Perspective from Practice

White Spaces in AI Research for CEOs

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Abstract: This paper focuses on the interplay of AI (Artificial Intelligence) and strategic management. Perhaps surprisingly, there is today no widely accepted definition of AI among computer scientists. Meanwhile, less scrupulous firms opportunistically relabel themselves as AI, without offering anything resembling AI ('AI washing'). This paper aims to shed light on the current state of AI adoption in practice, from the perspective of CEOs. We examine the content made public by AI incumbents (AI technology creators such as OpenAI or Google; and professional services firms such as Accenture, or McKinsey); and the AI research in strategic management, building on Keding (2021). Further, we survey 88 P&L owners, C-level executives, and board members. We find that, whereas AI today seems omnipresent, AI use cases are not: 41% of our respondents reported to find none, or very few AI use cases relevant to their organizations. But CEOs are aware that the missing link between AI in general and one's P&L is the AI use case. Further, the impact of AI on their P&Ls remains elusive: 72% of respondents reported that '*AI has not moved my P&L needle'* or '*it is too early to say*'. We conclude that several AI-related business questions remain unanswered, characterizing white spaces in AI research for CEOs. The 7 white spaces specified here are unlikely to be filled by AI incumbents (AI technology creators or professional services firms), and we explain why. Finally, we posit that strategic management scholars are uniquely positioned to fill research gaps in the 7 identified white spaces.

Keywords: Strategic management, firm performance, artificial intelligence, machine learning, literature review, CEO, competitive advantage.

Introduction

Relative firm performance (or competitive advantage) is central, and perhaps the most important construct in the field of strategic management (Rumelt *et al*, 1994)[1]. An important aspect of strategic management research concerns how leaders, especially CEOs, affect strategy and performance (Barnard, 1938)[2]. This paper's author is a business practitioner and, more specifically, a P&L owner in whose firm there is no separation of ownership and control per Berle & Means (1932),[3] as the same individual is both principal and agent. Like any other individual in a similar role, this author is constantly searching for opportunities to enhance firm performance as reflected in his P&L.

In a typical, present work day, practitioners and scholars alike are overwhelmed by the frequency with which the acronym AI (Artificial Intelligence) appears. AI seems omnipresent: in meetings; on-line; even ride share drivers mention AI to passengers on their way to the airport. The media report many AI use cases. Tradebot[4], the high-frequency equities trader, created their own in-house ML capabilities; logistics giant UPS is using AI in dynamic pricing tools, package volume flows, and warehouse management[5]; John Deere's See & Spray applies AI to optimize crop spraying[6]; Morgan Stanley partnered with OpenAI to support its financial advisors[7]; AirBNB is using AI in fraud detection and personalized listing matching8; GE Aerospace is applying AI in predictive maintenance9. This paper's author, and all others in a similar role, must ask: could AI enhance firm performance? This author thus decided to learn more about AI in a structured way. What sources are currently available for practitioners, especially CEOs, to learn more about AI? What would CEOs conclude from these sources? What types of questions would remain unanswered? This paper focuses on these questions.

This paper describes the AI learner's journey from the perspective of CEOs. As this paper's title implies, many AI-related questions remain unanswered, characterizing white spaces in AI research for CEOs. As will be seen, such white spaces are unlikely to be filled by incumbents such as AI technology creators (Microsoft, OpenAI, Google, and similar) or professional services firms developing AI use cases (Accenture, McKinsey, BCG, and similar). This paper posits that strategic management scholars are uniquely positioned to start filling the several white spaces in AI research for CEOs.

What is AI, anyways?

This author is cautious about sources, and aware that the digital age sweeps us in a tsunami of unverified, often misleading, sometimes deliberately false content. Because this author is fact and science-driven, the decision was to start this AI learning journey with Google Scholar[10] and a simple question: *how is AI actually defined*?

Perhaps surprisingly, there is today no widely accepted definition of AI among computer scientists (Wang, 2019)[11]. Attempts by practitioners to define AI are plentiful, such as this by IBM[12]: "*AI is anything capable of mimicking human behavior.*" But no AI definition is widely accepted, and Monett & Lewis (2018)[13] explain why: "*intelligence remains ill-defined. Theories of intelligence and the goal of AI have been the source of much confusion both within the field and among the general public.*" An international standards group dedicated to information technology (the ISO-IEC Joint Technical Committee JTC 1)[14] is working on the formalization of AI definitions and practices; in the meantime, practitioners seek clarity. This paper's author made a mental note: this lack of clarity is exploited by the less scrupulous, which opportunistically relabel themselves as AI firms, without using anything resembling AI. This resurfaces memories of the 1990s dotcom bubble, as the opportunistic renamed themselves as dotcom, hoping for and sometimes witnessing a pop in their stock market valuations (Cooper *et al*, 2005).[15] History rhymes: CEOs saw dotcom washing, then greenwashing (de Freitas Netto *et al*, 2020),[16] and now AI washing. Leffrang & Mueller (2023) explain: *"providers engage in 'AI washing', relabeling solutions that use simple statistical models as AI systems."*[17] The implication for CEOs is clear: *caveat emptor*. Whereas AI washing does not necessarily imply that AI *per se* may or may not work, this is a phenomenon that deserves the attention of researchers. What may be the antecedents of AI washing? Ignorance? Self-interest with guile? Both? Other drivers?

Back to this author's AI learning journey: recognizing there is no widely accepted definition of AI, this author decided to examine today's touted AI technologies: generative AI, machine learning, machine vision, natural language processing, automated-guided vehicles, and sentiment analysis.[18] Wondering which of these currently attracts the most attention in the business and popular press, this author noticed that the AI technology with (by far) the most widespread share-of-voice is generative AI (including Chat GPT).[19] Is it because generative AI is unsupervised, meaning that output quality cannot be immediately, effortlessly evaluated? Could the unsuspecting public be tricked into accepting made-up content for high-quality output, as the average user is unlikely to manually fact-check the sources that generative AI claims to draw from? More on this below.

Next, this author looked beyond the day-to-day fog of war in the business press, popular press, and social media. Google Books Ngram Viewer[20] just reached a milestone: 20 million scanned books, or one-seventh of all books ever published worldwide since the Gutenberg printing press.[21] This author searched for ‘artificial intelligence’ on Google Books Ngram Viewer, and observed the chart shown in Figure 1: a flat line at rock bottom from 1960 to 1980; the line decidedly kinks up around 1980, peaks in the late 1980s, then declines slowly well into the 2010s. The line then explodes from 2015 to present day, as AI attracts ever-growing share-of-voice in books. The AI phenomenon seems real in books, where the publishing barrier is much higher than in digital sources.

<Insert Figure 1 here>

This author’s next step was to examine the firms developing AI technology, and firms deploying AI use cases. The first stop in this AI learning journey is the AI technology creators.

First stop: the AI technology creators

This author examined the content offered by some of the largest AI technology creators: Apple,[22] Microsoft,[23] OpenAI,[24] Alphabet,[25] Amazon/AWS,[26] and IBM.[27] What can CEOs learn from these firms’ websites? In aggregate, AI technology creators share similar content: the upside of their proprietary technologies, from a (very) technical viewpoint. This author was unable to locate detailed use cases or business applications that may be relevant for his P&L. It is perplexing that some AI technology creators do not bother showcasing any AI use cases at all. This author noticed that only Microsoft, IBM, and Amazon/AWS share (very few) use cases on their websites. This is curious, as this author is aware that the missing link between AI in general and his personal P&L is the AI use case, which should describe in detail what business problem (or opportunity) AI will tackle; how AI will address the issue; and what is the expected outcome: more revenues, less cost, lower capital utilization, higher productivity, or any quantifiable business outcome. As this author repeatedly reminded anyone pitching business improvement ideas: no business case? Project rejected (of any type, not only AI).

Further, this author made a mental note after widening his research to independent sources: none of the AI technology creators mentions on their websites anything remotely negative about their AI. Meta's website does not mention their sale of personally identifiable data on 87 million users in the Cambridge Analytica scandal (Rehman, 2019),[28] albeit it does post a piece in which Meta claims to support responsible AI principles (this author remains unconvinced). Amazon/AWS's website does not mention its AI has been biased (sexist); but others do.[29] Apple AI's website does not mention Apple engineers showed how its AI reasoning can be rather flimsy,[30] or that Apple is being sued for privacy violations.[31] This author interprets content from AI technology creators with caution. The next stop in this AI learning journey is professional services firms.

Second stop: the professional services firms developing AI use cases

This author then examined the AI content offered by some of the largest professional services firms: Accenture,[32] McKinsey,[33] Bain,[34] BCG,[35] Deloitte,[36] PWC,[37] and EY.[38] In aggregate, their AI content is surprisingly homogeneous, given that some of these firms track back to very different origins (i.e. Accenture versus McKinsey). All firms focus on their AI competencies helping clients, showcasing (very) few high-level AI use cases by industry or by function. They also offer high-level points-of-view on broad AI topics (i.e. similar thoughts about responsible AI), and on whatever is recently spiking in the popular media (i.e. generative AI). This author sensed a disconnect at first: if AI is meant to be so pervasive, transformative, and life-changing as many experts (and laypeople posing as experts) claim, where are the dozens if not hundreds of AI use cases? So far, this author has not been able to locate more than a couple of AI use cases relevant to his personal P&L, but these unfortunately are not material from a P&L perspective[39].

To this author, even more interesting was the content that professional services firms did *not* write about on their websites: the potential downside of the AI they are working with. Professional services firms state in unison how they all support responsible AI in general, but no connections to any of their (few) use cases is offered. This is unsurprising to this paper's author. Relatedly, CEOs learned long ago that investment banking 'research' (O'Brien *et al*, 2005)[40] is better understood as a business development expense meant to drive investment banking revenues, rather than to selflessly contribute to public knowledge. Next, this author did hire consultants before, and is familiar with the hourly rate typically charged by professional services firms. The typical AI piece on a consulting website certainly cost the backing firm hundreds of thousands of dollars, if not millions for the larger surveys. This is one reason why this author does not expect to find dozens of detailed AI use cases produced by professional services firms. Another reason is that professional services firms are not interested in triggering mimetic behavior in their competition. A third reason is that consultants prefer to spend their billable hours talking directly to clients about specific demands. All of this, of course, assuming that the professional services firm's legal department would actually sign off to any 'research' without much heavy censoring.

This author's conclusions after the second stop in his AI learning journey are clear: first, CEOs would like to see more specific AI use cases that might move one's P&L needle. Second, professional services firms are unlikely to fill this void. Next, this author examined strategic management research as his third and final stop in his AI learning journey.

Third stop: AI in strategic management research

The third and final stop started with a literature review of AI in strategic management by Keding (2021)[41]. This study reviewed 58 papers from 1979 to 2019, classifying output in two categories: the antecedents of AI in strategic management; and the consequences thereof. Keding described that 'expert systems' (how AI was then named) were popular in the 1980s. What happened next? Gill (1995)[42] showed that *"most of these* [AI] *systems fell into disuse or were abandoned during a five-year period from 1987 to 1992"* as *"many well-publicized applications have proven to be pure hype"* and *"even Wall Street has become disillusioned."* In line with this, Google Books Ngram Viewer shows a steady AI decline from the late 1980s into the 2000s, in an infamous 'AI Winter' (i.e. Hendler, 2008).[43] Could such an outcome replay by the late 2020s? Only time will tell.

Regardless, this author picked up where Keding left, focusing on some of the most prestigious journals in strategic management.[44] This author searched for 'AI', 'Generative AI', 'ML', 'Deep Learning', or 'Reinforcement Learning', in paper titles. This author examined papers published in 2023 and 2024, as the goal was to understand the current state of AI, as opposed to building a longitudinal view. The search yielded 17 papers. Keding's original classification (AI antecedents and consequences) was extended to add a third category: AI use cases, in which CEOs are most interested. Next, this author differentiated practitioner-oriented (aimed at CEOs) papers from researcher-oriented papers. This classification scheme is shown in Table 1. Each one of the 17 AI papers was then classified into this six-celled table.

<Insert Table 1 here>

Taking these 17 papers altogether, the first conclusion is that strategic management scholars seem to constitute an introverted community: more researcher-oriented than practitioner-oriented papers appear. As a practitioner and P&L owner, this author would like to see more content in the top line of this six-celled matrix. Next, this author summarizes his findings in each one of the six cells, instead of summarizing each paper individually.

- *Antecedents of AI, practitioner-oriented:* only one contribution appeared in this cell. But CEOs are interested in understanding what may facilitate or hinder AI adoption in specific use cases, as this understanding will improve her/his firm's ability to successfully implement such AI use cases. This characterizes a research white space (more below).

- *Consequences of AI, practitioner-oriented:* four papers appeared in this cell, which is highly relevant to CEOs. Scholarly work in this cell could warn CEOs of unintended consequences of AI use cases, a topic unlikely to be explored by AI technology creators or professional services firms, as seen above. This also characterizes a research white space (more below).

- *AI use cases, practitioner-oriented:* only one paper appeared in this cell, which is perhaps the most important one to CEOs (who have P&Ls to live or die by). This paper by Banerjee *et al* (2023)[45] offers an intriguing AI use case relevant for practitioners, especially art marketers, art gallery owners, and art auctioneers. Even if this is not the economic sector where a given CEO operates, this use case could still provide practitioners with ideas for related use cases. Further, this author approached colleagues (who are also P&L owners) and found out that most of them are asking themselves similar questions: what AI use cases are relevant for my firm? Are my competitors adopting these? Are these AI use cases hyped-up, or do results really move the P&L needle? This characterizes a very significant research white space (more below).

- *Antecedents of AI, researcher-oriented:* only one contribution appeared in this cell, but this is not a space where CEOs would necessarily clamour for more scholarly work at the moment.

- *Consequences of AI, researcher-oriented:* four contributions appeared in this cell. Whereas it is interesting to observe new AI methods bringing new light to older strategic management theory, this is not a domain where CEOs necessarily look for more scholarly work.

- *AI use cases, researcher-oriented:* six papers appeared in this cell. It is interesting to see strategic management scholars applying AI in their own day-to-day research. Many CEOs would consider this type of research useful: savvy practitioners will borrow academic use cases to address their own business problems or opportunities. Example: in his doctoral work, this author attempted to predict acquisition targets (Chaddad, 2009)[46] with event history analysis (traditional statistical techniques: probit, logit, rare events logit, and Cox proportional hazards). Would acquisition target predictions improve today, with the open-source software R[47] and machine learning models available in the R survival analysis package[48]? These include linear discriminant analysis (LDA), classification and regression trees (CART), k-nearest neighbors (kNN), support vector machines (SVM), random forest (RF), and naive Bayes (NB). To this author's dismay and after a non-trivial effort, *none* of these six ML models yielded better predictions than good, old-fashioned event history analysis. This author is careful not to jump into false conclusions: one may not state that ML does not deliver in general; but one may conclude that ML did not deliver this specific use case, with the given data set. This author now wonders how many business problems are being approached with fashionable AI first, even though older, simpler, proven statistical techniques might work better, faster, or cheaper. This also characterizes a white space in AI research for CEOs (more below).

Wrapping up this AI learning journey: white spaces

This author's initial AI learning journey is now complete. Much has been learned. But this author is still left to his own devices with regards to several questions, none of which any of the three journey stops above were able to address. This characterizes white spaces in AI research for CEOs. These are:

- **White space #1: what do CEOs *really* think of AI?** As noted, practitioners will learn much about AI from professional services firms, including their CEO surveys on AI. But AI learners must look beyond these for several reasons. First, the business of professional services firms is not research; it is (unsurprisingly) professional services. Any content that does not help either drive revenues or build image is unlikely to be published (with a focus on the sooner, not the latter). Shouldn't AI learners source research from organizations or individuals whose core business is actually research? Second, survey sampling by professional services firms tends to be biased towards large if not huge size, as professional services firms prefer to engage with clients that can afford their services. Third, the AI washing phenomenon (perhaps the elephant in the AI room), remains ignored by professional services firms. But AI washing occurs repeatedly in practice. Example: a board member confides she has no choice but ask management what they are doing about AI, regardless of what she really thinks of AI, lest she appears out of touch with the zeitgeist. The CEO reporting to this board now must do something (anything) AI-related. This is fertile context for AI washing. The opportunity for strategic management scholars is clear: they are uniquely positioned to run independent AI surveys with questions that professional services firms are uninterested in. They are also better positioned to address potential sampling issues. Following McElheran & Brynjolfsson (2017)[49], who show how even firms not in the technology industry adopt analytics, strategic management scholars could offer a more systematic, stratified study of AI adoption. Next, Iansiti & Lakhani (2020)[50] argue that firms born around AI-centric operating models gain compounding advantages; the contrast between such firms and other firms experimenting with AI could explain why some CEOs see little promise in AI, while others see dramatic benefits. More broadly, the question as of how CEOs shape AI-related strategic behavior may represent a research opportunity: the intersection of AI and the CEO effects literature (i.e. Lieberson & O'Connor, 1972).[51] More recently, Hambrick & Quigley (2014) introduced a technique to attempt the disentangling of contextual and CEO influences on firm performance, and found that 38% of ROA variance can be attributed to CEOs. They state that two distinct research agendas (attention to overall CEO effects, and attention to specific CEO attributes) in this literature are symbiotic. Could previous AI experience be a novel type of CEO attribute, yet to be empirically tested in this research domain? Whereas the methodological challenges in this domain are not trivial (i.e. Mackey, 2008[52]; Blettner *et al*, 2012[53]; Quigley & Graffin, 2017[54]), the question as of whether AI may impact CEO effects remains unexplored. And finally, if knowledge is the most strategically significant resource for competitive advantage (i.e. Grant, 1996)[55], knowledge-based view researchers could examine whether AI experience or adoption may impact a firm's capacity for organizational learning, and then performance.

- **White space #2: why does AI washing exist, how widespread is it, and where is it likely to appear?** Just like AI washing remains ignored by professional services firms, so it is in the field of strategic management. Should scholars interested in agency theory (i.e. Eisenhardt, 1989)[56] expect to see more AI washing in public corporations, where the separation of ownership and control leads to self-interest with guile per Williamson (1985)[57]? Next, as shown by Kaplan & Haenlein (2019)[58], AI is not one monolithic term but instead should be seen in a more nuanced way. But this is of little concern to salespeople washing AI in a rush to meet their sales quotas. What are the implications of AI washing in the context of corporate social responsibility (CSR)? Binns (2018)[59] examines moral and ethical concerns surrounding algorithmic decision-making. Do misaligned incentives and / or little accountability drive AI-washed claims, especially when compliance or reputational risks are low? Finally, researchers interested in item response theory (IRT) could refer to Carroll *et al* (2016)[60] to see how a company like Apple may not be as 'good' as previously thought in the CSR domain. Could AI washing shed new light into both IRT and CSR? These questions remain open.

- **White space #3: where are the dozens if not hundreds of relevant, specific AI use cases?** To CEOs, it is puzzling to notice that, whereas AI touting seems omnipresent today, relevant AI use cases by industry are actually far and few in between. As seen, professional services firms are unlikely to close this gap. Strategic management scholars are uniquely positioned to fill this void by developing their own AI use cases, and some have already started doing so. Yet many economic sectors still enjoy little or no AI use case coverage at all. As a counterpoint, Cockburn *et al* (2018)[61] show how AI tools seem to reshape R&D in many industries, but remain limited to supporting functions. Could it be that AI use cases in supporting functions are under-reported in AI adoption surveys? More on this below. Scholars interested in the attention-based view of the firm (i.e. Ocasio, 1997)[62] could explain why CEOs are unaware of all AI their employees might be experimenting with. Finally, Brynjolfsson & McAfee (2014)[63] explain that AI-enabled productivity shifts and their benefits may take a long time to appear in P&Ls.

- **White space #4: do AI use cases deliver as promised, net of side effects?** Are specific use cases hyped-up, or for real? Even if a given AI use case is for real, does it produce side effects negative enough to render positive outcomes moot? As seen above, independent researchers found Amazon's AI recruiting tool to be biased (sexist). Another example: Wagner *et at* (2023)[64] found that Chat GPT-3 answered only 67% of radiological questions correctly and, more shockingly, found that only 36% of the references provided by Chat GPT-3 could be located via a manual internet search and check. In other words: most of Chat GPT-3 'references' were simply invented: they do not exist. More broadly, strategic management scholars are uniquely positioned to verify whether AI delivers as promised in the dozens if not hundreds of use cases that should be available. Perhaps the most widely touted AI use case today aims to substitute human agents for virtual AI agents in banks, airlines, telecoms, or any B2C firm with large call centers. This AI use case promises a reduction in operating costs. How about side effects such as declining customer satisfaction? This has not been evaluated independently by scholars. Next, could such an independent study identify areas where AI should be avoided, unpacking factors that hinder AI use case adoption? Next, Arrieta *et al* (2020)[65] review explainability tools in AI and enable a nuanced view of why side effects might be difficult to predict, including: diminished interpretability, unexpected bias, and regulatory exposure. Additional, sobering thoughts are offered by Raisch & Krakowski (2021):[66] AI can simultaneously substitute and augment human roles, leading to paradoxical outcomes and unintended side effects. Scholars interested in complexity theory (i.e. Levy, 2000)[67] may choose to tackle these vexing open questions.
- **White space #5: even if an AI use case delivers net-positive results, does it actually outperform legacy technologies?** The AI use case on predicting acquisition targets (above) is only one example of potentially many. Note that this question is related to the AI washing phenomenon. Further, Teece (2018)[68] shows how digital capabilities, including AI, must be embedded in evolving business models to create sustained competitive advantage. Under what circumstances would AI outperform legacy systems? Relatedly, how is the successful deployment of AI use cases associated with dynamic capabilities? Dynamic capabilities, which are underpinned by organizational routines and managerial skills, are the firm's ability to integrate, build, and reconfigure internal competences to address or bring about changes in the business environment (Teece, 2007)[69]. Could AI constitute a dynamic capability? Could AI help build or evolve a dynamic capability? These questions remain unexplored in strategic management research.

- **White space #6: should CEOs make or buy a promising AI use case?** What constitutes an AI use case of strategic significance? Which AI use cases should CEOs develop in-house, secretively, or not at all? Which AI use cases should CEOs buy from consultants or entrepreneurial academics, not worrying about competitor imitation? Leiblein *et al* (2002)[70] show that make-or-buy decisions do matter, and that cost is just one factor to be considered; neither outsourcing nor internalization *per se* result in superior performance. But is there something fundamentally different about AI that could change the way researchers evaluate make-or-buy decisions? The same question applies to research in firm boundary choices (i.e. Poppo & Zenger, 1998)[71]. A vivid example is Tradebot[72], the Kansas City high-frequency equities trading firm. In 1999, Tradebot founder and computer scientist Dave Cummings decided to create in-house his own automated trading systems, which then evolved into machine learning (ML). By 2008, this adaptive ML enabled fantastic results: Tradebot had no losing days in the previous four years[73]. Relatedly, von Krogh (2018)[74] advocates for in-depth studies of AI in organizational practice, especially as a boundary-spanning phenomenon. Next, Foss (2003)[75] states that transaction cost economics (TCE) insights are necessary for understanding the nature of strategizing. Strategic management scholars have yet to examine AI make-or-buy decisions from a TCE vantage point, perhaps also contrasting with other theoretical perspectives such as the resource-based view of the firm (RBV).

- **White space #7: does AI change scholarly thinking about competitive advantage?** Note that this author is reluctant to frame this question as: could AI lead to competitive advantage? It is this author's humble opinion that attempts to directly connect AI to competitive advantage circa 2025 would be as (un)informative as attempts to connect the internet to competitive advantage circa 2000, or the radio to competitive advantage circa 1925. This very high level of analysis seems to be a bridge too far. A more tractable question circa 2000 would have been: what types of internet use cases are apt to lead to competitive advantage? Under what conditions would internet use cases be successful? As an example, Netflix launched its internet use case in 2007: the transition from DVDs to over-the-top, on-line programming. Could the framework provided by Hambrick *et al* (2001)[76] have allowed researchers to evaluate internet use case success probability circa 2000? Likewise, a more tractable question circa 2025 would be: what types of AI use cases may lead to competitive advantage? Tradebot launched its AI use case in the early to mid 2000s: the transition from human to electronic market-making, enabled by adaptive ML, evolving into high-frequency trading. Under what conditions would AI use cases lead to competitive advantage (i.e. Barney & Reeves, 2024)[77]? Next, as strategy scholars move away from sustainable competitive advantage to focus on how firms may achieve a sequence of temporary advantages (Dagnino *et al,* 2021)[78], could research on AI use cases offer new perspectives on how to gain temporary advantages? These open questions are closely related to a potential relationship between AI and dynamic capabilities as discussed above. Relatedly, another intriguing research domain could be the intersection of dynamic capabilities and hybrid AI models (systems that combine different types of AI to combine the strengths of each; i.e. Mehra, 2024)79. Is hybrid AI a novel example of a dynamic capability, or would it enable a new one? Under what circumstances? Finally, Mark Burgin's General Theory of Information (GTI) could be seen as a potential bridge to mindful machines (Mikkilineni, 2024)80. GTI reimagines traditional computing by introducing cognitive, self-regulating capabilities in digital systems, enabling them to perceive, adapt, and respond autonomously to changing conditions. Mikkilineni (2024)81 writes that mindful machines may in the (far?) future bridge the divide between biological intelligence and digital automation. The implications of these potential developments to dynamic capabilities and competitive advantage could be far-reaching.

Initial work in white space #1: what senior executives *really* think of AI

Next, this author decided to do some initial work in the first white space above, launching his own informal, independent survey to understand what senior executives *really* think of AI. Three types of practitioners were engaged: P&L owners (CEOs, presidents, business unit heads, managing partners, etc); board members (to whom P&L owners report); and C-level executives reporting directly to P&L owners (COO, CFO, CIO, CMO, and similar). The geographical scope was global, across all economic sectors, ranging from small to very large organizations. This author first reached out to his professional network, which then snowballed this survey into their own professional networks. By early 2025, this author received 88 full replies to the survey questionnaire. The conclusions are as follows.

- **First, whereas AI seems omnipresent today, relevant AI use cases are clearly not.** Whereas most respondents (59%) reported they were able to locate many AI use cases relevant to their organizations, a significant share (41%) reported that they found none, a few, or some (but not many) relevant AI use cases.

- **Second, the impact of AI use cases on P&Ls remains elusive.** 72% of respondents reported either that "*AI has not moved the needle of my P&L*" or that "*it is too early to say.*" Only 21% of respondents reported that "*AI has significantly moved my P&L needle.*" And only 7% reported that "*AI has enabled me to stay in business, or has already driven competitors out of my industry.*"
- **Third, the connection between AI and competitive advantage remains unclear to most.** 66% of respondents reported that the connection between AI and competitive advantage is unclear in their industry. Only 34% of respondents reported that AI already leads to, or may lead to competitive advantage in the future.
- **Finally, executives perceive AI as both hyped-up, and for real:** 49% of respondents reported that AI is over-hyped by the business and popular media; 26% reported that AI is underestimated; and 25% reported that AI is depicted accurately by the media.

Taken altogether, these results seem consistent with the overall conclusion that most CEOs are currently experimenting with AI, but very few have been able to report significant outcomes to date. But the results of this informal, independent survey should not be interpreted as the last word on AI adoption. As noted, the sample size was not large to begin with. Further, the geographical scope of respondents was tilted towards the Americas; and the sample was not large enough to allow for a breakdown by industry, geography, firm size, or the respondent's role. Another limitation of any CEO or senior executive survey on AI adoption (including this one) is that CEOs are unlikely to know of every single AI initiative in their firms, especially early-stage initiatives in large firms. AI adoption surveys in more junior levels may lead to different results in the same large firms. In sum: this survey should be interpreted as an invitation to conduct more independent research in this white space.

Future surveys could benefit from more rigorous sampling methods, or collaboration with academic survey centers. Further, future surveys may aim for finer-grained questions, allowing perhaps for a better understanding of the AI washing phenomenon; or a high-level unpacking of some of the AI use cases successfully adopted. A framework that allows for a better understanding of how AI impacts the P&L (e.g., lower costs, more revenues, more customer satisfaction, higher employee productivity, better capital utilization) may be insightful. Further, difference response breakdowns are possible: by industry, geography, firm size, respondent's role, or type of AI use case. Do AI sellers (AI technology creators, professional services firms, and 'bundled AI' sellers such as John Deere, as seen above) report different results than the ones reported by AI buyers (all other firms)? This would be another insightful breakdown. Finally, scholars interested in AI adoption surveys may draw further inspiration from McElheran *et al* (2024).[82]

Final thoughts, and an invitation

As a student of the history of AI, this author echoes Licklider & Clapp (1965)[83]: individuals tend to overestimate what can be done in one year, and to underestimate what can be done in five or ten years. The next steps are up to strategic management scholars. Practitioners in general and CEOs in specific would very much appreciate scholarly contributions in any of the seven white spaces above.

Figure 1

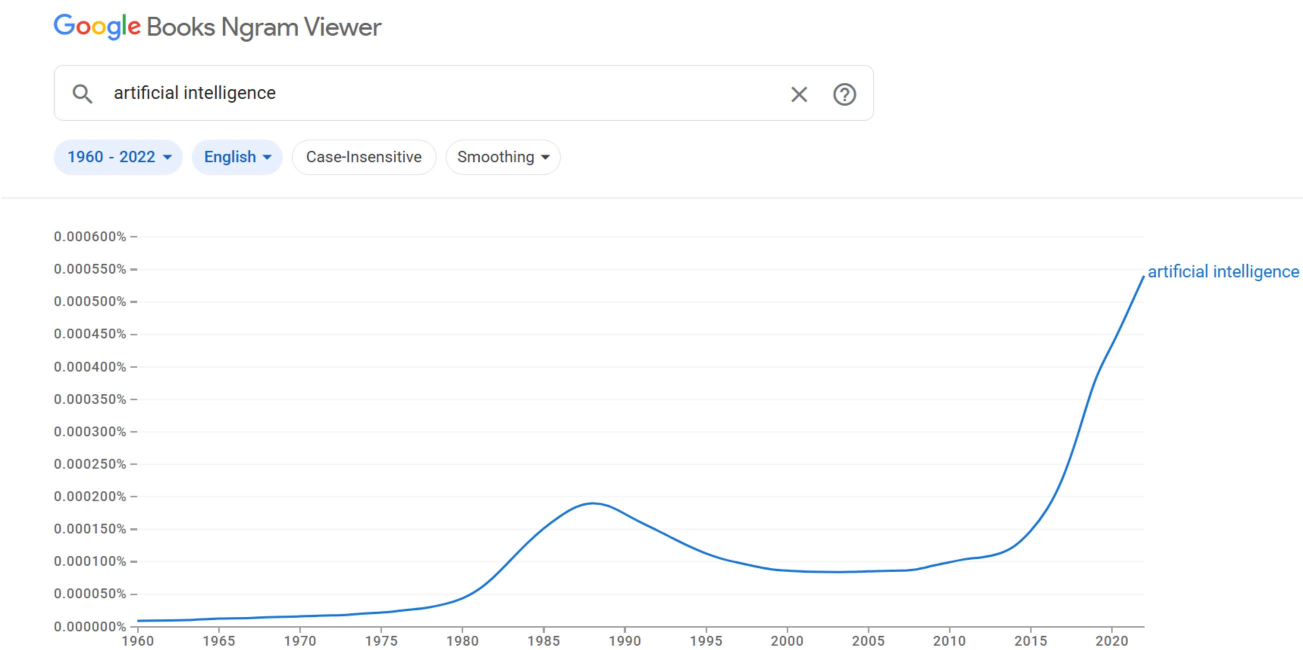
Google Books Ngram Viewer
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Table 1

	Antecedents of AI	**Consequences of AI**	**AI use cases**
Practitioner-oriented	Chen *et al* (2024)[84]	Jia *et al* (2024)[85] Zhang *et al* (2023)[86] Boussioux *et al* (2024)[87] Anthony *et al* (2023)[88]	Banerjee *et al* (2023)[89]
Researcher-oriented	von Krogh *et al* (2023)[90]	Grimes *et al* (2023)[91] Kemp (2023)[92] Abada *et al* (2023)[93] Krakowski *et al* (2022)[94]	Bosma *et al* (2024)[95] Wu *et al* (2023)[96] Rathje et al (2024)[97] Luo *et al* (2024)[98] Gaessler *et al* (2023)[99] Miric *et al* (2022)[100]

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39 This author successfully implemented one AI use case in his organization, which is dedicated to quantitative trading of financial instruments. The impact has been marginal: a sub-process that used to take one person, one day per month to execute, now takes the same person a couple of hours per month. This is not material from a P&L perspective.

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