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The role of AI for sustainability and economic performance: Evidence from the pharmaceutical industry

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ABSTRACT

In today's rapidly evolving business landscape, organizations across industries are increasingly seeking to capitalize on the opportunities offered by digital transformation, particularly through Artificial Intelligence (AI). Yet, many organizations struggle to fully harness the potential of these emerging technologies. This study contributes to the ongoing discourse on the organizational factors that drive effective AI adoption, focusing on how organizational readiness influences AI adoption and performance. Specifically, we explore the relationship between Strategic and Cognitive readiness and AI adoption, examining their roles in advancing Sustainability and Economic outcomes. Using data from 511 employees in the pharmaceutical industry and employing Structural Equation Modeling, our analysis reveals that (i) strategic and cognitive readiness positively influence AI adoption; (ii) AI adoption mediates the positive relation between strategic and cognitive readiness and SDG performance; (iii) SDGs attainment mediates the relationship between AI adoption and economic performance; (iv) SDGs performance enhances economic performance; and that (v) this relationship is more pronounced in smaller organizations. Our findings contribute to the ongoing research on the organizational determinants of effective AI adoption and highlight the critical role of this technology in supporting both SDGs achievement and economic viability.

1. Introduction

Digital transformation, particularly Artificial Intelligence (AI), is nowadays regarded as a crucial element for enhancing efficiency and improving the quality of a wide range of organizational activities (Davenport and Ronanki, 2018; Iansiti and Lakhani, 2020). However, despite its vast potential and significant company investments, AI does not always yield the expected benefits (Kinkel et al., 2022; Zirar et al., 2023; Cubric and Li, 2024). The complexity of this technology requires for organizations to be adequately prepared and ready for adoption to fully leverage its anticipated benefits (Agarwal et al., 2010; Cao et al., 2021). One of the areas where AI has the most significant potential, but also the greatest risks, is sustainability. The reported potential impacts of AI on sustainable development point to both positive and negative (e.g., Courtland, 2018) effects. For example, AI can help organizations operate more efficiently, use resources more sustainably, and reduce and manage waste more effectively. On the other hand, excessive reliance on AI technologies can lead to negative sustainability impacts, including the possibility of fueling massive energy-consuming data sets and large data centers (Nishant et al., 2020). This suggests that more research is needed to recognize how organizations propel and manage AI, what models and structures can favorably support its adoption, and what boundary conditions influence the relationship between AI adoption and sustainable outcomes. The present study aims to contribute to this debate, firstly, by shedding new light on the organizational conditions that foster AI adoption, and consequently what are the overall sustainability and economic outcomes, particularly in the pharmaceutical industry. Despite multiple research attempts elaborating on AI adoption in this context (e.g. Junaid et al., 2023; Kulkov, 2021; Reinhardt et al., 2020), the relationship with organizational capabilities remains unclear, as does the impact of strategic and cognitive configural conditions on effective deployment. The pharmaceutical organizations represent a compelling context for conducting organizational readiness for digital innovation, AI and Sustainability research. First, pharmaceutical industry is highly institutionalized, where strategic and business decisions are strongly embedded in consolidated governance and compliance

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dynamics. As a result, the adoption of new digital technologies tends to be more cautious and slower compared other industries (Miozza et al., 2025). Secondly, pharmaceutical companies are at the same time highly influenced by - and resistant to - the adoption of AI. The integration of AI across the pharmaceutical value chain offers transformative potential—accelerating research and development (Mak and Pichika, 2019) streamlining operations while reducing production waste (Kulkov, 2021) and enabling patient's personalized treatment (Miozza et al., 2024). However, the strict regulatory requirements and uncompromising product quality standards create significant barriers to AI adoption and implementation (Satwekar et al., 2022). Thirdly, sustainability in the pharmaceutical industry depends on a delicate balance between scientific innovation, market dynamics, regulatory requirements, and financial constraints (Milanesi et al., 2020). Consequently, relevant initiatives may face resistance from industry stakeholders—such as shareholders—who may perceive them as potential threats to profitability (Blum-Kusterer and Hussain, 2001). This significant misalignment warrants further scholarly investigation, particularly in light of the introduction of AI, which may serve as a powerful enabler of sustainable development itself.

The Sustainable Development Goals (SDGs) provide robust framework to approach sustainability, especially in the pharmaceutical industry as they reflect the expectations of regulators, healthcare systems, patients, and society at large (Saxena et al., 2022; Mastrantonas et al., 2024). Yet research remains limited in explicating single SDGs implications. The SDG framework is especially suited to understand AI and sustainability impacts the pharmaceutical context, as it explicitly encompasses goals that are central to the industry's mission and operations, such as public health (SDG 3), innovation and industrial infrastructure (SDG 9), responsible production (SDG 12), and cross-sector collaboration (SDG 17). Unlike generic sustainability measures, the SDGs allow sustainability to be operationalized in a way that is both industry-relevant and comparable across organizational and institutional settings. This is particularly important in a highly regulated and globally interconnected sector, where firms are increasingly expected to demonstrate alignment with social and environmental sustainability agendas rather than relying solely on profitability. As a result, this study employs SDGs as a main research lens to move beyond firm-centric or vague sustainability perspectives and to detail how AI contributes to broader sustainability objectives in the pharmaceutical industry, addressing the following research questions.

- RQ1: *How does organizational readiness facilitate AI adoption?*
- RQ2: *How does organizational readiness facilitate* SDGs *performance?*
- RQ3: *Does engaging SDGs provide benefits in terms of economic performance?*
- RQ4: *What is the role of AI adoption in engaging SDGs?*
- RQ5: *What firm's size conditions support these relationships?*

The underlying rationale of this paper is to conceptualize organizational readiness as a critical antecedent of AI adoption and, in turn, of SDG and Economic performance. While AI has been demonstrated as enabler for SDGs (e.g. Platania et al., 2025), its contribution to SDGs cannot be taken for granted as it depends on the organizational conditions under which it is deployed. This study therefore investigates whether AI adoption effectively supports SDGs outcomes, while explicitly acknowledging that such adoption requires firms to be strategically and cognitively prepared in engaging digital innovation at large. We argue that in absence of adequate readiness, AI initiatives are likely to remain fragmented, underutilized, or misaligned with sustainability objectives. On the other hand, through organizational readiness lens, this study integrates AI adoption into a unified analytical framework, particularly clarifying the mechanisms through SDGs are achieved. Finally, the paper seeks to assess whether engagement with the SDGs ultimately leads to enhanced economic performance, thereby addressing the enduring tension between sustainable innovation and firm-level competitiveness (e.g. Toniolo et al., 2020; X. Zhang et al., 2023).

Given the lack of empirical research examining the relationship between AI and the SDGs within the pharmaceutical industry, this study adopted an exploratory approach to operationalize the SDG key construct. Specifically, the study first relied on evidence derived from prior academic literature and industry reports to identify AI–SDG linkages within the pharmaceutical industry and develop AI-SDG based measurement scale. Subsequently, these items were pretested by 16 key experts to validate AI–SDG-related implications across the pharmaceutical value chain and inform the subsequent operationalization of SDG construct (Kumar et al., 2024), revealing that AI supports: (i) SDG 3 by enhancing drug development and addressing global health needs; (ii) SDG 9 through fostering innovation and improving industrial processes; (iii) SDG 12 by enabling sustainable production and responsible resource use and (iv) SDG 17 via collaborations that expand access to medicines and promote shared solutions. Afterwards, we developed and tested research hypotheses based on data collected on a sample of 511 employees in the pharmaceutical industry, through Structural Equation Modeling (SEM) in Lisrel (Jöreskog, 1970).

This paper provides several contributions to existing literature. First, the hypothesized model advances the emerging scientific debate on the role of AI in achieving the SDGs (Khakurel et al., 2018; Nishant et al., 2020; Appio et al., 2023). The hypothesized model does not validate a direct relationship between AI and SDGs, but on the other hand demonstrate that AI adoption components mediate the relationship between organizational readiness and SDGs performance, which, in turn, is positively associated with improved economic performance. Previous research has highlighted the ambivalent relationship between AI and SDGs, noting that AI can yield positive outcomes (Platania et al., 2025). Our results reveal that organizational readiness is a critical factor influencing AI adoption, acting as a crucial organizational lever to enhance both sustainability and economic performance. Second, by illustrating that both strategic and cognitive readiness positively predict AI adoption, our study sheds light on the factors that facilitate the adoption of AI within organizations. While much of the existing literature on technology adoption (e.g. Su, Zhang and Wu, 2023) has predominantly focused on organizational readiness for change, our study introduces new insights by showing that the ability to fully leverage AI's potential is closely tied to the strategic importance attributed to the technology and the cognitive preparedness of organizational users. Third, this study contributes to the ongoing debate regarding the impact of AI in the pharmaceutical industry (e.g. Dicuonzo et al., 2023; Miozza et al., 2024). While prior research has extensively examined the role of AI across various segments of the value chain—including drug development, testing, distribution, market access, and pharmacovigilance (Satwekar et al., 2022, 2023)—our findings offer a fresh perspective. We demonstrate that organizational readiness and AI adoption can lead to enhanced performance across various areas of the pharmaceutical value chain, with small and medium-sized enterprises (SMEs) being particularly well-positioned to reap the benefits of AI adoption due to their more streamlined business structures. To conclude, this study underscores that AI can meaningfully contribute to SDGs and economic performance in the pharmaceutical industry, if supported by adequate organizational readiness. This highlights the pivotal role of strategic and cognitive readiness in aligning digital innovation with both societal goals and competitive advantage.

2. Literature review and hypothesis development

AI is widely recognized as one of the most significant technologies driving digital transformation in the contemporary era (Davenport and Ronanki, 2018; Di Vaio et al., 2020; Kinkel et al., 2022; Sjödin et al., 2023). Particularly, this technology retains interesting implications for the pharmaceutical industry, as numerous studies have highlighted its potential to disrupt the entire drug value chain. Its impact is profound, enhancing decision-making processes (e.g. Ertz et al., 2022), operational efficiency (e.g. Arief et al., 2022; Coito et al., 2022), organizational performance (Aquino et al., 2018; Alharthi et al., 2020), environmental resource deployment, waste management, and supply chain footprint (e.g. Ding, 2018) patient profiling (Liu et al., 2021) and drug discovery activities (Mak and Pichika, 2019). However, empirical evidence, both from literature and practice (Reinhardt et al., 2020; Silva et al., 2020; Satwekar et al., 2022; Volpentesta et al., 2022; Miozza et al., 2024; Satwekar et al., 2024; Deloitte Report, 2022, Deloitte Report, 2024, Mckinsey Report, 2025) suggests that pharmaceutical organizations often struggle to successfully exploit and adopt AI, particularly, at the individual and social levels (Argiyantari et al., 2020; Denicolai and Previtali, 2020), and the lack of organizational readiness is among the factors that contribute to explaining AI adoption failures (Kulkov, 2021; Holmström, 2022; Miozza et al., 2024).

The use of expert systems to augment or even substitute decision-making is well-documented in the literature (Bader et al., 1988; Kahneman et al., 2016). However, the mere implementation of such systems does not automatically translate into improved organizational efficiency or effectiveness. Previous research has highlighted that strategic commitment to digital technology is crucial to deploy AI (Vial, 2019), emphasizing that organizational failures arise from the absence of clear long-term objectives and strategic goals underlying its deployment (Shao et al., 2020; Cao et al., 2021; Mariani et al., 2023). Together, these factors are essential components of an organization's strategic readiness — its ability to align resources, capabilities, and strategic initiatives to effectively respond to current and future challenges, including those posed by emerging technologies (Lokuge et al., 2019; Holmström, 2022; Zirar et al., 2023). Equally crucial for the successful adoption of AI is the organization's readiness to embrace and effectively utilize the technology. This concept, often referred to as cognitive readiness, identifies the preparedness and capacity of individuals, groups, or entire organizations to respond effectively to complex and dynamic situations by applying cognitive skills (Lokuge et al., 2019; Holmström, 2022). Cognitive readiness encompasses employees' general predisposition toward new technology, their perceptions of possessing the necessary skills to use AI, and their ability to understand the rationale behind specific decisions, classifications, or forecasts generated by AI systems (Dwivedi et al., 2021; Schneider and Leyer, 2019). Given that the pharmaceutical industry has traditionally been considered lagging behind in the adoption of AI, because of strict regulatory thresholds and high-quality product control standards (Satwekar et al., 2022; Deloitte Report, 2022; Deloitte Report, 2024; Mckinsey Report, 2025), the first objective of this research is to investigate whether pharmaceutical organizations that are cognitively and strategically prepared to embrace emerging digital innovation paradigms are more likely to foster positive individual adoption of AI. More formally, we thus hypothesize that.

H1.a. Strategic readiness is positively related to AI adoption.

H1.b. Cognitive readiness is positively related to AI adoption.

While H1 hypothesized that organizational readiness contributing to the effective deployment of AI, H2 aims to further validate whether this configuration enhances sustainability outcomes (Courtland, 2018; Vinuesa et al., 2020; Mikalef and Gupta, 2021). The underlying rationale is the following. First, by strategically embracing digital innovation and AI, organizations empower employees to learn, allocate resources more effectively, and optimize processes, collectively improving performance while advancing sustainability objectives (El-Haddadeh et al., 2021; Li, 2022). Additionally, organizations with strong cognitive readiness are better equipped to integrate digital technologies into their operational frameworks, leading to enhanced operational efficiency, superior decision-making, and innovative business solutions that address societal and environmental challenges (Mikalef and Gupta, 2021; Hradecky et al., 2022; Akbarighatar et al., 2023). These perspectives are aligned with diverse pharmaceutical industry reports (Deloitte Report, 2024; Deloitte, 2021; Deloitte Report, 2022), which document recent trends in experimenting with AI to monitor and model the environmental impacts, optimize renewable energy systems, and reduce waste. However, despite growing interest and strategic intent, there remains a notable lack of empirical research examining AI and sustainability. This study addresses this gap by investigating sustainability performance through the lens of the SDG framework. Multiple scholarly and practice fieldworks emphasize the need for further investigation into how AI impacts SDGs and the strategic interests in terms of economic and sustainable performance (Ding, 2018; Di Vaio et al., 2020; Vinuesa et al., 2020; Kulkov, 2021; Miozza et al., 2024). In a recent study published in Nature, Vinuesa et al. (2020) suggest that AI could help achieve 79 % of the SDGs. Building on this evidence, this paper's second objective is to demonstrate that full exploitation materializes from the organizational level, in particular from readiness to digital innovation, as effectively deploying AI means that firms approach data-driven decision-making, resource optimization, enhanced monitoring over social and environmental impacts. We argue that this leads to improvement in SDGs' performance. More formally, we propose the following research hypotheses.

H2. AI adoption is positively related to SDGs performance

H3.a. AI adoption mediates the positive relationship between Strategic Readiness and SDGs performance

H3.b. AI adoption mediates the positive relationship between Cognitive Readiness and SDGs performance

In addition, AI is deemed particularly promising for its potential benefits in terms of business performance (e.g. Sjödin et al., 2023), converging on the view that this technology also has the potential to integrate economic and sustainability outcomes (Nishant et al., 2020; Merín-Rodrigáñez et al., 2024). Achieving sustainability goals is increasingly recognized as being closely intertwined with attaining economic and profitability objectives (Nishant et al., 2020; Toniolo et al., 2020), particularly in highly institutionalized fields, such as pharmaceutical industry, where key stakeholders demand that business activities align with traditional profit-oriented logic while simultaneously prioritizing sustainability (Ertz et al., 2022; Ghadge et al., 2022; Junaid et al., 2023). However, industry literature show that SDGs strategies, to be effective, in the pharmaceutical industry should be aligned with organization's core objectives, balancing regulatory compliance, scientific progress, and financial performance (e.g. Milanesi et al., 2020). Given the sector's critical role in safeguarding public health (SDG3), fostering scientific innovation (SDG9), being less environmentally impactful (SDG12) and managing complex global value chains (SDG17), it is interesting to analyze the implications in the AI era. Overall, this research addresses whether organizations – strategically and cognitively ready for digital innovation– while deploying AI can generate enhanced sustainability and economic outcomes. Firstly, organizations that contribute effectively to SDG 3 by improving access to medicines, enhancing patient safety, and supporting health outcomes tend to strengthen their legitimacy among regulators, healthcare systems, and patients (Kulkov, 2021). This legitimacy can translate into more favorable market access conditions, reduced regulatory frictions, and stronger demand for products. Similarly, alignment with SDG 9 through sustained investment in R&D (e.g. new drugs), advanced manufacturing technologies, and resilient innovation infrastructures supports productivity growth and competitive advantage. Thirdly, pharmaceutical organizations that embed responsible production principles in line with SDG 12 can achieve manufacturing cost efficiencies through waste reduction or energy optimization, while simultaneously mitigating environmental and operational risks. Lastly, engagement in cross-sector collaborations and public–private partnerships consistent with SDG 17 enhances knowledge sharing, accelerates innovation, and facilitates entry into new markets (Miozza et al., 2024). Collectively, the third paper's objective is to validate whether SDG-related practices reinforce pharmaceutical organization's strategic positioning and support superior economic performance. We thus hypothesize that.

H4. SDGs performance is positively related to economic performance

As already mentioned, AI has the potential to transform the entire pharmaceutical value chain, but most importantly it is pivotal to achieve the above SDGs outcomes. For instance, by enabling the automated analysis of large-scale data, AI accelerates the development of novel drugs contributing to SDG3 and SDG 9, shortening time-to-market cost which are considered as one of the most pressing failures in the pharmaceutical industry (Mak and Pichika, 2019). From an operational perspective, AI drives to process optimization, supporting SDG 12 by reducing resource consumption and minimizing manufacturing waste production (Reinhardt et al., 2020). Furthermore, AI facilitates collaboration across organizational, lowering boundaries by enabling data sharing between different organizations, thereby strengthening partnerships aligned with SDG 17 (Miozza et al., 2024). Through these mechanisms, this paper's fourth goal is to understand whether AI acts as enabler of sustainable development. More formally, we hypothesize that.

H5. AI Adoption is positively related to economic performance

H6. SDGs performance mediates the positive relationship between AI adoption and economic performance

Last, the pharmaceutical industry is characterized by the coexistence of diverse populations of organizations, including the so-called big pharma and small and medium-sized SMEs. Often, big pharma faces challenges in fostering innovation with continuity, given their complex and often rigid organizational structures (Wickert et al., 2016). For this reason, a common strategy is to collaborate with highly innovative SMEs (Keshavarzi Arshadi et al., 2020; Kamran et al., 2023), which are less hierarchical, bureaucratic (Polites and Karahanna, 2012; Bohlmann et al., 2024). Recent literature suggests that SMEs are more likely to benefit from adopting emerging digital technologies, including AI, as they are often led by more educated, experienced, and younger owners (McElheran et al., 2024), shaping competitive dynamics, innovation processes, and operational strategies (e.g., Corvello et al., 2024; Cubric and Li, 2024). Additionally, small firms in the pharmaceutical industry tend to have more substantive and effective approaches to sustainability, driven by implicit convictions and beliefs rather than formal structures and codes of conduct, which are more common in larger organizations (Wickert et al., 2016). This orientation makes SMEs more inclined to adopt AI and embrace the sustainability for enhanced flexibility, creativity, and innovation performance (Rafols et al., 2014; Dosi et al., 2023; Schuhmacher et al., 2023). Overall, by leveraging agile and flexible infrastructures, SMEs play a crucial role in bridging the gaps in AI implementation. Given that the pharmaceutical industry is inherently characterized by the interaction between large corporations and SMEs to drive innovative paradigms, analyzing the diverse impacts of sustainability on economic performance— depending on company size—provides a valuable context to critically reflect on future policy development, industry collaborations, and targeted investments. More formally, this paper's fifth goal is to investigate the boundary conditions in pharmaceutical industry, we hypothesize that.

H7. *Organizational size moderates the relationship between* SDGs *performance and economic performance, such that this relationship is stronger for small and medium-sized organizations rather than large organizations.*

Fig. 1 illustrates our conceptual model.

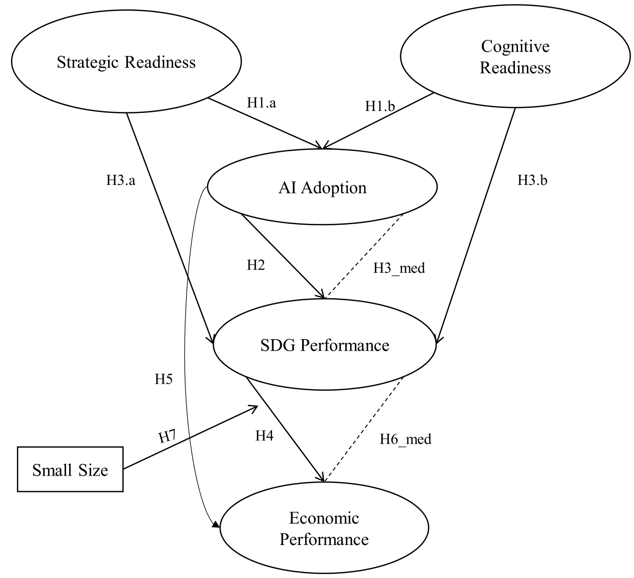

Fig. 1. Conceptual model.

3. Methodology

3.1. Research setting

We empirically tested the above hypotheses through Structural Equation Modeling (SEM) in the pharmaceutical industry – one of the industries in which AI has the most significant potential as it affects the whole drug value chain, from discovery to market access activities (Hariry et al., 2022; Harrer et al., 2019; Miozza et al., 2024).

Firstly, we started our research by contextualizing the role of AI in the pharmaceutical industry, through the consultation of archival material (academic literature and consulting reports). Table 1 summarizes the impact of AI on the various phases of the drug value chain. The first phase of the drug value chain consists of drug development activities. In this context, AI offers the potential to accelerate the cure for a wide range of diseases, including rare conditions such as Alzheimer (e.g. Wojtara et al., 2023; Zhang et al., 2023), by analyzing vast amounts of data — including molecular structures and biological pathways— to identify promising drug candidates. Furthermore, AI can support the organization of the clinical trials phase, particularly by integrating and analyzing patient-specific data, such as electronic medical records, handwritten documents, medical imagery, and socioeconomic data, to identify eligible participants more efficiently and accurately than traditional trial methodologies (Hariry et al., 2022).

The second phase of the drug value chain is manufacturing. This phase involves several highly regulated stages, from raw material processing to final product packaging, where AI offers significant improvements. In particular, AI-powered predictions can optimize equipment utilization, forecast maintenance needs, production waste, energy consumption, and product quality control, leading to more efficient and reliable processes that adhere to the high standards required for drug production (Kulkov, 2021; Hariry et al., 2022).

The third phase of the drug value chain encompasses all activities related to delivering drugs to patients, from storage and logistics to final usage. AI's relevance in this phase is multifaceted. In particular, when coupled with IoT devices and blockchain technology, AI can enhance cold chain management by continuously monitoring environmental parameters during drug transportation, as well as planning more environmentally friendly routes for transporting drugs. This real-time data transmission enables better decision-making and optimization of supply chain environmental and social performance, most importantly, preventing the commercialization of expired and counterfeit drugs (Chamekh et al., 2017). Moreover, AI, integrated with other digital technologies such as Augmented Reality, Virtual Reality, and Robotics, can support inventory management activities by automating warehouse operations that would otherwise require human labor, particularly in

Table 1
AI relevance within pharmaceutical industry and SDG framework.

Value Chain Phase	AI Benefits	SDG Related	Source
Drug Development and Research	• Facilitating the discovery of novel drug candidates • Enhanced support to discover new treatments for rare diseases • Potentially substituting initial clinical trial phases • Supporting in the evaluation and matching of Patient-Site for Trials • Minimizing delays related to trial activities • Enabling cross-disciplinary partnerships	SDG 3 - Good Health and Well-being SDG 9 - Industry, Innovation, and Infrastructure SDG 17 - Partnerships for the Goals	*Archival Material:* (Hariry et al., 2022; Wojtara et al., 2023; Zhang et al., 2023; Miozza et al., 2024) Deloitte Report 2018, European Federation of Pharmaceutical industries and Associations Report 2024, Deloitte Report 2022, Deloitte Report 2024, Mckinsey Report 2025 *+ Interviews*
Manufacturing	• Predicting equipment breakdowns and Maintenance • Enhancing drug quality Assurance • Minimizing Resource Waste • Supporting in Energy efficiency practices • Fine-tuning production volumes through real-time demand insights	SDG 3 - Good Health and Well-being SDG 9 - Industry, Innovation, and Infrastructure SDG 12 - Responsible Consumption and Production	*Archival Material:* Kulkov (2021); Miozza et al. (2024); Reinhardt et al. (2020); A. Sharma et al. (2020); Trenfield et al. (2022); Deloitte Report 2018, European Federation of Pharmaceutical industries and Associations Report 2024, Deloitte Report 2022, Deloitte Report 2024, Mckinsey Report 2025 *+ Interviews*
Patient Access	• Optimize warehouse Management • Detect counterfeited drugs • Automating Procurement Management • Supporting staff and material shortages Management • Personalized Medicine	SDG 3 - Good Health and Well-being SDG 9 - Industry, Innovation, and Infrastructure SDG 12 - Responsible Consumption and Production SDG 17 - Partnerships for the Goals	*Archival Material:* Chamekh et al. (2017); Kulkov (2021); Miozza et al. (2024); Trenfield et al. (2022); Deloitte Report 2018, European Federation of Pharmaceutical industries and Associations Report 2024, Deloitte Report 2022, Deloitte Report 2024, Deloitte 2021, Mckinsey Report 2025 *+ Interviews*

potentially hazardous environments, thereby improving safety.

Despite documented benefits, multiple empirical and field works point out that the pharmaceutical industry is lagging behind in the implementation of digital technologies, in particular AI, because of strict regulatory requirements and high product quality standards. This tension between innovation potential and structural resistance makes the pharmaceutical industry a rich and relevant setting for investigating the role of AI. Furthermore, our study aims to understand the role of AI in achieving sustainability, particularly within the framework of the SDGs.

Due to the general lack of indicators and literature linking AI and the SDGs in the context of the pharmaceutical industry, we supplemented archival material with fieldwork (industry reports and published literature) to come up with relevant measurement scale. Afterwards we interviewed 16 key experts to provide context for the use of AI in achieving the SDGs within the pharmaceutical industry. Interviews were conducted with diverse professionals holding managerial roles, including CEOs, Chief Industrial Operations Officers, Chief Institutional Affairs Officers, Supply Chain Managers, Manufacturing Quality Control Managers, and R&D Managers, who offered comprehensive insights into AI and SDG challenges and opportunities across different organizational levels and value chain phases, in particular.

(i) SDG 3 – Good Health and Well-being: By accelerating the development of new drugs and clinical trials, AI contributes to improving global health outcomes and reducing the burden of diseases, as more efficient drug development processes can potentially result in life-saving medications being made available sooner. Additionally, by enhancing manufacturing efficiency and quality control, AI ensures the consistent availability of safe and effective medications. Through integration with technologies such as IoT and blockchain, AI also helps prevent the commercialization of expired and counterfeit drugs;

(ii) SDG 9 - Industry, Innovation, and Infrastructure: AI drives innovation in drug development processes, fostering the creation of smart factories, leading to production line optimization, predictive maintenance, smart logistics, and supporting the realization of personalized medicine.

(iii) SDG 12 – Responsible Consumption and Production: AI-driven optimization in manufacturing directly supports responsible production practices. Specifically, the implementation of AI enables companies to optimize resource utilization during operations and plan transport routes that reduce transportation costs and fuel consumption.

(iv) SDG 17 – Partnerships for the Goals: The development and implementation of AI in drug development often involve collaborations between scientific researchers and a wide range of stakeholders, such as cloud computing providers, regulatory bodies, and research institutions for drug approvals fostering knowledge sharing, supply chain sustainability and preventing the commercialization of expired and counterfeit drugs.

3.2. Data collection

We collected data on 511 employees in the pharmaceutical industry through a survey questionnaire to gather their perceptions on AI adoption, strategic and cognitive readiness, economic performance, and SDGs performance. The survey items related to organizational readiness and AI adoption were drawn from existing literature. At the same time, due to a lack of relevant measurement scales, insights from our archival material and expert interviews were used to operationalize the relationship between AI and SDGs in the pharmaceutical industry (Kumar et al., 2024). Before distribution, we conducted a pilot test of the questionnaire to gather feedback and enhance its clarity and ease of use (Agarwal et al., 2025). Once the survey items were qualitatively validated, the survey was administered between June and December 2023.

Data collection was conducted through Prolific, a well-established academic platform that has seen growing adoption in recent research within management and technology domains (e.g. Agarwal et al., 2025; Chong et al., 2025). Prolific was chosen due to its ability to provide access to a broad and heterogeneous pool of professionally active respondents, while simultaneously allowing researchers to apply detailed pre-screening criteria tailored to specific research contexts, in this case Pharmaceutical Industry. A key advantage of the Prolific Platform lies in its capacity to implement refined eligibility filters, which improves sample precision and supports data quality—an approach that has been highlighted as particularly effective when studying narrowly defined professional groups that are otherwise difficult to access (Vinoi et al., 2024). Furthermore, Prolific maintains ongoing verification of participant profiles and actively oversees response reliability, thereby limiting common concerns associated with inattentive participation or low-quality data (Agarwal et al., 2024).

Although the use of online research platforms entails certain methodological constraints, these were addressed through rigorous sampling strategies, screening mechanisms, and validation procedures. To ensure a high level of respondent suitability, survey participation was anonymous and limited to individuals who satisfied a set of predefined conditions, including prior exposure to AI adoption, knowledge of sustainability practices, and involvement in organizational decision-making or implementation activities within a pharmaceutical setting. We acknowledge that anonymous responses represent a limitation, preventing us from gathering additional information on the organizations of survey respondents. At the same time, however, this choice increased the openness of respondents along with their propensity to provide their true perceptions regarding the main dimensions we explore in our research.

To conclude, the final sample is considered both methodologically sound and well aligned with the objectives of the study.

3.3. Sample

Our data encompasses the primary stages of the industry's value chain, specifically Drug Research & Development, Manufacturing, and Patient Access. These stages are crucial for adopting AI in terms of operational efficiency and sustainability. Moreover, the sample captures diverse backgrounds of respondents, ensuring a comprehensive perspective on AI-driven changes across the whole pharmaceutical value chain. In general, the pharmaceutical industry is constrained and limited by stringent regulatory and quality standards whose primary objective is to safeguard patient safety (Harrer et al., 2019; Kulkov, 2021; Satwekar et al., 2022). Despite the heterogeneous nature of the pharmaceutical industry, encompassing various companies such as Biotech, Generic Manufacturers, and highly innovative startups, our sample is representative in terms of innovation strategies towards AI. This technology, indeed, is being deployed following a slow yet uniformly defined trend across all industry players irrespective of value chain phase or business model strategy, as highlighted in multiple industry reports (e.g. Deloitte Report, 2022; Deloitte Report, 2024; Mckinsey Report, 2025). Both reports and literature highlight that the industry is consistently investing and implementing AI, as it not only brings organizational-level improvements (e.g., process optimization, energy efficiency), but also contributes to the broader macro trend envisioned and acknowledged by all industry experts: Personalized Medicine (Trenfield et al., 2022). Therefore, regardless of a company's specific characteristics or business model, firms are collectively moving toward AI adoption. Through our survey, we gathered information about company size and turnover. Such information allowed us to ensure our sample validly represents the pharmaceutical sector, ranging from large multinational corporations to smaller, specialized firms (e.g. Deloitte Report, 2024; Mckinsey Report, 2025). Overall, our sample well represents the pharmaceutical sector, including different types of companies in terms of organizational size (Table 2) and revenue distribution (Fig. 2).

Table 2
Demographics of the sample.

Firm Size		
N. of Employees	Frequency	Percentage
0-249 Employees	326	63.8
+250 Employees	185	36.2
Total	511	100
Pharmaceutical Value Chain Area		
Value Chain Areas	Frequency	Percentage
Drug Development and Research	110	21.53
Manufacturing	177	34.64
Customer and Patient Access	224	43.83
Total	511	100
Turnover		
Range	Frequency	Percentage
0 - 1M$	88	17.22
1M$ - 50M$	154	30.14
50M$ - 500M$	126	24.65
+500M$	143	27.99
Total	511	100

3.4. Variables and measures

3.4.1. Cognitive readiness and strategic readiness

Two key dimensions to comprehensively assess an organization's preparedness for digital innovation were identified in our study: Strategic Readiness and Cognitive Readiness. Each dimension is measured using specific items that capture different aspects of the organization's capacity to embrace and implement new digital technologies identified by Lokuge et al. (2019). Strategic Readiness is composed of three items capturing how well the organization is positioned in terms of planning, goal setting, and communication regarding the adoption of new digital technologies. An example item is: “The organization has effectively communicated its strategic goals concerning the new technology to stakeholders.” Cognitive Readiness is composed of three items focused on the individual capabilities within the organization, specifically the knowledge, skills, and adaptability required for successful technology deployment. An example item is: “The organization owns the necessary know-how to effectively implement the new technology”. Items are rated on a 7-point Likert-type answering scale ranging from 1 to 7.

3.4.2. AI adoption

Individual behaviors have been recognized as critical influential factors in technology adoption literature (Venkatesh et al., 2003, 2012; Venkatesh, 2022), and there is a growing discussion among scholars to address this issue in the context of AI (Venkatesh, 2022; Ho et al., 2023). To assess the adoption of new technologies within an organization, we use the following constructs: *Performance Expectancy, Behavioral Intention, Social influence and Effort Expectancy* (Venkatesh et al., 2003, 2012; Venkatesh, 2022). Each of these constructs is measured using specific items rated on a 7-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (7). Using this measurement scale allowed for a comprehensive understanding of how employees perceive, intend to use and are influenced by adopting AI. In particular, Effort Expectancy refers to the degree of AI easiness to learn and use. This construct captures perceptions related to the simplicity and intuitiveness of the technology. Behavioral Intention measures the likelihood that employees will adopt and use AI in the future, assessing their willingness and plans regarding the adoption of AI. Performance Expectancy examines the perceived benefits of AI in enhancing job performance and efficiency. This construct focuses on how employees believe AI will help them to complete tasks more quickly, improve the quality of their work, and increase their overall productivity. Finally, Social Influence evaluates the extent to which employees perceive that the adoption of the AI is supported and encouraged by their managers and peers, therefore considering the role of leaders and other organizational members to support and sustain adoption.

3.4.3. SDGs performance

Sustainability is generally understood as a multidimensional construct that integrates environmental, social and economic sustainability (Elkington, 2018). In the pharmaceutical sector, these dimensions are closely interconnected, as economic performance relies on

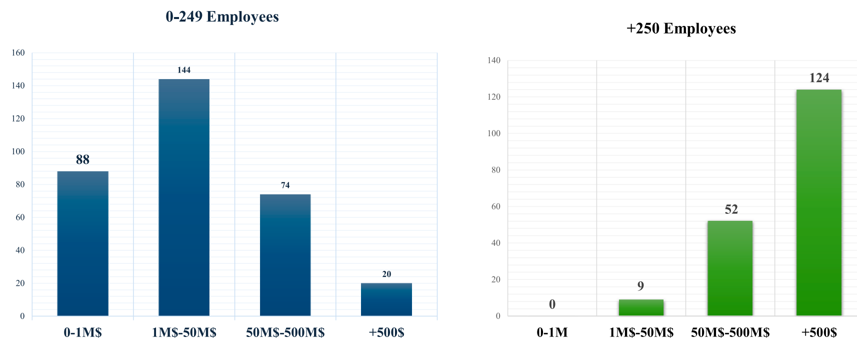

Fig. 2. – Sample representation size/turnover.

innovation that simultaneously supports public (social) health outcomes, while minimizing environmental impacts. In light of this complexity, we employed SDGs as theoretical lens to conceptualize and measure sustainability performance. However, given that research on the linkage between AI and the SDGs in the pharmaceutical industry is scarce, and hence the lack of validated measures,[1] we draw on archival data (literature and industry reports) and field interviews to develop our survey items (Kumar et al., 2024). Specifically, AI interacts directly with SDGs #3, #9, #12, and #17, as identified through this analysis. Particularly, for SDG #3″Good Health and Well Being" we gained a detailed perspective on how pharmaceutical companies are addressing global health challenges, improving, and getting more efficient drug development phases through the adoption of AI technologies. For SDG #9, we learned that "Industry, innovation and infrastructure" are also relevant in the field, as AI helps organizations to innovate across the whole value chain. Regarding SDG #12 "Responsible Consumption and Production", we understood that responsible production is central in the pharma industry to ensure that drug production occurs sustainably, reducing environmental impacts and promoting ethical practices. Interviewees provided AI-relevant information on sustainable initiatives, such as proposing new activities for responsible waste management and green production principles. Finally, for SDG #17 our interviews revealed that "Partnerships for the Goals" are of particular importance because the capability to deploy AI technologies and consequently address global issues such as access to medicines, shared research, and the promotion of sustainable solutions, happens mostly through alliances and partnerships.

Overall, the SDG framework represents an appropriate operational lens in the pharmaceutical context because it translates the broad and abstract notion of sustainability into concrete, policy-endorsed, sector aligned with AI relevant implications. Given the increasing deployment of AI in the pharmaceutical industry to address grand societal and environmental challenges, the SDG framework offers a theoretically robust and practically meaningful proxy for sustainability performance. At the same time, this operationalization may overlook the three sustainability dimensions considered in this study- Economic, Social and Environmental. In particular, SDGs do not explicitly capture Economic performance. For this reason, we decided to further capture this dimension as a distinct construct, recognizing its importance alongside the dimensions of sustainability, as detailed in the following subparagraph.

[1] A notable exception is represented by the Overview Report on "Embedding Environmental Sustainability into Pharma's DNA Contents, year 2022", which we carefully considered to finalize our questionnaire.

3.4.4. Economic performance

Economic performance is a widely used dependent variable in management research. Accordingly, in the context of our research, we operationalize economic performance in terms of the following self-reported financial indicators (Latifi et al., 2021; Khan et al., 2022): (i) Profits, reflecting the organization's ability to generate profit from its operations; (ii) Revenue Streams, assessing the stability and diversity of the firm's revenue sources; and (iii) Market Share, evaluating the firm's market presence relative to its competitors. We asked respondents to report on a 7-point Likert scale their firm's economic performance.

3.4.5. Moderating variable: organizational size

To test the hypothesized role of organizational size as a moderator in our model, we consider the size of the organizations in which respondents were employed. Specifically, we use a binary variable that takes the value of 1 if the respondent is employed in a small to medium-sized organization, and 0 if they are employed in a large organization instead. The threshold of 250 employees, routinely used in existing research (Kotey and Folker, 2007), is used to distinguish between small-medium and large firms. Table 3 represents descriptive statistics of the model's variables.

4. Analysis and results

Our analysis was conducted in several stages. We began by validating our measurement scales through Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Then, we employed Structural Equation Modeling (SEM) to test our research hypotheses regarding the relationships between organizational readiness, AI adoption, SDGs performance, and economic performance. SPSS was utilized for the EFA, while Lisrel was used for both the CFA and SEM analyses. Mediation effects were tested using the Prodclin software package, following the methodological approach outlined by authors (Jöreskog, 1970; Churchill Jr, 1979; Steenkamp and Van Trijp, 1991).

Table 3
Descriptive statistics.

Constructs	Mean	S.D.	Skewness	Kurtosis
Effort Expectancy (E_Exp)	5.34	1.32	−0.78	0.33
Behavioral Intention (B_Int)	5.88	1.17	−1.13	1.16
Performance Expectancy (P_Exp)	5.94	1.10	−1.28	1.98
Social Influence (Si)	5.40	1.24	−0.81	0.67
Cognitive Readiness (Cog_Read)	5.07	1.38	−0.68	0.03
Strategic Readiness (S_Read)	5.22	1.42	−0.81	0.23
SDG Performance (SDG)	4.89	1.57	−0.66	−0.15
Economic Performance (ECP)	5.10	1.36	−0.76	0.57

4.1. Measurement model

We began by testing the reliability of our scale to ensure that the selected items accurately represent the hypothesized constructs. Internal consistency was assessed using Cronbach's α (Jöreskog, 1970; Churchill Jr, 1979; Steenkamp and Van Trijp, 1991). As shown in Table 4, the criteria for proceeding with Exploratory Factor Analysis (EFA) were satisfied, with most constructs achieving Cronbach's α coefficients greater than 0.8 (Jöreskog, 1970; Churchill Jr, 1979; Steenkamp and Van Trijp, 1991). We then conducted an EFA to identify the smallest number of factors that effectively summarize the original set of items, ensuring that $m > n$ (Jöreskog, 1970; Churchill Jr, 1979; Steenkamp and Van Trijp, 1991). Typically, EFA can result in some loss of variance; therefore, retaining as much variance as possible is crucial. In our analysis, this condition was successfully met. Using Maximum Likelihood Analysis with VARIMAX rotation, we achieved a variance of 72.62%, accounting for 8 factors out of 22, with no significant cross-loadings (greater than 0.4) (Jöreskog, 1970; Churchill Jr, 1979; Steenkamp and Van Trijp, 1991). Following this step, we aimed at understanding the degree of consistency between repeated measures of the same construct by testing convergent and discriminant validity conditions through a CFA (Jöreskog, 1970; Churchill Jr, 1979; Steenkamp and Van Trijp, 1991). The correlation matrix reported in Table 5 shows high levels of correlation (ϕ_{12}) between the different constructs. Despite such high correlation values, all of them exceed the conditions of convergent and discriminant validity provided by Fornell and Larcker (1981), which entails $AVE\xi_1 > \phi_{12}^2$; $AVE\xi_2 > \phi_{12}^2$ verified in all cases.

- $\left\{\begin{array}{l}\mathrm{AVE}(\mathit{Behavioral\ Intention}) = 0.686 \\ \mathit{AVE}(\mathit{Performance\ Expectancy}) = 0.630\end{array}\right. > (\phi_{12}^2 = (0.743)^2 = 0.552)$
- $\left\{\begin{array}{l}\mathrm{AVE}(\mathit{Social\ Influence}) = 0.716 \\ \mathit{AVE}(\mathit{Performance\ Expectancy}) = 0.630\end{array}\right. > (\phi_{12}^2 = (0.641)^2 = 0.410)$
- $\left\{\begin{array}{l}\mathrm{AVE}(\mathit{Cognitive\ Readiness}) = 0.704 \\ \mathit{AVE}(\mathit{SDGs\ Performance}) = 0.524\end{array}\right. > (\phi_{12}^2 = (0.626)^2 = 0.391)$
- $\left\{\begin{array}{l}\mathrm{AVE}(\mathit{Strategic\ Readiness}) = 0.610 \\ \mathit{AVE}(\mathit{SDGs\ Performance}) = 0.524\end{array}\right. > (\phi_{12}^2 = (0.687)^2 = 0.471)$
- $\left\{\begin{array}{l}\mathrm{AVE}(\mathit{Cognitive\ Readiness}) = 0.704 \\ \mathit{AVE}(\mathit{Strategic\ Readiness}) = 0.610\end{array}\right. > (\phi_{12}^2 = (0.719)^2 = 0.568)$

This allowed us to claim that the scale was reliable, valid, and ready to be tested for SEM analysis (Jöreskog, 1970; Churchill Jr, 1979; Steenkamp and Van Trijp, 1991).

4.2. Structural model

In the final step, we aimed to evaluate the structural equation model by testing the significance of the paths, examining the effects of the hypothesized relationships, and assessing the explanatory power of our research model. The specified model was found to fit the data well, as all relevant indicators satisfy the SEM conditions (Jöreskog, 1970; Churchill Jr, 1979; Steenkamp and Van Trijp, 1991): $\chi2$ (degrees of freedom) = 347.051 (183); *Global Fit Index* (GFI) = 0.942; *Adjusted Goodness of Fit Index* (AGFI) = 0.920; *Comparative Fit Index* (CFI) = 0.992; *Root Mean Square Error Of Approximation* (RMSEA) = 0.0415, *P-Value for Test of Close Fit* (RMSEA <0.05) = 0.982, *Standardized RMR* = 0.0375. Tables 6 and 7 present the results of the Structural Equation Modeling (SEM) analysis. Specifically, Table 6 details the direct hypothesized effects, while Table 7 illustrates the mediation effects tested using the asymmetric confidence interval technique available in Prodclin Software (MacKinnon, 2012). Tables 8 and 9 provide the results for the moderating effect of organizational size on the

Table 4
Validity and reliability items.

Constructs	Items	Questionnaire item	CFA Loadings	Cronbach's α	Composite Reliability	AVE
Effort Expectancy (E_Exp)	E_Exp 1	I find AI Easy to learn	0.634	0.831	0.788	0.654
	E_Exp 2	I find AI Easy to use	0.809			
Behavioural Intention (B_Int)	B_Int 1	I intend to adopt AI in the next year	0.707	0.896	0.867	0.686
	B_Int 2	I predict I would use AI in the next year	0.732			
	B_Int 3	I plan to adopt AI in the next year	0.798			
Performance Expectancy (P_exp)	P_exp 1	I find AI useful in my job	0.710	0.828	0.773	0.630
	P_exp 2	I find AI useful to accomplish tasks more quickly	0.704			
Social Influence (Si)	Si_1	Adoption of AI is supported by management	0.764	0.869	0.834	0.716
	Si_2	Adoption of AI is supported by the organization	0.770			
Cognitive Readiness (Cog_Read)	Cog_Read 1	Members of my organization have the appropriate knowledge for new technology deployment	0.789	0.903	0.876	0.704
	Cog_Read 2	Members of my organization have the appropriate skills for new technology deployment	0.797			
	Cog_Read 3	Members of my organization have the appropriate digital adaptability for new technology deployment	0.688			
Strategic Readiness (S_Read)	S_Read 1	My company has clear long-term objectives for new technology deployment	0.687	0.869	0.824	0.610
	S_Read 2	My company has coherent strategic goals for new technology deployment	0.755			
	S_Read 3	My company communicates clearly its strategic goals for new technology deployment	0.636			
Economic Performance (ECP)	ECP 1	In the last years, my company increased Profits	0.755	0.849	0.801	0.581
	ECP 2	In the last years, my company increased Revenues	0.756			
	ECP 3	In the last years, my company increased Market Share	0.493			
SDG Performance (SDG)	SDG 1	My company adopts new equipment aimed at reducing the environmental footprint	0.653	0.872	0.813	0.524
	SDG 2	My company adopts continuous manufacturing and green chemistry principles	0.663			
	SDG 3	My company established new collaborations to ensure fair and equitable treatment accessibility	0.679			
	SDG 4	My company is committed to ensuring equal access to treatments across the world	0.538			

Table 5
Correlation matrix.

	Variable	1	2	3	4	5	6	7
1	Ecp	-						
2	Sdg	0.497	-					
3	B_Int	0.510	0.457	-				
4	Si	0.528	0.554	0.607	-			
5	E_Exp	0.413	0.446	0.444	0.458	-		
6	P_Exp	0.548	0.435	**0.743**	**0.641**	0.547	-	
7	S_Read	0.481	**0.687**	0.548	**0.641**	0.467	0.571	-
8	Cog_Read	0.430	**0.626**	0.446	0.581	0.543	0.483	**0.719**

Note: coefficients in bold represents high correlations.

Table 6
Direct effects.

Hypothesis	Loadings	Standard Deviation	T Statistics	*p*-value	Interpretation
H1.a.I: S_read → B_Int	$\gamma = 0.392$	0.060	6.549	***	Accepted
H1.a.II: S_read →Si	$\gamma = 0.419$	0.062	6.810	***	Accepted
H1.a.III: S_read →E_Exp	$\gamma = 0.148$	0.066	2.234	**	Accepted
H1.a.IV: S_read → P_Exp	$\gamma = 0.348$	0.056	6.255	***	Accepted
H1.b.I: Cog_read → B_Int	$\gamma = 0.086$	0.055	1.558	—	Rejected
H1.b.II: Cog_read →Si	$\gamma = 0.219$	0.057	3.812	***	Accepted
H1.b.III: Cog_read →E_Exp	$\gamma = 0.386$	0.066	5.827	***	Accepted
H1.b.IV: Cog_read → P_Exp	$\gamma = 0.109$	0.052	2.104	**	Accepted
H2.a: B_Int →SDG	$\beta = 0.131$	0.092	1.433	—	Rejected
H2.b: Si→SDG	$\beta = 0.174$	0.080	2.177	**	Accepted
H2.c: E_Exp →SDG	$\beta = 0.119$	0.066	1.807	—	Rejected
H2.d: P_Exp→SDG	$\beta = -0.179$	0.120	−1.493	—	Rejected
H3.a.I: S_Read→SDG	$\gamma = 0.558$	0.075	7.986	***	Accepted
H3.b.I: Cog_Read→SDG	$\gamma = 0.303$	0.069	4.442	***	Accepted
H4: SDG → ECP	$\beta = 0.194$	0.046	4.183	***	Accepted
H5.a: B_Int → ECP	$\beta = 0.151$	0.084	1.799	—	Rejected
H5.b: Si→ECP	$\beta = 0.196$	0.068	2.870	***	Accepted
H5.c: E_Exp → ECP	$\beta = 0.088$	0.057	1.557	—	Rejected
H5.d: P_Exp→ECP	$\beta = 0.260$	0.109	2.384	**	Accepted

Note: $p < 0.001$ = ***; $p < 0.005$ = **.

Table 7
Mediation effects.

Hypothesis	Indirect effect	Standard Deviation	*p*-value	Interpretation
H3.a.II: S_read → B_Int→SDG	$\beta = 0.051$	0.037	***	Accepted
H3.a.III: S_read → Si →SDG	$\beta = 0.073$	0.035	***	Accepted
H3.a.IV: S_read →E_Exp→SDG	$\beta = 0.018$	0.013	***	Accepted
H3.a.IV: S_read → P_Exp → SDG	$\beta = -0.062$	0.043	***	Accepted
H3.b.II: Cog_read → B_Int → SDG	$\beta = 0.011$	0.011	***	Accepted
H3.b.III: Cog_read →Si →SDG	$\beta = 0.038$	0.020	***	Accepted
H3.b.IV: Cog_read → E_Exp → SDG	$\beta = 0.046$	0.027	***	Accepted
H3.b.IV: Cog_read → P_Exp → SDG	$\beta = -0.020$	0.016	***	Accepted
H6.a: B_Int → SDG →ECP	$\beta = 0.034$	0.017	***	Accepted
H6.b: Si → SDG →ECP	$\beta = 0.025$	0.019	***	Accepted
H6.c: E_Exp → SDG →ECP	$\beta = 0.023$	0.014	***	Accepted
H6.d: P_Exp → SDG →ECP	$\beta = -0.035$	0.025	***	Accepted

Note: $p < 0.001$ = *** The indirect effect corresponds to the product of path “a” and path “b”; significance was assessed through Prodclin Software.

relationship between SDGs performance and economic performance (Byrne et al., 2005). The moderation analysis compares nested models: an unconstrained model, where the moderation parameter is freely estimated across groups (Small and Large Companies), and a constrained model, where the moderation effect parameters are set to be equal across these groups. As shown in the invariance analysis (Table 8), the model adheres to Scalar Invariance principles ($p < 0.01$), allowing for a valid comparison of the constructs' basic structure, structural relationships, covariances, and latent variable means across the two groups. This ensures that the hypothesized moderation effects can be meaningfully compared. In evaluating the nested models to confirm the moderation effects (Table 9), the model with the lower chi-square value is favored, indicating a significant difference between the groups and confirming the presence of moderation. Finally, Table 10 compares the significance of moderating effects between small-medium and large-sized organizations. The results indicate that small-sized firms serve as a statistically significant moderator (H7: $\beta = 0.327$, $p < 0.01$).

The results overall address strategic and cognitive readiness as antecedent dimensions for AI Adoption and, in turn, achieving higher SDGs performance. In particular, we find that the strategic (H1.a) and cognitive (H1.b) readiness variables are positively and significantly associated with AI Adoption components (H1.a.I $\gamma = 0.392$, $p < 0.01$), (H1.a.II $\gamma = 0.419$, $p < 0.01$), (H1.a.III $\gamma = 0.148$, $p < 0.05$), (H1.a.4 $\gamma = 0.348$, $p < 0.01$), (H1.b.II $\gamma = 0.219$, $p < 0.01$), (H1.b.III $\gamma = 0.386$, $p < 0.01$), (H1.b.IV $\gamma = 0.109$, $p < 0.05$). An exception is the relationship between cognitive readiness and the “Behavioral intention” component of adopt AI, which although positive is not statistically significant. In addition, as hypothesized, strategic and cognitive readiness are positively and significantly related to SDGs performance (H3.a.I $\beta = 0.558$, $p < 0.01$) (H3.b.I $\beta = 0.303$, $p < 0.01$).

Our findings also show that, while the relationship between AI Adoption components and SDGs Performance hypotheses (H2) is not supported (except for the Social Influence component H2.b, $\beta = 0.174$, $p < 0.05$), AI Adoption mediates the relationship between strategic

Table 8
Invariance analysis.

Model	χ^2	df	$\Delta\chi^2$	Delta df	*p*-value	CFI	ΔCFI	RMSEA	p close-fit
Configural Invariance	596.105	366	—	—	—	0.989	—	0.046	0.811
Metric Invariance	618.218	380	22.113	14	0.07	0.989	0	0.0459	0.820
Scalar Invariance	638.553	402	20.335	22	0.56	0.989	0	0.0438	0.921

Table 9
Comparing free and constrained models for moderation.

Model	χ^2	df	$\Delta\chi^2$	Delta df	*p*-value	CFI	ΔCFI	RMSEA
Free	639	402	—	—	—	0.989	—	0.0438
Constrained	828	413	189.225	11	***	0.981	−0,007	0.0543

Note: $p < 0.001$ = ***.

Table 10
Moderating Effects - Small versus Big Sized Firms effect.

Hypothesis	Loadings	Standard Deviation	T Statistics	*p*-value	Interpretation
H7: SDG → Mo: Small Size →ECP	$\beta = 0.327$	0.059	5.508	***	Accepted
H7: SDG → Mo: Big Size →ECP	$\beta = -0.026$	0.059	−0.443	—	Rejected

Note: $p < 0.001$ = ***.

readiness and cognitive readiness and SDGs performance (H3.a. II, $\beta = 0.051$, $p < 0.01$), (H3.a.III, $\beta = 0.073$, $p < 0.01$), (H3.a.IV: $\beta = 0.018$, $p < 0.01$), (H3.a.V: $\beta = -0.062$, $p < 0.01$), (H3.b.II: $\beta = 0.011$, $p < 0.01$), (H3.b.III: $\beta = 0.038$, $p < 0.01$), (H3.b.IV: $\beta = 0.046$, $p < 0.01$), (H3.b.V $\beta = -0.020$ $p < 0.01$). Moreover, our results confirm that – although only for the two components "Social Influence" (H5.b $\beta = 0.196$, $p < 0.01$) and "Performance Expectancy" (H5.d $\beta = 0.260$, $p = p < 0.05$) – there is a positive relationship between AI Adoption and economic performance, and that SDGS performance mediates the relationship between AI Adoption and economic performance (H6.a: $\beta = 0.034$, $p < 0.01$), (H6.b $\beta = 0.025$, $p < 0.01$), (H6.c: $\beta = 0.023$, $p < 0.01$) in all its components. Overall, this confirms that a positive AI Adoption, facilitated by a greater strategic and cognitive readiness, mediates of SDGs attainment, which in turn is associated with greater economic performance.

Finally, our results show that SDGs is related to ECP significantly and positively (H4 $\beta = 0.194$, $p < 0.01$), and that organizational size moderates this relationship such that it is stronger for small-medium firms, rather than large companies (H7: $\beta = 0.327$, $p < 0.01$).

5. Discussions

5.1. *Theoretical contributions*

This study advances theoretical understanding of the organizational dynamics that enable AI adoption and its impact on sustainability and economic outcomes, particularly in the context of the pharmaceutical industry. The findings offer both confirmation of existing assumptions and novel insights that extend the current academic discourse across multiple fronts. Guided by this perspective, this paper adopts organizational readiness as enabler of AI adoption, positing that firms' strategic and cognitive readiness shapes not only the extent of AI deployment but also its ability to generate sustainability outcomes, analyzed through the SDGs theoretical framework, further analyzing the economic performance implications.

First, the hypothesized model empirically demonstrates that organizational readiness is not merely a precursor to AI adoption but a determining factor for successful, full-scale deployment within organizations, confirming prior literature elaborations that encompass both strategic foresight (e.g., clear long-term objectives) and cognitive preparedness (e.g., employees' ability to understand and work with AI technologies) (Lokuge et al., 2019; Cao et al., 2021; Holmström, 2022; Belhadi et al., 2024). Within this framework, AI is not treated as an independent driver of sustainability, but rather as a mechanism whose effectiveness depends on pre-existing organizational conditions. The hypothesized model, indeed, highlights that both Strategic (H1.a) and Cognitive (H1.b) readiness are critical factors underlying AI Adoption, as well as achieving higher performance in terms of SDGs (H3). This alignment emerges as a fundamental cornerstone, especially for the pharmaceutical industry, where organizational strategies, policies, and structures to embrace AI are shifting towards sustainability (Hao, 2019; Strubell et al., 2019; Brevini, 2020; Floridi et al., 2021; Lin, 2021; Yu et al., 2022). It is worth mentioning that while the positive relationship between Cognitive and Strategic Readiness with Social Influence, Effort Expectancy, and Performance Expectancy is validated (H1.a and H1.b), Behavioral Intention to Use AI and Cognitive Readiness is not statistically significant (H1.b.I), suggesting this relation may be influenced by different factors, as indicated by various perspectives in the literature, characterizing AI as ambiguous, challenging to understand the reasoning behind decision-making, and worrying in terms of job replacement (Tversky and Shafir, 1992; Anderson, 2003; Schneider and Leyer, 2019; Cao et al., 2021; Dwivedi et al., 2021). These findings reinforce the notion that, particularly in the pharmaceutical industry less reactive to deploy digital innovation, AI adoption is contingent upon an organizational structure that aligns strategic with cognitive intentions.

Second, our hypothesized model does not validate the direct relationship between AI adoption components and SDGs (H2), except for Social Influence (H2.b). However, as a second theoretical contribution, the hypothesized model demonstrates all individual components of AI Adoption (H3) as mediators in the relationship between Strategic and Cognitive Readiness and to achieve enhanced SDGs performance. This underscores the centrality of AI not merely as a technological layer, but as a conduit through which organizational capacity is translated into sustainability outcomes, unveiling the intricate interplay between Strategic and Cognitive Readiness and the realization of enhanced SDGs performance (Courtland, 2018; Gupta et al., 2021). This suggests that the organizational landscape and its readiness profoundly shape the ability to leverage AI technologies effectively, subsequently driving progress toward SDGs objectives (Vinuesa et al., 2020). Building on this logic, this paper challenges deterministic views of AI as an automatic enabler of sustainability outcomes, suggesting instead that its impact is substantiated, when embedded within a readiness-driven organizational architecture.

Third, extending this reasoning, the model further examines whether AI leads to superior economic performance (H5), particularly in conjunction with SDGs as the underlying mediating factor (H6). This structure adds depth to previous studies that examined these links in isolation (Dwivedi et al., 2021; Sjödin et al., 2023). By explicitly modeling the role of SDGs performance as a mediator between AI adoption and economic outcomes, our findings suggest that SDGs performance is not a by-product but a prerequisite to long-term financial gains in digital transformation contexts. This supports a shared value perspective (Kramer and Porter, 2011) and contributes to a growing body of work emphasizing the business case for sustainability (Eccles et al., 2014) demonstrating that SDGs achievements can serve as a bridge between AI investments and long-term economic gains (Tversky and Shafir, 1992; Anderson, 2003; Schneider and Leyer, 2019; Dwivedi et al., 2021). It is noteworthy that while Social Influence and Performance Expectancy to use AI exhibit a positive relation with ECP (H5.b, H5.d), Effort Expectancy and Behavioral Intention do not (H5.a, H5.c). This suggests that, on the one hand, the social context and the perceived performance benefits of AI contribute positively to a firm's economic outcomes. On the other hand, further investigation into the underlying mechanisms driving perceived performance benefits and behavioral intention of AI would benefit a comprehensive understanding of the relationship.

Fourth, this study addresses the longstanding tension between sustainability-oriented initiatives economic performance, positioning SDGs as a strategic pathway to competitive advantage, highlighting a significant and positive relationship between SDGs and Economic Performance (H4). This finding further emphasizes the pivotal role of SDGs in driving superior outcomes such as increased revenues, market share, and profits within organizations. This suggests again that organizations that prioritize SDGs initiatives are better positioned to achieve not only financial prosperity but also long-term resilience and competitiveness. This is particularly salient in the pharmaceutical industry, where patient outcomes, regulatory compliance, and public trust are closely linked to financial performance (Satwekar et al., 2024)

Fifth, this study explores the boundary conditions under which these relationships unfold, highlighting organizational size as a critical contextual factor of the hypothesized model. We contribute to the existing literature and practitioner debate by addressing that within the pharmaceutical industry, small and medium-sized organizations are particularly well placed to exploit the benefits of AI adoption to improve their overall economic performance, through their SDGs attainment (Nishant et al., 2020; Toniolo et al., 2020; Mariani et al., 2023; Corvello et al., 2024; Cubric and Li, 2024). This implies that organizations that are strategically and cognitively oriented towards digital innovation are typically smaller, making it less burdensome and more accessible for them to initiate more effective adoption of AI. The hypothesized model does not validate direct relation between AI and SDGs but validates AI as mediator between organizational readiness and SDGs. This contribution is particularly relevant as it suggests how small organizational size, cognitively and strategically ready, can impact SDGs and ultimately economic outcomes, with smaller organizations standing to gain more economic viability through sustainable practices (moderator). This reinforces recent research on digital agility in SMEs (Nambisan et al., 2019; Mariani et al., 2023), and suggests that organizational scale is not necessarily a barrier to innovation, but may enable faster iteration, less bureaucratic inertia, and greater absorptive capacity for emerging technologies. In contrast to resource-based views that privilege large-scale firms, this finding aligns with a capability-based view (Zahra and George, 2002), where smaller firms leverage focus and flexibility as innovation assets. For policymakers, this has implications for designing targeted digitalization incentives to support sustainable transformation in the long tail of the pharmaceutical ecosystem.

Taken together, these contributions articulate a coherent explanatory framework in which organizational readiness operates as the primary antecedent of AI adoption, AI acts as an enabling mechanism for SDGs achievement, and ultimately enhancing economic performance in the pharmaceutical industry.

6. Limitations and future research

This study has limitations that also open promising avenues for future research. First, the data are drawn from the pharmaceutical industry through a cross-sectional survey. While this focus enhances the relevance of our findings for a highly regulated and innovation-driven sector, future research could extend to other industries and adopt longitudinal designs to increase generalizability and capture dynamic effects over time. Second, our reliance on employees' self-reported perceptions provides valuable insights into how individuals experience AI and sustainability in their organizations. However, such data are inevitably subjective. Future research is encouraged to address this limitation by integrating secondary data, such as professional development investments, financial reports, patent records, to complement survey-based analyses and assess the robustness of our findings. Moreover, although the study ensured that respondents had prior experience with AI in their professional activities, it did not capture detailed information about the specific nature of their roles, the tasks in which AI was embedded, or their level of expertise with the technology. Such heterogeneity may shape how individuals perceive and interpret organizational AI initiatives, as employees with different responsibilities, technical backgrounds, or exposure to AI systems are likely to develop distinct viewpoints. This limitation raises the possibility that some of the observed patterns reflect variation in role-specific experiences rather than generalizable attitudes toward AI. Future research could address this gap by collecting more fine-grained information on respondents' positions and expertise, for example through qualitative interviews, mixed-methods designs, or longitudinal studies that trace how perceptions evolve with increasing AI familiarity and competence. Such approaches would offer richer insights into how diverse organizational actors make sense of AI and contribute to its effective integration.

Third, our operationalization of AI adoption and SDG performance, though based on established models and careful scientifical validation, inevitably simplifies complex constructs. Firstly, measuring AI adoption presents conceptual and methodological challenges, particularly given the socio-technical nature of AI as a technology that shapes, and is shaped by, user behavior, organizational processes, and decision-making dynamics. Rather than relying on single-item measures—-which are widely recognized in the literature as limited in terms of reliability and validity -we drew on the well-established Unified Theory of Acceptance and Use of Technology (UTAUT) model to operationalize AI adoption through a multi-dimensional construct. Secondly, as for SDG performance, while several macro-level indices exist to measure national or organizational contributions to sustainable development, we found no validated scale specifically tailored to capture AI-related SDG impacts within the pharmaceutical sector. To address this gap, we triangulated data from exploratory interviews and archival sources to identify context-relevant SDG targets, which were then explicitly linked to individual survey items. The SDGs construct was further tested and validated within the SEM framework to ensure internal consistency and construct validity. Despite these efforts to strengthen methodological rigor, developing more granular measures, such as differentiating AI applications across functional areas or tailoring SDG indicators to specific sector contexts, would provide deeper insights, future research could address this gap. Finally, a further limitation relates to the granularity of the sample in terms of the characteristics of participating firms. While the dataset includes respondents from pharmaceutical organizations, covering various phases of the value chain, company size, and revenue streams, it cannot explicitly distinguish between firms' specific AI strategies due to the anonymity of the respondents. To mitigate this limitation, we ensured that participants were knowledgeable about and engaged with AI by implementing a cut-off question checking respondents' AI experience prior to completing the questionnaire. Nonetheless, future research could benefit from a more detailed classification of firms to refine the analysis further and capture potential nuances in AI adoption dynamics. In sum, while our study is exploratory in scope, these limitations highlight opportunities for richer, multi-method, and cross-industry investigations that can advance understanding of how AI adoption and sustainability jointly shape economic outcomes.

7. Conclusion

What is the relationship between AI, SDGs, and organizational performance? This paper takes a first step in addressing this important question, shedding new light on the enablers of AI adoption and its consequences. Our conceptual model and empirical investigation jointly suggest that AI adoption, supported by organizational readiness, is conducive to the achievement of the SDGs and, in turn, to economic performance. We show that strategic and cognitive readiness are essential for AI adoption, as they enable effective integration of this technology into the operational framework, thus predicting SDGs and economic performance. Our paper contributes to the emerging debate on the conditions under which AI positively supports sustainability and economic performance in organizations.

CRediT authorship contribution statement

Mario Miozza: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Daniele Mascia:** Supervision, Validation, Writing – original draft, Writing – review & editing. **Angelo Paletta:** Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

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