repertoire of categories for making sense of the environment, and (b) answers: the available repertoire of alternative actions*” (Ocasio 1997, p. 189). The ABV states that the structuring and allocation of attention, together with other factors, is an important explanation for the behavior of decision-makers and thus of their organizations, as it influences the spectrum of decision-relevant information that can be considered (Kammerlander and Ganter 2015). This makes managerial attention crucial as it significantly shapes decision maker’s behavior (Ocasio 2011).

Building on the findings of ABV and the field of managerial cognition, research has highlighted the importance of attention allocation for the ability to notice environmental changes (Cho and Hambrick 2006; Eggers and Kaplan 2009; Kiss and Barr 2015; Shepherd et al. 2007). Studies have shown that managerial attention allocation plays an important role in effectively detecting and dealing with uncertain environmental changes such as discontinuity (Eggers and Kaplan 2009) by

distributing attention to those stimuli that appear relevant (Ocasio 1997), thereby significantly influencing the strategic agenda and the use of resources (Ocasio and Joseph 2005).

Confronted with a highly complex and uncertain environment characterized by ambiguous and unstructured information (S. Kaplan and Tripsas 2008; Simon and Newell 1958) managers often fail to pay attention to discontinuous changes (Gatignon et al. 2002), for example due to deviating patterns of experience (Nadkarni and Barr 2008) or inattentional blindness (Mack 2003). Thus, to better understand why managers often struggle to focus their attention on discontinuous changes and whether AI can support these processes, first the structural determinants of attention need to be ascertained.

This paper draws on Shepherd and colleagues' (2017) comprehensive *Attention Model of Top Manager's Opportunity Beliefs* as a central concept. In line with the current ABV literature, this model assumes that attention is not to be understood as a unified process, but as a series of distinct interconnected process steps that culminate in an action (Posner and Rothbart 2007). It therefore considers two aspects of attention: the transient attentional phase, in which decision makers actually perceive changes in the environment, and the sustained attentional phase, in which they form an opinion about the recognized changes (Shepherd et al. 2017). Research findings suggest that a central reason why decision makers often fail to recognize discontinuous change can be found in the extent to which they engage in top-down processes during the transient attentional phase (Nadkarni and Narayanan 2007; Shepherd et al. 2017). Since I am only interested in the detection of discontinuous changes as such, I will only focus on the transient attention phase. The attention allocation during the transient attention phase is mostly determined by manager's task demands and knowledge structures (Shepherd et al. 2017). Despite the large body of research on the impact of managerial attention on environmental change detection, only few studies have addressed approaches to improve this situation. Here, AI with its specific capabilities might help and make a meaningful contribution to a much-studied problem by providing technological solutions to achieve a more balanced allocation of top-down and bottom-up processes. Most studies in ABV research focus exclusively on top-down approaches in the attention allocation that can be derived from decision makers' action logics (Thornton and Ocasio 1999), while ignoring bottom-up approaches, in which attention is directed to specific environmental cues rather than cognitive patterns (Joseph and Wilson 2017). Shepherd and colleagues' (2017) attentional model, in contrast, integrates both approaches, resulting in a more holistic and balanced approach when studying discontinuous change. These attributes make the model ideal as basis for an in-depth look at the influence of AI on the detection of discontinuous changes.

How environmental changes are perceived by top managers during the transient attention phase is largely influenced by the extent to which decision-makers rely on top-down (schema-driven) or bottom-up (stimulus-driven) approaches in their attention allocation (Joseph and Wilson 2017; McMullen and Shepherd 2006; Shepherd et al. 2007). According to research findings, the extent of top-down processes in attention allocation is essentially shaped by the decision maker's goals (Greve 2008), identity and accountability (Hoffman and Ocasio 2001) and cognitive

structures (Bouquet and Birkinshaw 2008), which can be clustered under two main influencing variables: task demand and the complexity of knowledge structures (Shepherd et al. 2017).

Hambrick et al. (2005) define task demand of top managers, also called executive job demands, as the requirements necessary to achieve a given level of performance. According to them task demand is composed of (1) task challenges, (2) performance challenges, and (3) executive aspiration. When exposed to high task demand, managers' limited attentional capacity (Ocasio 1997) makes them incapable of detecting discontinuous changes at the same time, as they rely more heavily on experience-based top-down processes in such moments of high cognitive load (Hambrick and Mason 1984; Shepherd et al. 2017).

Knowledge structures (also called strategic schemas or cognitive frames) are cognitive structures that represent organized knowledge about individual concepts or domains (Daft and Weick 1984; Kiss and Barr 2015). They differ in their centrality (Eden et al. 1992) and complexity (Calori et al. 1994). Research on knowledge structures indicates that a higher complexity of knowledge structures can have a positive impact on the detection of discontinuous changes by helping decision makers increase their strategic flexibility (Nadkarni and Narayanan 2007) and thereby becoming more open to changes from the environment (Walsh 1995).

3 Methodology

To provide a more comprehensive picture of exogenous (bottom-up) and endogenous (top-down) influences in attentional research related to change, I have conducted a SLR. The methodological basis of the SLR of this paper is based on Tranfield et al. (2003). Its main objective is to present a structured and replicable state of research based on a three-step process—planning, conducting, and reporting and dissemination—on which a conceptual model can be built. In order to understand how attention impacts the detection of environmental changes, it's important to identify both the top-down (endogenous) and bottom-up (exogenous) factors that affect this process. In 4 steps, relevant research articles were identified and clustered.

In the first step, topically relevant keywords were identified and used for a structured database search on Web of Science. Web of Science is a comprehensive online database of scientific publications and is widely used for literature reviews in science (Brielmaier and Friesl 2023). The keywords used were divided into two groups and linked with the Boolean operator "AND". The first group contained the keywords "*attention*" or "*attention allocation*" or "*attention-based view*" or "*ABV*" or "*managerial attention*". The second group contained "*discontinuous change*" or "*environmental change*" or "*change*" or "*change detection*" or "*opportunity recognition*". The search was limited to empirical, theoretical, and review articles from 1997, the year Ocasio's, (1997) ABV theory was published, to 2023. To ensure high scientific quality of the literature search, the survey-based VHB-Jourqual 3 ranking was also used to filter published articles from leading journals, in line with other SLR articles (Grisar and Meyer 2016; Keding 2021). Only peer-reviewed journals that had both a

ranking of B "important and prestigious" or higher and a clear link to management research were included. This resulted in a selection of 508 articles from 19 journals that met the above criteria.

In a second step, following Tranfield et al. (2003), I first excluded all articles that did not contain either "attention" or "change" in the title, abstract, or keywords, and that had no substantive relation to management research or ABV. Variations of the keywords such as "attentional" were also considered. As a backup, the full texts of all excluded articles were rechecked for content matches. Articles that had a match to the keywords in the full text but did not have sufficient content related to the research field were removed. This resulted in a selection of 54 articles.

In a third step, the remaining articles were subjected to an in-depth review. In this process, the articles were read carefully. 11 articles were excluded because, although they met the SLR search criteria in terms of keywords and research orientation, on closer inspection they did not have content related to the research question. This left 43 articles (see Table 1). In the final step, the effects on attention described in the articles were categorized as either endogenous (top-down), internally induced processes or exogenous (bottom-up), externally induced processes (Corbetta and Shulman 2002). This categorization was based on the transient attention phase of the attention model of top managers by Shepherd et al. (2017).

4 Results of the literature review

The results of the SLR show, that previous publications extensively studied the relationship between attention and change detection in management, considering individual traits like future-oriented thinking (Back et al. 2020), narcissistic tendencies (Gerstner et al. 2013), acquired knowledge (Grégoire et al. 2010), and cognitive information processing (Gavetti and Levinthal 2000). These endogenous characteristics affect how managers allocate their attention and thus how they perceive and effectively manage change. Moreover, organizational factors, including impending change (Bansal et al. 2018), organizational structure (Fu et al. 2020), interorganizational relationships (Maula et al. 2013), shareholder influence (Hoffman and Ocasio 2001), and industry environmental dynamism (Ghobadian et al. 2022) show significant effects on the relationship between attention and environmental change detection. This systematic review provides an overview of these endogenous and exogenous influences that have been studied by researchers, but lacks specific guidance for individuals, top management teams (TMT), or organizations. While attention's significance in strategic decision-making is widely acknowledged (Ocasio 2011), there is a dearth of theoretical models addressing how to mitigate the negative effects of endogenous/exogenous factors on attention allocation during change detection. AI research in management presents a promising solution, offering valuable insights and strategies for effectively managing attention in change processes (Jarrahi 2018; Robinson et al. 2020).

Table 1 Studies with endogenous/exogenous effects on attention

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2020	Back, P; Rosing, K; Dickler, TA; Kraft, PS; Bausch, A	Empirical	324 manufacturing firms over a time frame of 17 years retrieved from various databases.	Individual	Endogenous (top-down)	High levels of past and future focus help CEOs make strategic changes, especially in strategic change, especially in highly dynamic environments, and that a predominance of one of these negatively affects the implementation of strategic change.
2018	Bansal, P; Kim, A; Wood, MO	Theoretical/ conceptual		Organizational	Exogenous (bottom-up)	The magnitude of change significantly might influence an organization's allocation of attention and resources, and existing processes may hinder the proper allocation, leading to a failure in perceiving necessary changes.
2019	Belenzon, S; Hashai, N; Pataconi, A	Empirical	Sample of 53,944 corporate groups from 15 West European countries retrieved from two databases.	Organizational	Endogenous (top-down)	A smaller organizational distance between headquarters and subsidiaries leads to more organizational attention to changing external conditions in the form of greater control and support from headquarters, while more remote subsidiaries operate autonomously.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2018	Bikard, M	Empirical	Examination of inventors' patent references to industrial or academic origin using 924 patent-paper dyads and 48 interviews.	Individual	Endogenous (top-down)	For scientific discoveries, the allocation of inventors' attention determines whether patents are more likely to cite the academic or the industrial publication. Inventors are twice as likely to cite the industrial publication as the academic publication.
2012	Bock, AJ; Opsahl, T; George, G; Gann, DM	Empirical	Analysis of 107 semi-structured interviews with CEOs of multinational companies from various countries and industries in 2006.	Individual	Exogenous (bottom-up)	The ability to respond to change requires simplifying organizational structures to reduce management's focus of attention while not losing control. This is also linked to strategic flexibility.
2015	Buyl, T; Boone, C; Wade, JB	Empirical	Sample of 1168 observations from 197 US organizations (2000-2011) from four different industries ranging from stable to dynamic environments.	TMT	Endogenous (top-down)	The level of inflow of new executives is related to the strategic focus of the incumbent TMT's attention. The incumbent TMT's level of exploratory attention is positively associated with the likelihood of non-CEO executive inflow, while the level of exploitative attention is negatively associated.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2016	Chng, DHM; Wang, JCY	Empirical	Experimental managerial decision-making scenario with 216 Chinese managers enrolled in a part-time MBA program.	Individual	Endogenous (top-down)	Managers' individual task attention strengthens the positive relationship between incentive compensation and managers' strategic risk-taking and performance declines, but not when firm performance increases.
2006	Cho, TS; Hambrick, DC	Empirical	A dataset of 30 airlines operating between 1983 and 1986 with revenues greater than \$100 million is used to test the effect of airline deregulation on attention.	TMT	Exogenous (bottom-up)	Change in the form of deregulation leads to a shift in collective management attention, which is greatest for those firms that changed the TMT composition of the firm. TMT characteristics influence strategy, but attention mediates this relationship, attenuating the effects of TMT changes on strategy.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top–down)/ exogenous (bottom–up)	Findings
2009	Christen, M; Boulding, W; Staelin, R	Empirical	Mathematical model of two identical firms facing the same market conditions but with different attentional capacity to process data.	Organizational	Exogenous (bottom–up)	A firm's optimal market intelligence strategy depends on available attention, especially when attention is scarce and thus costly, and independent of market differences or core capabilities. Attention capacity is the data processing capacity.
2018	Dhanorkar, SS; Siemsen, E; Linderman, KW	Empirical	Analysis of a longitudinal dataset from two state environmental agencies in Minnesota that includes 1089 supportive environmental improvement projects combined with temporary punitive measures.	Organizational	Exogenous (bottom–up)	The timing, severity, and context of regulatory penalties are critical to directing managerial attention to environmental compliance and thus improving the effectiveness of supporting actions.
2018	Drover, W; Wood, MS; Corbett, AC	Theoretical/ conceptual		Individual	Endogenous (top–down)	Attentional control might influence which signals individuals pay attention to, with top–down processing paying more attention to organizational signals and bottom–up processing paying less attention to signals with low observability.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2009	Eggers, JP; Kaplan, S	Empirical	Longitudinal study using company letters to shareholders from 29 listed communication technology firms from 1976 to 2001.	Individual	Endogenous (top-down)	CEO attention, directed either towards emerging technology or the affected industry, can either accelerate or slow down firm behavior, with the impact dependent on the firm's organizational orientation and capabilities.
2019	Frankenberger, K; Sauer, R	Empirical	Case-study approach by conducting exploratory and semi-structured interviews to gather primary data from four markets.	TMT	Endogenous (top-down)	Both external and internal attention targets play an important role in the development of novel business model (BM) designs, with external targets enabling companies to identify and exploit new opportunities and internal targets contributing to BM coherence and the identification of necessary changes. It is important to consider multiple attention goals and intensity, with different goals reinforcing each other and moderate attention intensities leading to highly efficient BM designs.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2020	Fu, RCY; Tang, Y; Chen, GL	Empirical	Analysis of a sample of S&P 500 companies for the period 2005–2014.	Organizational	Exogenous (bottom-up)	A chief sustainability officer (CSO) influences the distribution of attention asymmetrically, with a greater focus on reducing socially irresponsible activities (CSiR) compared to increasing socially responsible activities (CSR), due to a negativity bias in attention allocation. The relationship between CSO presence and CSR becomes weaker when a company has a sustainability committee, indicating potential competition for attention and resources.
2000	Gavetti, G; Levinthal, D	Empirical	Simulation model with 90 organizations, divided into subsets of 45 organizations each.	Individual	Endogenous (top-down)	Changes in cognitive representations can improve adaptation to environmental change by facilitating sequential attention to different facets of the actor's environment. Thus, even with limited cognitive mapping, the full dimensionality of the problem space can be captured over time.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2013	Gerstner, WC; Konig, A; Enders, A; Hambrick, DC	Empirical	Sample of 72 CEOs from 33 U.S. pharmaceutical companies from multiple databases covering the period 1980 to 2008 and 521 company years.	Individual	Endogenous (top-down)	CEO narcissism promotes managerial attention to a discontinuous technology, and the association between managerial attention and subsequent strategic actions is stronger in the early stages of a phenomenon. In addition, audience engagement moderates the relationship between CEO narcissism and managerial attention.
2022	Ghobadian, A; Han, T; Zhang, XZ; O'Regan, N; Troise, C; Bresciani, S; Narayanan, V	Empirical	Using financial and company data from 2015 to 2019/2020 from 1,153 Chinese and 1,861 U.S. firms, representing 61 and 45 industries, respectively.	Organizational	Exogenous (bottom-up)	Managers increase their attention to COVID-19 when their firms experience greater disruption, but industry dynamism negatively affects this relationship. The results differ between the U.S. and China, highlighting the influence of the business-government relationship and raising questions about the generalizability of management theories.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2010	Gregoire, DA; Barr, PS; Shepherd, DA	Empirical	Think-aloud verbaliza- tion experiment with 18 verbal protocols of 9 senior executives with new venture founding and management experience in life science technologies and marketing services.	Individual	Endogenous (top-down)	In opportunity recognition, drawing on higher levels of prior knowledge requires more cognitive effort (atten- tion) to match structural relationships than to match surface features. Different types of mental connec- tions play different roles in opportunity recognition and lead to different conse- quences.
2013	Guiette, A; Vandenbempt, K	Theoretical/ conceptual		Individual	Endogenous (top-down)	Management attention is criti- cal in reconciling different mental models during stra- tegic change. Implementing change disrupts routines and expectations in organi- zations, which might lead to feelings of inadequacy in management. This lengthy process of raising aware- ness, combined with a lack of management attention, can create tension and anxi- ety among individuals.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2023	Harvey, JF; Kudesia, RS	Empirical	Conducted a survey with 88 North American teams from the mortgage industry at three different time points.	Individual	Endogenous (top-down)	Team leaders with low levels of mindful attention, when confronted with ambiguous goals, lack the cognitive capabilities to engage in experimental behaviors, whereas team leaders with high mindfulness are unaffected by ambiguous goals. This leads to greater experimental behaviors within their team and reduces the team's negative emotional response to change.
2001	Hoffman, AJ; Ocasio, W	Empirical	Comparison of media coverage in three newspapers of eight non-routine events affecting the natural environment and chemical industry in the U.S.	Organizational	Exogenous (bottom-up)	Industry-level attention to an event is influenced by external stakeholders holding the industry accountable or by internal concerns about the industry's image.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2017	Hu, SC; He, ZL; Blettner, DP; Bettis, RA	Empirical	Measuring the economic and political reference point for multidivisional companies in a sample of 267 German magazines with national coverage from 1972 to 2010.	Organizational	Endogenous (top-down)	Consistent feedback leads to more attention to the focal experience, whereas inconsistent feedback leads to more attention to the social reference point, in which the focal division performs worse. The results indicate that the political reference point plays an important role in the allocation of attention by management.
2019	Huy, Q; Zott, C	Empirical	Inductive field study interviews with 6 entrepreneurs from UK.	Individual	Endogenous (top-down)	Managers who prioritize a cognitive-rational approach and allocate moderate conscious attention to emotion regulation (ER) can still effectively mobilize resources for their firms under certain conditions, such as operating in resource-rich environments.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2012	Joseph, J; Ocasio, W	Empirical	In-depth case study of GE's governance system across four organizational architectures from 1951 to 2001.	Organizational	Endogenous (top-down)	Effective attention integration, facilitated by cross-level governance channels, plays a critical role in resolving divergent perceptions of environmental change and promoting adaptive behavior in organizations.
2018	Joshi, AM; Hemmatian, I	Empirical	Examined 992 false patent marking cases filed in the U.S. from 2009 to 2011.	Organizational	Exogenous (bottom-up)	Temporal focus and evidence presentation are relevant organizational attention cues in legal surprise lawsuits and serve as significant predictors of the manner and timing of case resolution.
2014	Kannan-Narasimhan, R	Empirical	Field study of 25 Silicon Valley managers and innovators, based on 99 interviews and secondary data, including archives, public records, and site visits.	Individual	Endogenous (top-down)	For resource acquisition, successful innovators maximize management attention when they use material ingenuity and minimize management attention when they use process ingenuity.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2017	Khanagha, S; Volberda, H; Oshri, I	Empirical	Multi-method approach based on a multiple case study of 6 cloud computing companies and an online survey of 131 Dutch cloud computing companies.	Individual	Endogenous (top-down)	Managerial attention is crucial for effective responses to new technologies, as it mediates the relationship between co-creation and exploratory innovation, alongside managerial innovation.
2013	Maula, MVJ; Keil, T; Zahra, SA	Empirical	Analysis of longitudinal data from the largest U.S.-based information and communication technology companies from 1989 - 2000.	Individual	Exogenous (bottom-up)	Interorganizational relationships with high-level partners, particularly through co-investment with high-level venture capitalists, have a significant impact on top manager's timely attention to technological discontinuities over time and underscore the importance of diverse and credible sources of information for adapting to environmental change.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2012	Mitsuhashi, H	Empirical	Analysis of error data by the Japan Nuclear Energy Safety Organization from 1966 to 2007.	Organizational	Exogenous (bottom-up)	Cognitive constraints lead to the failure of vicarious learning because managers pay disproportionately less attention to external events that have similar characteristics to their own and their colleagues' experiences, underscoring the importance of attentional processes and the need for appropriate attentional allocation to events for effective organizational learning.
2021	Nicolini, D; Korica, M	Empirical	Two-year ethnographic study of seven CEOs from NHS healthcare organizations from 2011 to 2013 based on observation with interviews and document analysis.	Individual	Endogenous (top-down)	CEOs facing challenges related to attention engagement, avoid or minimize attention dysfunction by using an attention infrastructure that includes attention activation and regulation practices, focus practices, and attention prioritization practices.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2010	Nigam, A; Ocasio, W	Empirical	Inductive qualitative text analysis of 205 journal articles on hospital health care reform published between 1992 and 1995.	Organizational	Exogenous (bottom-up)	Attention and environmental sensemaking during an event led to the development and acceptance of a field-level logic of managed care, with bottom-up processes of representation and theorization, vocabulary change, and the influence of cognitive context shaping the emergence of new institutional logics.
2011	Ocasio, W	Theoretical/ conceptual		Organizational	Endogenous (top-down)	Three types of attention might exist (selective attention, executive attention, and vigilance) that are shaped by both top-down and bottom-up attentional processes. Attention provides a theoretical alternative for explaining organizational adaptation and change.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2018	Ocasio, W; Laamanen, T; Vaara, E	Theoretical/ conceptual		Organizational	Exogenous (bottom-up)	A more dynamic approach to allocating attention, especially by emphasizing the role of communication practices, can contribute to a better understanding of strategic change and renewal in organizations.
2014	Peeters, C; Massini, S; Lewin, AY	Empirical	Comparative in-depth study with two multi-national US-based companies.	Organizational	Endogenous (top-down)	Attentional direction and the development of absorptive capacity (AC) routines play a critical role in facilitating the timely implementation of a management innovation, with organizational-level change agents influencing the legitimacy and adoption of AC routines during the innovation process.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2013	Petkova, AP; Rindova, VP; Gupta, AK	Empirical	Statistical path analysis based on a sample of 398 IT start-up companies that received VC funding between 1997 and 2004.	Organizational	Exogenous (bottom-up)	Organizations that engage in intensive and diverse sensegiving activities receive greater industry media attention, with the influence being amplified by the human capital of their founders and leaders. While sensegiving activities correlate with general media attention, specialized industry media attention positively affects the amount of venture capital funding received.
2022	Schulze, A; Brusoni, S	Empirical	Longitudinal single case study from 2012 to 2014 on Newpro organization based on interviews, observation, and documents.	Organizational	Exogenous (bottom-up)	Attentional control and problem solving play a central role in the development of dynamic capabilities, with attentional engagement serving as a fundamental driver for sustained focus on change processes. By effectively directing attention through clear goals and KPIs, organizations can improve their dynamic capabilities and transform ordinary capabilities.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2007	Shepherd, DA; McMullen, JS; Jennings, PD	Theoretical/ conceptual		Individual	Endogenous (top-down) & exogenous (bottom-up)	Entrepreneurs form opportunity beliefs through bottom-up and top-down processes, emphasizing situational contingencies and trade-offs. Continuous attention is advantageous in incremental, while oscillating attention is in both incremental and discontinuous environments.
2017	Shepherd, DA; McMullen, JS; Ocasio, W	Theoretical/ conceptual		Individual	Endogenous (top-down) & exogenous (bottom-up)	Attentional model of managers' opportunity beliefs divided into transient and sustained attentional phases.
2010	Sullivan, BN	Empirical	Analysis of a dataset of U.S. airline industry problems and corresponding FAA regulations between 1983 and 2000.	Organizational	Exogenous (bottom-up)	In seeking solutions to problems, organizational attention in the rulemaking phase is driven by the "urgency" of the problem. Areas with more problems also receive more attention.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2010	Tuggle, CS; Sirmon, DG; Reutzel, CR; Bierman, L	Empirical	Analysis of board transcripts from 178 publicly traded companies in 18 industries from 1994 to 2000, resulting in a panel dataset of 979 firm-year observations.	TMT	Exogenous (bottom-up)	Board meetings provide evidence that board members devote varying amounts of attention to monitoring activities. Board members' monitoring behavior is context dependent. The context-dependency of board members' monitoring behavior suggests that additional efforts may be needed to ensure the protection of shareholder interests.
2016	Vergne, JP; Depeyre, C	Empirical	Survey and fuzzy set qualitative comparative analysis of 17 U.S. defense contractors' adaptation to 9/11.	Organizational	Endogenous (top-down)	Attention timing is associated with four types of adapters (anticipatory, reactive, opportunistic, and decisive). Delayed attention leads to delayed response, which then tends to involve greater action to adapt to change.

Table 1 (continued)

Year	Author	Type	Sample	Level	Endogenous (top-down)/ exogenous (bottom-up)	Findings
2017	Walrave, B; Romme, AGL; van Oorschot, KE; Langerak, F	Empirical	Longitudinal data on recession and recovery for 86 IT companies in the US and Europe from 2006 to 2010.	Individual	Endogenous (top-down)	During economic upheaval, managers must dynamically adjust their attention allocation between exploitation and exploration, with recession requiring more attention to exploration and recovery demanding more attention to exploitation.
2019	Zeng, J; Mackay, D	Empirical	Two comparative case study analyses on Alibaba and Tencent based on 25 semi-structured interviews and secondary data.	Individual	Endogenous (top-down)	Continuing focus of managerial attention on specific aspects of the organization leads to the deployment of dynamic capabilities, including core dynamic capabilities, which are continuously used to align the resource base with strategic goals in times of change.

5 Impact of AI on managerial attention

This section integrates insights from the previous theories and SLR with current AI research to develop a conceptual framework. This framework aims to enhance top managers' ability to identify discontinuous change by contributing to a more balanced use of top-down and bottom-up approaches during the transient attention phase. As shown in Fig. 1 I build on the attention model of Shepherd et al. (2017).

5.1 Capabilities of modern AI in management decisions

The application of AI in the context of management decisions in its current form is based, firstly, on the rapid advances in the computing power of data-processing machines and, secondly, on the availability of Big Data (Shrestha et al. 2021; Topol 2019). Together they enable the core capability of today's AI systems in the area of strategic management, the prediction making (Amodei and Hernandez 2018; Duan et al. 2019). These capabilities can be beneficial for strategic decision-making by extracting previously unknown patterns of information from large amounts of data to detect discontinuous changes, e.g. emerging trends, at an early stage and hence make better decisions (Ghasemaghaei 2018).

5.1.1 Computing power

Improvements in computing power are a key component of progress in today's overarching use of AI. To execute algorithmic commands, conventional computers as well as complex AI systems require sufficient computing power to process inputs and deliver corresponding outputs through algorithms (George et al. 2014). The

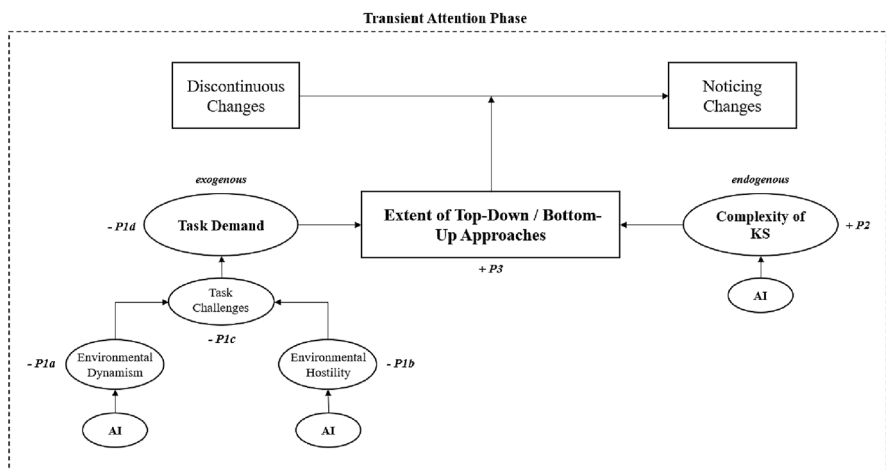


Fig. 1 Proposed effects of task demand and complexity of knowledge structures (ks) on the managerial attention allocation

greater the computing power, the faster complex commands can be processed using large amounts of data.

Unlike humans, who have limited cognitive capacity to process information (Turner and Makhija 2012), AI systems are mostly free from constraints in handling and weighing decision alternatives due to their technical scalability of computing power (Krogh 2018). This makes them useful in detecting discontinuous changes by simplifying tasks of top managers and thus contributing to a reduction of task demand.

5.1.2 Data availability

From the perspective of organizational theory as well as strategy, information is considered a crucial resource for shaping organizations to reduce contextual uncertainty and ambiguity by processing it (Daft and Lengel 1986; Nicolas 2004). Therefore, in addition to high computing power, the skyrocketing availability of data, also referred to as Big Data (Kowalczyk and Buxmann 2014), is considered a key driver for the performance of today's AI systems in management science (Gupta et al. 2018). Big Data differs from normal data sets in terms of data growth in its velocity, volume and variety (McAfee and Brynjolfsson 2012).

AI technologies, such as machine learning (ML), occupy a key position in Big Data analytics by being able to quickly, cheaply and independently of form identify patterns and relationships in the aggregated data from which valuable insights can be gained for more objective decision-making (Intezari and Gressel 2017; O'Leary 2013).

This would enable top managers to improve their own decision-making behavior, as AI exposes previously unknown information correlations to them and thus helps to increase the complexity of knowledge structure to ease the detection of discontinuous changes.

5.1.3 Prediction making

The advances in computing power and data availability lead to the most important capability, prediction making. Prediction making describes the process of to „*use information you do have to produce information you do not have*” (Agrawal et al. 2019, p. 1). This means that whenever predictive statements about the future are to be made, historical data serve as a basis of information from which to draw conclusions about future developments (Jordan and Mitchell 2015).

Here, AI has an advantage over other methods, as it can recognize generalizable patterns and structures in data, without having to specify in detail beforehand (Mullainathan and Spiess 2017). In this way, prediction techniques such as machine learning help decision-makers in organizations to acquire new knowledge by also considering unknown knowledge domains that are suggested by the machine (Calvard 2016). Extant research already shows promising results of AI in predicting government economic growth and recessions (Wu et al. 2020), in investment decisions by predicting stock returns (Avramov et al. 2019), in early identification of emerging

technologies (C. Lee et al. 2018) or in recognizing the strategic direction of organizations (Suominen et al. 2017).

Coupled with large-scale computing power and data processing, the predictive capabilities of today's AI systems make them a suitable approach for enhancing the strategic capabilities of decision-makers and can assist them in allocating attention to monitoring and detecting relevant signals of discontinuous changes.

5.2 AI and task demand

Managers are exposed to a variety of demanding, complex tasks in their daily work, but their attention span (Ocasio 1997) and cognitive computational capacity is limited (Simon 1947). As a consequence, attention must be allocated to tasks individually, which can lead to limitations in attention to other tasks, such as noticing important environmental changes (Shepherd et al. 2017).

According to Hambrick et al. (2005), task demand consists of two contextual factors—task challenges and performance challenges—and one personality-related factor—executive aspiration. Performance challenges are mainly defined by exogenous forces, such as higher-ranking persons, whereas executive aspiration describes the intrinsic motivation of top managers to pursue tasks with determination (Hambrick et al. 2005). I posit that the influence of AI is limited to contextual factors, specifically task challenges faced by top managers, as it cannot directly shape the behavior or motivation of individuals by influencing their attention. Task challenges arise primarily from environmental dynamism and hostility (Hambrick et al. 2005; Zhu et al. 2021).

5.2.1 Environmental dynamism

In this context, environmental dynamism describes the frequency and extent of unforeseen, irregular environmental changes (Cooper et al. 2014; Dess and Beard 1984) and is determined in its extent, for example, by the number and size of competitors in an industry or the diffusion of technologies (Jansen et al. 2006). The higher the level of environmental dynamism in a market, the higher the associated uncertainty (Baum and Wally 2003) and instability of the top manager's market information (Dess and Beard 1984).

This creates particular challenges for top managers. As extant research on environmental dynamism shows, the inherent uncertainty of highly dynamic environmental conditions brings conflicting information that lead to the splitting of attention (Ocasio 1997) and in turn less rational strategic decision-making (Hough and White 2003). In such moments of high cognitive demand, top managers increasingly rely on selective perception of environmental stimuli (Hambrick and Mason 1984) and heuristic, i.e. experience-driven, decision-making processes (Bingham and Eisenhardt 2011). This poses the risk that high environmental dynamism may also lead to a perception of less discontinuous environmental changes and trends (Bazerman and Moore 2012; Tripass and Gavetti 2000; Zhu et al. 2021), because it is precisely these changes that represent an innovation in themselves and cannot

be identified by heuristic decision-making processes in the large amount of environmental information.

According to an empirical study by Abebe (2012), environmental dynamism takes on a moderating role that negatively affects firm performance insofar as decision-makers in highly dynamic environments focus a disproportionate share of their attention on internal (input-related) rather than external (market-related) issues. This result also underlines an earlier finding by Eisenhardt and Martin (2000), that in highly dynamic environments, the creation of dynamic capabilities, that are needed to achieve new strategic resource configurations (Teece et al. 1997), depends on newly acquired market-related knowledge outside one's own organization. In markets with high environmental dynamism, the distribution of attention thus plays a critical role in the strategy development of organizations (Levy 2005).

When considering task challenges, it becomes clear that environmental dynamism is determined to a large extent by the uncertainty that has emerged as a result of missing or ambiguous market information.

In addition to the lack of sufficient information, top managers today often have to deal with an overload of available information. Given limited cognitive capacity, too much unstructured information can lead to information overload, resulting in more confusion and poorer decisions (B.-K. Lee and Lee 2004). Thus, according to Eggers and Kaplan (2009), to focus attention on discontinuous changes, limitations of structural or cognitive information processing must first be overcome (Williams and Mitchell 2004), which can also affect perceived environmental dynamism.

Today's AI systems are capable of overcoming these limitations in many areas of human information processing. For example, unlike human decision-makers, a highly dynamic environment does not necessarily lead to limitations in information processing for modern AI systems due to their large computing power (Shrestha et al. 2019). Rather, the emergence and performance of AI is even closely linked to the availability of vast amounts of data, especially Big Data. Nowadays, systems are so advanced that even unstructured data sets in a wide variety of media forms can be evaluated by machines (Duan et al. 2019), which are particularly important for strategic decisions in organizations (Merendino et al. 2018). This, in turn, enables advanced AI-based decision support systems to make accurate predictions about market developments (Agrawal et al. 2019) even under conditions of high environmental dynamism.

Thus, while top managers in dynamic environments are often unable to focus their attention on all relevant new market information due to cognitive limitations, AI systems benefit in their informative power through the increasing information density of dynamic environments. As a result, they support top managers in information processing and thus contribute to lower perceived environmental dynamism by systematically collecting and processing information. Consequently, I propose:

Proposition 1a: The use of AI in the detection of relevant environmental changes reduces perceived environmental dynamism.

5.2.2 Environmental hostility

Furthermore, task challenges are influenced by environmental hostility, which describes the degree of threat posed by the environment (Dean and Sharfman 1993; Miller and Friesen 1983). In a hostile environment, information and resources are scarce and can lead to market-specific competitive advantages when owned by organizations (Barton and Court 2012; George et al. 2014).

This directly impacts the strategic decision-making behavior and attention allocation of top managers. Extensive empirical research demonstrates the negative effects of hostile environments in terms of slower decision-making processes (Baum and Wally 2003) and poorer judgement quality. For example, Mitchell et al. (2011) suggest that high levels of environmental hostility lead to more erratic strategic decision-making. However, consistency is essential for effective strategic decision-making (Mintzberg 1987).

Another empirical study by Kreiser and colleagues (2020) has found a negative relationship between environmental hostility and entrepreneurial orientation, i.e. the ability of organizations to innovate and change. The results indicate that organizations reduce their entrepreneurial activities, which also include information processing, when the environmental context becomes more hostile, although it would make sense to strengthen them at this point. Ultimately, this may have an impact on the attention allocation of top managers as less attention and cognitive capacity is devoted to recognizing and processing new topics but more existing ones.

The integration of AI can also be advantageous when dealing with hostile environments of top managers. According to Jarrahi (2018), recombining existing information using AI techniques with high computing power, such as Deep Learning, presents an opportunity to uncover previously unknown relationships between factors that help to predict market activities. Current empirical research findings support this thesis. For example, it has been demonstrated that AI can positively contribute to a more accurate prediction of future product sales in the textile industry (Jian et al. 2020) or to the early identification and strategic planning of emerging pharmaceutical technologies (C. Lee et al. 2018).

As the studies show, AI systems are already used today in various areas to anticipate market developments at an early stage despite contextual uncertainty and ambiguity in order to react effectively. I therefore assume that AI capabilities, such as high computing power, data availability and prediction making, can not only be applied to identify early market developments, but also to reduce the effects of perceived environmental hostility on the basis of acquired information. Therefore, I propose:

Proposition 1b: The use of AI in the detection of relevant environmental changes reduces perceived environmental hostility.

Finally, reduced environmental dynamism and hostility through the use of AI also might have a mitigating impact on the overall perceived task demand of top managers. Although, as described at the beginning, I assume that the performance challenges and executive aspiration remain unchanged during the use of AI, the reduced level of environmental dynamism and hostility will also lower the perceived

difficulty of task challenges. This in turn leads to a reduction of the overall task demand. Therefore, I propose:

Proposition 1c: The use of AI in the detection of relevant environmental changes reduces perceived task challenges through mitigating effects on environmental dynamics and environmental hostility.

Proposition 1d: The use of AI in the detection of relevant environmental changes reduces perceived task demand through mitigating effects on task challenge.

5.3 AI and complexity of knowledge structures

In addition to task demand, knowledge structures also play a significant role in managerial cognition literature (Calori et al. 1994; Carley and Palmquist 1992; Kiss and Barr 2015; Nadkarni and Barr 2008). Their complexity represents the comprehensiveness (number of mental concepts) and connectedness (number of causal links between them) of a person's embedded domain knowledge (Nadkarni and Narayanan 2005; Walsh 1995).

Knowledge or belief structures, and especially their complexity, have a major influence on attention at the individual level (Kiss and Barr 2015) and ultimately on the strategic decision-making behavior of top managers (Bogner and Barr 2000; Calori et al. 1994). For instance, the results of an empirical study by Nadkarni and Barr (2007) suggest that higher complexity of knowledge structures, which they call strategic schemas, lead to higher strategic flexibility and better firm performance because the extensive knowledge helps to adapt effectively to rapidly changing market conditions. According to previous research, this is mainly because more complex knowledge structures enable top managers to perceive more stimuli from the environment (Weick 1995), establish more diverse relationships between the information they acquire (Bogner and Barr 2000), and thus provide a wider range of alternative solutions for the strategic decision-making process (Dollinger 1984; Levy 2005). People with more complex knowledge structures are also more creative, following a study by Rodan and Galunic (2004), and have a positive influence on the innovative capacity of organizations. Moreover, complex knowledge also makes it easier for them to handle and process environmental signals, which makes them superior in information processing (Kiss and Barr 2015). It can therefore be assumed that top managers with more complex knowledge structures can more easily recognize relevant environmental changes and effectively distribute their attention accordingly (Shepherd et al. 2017).

Although knowledge structures enable top managers to cognitively simplify the perception and processing of environmental signals, they also hold potential risks for organizations. McNamara et al. (2002) assume that individuals with distinct knowledge structures ignore supposedly irrelevant information for the purpose of simplification and thus distort a holistic interpretation of information (Schwenk 1984). Moreover, complex knowledge is difficult to share between actors within an organization (Pil and Cohen 2006; Rivkin 2001), which in turn can have disadvantages in strategic decision-making by top management teams (Srivastava et al. 2006).

They also lead to more ineffective or local search routines (Eggers and Kaplan 2009). In an extensive case study, Tripsas and Gavetti (2000) demonstrated that a major challenge for top managers in the face of discontinuous change is to distinguish it from incremental change because it is based on new knowledge not contained in their knowledge domains. As a result, knowledge domains that are structurally less complex lead to limitations in the search for and perception of especially new, more radical trends, since the information associated with the environmental signals of such discontinuities often does not overlap with the knowledge of top managers (S. Kaplan and Tripsas 2008).

Thus, to be more attentively receptive to discontinuous environmental changes, complex knowledge structures are required among top managers. These can be fostered through access to extensive sources of information with a high qualitative and heterogeneous composition (G. K. Lee 2007) and repeated training of available complicated, multidimensional content (Carley and Palmquist 1992).

I argue that AI's capabilities can increase the complexity of managers' knowledge structures. Due to their high computing power and data processing capabilities, many of these systems, once set up, are able to collect relevant market information from different un/structured databases almost automatically and make it available to top managers for decision support (Duan et al. 2019; Paschen et al. 2019), without being subject to cognitive performance limitations, unlike human decision makers (Jarrahi 2018). In addition, AI can focus on multiple goals simultaneously when seeking information with little to no performance degradation (Krogh 2018). Combined with increasing prediction making capabilities, this results in two other concrete benefits of AI, according to Ferraris et al. (2019). First, the nature of advanced analytics and the volume and form of data analyzed can reveal previously unknown patterns in data that are usually hidden from humans. These could positively contribute to the creation of qualitative sources of information. Second, this also enables AI to make predictive statements that confront top managers with their own opinions and possibly lead to learning effects and the resulting increase in complexity. Independently of other factors influencing learning, I assume that pure confrontation with AI-generated search results on environmental changes can also lead to either a confirmation of the intended strategic action because it corresponds to the knowledge structure of the top manager. Or, on the contrary, trigger thought-provoking impulses because the top manager now has to question whether established knowledge structures are still correct. This could also reduce the effects of a possible confirmation bias, which describes the unconscious tendency of people to seek selective evidence in information that is consistent with their own beliefs (Nickerson 1998; Rollwage et al. 2020). According to Kahneman et al. (2011), questioning one's own opinion by considering further alternatives, in this case generated by an AI, can lead to a reduction of confirmation bias. This could also contribute to more complex knowledge on the part of top managers in the form of regular training.

Although current research on AI for strategic decision-making is primarily conceptual, there are already a few empirical studies on its application in the context of environmental scanning and related information gathering and processing. For example, Mühlroth and Grottko (2020) have shown that AI can predict the emergence of new technologies in data sets years earlier and thus support organizations

in their strategic reorientation at an early stage. In another earlier contribution, Aasheim and Koehler (2006) apply AI techniques to prove that predictive signals can be used to successfully make statements about the development of selected stock returns. Both the conceptual and empirical studies indicate that AI is already generally capable of supporting top managers in areas where strategic decisions are subject to a high cognitive load.

Based on these findings, I therefore assume that AI, through its computing power, data availability and prediction making, is able to positively influence top managers in both information acquisition and the subsequent learning process and can thus lead to the enhancement of more complex knowledge structures. Therefore, I propose:

Proposition 2: The use of AI in the detection of relevant environmental changes increases the complexity of knowledge structures.

5.4 AI and top–down/bottom–up approaches of attention allocation

According to Shepherd et al. (2017), whether the allocation of management attention in a situation is more top–down or bottom–up is also significantly influenced by the complexity of knowledge structures. It is assumed that top–down processes of attention allocation are based on knowledge structures (Bogner and Barr 2000; Walsh 1995), which direct the attention of top managers to environmental signals that are most similar to their own knowledge (S. Kaplan and Tripsas 2008), so that they can interact deductively with the environment. If the knowledge structures of a top manager are highly developed, e.g. very complex, it is easier for the person to discover opportunities for incremental changes in the existing structures, as the person directs the attention to aspects from which change is expected (Nadkarni and Barr 2008). In contrast, bottom–up processes describe an inductive form of allocation (Shepherd et al. 2017), in which attention is determined and guided by the external influence of environmental stimuli (Shepherd et al. 2007). This makes top managers more receptive to discontinuous change, because by not seeking change themselves but being guided by environmental stimuli, they find it easier to discover novelties outside their own knowledge structures (Eggers and Kaplan 2009; Shepherd et al. 2007).

To increase the share of bottom–up processing in attention allocation for discontinuous change detection, Shepherd et al. (2017) see task demand as an important influencing factor in their model. Since top managers have limited attentional capacities (Ocasio 1997), they are less likely to resort to top–down processes for cognitive facilitation in situations with lower task demands. However, since, as described above, attentional allocation processes always consist of both top–down and bottom–up processes, systems that support the detection of discontinuous change must necessarily be capable of supporting both equally. Since the focus of this paper is specifically on the detection of long-term trends, i.e. discontinuous changes, an AI should accordingly support bottom–up processes in particular.

In my view, AI also contributes to an increase in the complexity of knowledge structures (see Proposition (2)) and thus to improved top–down processes through

the representation of extensive information via its data availability and computing power capabilities. However, the detection of unknown changes is not conceivable without a foundation of domain-specific knowledge (McMullen and Shepherd 2006). Rather, the reduction of the perceived task demand by AI (see Proposition (1d)) leads to more possibilities in the detection of discontinuous changes despite complex knowledge structures, since more transient attention is available to be guided by stimuli from the environment (cf. Shepherd et al. 2017). Therefore, I propose:

Proposition 3: Using AI to detect relevant environmental changes makes top managers rely more on bottom-up processes of attention allocation to perceive discontinuous changes through mitigating effects on task demand and the complexity of knowledge structures.

6 Discussion and future research

The relationship between discontinuous change detection and managerial attention has become a much-studied topic in the field of MOC research. This is because, individual attention allocation provides an explanation why decision makers perceive change differently (Kammerlander and Ganter 2015; Ocasio 1997) and based on this, shape the strategic agenda of organizations (Ocasio and Joseph 2005; Shepherd et al. 2017). Despite growing research activities in this area, the question of how to consciously influence the attention allocation to better detect discontinuous changes remains unclear. At the same time, recent research findings on AI-based applications in the context of strategic decision-making call for investigating application areas where the potential of modern technology can be applied and understood (Borges et al. 2021; Krogh 2018; Shrestha et al. 2019). Consequently, in this paper, I focused on the research gap created therein by conceptually investigating the impact of AI on managers' attention allocation when detecting discontinuous environmental changes. Based on an SLR, an attentional-model and a wide range of AI-related scientific publications from different research disciplines, I derived a number of propositions (see Fig. 1).

Consistent with prior research (Eggers and Kaplan 2009; Kammerlander and Ganter 2015; Maula et al. 2013; Shepherd et al. 2017), I argue that the causes for the nexus between discontinuous change detection and managers' attention allocation lie in a complex array of exogenous and endogenous influencing variables. They all share the fundamental commonality that discontinuous change often impede decision makers in perceiving and processing relevant environmental stimuli by challenging established mental knowledge structures and assumptions necessary for this purpose (Daft and Weick 1984; König et al. 2012; Walsh 1995). As a consequence, decision-makers often react with inertia (Bockmühl et al. 2011), ignore or deny the change that obviously exists (Kammerlander et al. 2018), or simply do not pay attention to it (S. Kaplan et al. 2003), as it highly contradicts their own knowledge structures (Kiss and Barr 2015). In this conflicting array, analogous to the model of Shepherd et al. (2017), I explored in more detail the interplay of AI with task demand as exogenous and complexity of knowledge structures as endogenous

factors with respect to the share of top–down and bottom–up processes in managerial attention allocation. This step was necessary, because as highlighted in my study, the allocation of managerial attention is influenced by a number of exogenous and endogenous variables. However, despite the importance of this issue, no explicit measures or methods have been found to effectively address this situation. Technological advances like AI might help here.

Together, task demands and knowledge structures determine the extent of top–down and bottom–up processes in attention allocation, and thus the receptivity to perceive discontinuous change. In my view, AI-based decision support systems provide an appropriate tool to make decision makers more receptive to discontinuous change by influencing exogenous as well as endogenous forces. This is because their specific capabilities, computational power, data availability, and hence prediction making, can compensate for the shortcomings of human cognition in many domains (Agrawal et al. 2017; Duan et al. 2019). However, these systems play only a supporting role in this assumption, thus augmenting human capabilities in decision-making. Finally, intelligent decision support systems must be capable of supporting both top–down and bottom–up processes among decision makers, as other relevant types of change must be perceived in addition to discontinuous ones.

These results allow me to make two valuable contributions to the current research debate.

First, I add another research area to the field of applied AI in the context of attention allocation by linking theories of ABV to AI for the first time. In this context, I present arguments on how AI can influence the extent of top–down and bottom–up processes in attention allocation. Future research should address this point and empirically investigate whether the use of AI leads to the harmonization of both types of processes and thus improved attention allocation. Furthermore, it is unclear to what extent AI-based decision systems influence human biases during attention allocation. Particularly for discontinuous changes, perception is shaped by individual personality traits (Gerstner et al. 2013; Nadkarni and Narayanan 2007) and the organizational setting (Kammerlander and Ganter 2015; Kammerlander et al. 2018). However, previous research studies indicate that AI-based decisions may actually reinforce human biases in many cases (Shrestha et al. 2019) and therefore have negative effects on managerial attention. Here, a clear distinction as to whether this is also the case in the context of attention allocation is needed.

Second, I find that despite its immense importance for the strategic decision-making process and the large number of publications in high-ranking journals (see SLR), there are still no technological approaches to influence managerial attention allocation when detecting discontinuous changes. By conceptually integrating AI into such situations, I was able to derive concrete propositions for improving the perception of discontinuous environmental changes. These propositions need to be investigated empirically. It is also still uncertain what other exogenous and endogenous factors influencing attention allocation need to be considered. For example, the dynamic capabilities of organizations might be of interest here, since they play a crucial role in determining the adaptability of organizations (Teece et al. 1997). Furthermore, it seems interesting to question whether and to what extent deviations exist concerning different types of environmental change and for which type AI is

particularly suitable. In this context, it is particularly important to consider psychological components of decision-makers such as trust (Glikson and Woolley 2020) or the willingness to delegate tasks (Schneider and Leyer 2019) in addition to technical issues regarding the feasibility of AI-based support systems.

7 Limitations and concluding remarks

Despite the above-mentioned contributions, this paper is also based on a number of assumptions that imply limitations. First, each SLR is the result of a subjective selection and decision-making process, which can potentially impact the overall robustness of the evidence. To account for this, the SLR used established procedures from the literature (Tranfield et al. 2003). Second, the final selection of literature is relatively small at 43 articles. However, this number is consistent with similar conceptual studies based on literature (Neumann 2017). Third, the propositions presented on the effects of AI on attention allocation for improved detection of discontinuous changes exclusively consider task demand and the complexity of knowledge structures as socio-cognitive influence mechanisms. While these are undoubtedly highly relevant, as common in qualitative studies, a variety of other factors in the information processing process must be considered for a fully comprehensive understanding. Fourth, due to the conceptual nature of this paper, no conclusions can be drawn about the relative strength and relationship of task demand and the complexity of knowledge structures to attention allocation and each other, as no statistical analyses were done. Thus, my propositions should be empirically tested in an appropriate context in the future to determine their generalizability. Fifth, my propositions build on a model of attentional allocation by Shepherd et al. (2017), whose validity has not yet been empirically investigated, which in turn has a limiting effect on my results.

In conclusion, this paper represents a first attempt to connect the research fields of MOC and AI in management decision-making with respect to discontinuous change. My framework offers new perspectives on dealing with discontinuous change, emphasizing the role of human cognition and attention in the application of AI-based solution approaches. My results are intended to serve as a starting point for future research in this field, to provide a clear picture of the opportunities and risks of AI in management decisions through empirical testing.

Author contributions The author was solely involved in the conception and design of the study. Material preparation, data collection, and analysis were performed solely by the author. The first draft of the manuscript and all earlier versions of the manuscript were prepared solely by the author. The author read and approved the final manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL. The author declares that no funds, grants, or other support were received during the preparation of this manuscript.

Declarations

Conflict of interest The author has no relevant financial or non-financial interests to disclose.

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