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Using artificial intelligence to advance sustainable development in industrial markets: A complex adaptive systems perspective

Cinthia Beccacece Satornino[a,*], Shuili Du[b], Dhruv Grewal[c]

[a] Department of Marketing, UNH Sales Center, Peter T. Paul College of Business and Economics, University of New Hampshire, 10 Garrison Ave, Durham, NH 03824, 339.206.0293, United States of America

[b] Department of Marketing, Peter T. Paul College of Business and Economics, University of New Hampshire, 10 Garrison Ave, Durham, NH 03824, United States of America

[c] Toyota Professor of Commerce and Electronic Business, Marketing Division, Babson College, 213 Malloy Hall, Babson Park, MA 02457, United States of America

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ABSTRACT

The vast complexity involved in dealing responsibly with sustainable development is daunting. Such complexity increases significantly due to the interdependencies and trade-offs associated with the 17 UN Sustainable Development Goals (SDGs). To address sustainability across multiple domains, recent advances in technology and innovative adaptations offer some promise, as exemplified by the increased prominence of artificial intelligence (AI) in the marketplace. However, as more industrial firms leverage AI to address sustainable development goals, it becomes even more critical for them to account for these interdependencies and trade-offs among the SDGs. Relatively few existing studies guide industrial marketers in accounting for these interdependencies when deploying AI-enabled solutions. Herein, guided by complex adaptive systems theory and principles of systems engineering, the authors introduce a responsible AI deployment model that articulates key steps in the development and deployment of AI solutions to advance sustainable development firms.

> We have the power now, for the first time in the history of our species, to harness artificial intelligence, to help us really flourish, and help bring out the best in our humanity rather than the worst of it.
> —Max Tegmark, MIT Physicist (Fridman, 2023)

1. Introduction

The world is at a crossroads regarding sustainable development. Substantial evidence of the precariousness of the global situation reflects volatility in environmental, social, and economic systems, as exemplified in notable recent events. Regularly occurring heatwaves impose tens of billions of dollars in costs to societies, yet few firms have established plans for dealing with the associated shocks to their operations. Less predictable weather crises such as hurricanes can create trillions of dollars in losses, for which firms usually have only a few days to plan; geo-physical events, such as earthquakes, provide virtually no warning (Lund et al., 2020). In addition, the coronavirus pandemic highlighted flaws in supply chains (Mende et al., 2023) and demonstrated how vulnerable firms are to global risks, including those involving climate change (Engel, Enkvist, & Henderson, 2015). In 2020, retailers struggled to fill shelves and pharmacies to keep medical supplies in stock when their manufacturer supply chains were disrupted by the pandemic (Sneaders & Lund, 2020).

As the severity of natural disasters (e.g., flooding, hurricanes, wildfires, droughts) continues to increase, with jumps predicted every 2.8 to 3.7 years (Lund et al., 2020), the economic losses have become nearly unsustainable in many industries. For example, due to its heavy reliance on production from the western Pacific, the semiconductor industry faces significant risk exposure to hurricanes, which are likely to increase in both number and intensity in the next two decades; continually rising heat levels exacerbate this risk (Lund et al., 2020). The insurance broker Aon estimated that natural disasters in 2022 resulted in an estimated loss of $130 billion for businesses in the United States (Aon, 2023); the American Farm Bureau Federation estimates losses to crops and rangeland valued at more than $21.04 billion (Munch, 2023).

* Corresponding author.
E-mail addresses: cinthia.satornino@unh.edu (C.B. Satornino), shuili.du@unh.edu (S. Du), dgrewal@babson.edu (D. Grewal).

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1.1. Seeking sustainability: AI and the UN SDGs

To address sustainability across multiple domains, recent advances in technology and innovative adaptations offer some promise, as exemplified by the increased prominence of artificial intelligence (AI) in the marketplace (Davenport, Guha, Grewal, & Bressgott, 2020). Consider Artesian Solutions, which specializes in generating sales insights for customers, and its partnership with Volume, a business-to-business (B2B) tech agency, to create a conversational AI platform (chatbot) that can provide continuous service to Artesian's clients and thereby enhance brand perceptions cost-effectively (Harrison & Agarwal, 2023). Recently, 43% of respondents to a B2B survey indicated that they already had launched AI-enabled chatbots (Bruce & Pattnaik, 2023). Particularly during the COVID-19 pandemic, B2B firms embraced AI-enabled and technology-enabled tools (Mende et al., 2023), often to help them mitigate the pandemic-driven exoduses of workers from the workforce.

Noting such trends, scholars also have begun to take stock of the advantages of AI deployment in B2B and consumer domains (e.g., Satornino, Grewal, Guha, Schweiger, & Goodstein, 2023; Saura, Ribeiro-Soriano, & Palacios-Marqués, 2021), revealing some unprecedented opportunities, as well as possibilities for sustainable development efforts (Voola, Bandyopadhyay, Voola, Ray, & Carlson, 2022). Yet AI-enabled tools also present challenges regarding how B2B firms should deploy them optimally. For example, when firms scrambled to replace workers during the coronavirus pandemic, they frequently embraced AI-based tools designed to make hiring more effective and efficient.

But in doing so, these firms also incurred significant reputational and regulatory risk, because some AI tools have inherent biases (Hsu, 2023) that produce a lack of trust and potentially undermine relationships between industrial partners. A lack of trust also might result from power asymmetries that arise when one partner in a relationship possesses more AI capabilities than the other. Such AI-driven power asymmetries can lead industrial partners to perceive higher vulnerability to opportunism and increase their fear of being manipulated, further eroding trust (Grewal, Guha, Satornino, & Schweiger, 2021). These examples illustrate the light and dark sides of AI solutions, yet comprehensive studies of AI have yet to address this duality and central paradox in relation to the implications of AI use for sustainability.

One way to address such implications is to consider them in relation to the 17 UN Sustainable Development Goals (SDGs), as detailed in the UN's blueprint for global peace and prosperity in 2015, adopted by all U.N. member states as part of the 2030 Agenda for Sustainable Development. The 17 SDGs and their related targets (see the Appendix for a complete list) address global challenges and seek a more sustainable future (United Nations, 2015). In response, governments and regulators have implemented related regulatory actions. For example, the EU announced its intentions to be climate neutral by 2050, and similar commitments from the United States (Clune et al., 2022) increase pressures on firms to embrace sustainable development practices if they hope to survive and thrive (OECD, 2010).

Notably, the SDGs are intricately linked, as illustrated by an example scenario offered by Cerf (2019, p. 1900021):

> … a severe drought (environment) may latently prompt famine and exacerbate poverty ((socio)economic) that is attributed to rising food inflation (economic) while also increasing the incidence of infections (health) due to water scarcity and impurity (environment).

Likewise, eradicating poverty (SDG 1) has direct and indirect positive effects on health and well-being (SDG 3), quality education (SDG 4), and gender equality (SDG 5); climate action (SDG 13) is intrinsically linked to the other 16 SDGs (Fuso Nerini et al., 2019). Yet as Fonseca, Domingues, and Dima (2020) argue, positive progress on sustainable consumption and production patterns (SDG 12)—a primary and understandable focus in industrial marketing domains (Pradhan, Costa, Rybski, Lucht, & Kropp, 2017; Voola et al., 2022)—correlates *negatively* with good health and well-being (SDG 3), quality education (SDG 4), and industry, innovation, and infrastructure (SDG 9). Similarly, Pradhan et al. (2017) assert that sustainable consumption and production patterns correlate negatively with 10 other SDGs. Thus, no current solution allows for the achievement of all SDGs simultaneously (Fonseca et al., 2020). Fulfilling the 2030 Agenda for Sustainable Development instead demands novel solutions that can leverage synergies while also achieving reasonable trade-offs across the SDGs.

Relatively few existing studies account for such interdependencies. However, as more industrial firms leverage AI to address SDGs, it is increasingly critical that managers avoid assessing any specific SDG in isolation. Instead, they must carefully consider interdependencies in relation to AI. It shows great promise for tackling major environmental and social challenges, through its unprecedented processing capability, exponential learning, and superior ability to uncover pattern and insights from massive unstructured data. The potential SDG-related AI applications seem nearly limitless, from optimizing energy system forecasting and smart city designs, to precision agriculture, to habitat loss detection, machine-automated biodiversity analysis, and CO_2 removal, to inclusive product offerings (Cowls, Tsamados, Taddeo, & Floridi, 2021; Du & Sen, 2023). Yet if AI enhances operational efficiencies for industrial firms by recommending sustainable consumption and production patterns (SDG 12), it might simultaneously exacerbate social inequity, because of its dependence on available data. A general lack of data exists pertaining to disadvantaged and marginalized communities (e.g., Röösli, Rice, & Hernandez-Boussard, 2021), and those data that are available reflect current biases embedded in systems (O'Neil, 2016; Zou & Schiebinger, 2018). Thus, AI might increase efficiency and effectiveness, but it also can exclude marginalized people and poorer market segments or countries from consideration. The exclusion would reinforce current socio-economic injustices, as well as potentially increase climate change risks for industrial firms.

Finally, in addition to accounting for the interdependencies among SDGs, managers must address those between the SDGs and firms' business objectives; the relationship between a firm's engagement in SDGs and its financial performance is anything but unequivocal. Prior research has identified various links between a firm's environmental or sustainability performance and financial outcomes, ranging from negative (Duque-Grisales & Aguilera-Caracuel, 2021), to nonsignificant (Hawn, Chatterji, & Mitchell, 2018), to positive (Russo & Fouts, 1997; Servaes & Tamayo, 2013), as well as the contingent effects of industry- and firm-specific characteristics.

The challenge of sustainable development coupled with requisite attention to the interests of industrial firms is indeed complex. To address such complexity, the field requires "framework, guidelines, and toolkits for project management and development" as effective methods of ensuring consideration of ethical and human rights issues (SHERPA, 2020, p. 6). Herein, we propose a decision model grounded by complex adaptive systems (CAS) theory (Holland, 2006) and principles of systems engineering to guide industrial marketers in the deployment of AI solutions.

In essence, CAS theory asserts that all individual components of a given system are entangled, such that change in one element leads to unpredictable impacts on other elements in the system—exactly as has been described for the SDGs. Each element in the system learns and adapts through its interactions with the other elements (Holland, 2006). Using CAS theory as lens for viewing the utility and drawbacks of AI in industrial markets, we can acknowledge the inherent interdependencies among the different SDGs and between SDGs and firms' business objectives. By linking theory about the light and dark sides of AI (Grewal et al., 2021) with the clear objectives of the UN SDGs (United Nations, 2015), we also illuminate the dilemma associated with relying on AI to mitigate climate change–based risk for B2B firms. In turn, we propose an extended version of CAS theory, in the form of a Responsible Model of AI Deployment (RAID), which also reflects systems engineering principles and ethical AI paradigms. Finally, this article outlines promising avenues for scholarly work, recommendations for policy, and implications for B2B practice.

2. Background

In this section, we briefly overview the UN SDGs, explicate how B2B firms currently are trying to address sustainability, and introduce the RAID framework.

2.1. United Nations SDGs

The 17 SDGs can be subdivided into three interrelated domains: biosphere, society, and the economy (Fig. 1; Rockstrom & Sukhdev, 2016). They aim to effect change in interdependent, complex, and adaptive economic, societal, and environmental systems in which industrial firms are inherently embedded. Scholars have leveraged the SDG framework to advance various academic domains, including B2B

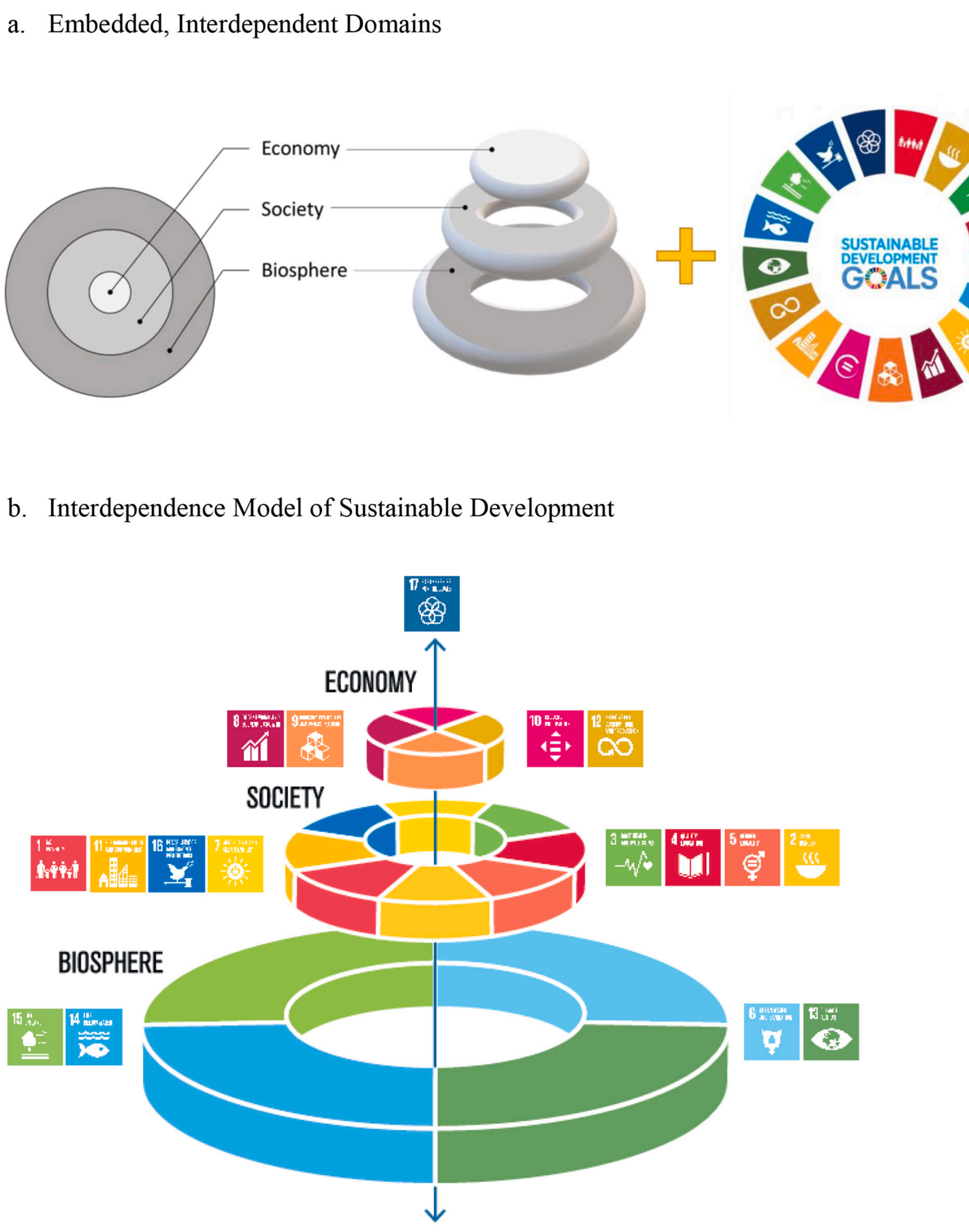

Fig. 1. Three dimensions of the SDGs (adapted from Rockstrom & Sukhdev, 2016).

marketing (Voola et al., 2022). Due to their unique expertise in studying complex networks (Naudé & Sutton-Brady, 2019) and netchains (Lazzarini, Chaddad, & Cook, 2001), industrial marketing scholars are uniquely well-positioned to explicate the interdependence of environmental, societal, and economic systems and help firms navigate significant, complex climate risks (Engel et al., 2015).

2.2. Climate change risks for industrial B2B firms

Among the 17 SDGs, climate action (i.e., taking urgent action to combat climate change and its impacts) is pivotal; climate change affects not only all other SDGs, but also every country, every business, and every individual. The Intergovernmental Panel on Climate Change (Intergovernmental Panel on Climate Change (IPCC), 2018) has warned that the average temperature must not exceed 1.5° Celsius above pre-industrial temperatures if we are to avoid the most catastrophic, irreversible impacts of climate change. Sustainable development and climate change are intricately linked and reciprocal: Choices related to sustainable development and the resulting trajectories strongly influence the intensity of climate change (Sathaye et al., 2007), and climate change creates both risks and opportunities for sustainable development (Engel et al., 2015). As vulnerable societal stakeholders, industrial firms must engage in efforts to mitigate climate change.

The risks associated with climate change have repercussions for all three domains of the SDGs too (Engel et al., 2015), such that they can adversely affect B2B firms by creating six main types of risk. Risk involving external stakeholders includes ratings (higher cost of capital), regulation (government action), and reputational (direct or indirect impacts on public perception) risks. Those emerging from the value chain include physical (damage to assets due to extreme weather events), price (increased volatility), and product (becoming unpopular or unsellable) risks. Engel et al. (2015) cite the case of Western Digital Technologies, whose sharp revenue declines in 2011 were attributed to flooding in Thailand that adversely affected its production. The diminished output and shortages in hard drive supply in turn adversely affected extensive computer manufacturing supply chains.

In humanity's collective efforts to tackle climate change, AI might facilitate efforts to improve energy and resource efficiency, as well as identify a wider array of innovative climate solutions (Cowls, Tsamados, Taddeo, & Floridi, 2023). Yet the complexity of responsible climate actions and their repercussions (positive and negative) for other SDGs and for industrial firms' short-term and long-term business objectives (Duque-Grisales & Aguilera-Caracuel, 2021; Hawn et al., 2018) suggests the need for an organizing framework of optimal AI-based climate actions. For firms and private organizations, embracing sustainable development is unavoidable, not only to deal with climate change but also to ensure their continued survival (Sathaye et al., 2007), so a framework that can help them do so seems invaluable.

2.3. Complex adaptive systems theory

As noted, sustainable development is a complex challenge (Hartvigsen, Kinzig, & Peterson, 1998). Complexity science describes complex adaptive systems (CAS), defined as self-organizing networks of entities engaged in continuous processes of co-evolution with other linked entities within an open system, which occur in response to contextual changes (Ellis & Herbert, 2010; Holden, 2005; Rodrıguez-Iturbe & Rinaldo, 1997). Complex adaptive systems exhibit four major features (Holland, 2006): (1) *parallelism*, such that many entities send and receive many signals from other linked entities simultaneously; (2) *conditional actions*, because actions of any entity in the system depend on signals received from other entities; (3) *modularity* that allows sets of rules to be used as building blocks for formulating reactions to another, novel set of signals; and (4) *adaptation and evolution*, pertaining to how entities in the system change nonrandomly over time, seeking to improve performance by optimizing the building blocks applied to address incoming signals.

Marketplaces for industrial firms can be characterized as CAS, in that the firms are embedded in a dynamic, intricate network of interactions with various self-organizing stakeholders (Oughton, Usher, Tyler, & Hall, 2018). Individual firm actions reflect changes in the wider industrial markets (i.e., economic domain), as well as in societal and biospheric domains (Hult, Hurley, & Knight, 2004; Li, 2022). Applying CAS theory to understand industrial firms in a sustainable development context requires (1) understanding the state of the industrial market as a system; (2) classifying relevant stakeholder goals and their values; (3) specifying the costs associated with any given sustainable development action by stakeholders; and (4) suggesting guidelines within the system for achieving predetermined stakeholder goals (Holden, 2005). In Table 1, we illustrate the interrelated nature of industrial marketing concerns of B2B firms, the light and dark sides of AI solutions, and the SDGs with an example related to hiring B2B salespeople. With this example, we explicate the perks and perils of AI, relevant primary and secondary SDGs, and key principles of ethical AI.

2.4. Contributions of AI

As noted, novel development paths that account for the SDGs require that B2B firms navigate complex, evolving, and unfamiliar territory. Turning to AI is an exciting, but potentially alarming, means to optimize solutions to complex problems. Currently, firms use AI to ensure sufficient convenience and increase buyers' engagement, while also enhancing the effectiveness and efficiency of their marketing efforts (Grewal et al., 2021). Because AI can make sense of complex data, which then can be used to train generative AI tools (McKinsey & Company, 2023), it should be possible to develop novel solutions to climate change risk that account for interdependencies among the SDGs by using AI tools.

Notably, AI already has shown promise in accelerating innovation and efficiency along the focal dimensions of the SDGs (Vinuesa et al., 2020). At a recent AI for Good summit, convened in partnership with the Government of Switzerland and the International Telecommunication Union, and attended by 40 UN partners, Ricardo Vinuesa (KTH Royal Institute of Technology) presented research-based evidence that AI had the potential to illuminate complex interdependencies among the SDGs (IISD, 2023). In detailing the synergies possible between AI and 134 of the 169 SDG targets, Vinuesa also acknowledged the inherent trade-offs with 59 targets, mostly in the social domain.

Key benefits that might be obtained by deploying AI to advance the SDGs include using satellite data to track poverty, matching energy supply to energy needs to improve efficiency, predicting pollution in urban areas, and enabling contact tracing during pandemics. Notable trade-offs include the gender gap in AI and the expansion of data workforces that can introduce bias into AI models (O'Neil, 2016), as well as potential blind spots in AI models with regard to SDG interdependencies. In addition, AI models themselves are not as efficient as they could be; given their complexity, they could intensify power asymmetries among nations and organizations (Mohamed, Png, & Isaac, 2020).

The dark sides of AI in various domains (e.g., Du & Xie, 2021; Satornino et al., 2023), including B2B markets (Grewal et al., 2021), also raise concerns about privacy, bias perpetuation, neglect of individual uniqueness, opportunism, and manipulation. These challenges are particularly manifest in contexts marked by asymmetries in power and information. The deployment of AI therefore might exacerbate risks stemming from interdependencies in economic, societal, and environmental systems. Acknowledging and navigating such pitfalls is critical for optimizing the use of AI to advance the SDGs. Specifically, understanding *both* SDG interdependencies *and* paradigms of ethical design for the deployment of AI might help avoid unintended consequences.

Table 1
AI solution use case: hiring B2B salespeople[a,b].

Examples of AI Perks	*Convenience*	AI tools can make hiring more convenient for both hiring managers and applicants by enhancing online hiring process and making job searching easier.
	Engagement	AI tools can attract candidates through channel optimization strategies and assess the fit of a candidate through online testing and automated evaluation.
	Effectiveness	AI tools can help managers select candidates who best fit the needs of the position and help applicants identify jobs for which they are well-suited.
	Efficiency	AI tools can help managers and applicants match each other more efficiently than manual review of applications allows.
Examples of AI Perils	*Privacy*	AI tools can find information not relevant to the ability for the candidate to perform on the job. An example is the use of AI to scrape social media and online content that is personal, thereby violating right to privacy.
	Bias	Biased social norms can be embedded in algorithms that use non–job-related data, such as race and gender, to score candidates as a suboptimal match for a given position.
	Uniqueness Neglect	AI tools aggregate big data and make inferences based on many cases, which can lead them to overlook unique combinations of attributes for individual applicants that may differ from the assessment of potential match by AI tools.
	Opportunism	Rather than compensation optimization, AI tools can assess individual earnings histories and lead to unfair compensation packages, particularly for female workers and workers from underrepresented minority groups and other marginalized groups, who traditionally have been underpaid relative to majority group counterparts.
	Manipulation	AI tools can identify vulnerable applicants (or flight risk employees), which can lead to manipulation by contractual constraints such as noncompete clauses and unfavorable hiring terms.
Sample SDG Monitoring	Primary SDG(s)	SDG 5: Gender equality SDG 8. Decent work and economic growth
	Secondary SDG(s) (Nilsson, 2017)	SDG 10. Reduced inequalities
Example Application of Ethical AI Principles (Floridi & Cowls, 2022)	*Beneficence:*	**Ethical AI in Design:** Developers of AI can quantitatively estimate inherent bias in data sets used to train AI tools and weight the results appropriately so that marginalized groups are not adversely affected.
	Non-Maleficence:	**Ethical AI in Design:** Developers can ensure that the AI tool is fit for purpose and that only job-relevant data are collected and used in the hiring decision.
	Autonomy:	**Ethical AI in Use:** Human oversight should be a critical component of assessing matches between applicants and positions.
	Justice:	**Ethical AI in Design and Use:** Firm diversity goals should be articulated, accounted for, and deliberately incorporated into the design of AI tools, as well as articulated to hiring managers.
	Explicability:	**Ethical AI in Design and Use**: The strengths and weaknesses of the AI tool should be clearly articulated and documented, and explicit guidelines for use should preserve human agency, then provided to hiring managers.

[a] Siocon (2023): https://www.businessnewsdaily.com/how-ai-is-changing-hr
[b] Lumis, Mehta, and Muscolino (2023): https://www.idc.com/getdoc.jsp?containerId=IDC_P39364

2.5. Ethical AI

Because the SDGs are inextricably linked, AI deployment models must account for these interdependencies to help B2B firms achieve operations near their production efficiency frontiers (i.e., the point at which they optimize their outputs given their inputs and technology; Aigner, Knox Lovell, & Schmidt, 1977). Furthermore, AI deployment models should mitigate concerns regarding the potential misuse of AI and threats to transparency, privacy, human rights, power asymmetry, and exploitation (Truby, 2020; Wei & Zhou, 2022). In response, various public and private organizations have proposed principles for the ethical deployment and use of AI (see https://www.aiethicist.org/frameworks-guidelines-toolkits for a comprehensive list of ethical AI frameworks and guidelines). Across these various iterations of guiding frameworks, the proposed individual principles range in number from 47 (Floridi & Cowls, 2022) to more than 200 (Corrêa et al., 2023). Even acknowledging some overlap in content, the proliferation of ethical AI principles represents a challenge. In Table 2, we denote the overlap of general principles across select entities developed after 2020 (for frameworks developed prior to 2020, see Hagendorff, 2020).

Still, a universally accepted set of principles remains missing, and unlikely (Dotan, 2022). Thus, although the unified principles paradigm proposed by Floridi and Cowls (2022) provide the most parsimonious yet comprehensive set ethical principles, practitioners lack sufficient, clear tools or guidelines for how to apply relevant principles (Gupta, Wright, Ganapini, Sweidan, & Butalid, 2022). Furthermore, even when convergence arises around some principle (e.g., accountability), definitions and interpretations differ significantly (Jobin, Ienca, & Vayena, 2019). In the PWC *Ten Core Principles of Ethical AI* framework for example, accountability is an *agent*-based construct ("Someone [or some group] should be clearly assigned responsibility for the ethical implications of AI models' use—or misuse"), but the European Commission's *Ethical Guidelines for Trustworthy AI* framework defines it as a *mechanism*-based construct ("Mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes"). Considering such divergent definitions and interpretations from experts that are dedicated to understanding ethical principles, how can firms ensure that their AI initiatives are truly ethical, and how can regulators and governing bodies measure and monitor ethicality?

Notably, some emerging research has started to examine options for putting high-level ethical AI principles into practice, by identifying concrete ways for business organizations to address ethical and social issues, using both technical and organizational tools (Theodorou & Dignum, 2020). For example, Benjamins, Barbado, and Sierra (2019) present the notion of responsible AI by design, according to which firms combine overall AI principles with machine learning–based training related to AI ethics, specific tools, and a governance process that defines responsibilities and accountability. Brännström, Theodorou, and Dignum (2022) offer a Responsible AI Norms (RAIN) framework that translates high-level ethical principles and policies (e.g., fairness, transparency, accountability) into concrete normative requirements and features, in an attempt to help industrial firms embed socio-ethical concerns into their AI software development. Yet neither identifying interdependency among the SDGs nor employing an ethical AI framework to apply to individual use cases is sufficient to guide the use of AI in advancing sustainable development. Instead, integrating these tools into a singular framework might provide more comprehensive guidance for deploying AI tools to advance the SDGs and mitigating climate change risks for industrial firms.

Therefore, we turn to CAS theory to link ethical AI frameworks with

Table 2
General principles in select ethical AI frameworks in practice (adapted from Hagendorff, 2020).

Framework	YR	ETHICAL PRINCIPLE														Source
		Accountability	Beneficence	Explainability	Focus/Fit for Purpose	Governance	Inclusion	Justice/ Fairness	Literacy	Non-maleficence	Oversight	Privacy	Rigor/ Reliability	Safety	Transparency	
Unified Framework of Principles for AI in Society (AI4People)	2018	✔	✔	✔				✔		✔						Floridi et al. (2018)
The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems	2019		✔		✔		✔	✔		✔	✔	✔	✔	✔	✔	IEEE (2019)
Artificial Intelligence Ethics Impact Group (AIEI)	2020	✔	✔					✔		✔		✔		✔	✔	AI Impact Group (2020)
Data Ethics Framework (UK Central Digital & Data Office)	2020	✔	✔					✔		✔		✔		✔	✔	Gov.uk (2020)
Shaping the ethical dimensions of smart information systems– a European perspective (SHERPA)	2020	✔	✔			✔		✔		✔			✔	✔	✔	Brey, Lundgren, Macnish, and Ryanm (2020)
Artificial Intelligence Accountability Framework Government Accountability Office (GAO)	2021	✔			✔	✔	✔	✔			✔				✔	U.S. Government Accountability Office (GAO) (2021)
Everyday Ethics for Artificial Intelligence (IBM)	2022	✔		✔			✔	✔	✔		✔					IBM Design Program Office (2022)
Artificial Intelligence Risk Management Framework (AI RMF 1.0)	2023	✔		✔	✔			✔	✔		✔	✔	✔	✔	✔	National Institute of Standards and Technology (2023)

SDG frameworks. Ethical AI frameworks provide rules of engagement with complex societal, economic, and biospheric systems, as specified by the SDG framework. Guided by CAS theory and principles of systems engineering, we propose a decision model that features interdependencies (requirement 1: understand the state of the industrial market system) among the SDGs (requirement 2: framework for classifying stakeholders' goals and their value) to provide guidelines regarding the ethicality of AI design and use (requirement 4: providing rules) while accounting for relevant trade-offs (requirement 3: specifying costs). Scholars and practitioners can apply this framework to predict unintended consequences of using AI to address climate change and sustainable development and to develop strategies for mitigating such risks.

2.6. Conceptual decision model for responsible AI deployment (RAID)

Any strategic initiative that employs AI must simultaneously consider two interactions (depicted as X and Y axes in Fig. 2): (1) synergies (positive correlation between primary and the interdependent SDGs) versus trade-offs (negative correlations or interdependent SDGs) and (2) losses and gains (impacts on business performance). Fig. 2 illustrates these two dimensions and also identifies an optimal strategic target, namely, the quadrant that represents Responsible Artificial Intelligence Deployment (RAID). In this highlighted quadrant, both business objectives and the positive impacts on primary SDGs are maximized.

We propose a RAID model in Fig. 3 to serve as a blueprint for developing and deploying AI to further business objectives and mitigate climate risk. This model reflects our application of the SIMILAR system engineering method (Bahill & Gissing, 1998), which calls for six stages: **S**tate the problem, **I**nvestigate alternatives, **M**odel the system, **I**ntegrate, **L**aunch the system, and **A**ssess performance. We modified this systems engineering design protocol to reflect the complexity of adaptive SDG systems for AI deployment in industrial firm contexts and thus undertook the following model development steps:

- **Identify** the goal of AI deployment (business objectives) and the primary SDGs that will be influenced (as well as interdependent SDGs). Firms also should identify key stakeholders and relevant principles for ethical AI design.
- **Formulate** alternative design models that weigh the trade-offs between SDGs and relevant ethical AI design principles, along with a stakeholder coordination strategy. Appropriate metrics should be determined to track adherence to ethical AI design principles.
- **Design (and redesign)** in an iterative process, such that the design of the ethical AI tools embeds SDG risk mitigation and stakeholder coordination strategies, according to the identified stakeholders, trade-offs, and interdependencies.
- **Test (and retest)** the resulting prototypes using checklists, baseline study comparisons, reviews of publicly available documentation, cost–benefit analyses, and other impact assessment tools (see Ayling & Chapman, 2022).
- **Evaluate (and reevaluate)** the results of each test and make necessary adjustments. The Design, Test, and Evaluate stages then repeat until the results have been optimized.
- **Deploy** by launching the AI tool.
- **Monitor** the AI tool continuously after its deployment, using appropriate metrics to identify unintended harms or unanticipated interdependencies, which may require returning to the beginning of the RAID model.

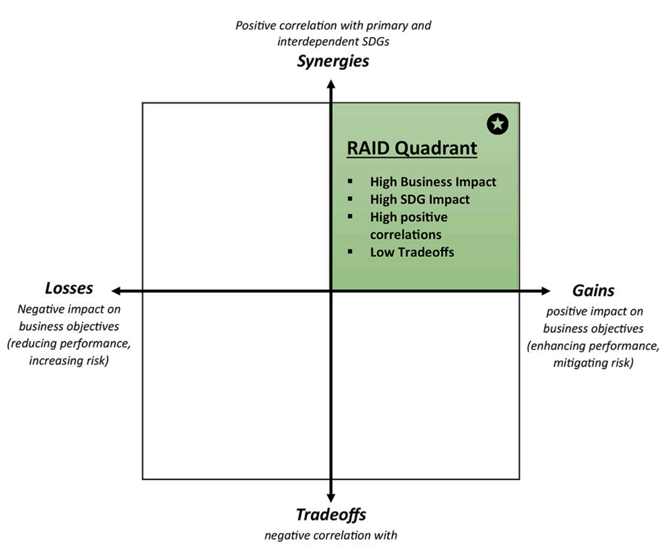

Fig. 2. RAID quadrant.

3. Illustrative RAID use case: MetLife

The insurance industry is exposed to substantial economic risk, due to the increased physical risk associated with climate change, which propagates an increasing number of extreme weather events (Aon, 2023; Engel et al., 2015). Considering the potential of AI to offer some relief from these climate change–linked economic losses, MetLife, one of the largest insurance companies in the world, has partnered with third-party developers to establish and deploy AI solutions that can detect fraudulent claims, coach agents, and improve property risk assessments (Pahuja, 2023). For example, to optimize property risk assessments, MetLife partnered with ZestyAI to deploy its Z-FIRE solution, an AI-enabled tool that makes sense of big data and aerial imagery, including owner mitigation efforts, building materials, and temporal changes in the property characteristics, to generate risk assessments for specific properties at a granular level using deep learning algorithms. Such assessments are unattainable by individual human examiners. Then ZestyAI applies underwriting criteria to derive a property's risk score. The partnership resulted in a major overhaul of MetLife's portfolio in California; according to ZestyAI's assessments, having Z-FIRE in place (in 2020) would have resulted in a 95% reduction in losses in the state due to wildfires at that time (Pahuja, 2023).

We use this example to present an application of our proposed RAID model, according to the steps established in the previous section.

3.1. Identify

At MetLife, a key business objective is to reduce exposure to wildfire losses. The primary SDG pursued with the deployment of the Z-FIRE AI likely is taking urgent action to combat climate change and its impacts (SDG 13); tangentially, it also might relate to goals to build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation (SDG 9). Developers as less likely to build in uninsurable properties that are at high risk of wildfires, but if property owners have the means to implement fire mitigation strategies, they might do so to secure insurance on their property or save on insurance costs. However, for lower socio-economic groups or marginalized communities, which often are relegated to housing in less desirable areas that face greater threats from natural disasters (Reid, 2013), sophisticated wildfire risk mitigation strategies might not be financially attainable. In turn, they may be unable to secure insurance for their properties or could face higher insurance premiums. Reduced access to insurance for those properties leaves disadvantaged groups further vulnerable, which constitutes an antagonistic interdependency with the SDGs of reducing inequality within and among countries (SDG 10) and making cities and human settlements inclusive, safe, resilient, and sustainable (SDG 11). Key stakeholders include property owners, MetLife,

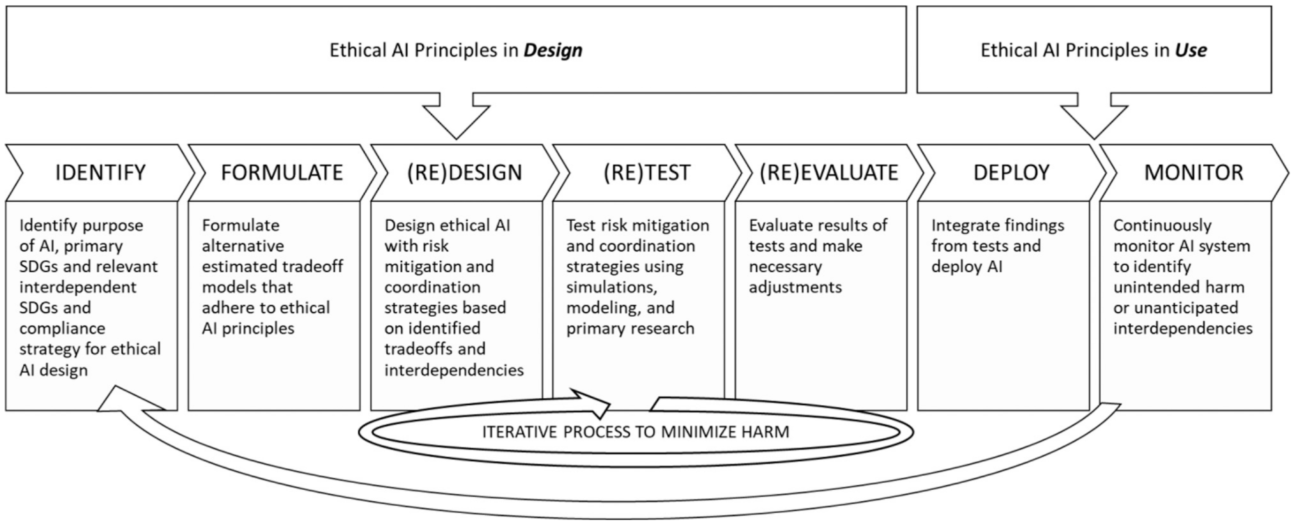

Fig. 3. RAID model.

ZestyAI, regulators, safety officers, local governments, and tenants. The relevant ethical AI principles include justice and fairness, inclusion, rigor and reliability, beneficence, fit for purpose, and transparency, oversight, and accountability.

3.2. Formulate

To mitigate the threat to efforts to reduce inequality within and among countries (SDG 10) and make cities and human settlements inclusive, safe, resilient, and sustainable (SDG 11), MetLife and ZestyAI might design an AI solution that identifies properties that can benefit from low-level risk mitigation strategies that would reduce their risk scores. For property owners who fall into this category but are financially disadvantaged, MetLife might design and implement a program that includes wildfire risk mitigation strategy education and free or reduced cost resources, made available to help reduce premiums for vulnerable groups. Such actions would address several ethical AI principles: literacy, justice and fairness, inclusion, and beneficence. It also would advance goals to build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation (SDG 9), as well as take urgent action to combat climate change and its impacts (SDG 13). Appropriate metrics can be developed from data already being tracked, such as the mitigation strategies implemented by property owners to reduce risk, and thus quantify the risk reductions achieved, to determine appropriate premium adjustments.

Another use of AI might be a solution that incorporates considerations of financial need together with fire risk in premium calculations, to help alleviate inequalities and promote social justice. Specifically, the tool could identify particularly high-risk properties and consider offering insurance to the owners, coupled with an incentive program for saving for relocation (perhaps an annuity product from the company's investment division) to less risky areas by saving on insurance premiums. Such an initiative would help advance multiple goals: to build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation (SDG 9); to take urgent action to combat climate change and its impacts (SDG 13); to reduce inequality within and among countries (SDG 10); and to make cities and human settlements inclusive, safe, resilient, and sustainable (SDG 11). Yet it also might appear contrary to the business objective of optimizing premiums and reducing exposure to wildfire risk in the short term. Therefore, MetLife would need to take a long-term perspective and recognize that the initiative could reduce its exposure to many climate change risks (Engel et al., 2015), increase the net number of insurable properties through relocation efforts, and mitigate external stakeholder risk. Metrics tracking the success of the savings program in terms of promoting relocation and financial stability would need to be developed in conjunction with this strategy.

3.3. Design (and redesign)

After selecting from the alternative models, MetLife and ZestyAI would develop prototype AI solutions that exhibit the features.

3.4. Test (and retest)

The AI prototypes could be tested using simulated data derived from their existing data.

3.5. Evaluate (and reevaluate)

In assessing the results of the simulation, the companies would need to identify optimal areas and consumers for deploying the intervention program.

3.6. Deploy

MetLife would launch the AI solution, while carefully ensuring compliance with the relevant ethical AI in use principles.

3.7. Monitor

MetLife and ZestyAI would carefully and continuously track the results of the AI solution deployment to ensure that progress toward the projected outcomes (e.g., reduced fire risk to property owners, participation in education programs, enrollment in savings programs) is moving as expected and that no unintended harms or unanticipated interdependencies are emerging or being revealed.

In cases for which the primary business objective specifically is to advance an SDG, in an effort to reduce external stakeholder risk (Engel et al., 2015), firms can carefully select the SDG that aligns most closely with their business purpose. Thereafter, they can assess AI deployments that advance that SDG for all related business objectives. By using the RAID model, they also can identify the related effects on secondary business objectives and interrelated SDGs.

4. Discussion

4.1. Contributions to literature

With this work, we offer several important contributions to scholarship at the intersection of AI and sustainable development. First, we identify a substantial gap related to the role of AI in sustainable development, then bridge it by suggesting the integration of the SDG framework with ethical AI frameworks in industrial markets. With this contribution to literature at the interface of business, AI, and sustainability, we also answer calls to explore (1) means for introducing AI solutions while advancing the SDGs and (2) the interconnections of SDGs according to a more in-depth, nuanced view of sustainable development, as required by industrial firms that answer to multiple stakeholders and must account for interdependencies within the SDG blueprint.

Second, we present a depiction of the decision space in which industrial firms operate when deploying AI solutions and identify the optimal quadrant for strategic action. The framework in Fig. 2 reveals other areas worthy of scholarly attention. For example, the appropriate strategic action may be clear in the RAID quadrant and in the quadrant with high trade-offs but low synergies and business gains (i.e., firms should not act). It is less clear what firms should do in the other quadrants across the decision space (e.g., when synergies and business gains are high, but so are trade-offs). Scholars might empirically unpack recommendations and cautions for these quadrants.

Third, we introduce the RAID model, which illuminates new pathways for industrial marketing researchers. The roles and responsibilities of marketers for implementing ethical, sustainable AI solutions, especially during the RAID implementation and monitoring steps, merit exploration. Continued empirical research might elucidate the most effective stages in which marketers should leverage the RAID process and their responsibilities for monitoring ethical AI and the SDG interdependencies, increasing literacy and transparency, or optimizing business gains and SDG synergies. The RAID model offers a framework for exploring these and other timely questions.

More broadly, continuing to establish more in-depth, nuanced research insights into AI is imperative. As a result of unprecedented access to large data sets, as well as the trend that sees university graduates in relevant fields entering industry rather than joining the academy, industry practitioners have taken the lead in advancing AI research (Ahmed, Wahed, & Thompson, 2023). But such developments also raise concerns regarding bias, opportunism, and manipulations if the research effort is tightly coupled with industry objectives and goals.

4.2. Contributions to practice

Faced with worsening climate change and social inequity, contributions to sustainable development are critical for B2B firms to protect corporate reputations, strengthen stakeholder relationships, and cultivate long-term competitive advantages (Sharma, 2020; Vesal, Siahtiri, & O'Cass, 2021). These firms simultaneously face the daunting challenge of grappling with AI, a disruptive technology that has enormous promise and numerous perils. For these B2B firms, we offer several key insights regarding how they can leverage AI to boost their social, environmental, and economic performance.

First, business managers should view sustainable development and sustainability performance not as a monolithic whole but as an interconnected system of components. The UN SDG framework provides an insightful, nuanced understanding of the complexity of sustainable development. But many examinations of sustainability and technologies that can advance sustainable development take a myopic approach, ignoring the inherent trade-offs. As we argue, it is critical for B2B firms to account for both synergistic and antagonistic interdependencies among SDGs. Accordingly, business managers should seek to identify the multidimensional consequences of their strategic actions and sustainable development initiatives. They also should craft performance metrics that align with not just their business objectives but also their achievements in the pursuit of primary and secondary (interdependent) SDGs.

Second, business managers need to pay attention to both the light and dark sides of AI (Grewal et al., 2021) and develop responsible strategies to maximize the upside and minimize the downside when deploying AI solutions to mitigate climate change risk. We delineate some ethical AI principles for B2B firms; we also propose a model that practitioners can use to anticipate the positive and negative spillover effects of AI solutions in a sustainable development context. By depicting the AI solution decision space, reflecting synergistic and antagonistic interdependencies across the SDG footprint, our Fig. 2 provides practitioners with a visual framework for understanding the constraints of deploying AI solutions in a responsible manner and accounting for the tensions inherent in advancing the SDGs.

Third, the proposed RAID model represents guidance for how to deploy AI solutions responsibly, in a way that promotes a symbiotic relationship among AI, society, and business. Considering current and ongoing controversies surrounding advanced AI systems—as exemplified by the March, 2023 open letter calling for a moratorium on giant AI experiments, signed by tech luminaries such as Tesla CEO Elon Musk and Apple cofounder Steve Wozniak (Future of Life Institute, 2023)—business managers must take the responsibility to ensure their firms are deploying AI in a systematically responsible way. Responsible AI solutions should exploit the power of AI to achieve business objectives while simultaneously mitigating any direct or spillover threat of AI to related SDGs. Our RAID model provides a roadmap that B2B firms can use to identify primary and secondary SDGs related to their business objectives and climate change risk mitigation efforts, and then formulate, design, and iteratively test a responsible AI solution. Considering the newness of AI technology and its poor explainability and transparency, we consider our iterative RAID model well-suited for guiding industrial firms along their AI learning journey. They can use it to define how they leverage AI and continuously adapt and fine-tune their AI solutions to better achieve firm performance, sustainable development, and risk mitigation objectives.

4.3. Contributions for policy

The RAID model illuminates opportunities for policy-based interventions to enhance trust in AI services by ensuring conformity across supply networks (Arnold et al., 2019), at the design and use stages of an AI solution. Specifically, new policy might compel firms that deploy AI solutions to identify and address power asymmetries (Zuboff, 2019). Similarly, policies might impose increased accountability, by requiring firms to specify and report on safeguards in place to slow down or disable AI tools that function unexpectedly. Policies addressing manipulation concerns and opportunism also can be crafted to help prevent bad actors from interfering with efforts to adhere to the beneficence and non-maleficence principles of ethical AI (Center for Humane Technology, 2022).

The European Commission (2020) asserts that fairness in competitive markets facilitates increased innovation and enhanced product quality, leading to higher customer satisfaction and greater efficiency. Threats to fair competition hinder the advancement of SDG 9 (build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation) by undermining innovation; they also inhibit advancement toward ensuring sustainable consumption and production patterns (SDG 12) by disincentivizing efficiency. Policies that ensure AI solutions minimize threats to competition thus are another important element of the effective implementation of the RAID model. In summary, policy makers can help simplify the complexity of responsible AI deployment by crafting regulations that reflect the interdependencies of the SDGs and provide safeguards against inadvertent, negative spillover effects by firms that deploy AI solutions to mitigate climate change risk or achieve business performance objectives and SDGs.

4.4. Limitations and further research

4.4.1. Scope of the model

Although a meaningful first step, our model is limited, in that we focus on the ethicality of AI solutions for advancing the SDGs. Scholarship should move beyond minimizing harm to maximizing the benefits of AI. Ethical AI represents a minimal standard for industrial firms; they also should consider how to deploy AI to achieve big outcomes and disruptive innovations, in ways that sustainably boost their competitive performance. To extend our findings, we call for studies based on interviews with senior managers, who might help tease out some nuances and insights that may be less obvious. Furthermore, combining our framework with recommendations for guiding the *development* of AI-enabled solutions, as detailed by Brännström et al. (2022), could enhance ethical deployments of AI solutions in concrete ways.

4.4.2. Principle paradigm selection and principle specificity

For our example application, we use the unified principles paradigm (Floridi & Cowls, 2022) for parsimony; continued research should explore and test some of the other sets of principles that have been introduced thus far and thereby construct a parsimonious paradigm, specific to industrial firms. Although we distinguish between principles for the design and use of AI tools, we do not offer specific guidance for applying individual ethical AI principles at specific stages of the design process. Additional research should explore the applicability and execution of specific principles at each stage of the design and deployment processes.

4.4.3. Refining interdependence

Although we account for interdependencies in the RAID model, interdependence remains an important, understudied factor for advancing the SDGs. We do not explore the types of interdependence across the SDGS, nor do we offer insights into the coordination strategies that are necessary to achieve them. Notably, three types of interdependence might describe the linkages among SDGs (see Fig. 4; Gulati & Singh, 1998; Thompson, 1967). *Pooled interdependence* is the aggregation of effort by discrete entities to reach a desired outcome, usually involving standardized tasks. *Sequential interdependence* produces an outcome that results from serial actions by two or more entities in a specified order, often associated with multistage tasks that combine standardization and customization across different stages. *Reciprocal interdependence* is similar to sequential interdependence, in that the outputs of one stage become inputs for the next one in sequence, but it also allows for recursive links, such that interdependence can flow in either direction between entities in the system, rather than being limited to a one-way flow of inputs and outputs.

Table 3 links each of these types of interdependence to different coordination strategies. Scholars might continue to refine this conceptualization of interdependency and explore how different types of interdependency and coordination strategies can serve as signals in the CAS, which in turn can hasten the achievement of the SDGs and a sustainable future for humankind.

4.5. Conclusion

Industrial firms are embedded in CAS that require adroit adaptation in response to instabilities in a rapidly changing world. To survive and thrive, industrial firms also are hard pressed to adapt to a more sustainable development model. The use of AI in industrial firms is a prevalent means to address these complex challenges; it offers significant benefits but also corresponding perils. We depict a visualization of the decision space to help guide practitioners, policymakers, and scholars in understanding the tension inherent in the use of AI to advance SDGs. We also present a model for Responsible Artificial Intelligence Deployment (RAID) to guides them through the design and deployment process, while maintaining constant consideration of the principles of ethical AI and accounting for interdependencies in SDGs. Accordingly, this article illuminates several options for continued scholarly exploration, practice, and policy development.

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Data availability

No data was used for the research described in the article.

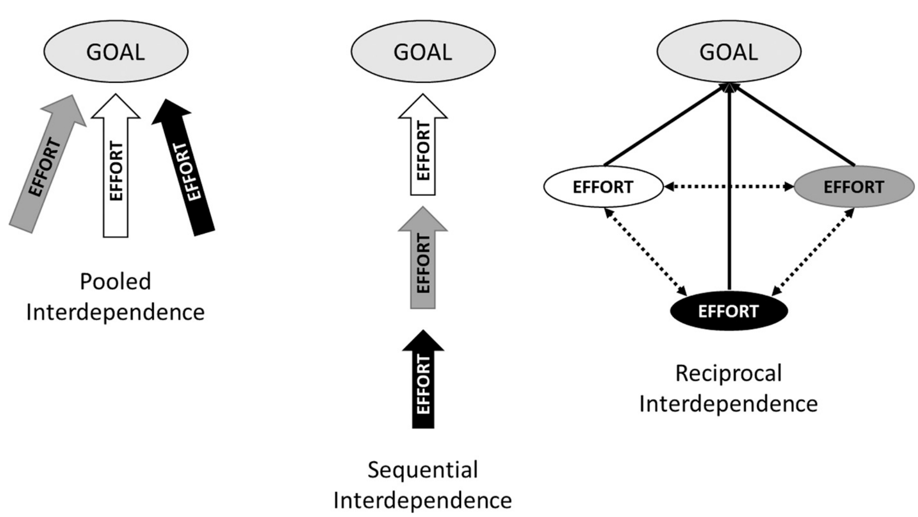

Fig. 4. Types of interdependence.

Table 3
Interdependence types, optimal task context, and coordination focus.

Interdependence type		Optimal task context	Coordination needed	
Pooled	Discrete individual effort is combined for the final result.	Standardized tasks	Standardization	Setting mutually agreed task execution rules and explicit processes that persist until conditions or requirements change.
Sequential	Individual output becomes input in the next stage; each person must complete their task before anyone later in the sequence can complete theirs.	Combination of standardized and customization at different stages of the process	Planning	Setting timeline and milestones for transitions. Identifying and addressing potential pain points.
Reciprocal	Similar to sequential interdependence, but the flow of inputs and outputs are recursive.	Tasks that require customized output	Mutual Adjustment	Setting expectations of uncertainty and risk. Setting communication standards to handle changes as they occur.

Appendix A. SDG classification

Class	Sustainable development goal	UN description	
ECONOMY	SDG 08	Decent work and economic growth	Promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all
	SDG 09	Industry, innovation, and infrastructure	Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation
	SDG 10	Reduced inequalities	Reduce inequality within and among countries
	SDG 12	Responsible consumption and production	Ensure sustainable consumption and production patterns
SOCIETY	SDG 01	No poverty	End poverty in all its forms, everywhere
	SDG 02	Zero hunger	End hunger, achieve food security and improved nutrition, and promote sustainable agriculture
	SDG 03	Good health and well-being	Ensure healthy lives and promote well-being for all at all ages
	SDG 04	Quality education	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all
	SDG 05	Gender equality	Achieve gender equality and empower all women and girls
	SDG 07	Affordable and clean energy	Ensure access to affordable, reliable, sustainable, and modern energy for all
	SDG 11	Sustainable cities and communities	Make cities and human settlements inclusive, safe, resilient and sustainable
	SDG 16	Peace, justice and strong institutions	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all, and build effective, accountable, and inclusive institutions at all levels
BIOSHPHERE	SDG 06	Clean water and sanitation	Ensure available and sustainable management of water and sanitation for all
	SDG 13	Climate action	Take urgent action to combat climate change and its impacts
	SDG 14	Life below water	Conserve and sustainably use the oceans, seas and marine resources for sustainable development
	SDG 15	Life on land	Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation, and halt biodiversity loss
	SDG 17	Partnerships for the goals	Strengthen the means of implementation and revitalize the global partnership for sustainable development

Source: Rockstrom & Sukhdev, 2016; United Nations (2019).

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