International Journal of Digital Strategy, Governance, and Business Transformation
Volume 13 • Issue 1

An Integrative Theoretical Framework for Responsible Artificial Intelligence

Ahmad Haidar, Université Paris-Saclay, Univ Evry, IMT-BS, LITEM, Evry-Courcouronnes, France & Institut Mines-Télécom Business School, 9 rue Charles Fourrier, Evry, France*
https://orcid.org/0000-0001-8045-1546

ABSTRACT

The rapid integration of Artificial Intelligence (AI) into various sectors has yielded significant benefits, such as enhanced business efficiency and customer satisfaction, while posing challenges, including privacy concerns, algorithmic bias, and threats to autonomy. In response to these multifaceted issues, this study proposes a novel integrative theoretical framework for Responsible AI (RAI), which addresses four key dimensions: technical, sustainable development, responsible innovation management, and legislation. The responsible innovation management and the legal dimensions form the foundational layers of the framework. The first embeds elements like anticipation and reflexivity into corporate culture, and the latter examines AI-specific laws from the European Union and the United States, providing a comparative perspective on legal frameworks governing AI. The study's findings may be helpful for businesses seeking to responsibly integrate AI, developers who focus on creating responsibly compliant AI, and policymakers looking to foster awareness and develop guidelines for RAI.

KEYWORDS

AI for Sustainability, AI Governance, Digital Strategy, Digital Transformation, Integrative Framework, IT Governance, Responsible AI, Responsible Innovation Management

INTRODUCTION

The International Data Corporation forecasts that global spending on Artificial Intelligence (AI), encompassing software, hardware, and services, will reach $154 billion in 2023, a 26.9% increase from 2022, and is expected to exceed $300 billion in 2026 with a compound annual growth rate of 27.0% from 2022 to 2026 (IDC, 2023). One classical definition for AI comes from Kaplan and Haenlein (2019) as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p. 15). The European Commission defined AI as any software that analyzes and interprets data to simulate human intelligence, including identifying patterns, making predictions, or generating creative content (EC, 2023).

DOI: 10.4018/IJDSGBT.334844
*Corresponding Author

The pervasive influence of AI is revolutionizing traditional business models and operational strategies. Mkrttchian & Voronin (2021) illustrate this in the tourism industry, where technologies like blockchain and digital twin avatars are reshaping operations. Similarly, Zhang (2023) explore the digital transformation in sports tourism in Hainan Province, demonstrating how digitalization, through the "Daubechies wavelet transform and Roughness Analysis Techniques (DRAT) model" (p. 7), deconstructs and redefines the industry with innovative technologies and new consumer-business collaboration models. This paradigm shift, as noted by Iansiti and Lakhani (2020) and Tarafdar et al. (2019), is fundamentally altering how companies operate and compete, extending beyond the realms of technology to redefine entire business ecosystems.

However, alongside these advancements, businesses face significant moral responsibilities due to potential risks such as discrimination and lack of transparency in data usage (Munoko et al., 2020). As organizations increasingly embed AI into their core operations, the evolution of traditional information technology (IT) governance becomes crucial. From a professional standpoint, effective IT governance is a pivotal mechanism that leverages information and processes to amplify profits and future benefits (Khther & Othman, 2013). De Haes & Van Grembergen (2009) emphasized the critical role of IT in maintaining business sustainability, and Wu et al. (2015) highlighted that strategic alignment serves as a crucial mediator in enhancing business operational efficiency. Thus, integrating a responsible AI (RAI) framework into an organization's IT strategy, which ensures that AI's deployment aligns with business objectives, regulatory requirements, and ethical considerations, is essential. RAI, as defined by De Laat (2021), means that AI should be "fair and non-biased, transparent and explainable, secure and safe, privacy-proof, accountable, and to the benefit of mankind" and revolves around governance, mechanisms, and participation (Dignum, 2019, pp. 102–104).

From a theoretical perspective, despite some studies addressing AI's integration into managerial procedures (Ransbotham et al., 2017), there is a lack of frameworks encompassing all dimensions relevant to responsible AI integration. Kearns and Sabherwal (2006) emphasize that implementing a practical IT governance framework can yield significant business value, suggesting the potential benefits of a well-structured AI governance approach. However, companies may fail to extract value from digital transformation due to the disconnection between strategy formulation and implementation. This study aims to bridge this gap by developing a comprehensive framework for integrating AI into businesses responsibly. Two primary research inquiries guide this study by employing a comprehensive review of existing AI principles and practices: What are all the dimensions essential for integrating AI into businesses in a responsible manner, and can an integrative framework be developed that unifies these dimensions to facilitate the effective adoption of AI systems?

The remainder of this article is structured as follows: The Literature Review section explores the existing literature on RAI, highlighting the growing need for comprehensive frameworks and discussing the limitations of previous approaches. In the subsequent section, the proposed integrative framework, a multidimensional approach to RAI, is presented. Following this, the Discussion section delves into the implications of the framework, drawing connections with current practices and theoretical perspectives. Finally, the Conclusion synthesizes the findings and suggests directions for future research.

LITERATURE REVIEW

The Need for AI Governance Within the Company

The adoption of AI is driven by exponential data growth, algorithmic advancements, cloud technologies, smart network evolution, cyber insecurity, and costly development errors, necessitating robust governance to ensure responsible AI deployment (Papagiannidis et al., 2023). Schneider (2022) highlights four main challenges in AI governance: the complex and opaque nature of AI outputs, unpredictable results that may evade control, data-driven biases in AI decisions, and rapid technological advancements. Wirtz et al. (2022) conducted a comprehensive literature review, identifying six AI risks: (1) technological, data, and analytical AI risks, which pertain to the underlying technology, data, and analytics involved in AI systems; (2) informational and communicational AI risks, such as manipulation of information and communication channels; (3) economic AI risks, including the potential misuse of market power by AI-driven entities; (4) social AI risks, encompassing issues like social discrimination arising from AI systems; (5) ethical AI risks, referring to AI's inability to reflect human qualities such as fairness and accountability; and (6) legal and regulatory AI risks, highlighting concerns that increasing scrutiny might hamper innovation and development in AI. Technological change rates are crucial, as Chatterjee et al. (2022) found that technological turbulence negatively impacts automated decision-making and operational efficiency in business-to-business relationships. Furthermore, resistance to compliance, investment costs, and a reactive approach to privacy practices pose additional challenges, underlining the need for a RAI approach to address these issues effectively (Halder et al., 2022).

From a particular perspective, several high-profile incidents involving well-known companies and brands have resulted from the increasing prevalence of AI technologies, highlighting the significance of addressing AI-related risks and the need for robust AI governance. The following are some examples recently explored:

1. Apple's Siri gender bias allegations: a 2021 UNESCO study found that Siri and other voice assistants reinforced gender bias by defaulting to female-sounding voices (West et al., 2021). The study argued that these AI systems perpetuated detrimental stereotypes by promoting the notion that women are submissive and should be aided. In response, Apple and other companies have begun providing users with multiple vocal options for their virtual assistants, addressing the gender bias concern.
2. Incidents involving ChatGPT: in March 2023, OpenAI faced accusations from the Italian Data Protection Authority for allegedly lacking a valid legal basis for collecting and processing personal data for training ChatGPT. Additionally, it claimed that OpenAI lacked an age-verification mechanism to protect children from exposure to inappropriate content and did not comply with the General Data Protection Regulation. This led to the chatbot being banned in Italy (Goujard, 2023).
3. Incidents involving Microsoft: users of Bing Chat observed that, during prolonged interactions, the chatbot not only tended to generate false information but also unexpectedly displayed emotional responses, suggesting the emergence of a seemingly unintended personality-like aspect in its responses (De Vynck et al., 2023).

Frameworks for Responsible AI

The growing recognition of AI development's importance has led to various guidelines and frameworks to ensure AI technologies' ethical, transparent, and accountable use. Dignum (2019) classifies existing approaches to implementing ethical reasoning in AI systems into three broad categories. Top-down approaches derive specific decisions from general principles, employing a given ethical theory within a computational framework and applying it to particular situations. Bottom-up approaches infer general rules from individual cases, providing the AI agent with sufficient observations of others' actions in comparable situations and the means to aggregate these observations. Hybrid approaches combine aspects of both top-down and bottom-up approaches, fostering the moral reflection deemed indispensable for ethical decision-making.

Most existing frameworks are principled approaches, linking sustainable AI as a multidisciplinary perspective in AI ethics (Larsson, 2020). Schiff et al. (2020) proposed a set of criteria for a practical framework for sustainable AI. The framework should be broad, considering AI's impacts across many ethical issues and social and economic life aspects. It should also be operationalizable, allowing users to turn conceptual principles and goals into specific strategies. Additionally, it should be flexible, able to adapt to various AI systems and organizational settings, and iterative, applied throughout the life cycle of an AI. The framework should be guided, with clear documentation for users of moderate skill to use, customize, and troubleshoot across different contexts. Finally, it should be participatory, incorporating input from stakeholders from various disciplines, particularly those who may be impacted by the AI system, including the public.

Jobin et al. (2019) analyzed 84 ethical guidelines, identifying 11 critical principles for RAI development: transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust, dignity, sustainability, and solidarity. Similarly, Eitel-Porter (2021) supports the notion of ethical AI and emphasizes five essential principles: fairness, accountability, transparency, explainability, and privacy. In this vein, organizations documented a set of high-level principles for sustainable AI. For instance, OpenAI[1] emphasizes its commitment to minimize harm, build trust, be a pioneer in trust and safety, and learn and iterate to improve data modeling.

Exploring the Limitations of the Principles-Approach for AI

Although defining rules for ethical, responsible, and sustainable AI using a principle-based approach is crucially important, this approach does have a few drawbacks that should be considered.

1. The interpretation of principles can vary, making it challenging to translate them into specific guidelines or standards that can be easily implemented (Floridi et al., 2018) and making it difficult for businesses to select which framework they should adopt (Qiang et al., 2023).
2. Principles are not always legally enforceable, which may limit their impact (Brundage et al., 2018).
3. Principles may not be universally applicable across different cultural and social contexts (Gunkel, 2018).
4. There may be a limited range of stakeholders involved in the development of principles, resulting in a lack of input from individuals and communities that could be affected by the use of AI (Diakopoulos et al., 2017).
5. According to Mittelstadt (2019), principles alone cannot guarantee ethical AI and may not provide clear guidance on how to ensure transparency and explainability in AI systems. Also, the same author mentioned, “outside of academic contexts, AI development lacks proven methods to translate principles into practice” (p. 5).
6. As AI technology evolves and new use cases emerge, principles that may have been applicable in the past may not be sufficient to address contemporary ethical and social issues that arise (Jobin et al., 2019).

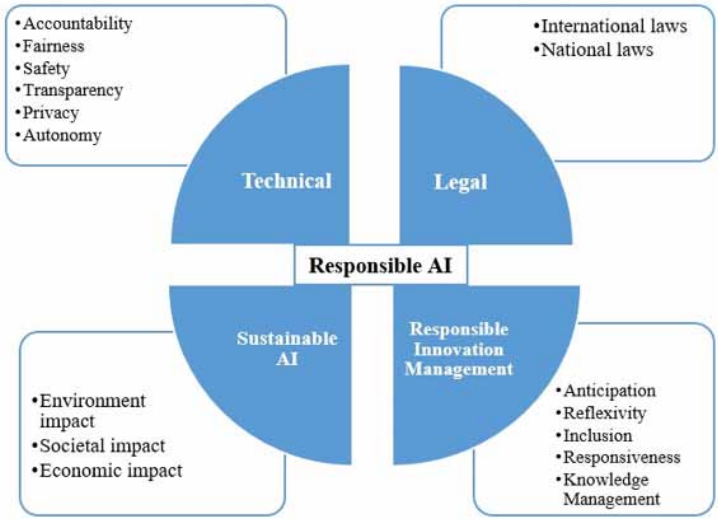
Proposed Integrative Theoretical Framework

These limitations suggest that while principles can be a useful starting point for developing guidelines for RAI, other approaches should complement them. Despite inherent limitations, it is argued that establishing foundational principles representing the technical dimension is crucial for effectively applying ethical AI (Eitel-Porter, 2021). Yet the technical dimension alone is insufficient; additional elements need to be considered, as shown in Fig. 1.

The second dimension involves translating responsible innovation management (RIM) principles into practice. The third dimension addresses the legislative aspect, focusing on the laws governing AI to ensure safe outcomes. The fourth and final dimension outlines sustainable AI impact pathways, ensuring that the implementation of AI does not harm the environment, economy, or society and is aligned with the sustainable development goals (SDGs).

The selection of these four dimensions—technical, legal, responsible innovation management, and influence on SDGs—is justified by their consistency with the current discourse and research on RAI. A comprehensive review of the relevant literature and extant theoretical frameworks reveals that these dimensions capture the most significant elements of RAI while remaining comprehensive and manageable. Also, the framework reflects the multidisciplinary nature of AI because each

Figure 1. Responsible AI framework



dimension is derived from distinct research areas in different disciplines, making the framework inherently pluridisciplinary. This cross-disciplinary enables a more comprehensive understanding of RAI, integrating diverse perspectives and insights to resolve the complex challenges associated with AI development and implementation. In addition, by combining these dimensions, the framework avoids introducing complexity or redundancy.

Technical Dimension

Data are the raw material for information (Zins, 2007) and are considered the new oil (The Economist, 2017). In the realm of managing and processing this invaluable resource, IT, as defined by Boar (1997), encompasses technologies dedicated to the collection, storage, transformation, and dissemination of information. Within this expansive domain of IT, AI stands as a beacon, transforming raw data into actionable insights and automating a myriad of complex tasks. However, the intricate relationship between AI and data gives rise to various technical challenges, like overfitting and data leakage, that can influence the efficacy of AI models, as illustrated and referenced in Table 1.

In recent years, scholars such as Jobin et al. (2019), Floridi & Cowls (2022), and Royakkers et al. (2018) have explored frameworks founded on principles to foster socially beneficial AI. Jobin et al. (2019) observed that while no single principle appeared in all declarations, themes of transparency, justice and fairness, non-maleficence, responsibility, and privacy appeared in more than half of them. Similarly, a systematic review of the literature on ethical technology revealed that themes of privacy, security, autonomy, justice, human dignity, technology control, and the balance of powers frequently recurred (Royakkers et al., 2018). One of the main reasons principles like transparency and accountability are emphasized in AI, much like in IT, is their proven benefits in various digital transformations such as in e-governance, where, as Yimer (2021) stated, “Once transparency is established, accountability will control government officials” (p. 4).

This article conducted a frequency test on ten AI-related declarations from 2017 to 2021 to identify prevailing ethical considerations in AI. Principles that appeared in at least half of these declarations were selected. This approach was adopted to emphasize the most frequently cited principles, which were therefore regarded as more prevalent and significant. This threshold of 50% ensured a balance between capturing the most vital principles and avoiding the inclusion of less agreed-upon or less-

Table 1. Key technical issues faced in AI implementation

Issue/Challenge	Description	References
Data Quality Issues	Generation of noisy, incorrect, or inconsistent data; calibration issues; poor sensor nodes quality; environmental effects.	Alwan et al. (2022); Bosu & MacDonnell (2019)
Sampling Bias	Sampling bias refers to the systematic error that arises when the sample collected is not representative of the entire population, potentially leading to inaccurate conclusions and misleading results.	Wang & Cheng, (2020); Vetter & Mascha (2017)
Data Drift	Data drift refers to the alteration or change in the input data distribution over time, which may affect the performance of predictive models.	Alsuwatet al. (2023); Sethi & Kantardzic (2017)
Quantization Error	A systematic error resulting from the difference between the continuous input value and its quantized output, and it is like round-off and truncation errors.	Colagrossi et al. (2023); Zhang et al. (2023)
Feature Redundancy	The inclusion of redundant or irrelevant features in the dataset reducing model generalization.	Lin et al. (2015); Tabakhi & Moradi (2015)
Data Leakage	Unauthorized access and exposure of sensitive information.	Alneyadi et al. (2016); Wang et al. (2019)
Memory Management Issues	Challenges related to efficiently managing memory usage during model training and inference, particularly critical when dealing with large models or datasets.	Cui et al. (2016); Zhang et al. (2015)
Overfitting	Overfitting is primarily a technical problem, arising when a model learns the training data too well, capturing its noise as if it were a real pattern, which leads to poor generalization to unseen data.	Burnham & Anderson (2002); Mutasa et al. (2020)
Underfitting	Underfitting occurs when the model is too simplistic to capture the underlying structure of the data.	Jabbar & Khan (2014); Wagner et al. (2021)

discussed aspects. Adopting this method facilitated a more efficient and targeted examination of AI's fundamental principles. These principles were divided into two main themes: (1) added value or impact on sustainability and (2) technical requirements for sustainable AI development. The latter encapsulates the technical aspects, emphasizing accountability, privacy, transparency, safety, fairness, and autonomy.

The established principles offer solutions and measures to address various technical challenges in AI development:

1. Accountability: ensures clear ownership and responsibility for any technical issues (Johnson, 2015). This framework:
    a. Offers avenues for rectifying mistakes or biases, thereby mitigating problems like overfitting and underfitting.
    b. Creates a culture of responsibility (Ramasastry, 2015), promoting best practices to prevent issues like data-quality errors and memory-management challenges.
2. Fairness: advocates for equitable treatment in algorithms (Giovanola & Tiribelli, 2022), focusing on:
    a. Addressing data-sampling biases that might skew predictions or classifications.
    b. Mandating that algorithms do not perpetuate or introduce harmful biases, thus reducing the chance of model misclassification due to overlooked bias.
3. Safety: prioritizes the robustness and integrity of AI models by:
    a. Emphasizing prevention of overfitting and underfitting, ensuring models are reliable.
    b. Guarding against technical challenges like data leakage that can compromise model validity and user trust.

4. Transparency: advocates for AI clarity and openness (Larsson & Heintz, 2020):
    a. Transparent modeling helps in diagnosing issues, allowing for the identification and rectification of problems like overfitting or feature redundancy.
    b. Boosts trust and understanding among stakeholders, ensuring models are used responsibly.
5. Privacy: focuses on the ethical handling and protection of data (Atlam & Wills, 2020):
    a. Emphasizes safeguarding sensitive information and mitigating risks associated with data leakage.
    b. Advocates for respectful data processing, crucial for training reliable models and maintaining user trust.
6. Autonomy: ensures that AI systems can operate independently without human intervention while maintaining safety and compliance (Firlej & Taeihagh, 2021):
    a. Reduces the risks associated with manual errors, which can lead to issues like data-quality challenges or sampling biases.
    b. Advocates for built-in checks and safeguards, ensuring that the AI's independent actions don't lead to unintended technical consequences such as quantization error or model drift.

Responsible Innovation Management Dimension

The concept of responsible innovation (RI) calls for firms to transform societal members' values and behaviors toward socio-ethical issues (Ceicyte & Petraite, 2018). According to Stilgoe et al. (2013), RI means "taking care of the future through collective stewardship of science and innovation in the present" (p. 1570). For the same authors, RI is simultaneously "old and new" (p. 1568), while for Tian and Tian (2021), it is considered a "new" (p. 3) approach that focuses on governance and innovation assessment, promoting democratization through stakeholder and public participation and addressing ethical and social concerns from the inception of innovation to mitigate any negative consequences. Accordingly, the concept is interpretively flexible, and there are competing narratives.

Although different approaches to responsible innovation exist (e.g., Burget et al., 2017), the framework for RI invented by Stilgoe et al. (2013) is one of the most dominant approaches in the literature on RI. Their framework consists of four dimensions: anticipation, reflexivity, inclusion and deliberation, and responsiveness, in addition to "knowledge management" introduced by Lubberink et al. (2017, p. 721), illustrated with more details in Table 2.

Anticipation requires a systematic approach to considering the known, probable, plausible, and potential impacts of innovation under development (Stilgoe et al., 2013). Reflexivity can be defined as the practice of critically evaluating one's actions, responsibilities, values and motivations, knowledge, and perceived realities and their impact on managing the innovation process toward desired outcomes (Lubberink et al., 2017). Inclusion suggests businesses should utilize multi-stakeholder partnerships to involve nonexpert members in responsible innovation efforts, striving for diverse inputs and approaches in the governance process (Silva et al., 2019). Responsiveness necessitates that the innovation process and its managers possess the ability to respond to the consequences arising from the implementation of the first three dimensions (Long et al., 2020). For instance, Koch and Altinkemer (2021) propose a framework that offers managers a structured tool for analysis when confronted with the emergence of new technologies, assisting them in determining appropriate investments and applications within their organizations.

Knowledge management can be defined as the process of creating or acquiring knowledge to address gaps in the processes and outcomes of innovation and integrating it into the innovation process (Lubberink et al., 2017). In this regard, various tools can be identified. One is a knowledge repository for configuring, analyzing, and comparing multiple business models (Gottschalk et al., 2023). Microsoft SharePoint, Confluence, and MediaWiki are examples of knowledge repositories. Also, learning-management systems (e.g., Moodle and Canvas) and document-management systems such as Dropbox and Google Drive are vital tools of knowledge management used by businesses

(Gupta et al., 2022). Decision-support systems (e.g., PowerBI) enhance and support organizations in decision-making processes (Kou et al., 2011).

In order not to remain solely within a theoretical framework, it is vital to consider how these RI dimensions can be applied practically. For example, Papagiannidis et al. (2023) provide practical insights, suggesting that companies must adopt new procedures when integrating AI to maintain competitive advantages and improve efficiency. These procedures can be linked to the RI dimensions. For instance, during the anticipation phase, companies evaluate how AI influences employees' roles and responsibilities, as AI is usually employed to automate repetitive tasks that employees generally dislike. In the reflexivity phase, organizations must set clear procedures, encompassing ongoing critical assessments of the AI systems' efficacy and addressing ethical considerations. The inclusion phase requires managers to establish transparent policies and guidelines that are well-communicated to and understood by employees. In terms of responsiveness, companies should use dashboards as an instrument for people and AI systems to communicate with each other. This ensures the company can quickly change in response to new ideas and challenges. Finally, for knowledge management, dashboards also function as information-management tools, monitoring key performance indicators and metrics, aiding in the integration of new knowledge into the innovation process.

Another practical aspect where RI can play a significant role is integrating AI into disruptive business models. As AI technologies continue to revolutionize various industries, they form the backbone of several innovative business models. Schmidt & Van der Sijde (2022) identify five archetypes of disruptive business models where AI can be a game-changer: (1) matchmakers, (2) standardizers, (3) service providers, (4) open collaborators, and (5) performance reducers. In the context of RI, these models must be approached with anticipation, reflexivity, inclusion, responsiveness, and knowledge management. For instance, AI algorithms in matchmaker models should anticipate the societal implications of data matching and ensure the privacy and security of user data. In open-collaborator models, inclusion is vital as diverse stakeholder inputs should be sought to make the collaborative processes more transparent and ethically sound. Also, in the context of RI, fostering an inclusive environment is crucial. A key aspect of inclusion is encouraging employee participation in innovation communities. Wendelken et al. (2014) underline that these motivations can be extrinsic, like career advancement, learning opportunities, monetary rewards, and recognition, or intrinsic, such as altruism, a sense of community, enjoyment, and personal connection to the task.

Legal Dimension

Recent technological advancements in AI, cloud computing, 5G, and Web3 necessitate either more regulatory actions, which may include laws, regulations, and antitrust initiatives, or more international data standards, improved data architecture, and greater interoperability of data via improved interfaces (Dąbrowska et al., 2022). The findings of Halder et al. (2022) underscored the influence of legal policy on organizations' privacy practices, emphasizing the pivotal role of legal frameworks in shaping responsible AI governance. The relevant legal frameworks for AI will depend on the specific context and application of AI challenges or following national or international laws. For instance, concerns about data privacy and protection have led to various laws and regulations worldwide. Table 3 compares some fundamental laws highlighting the differences in AI regulations between the EU and the United States (US). We employed descriptive and analytical approaches in our comparative analysis of AI legal frameworks between the EU and the US. We detailed specific laws and regulations in each region (descriptive comparison) and analyzed their implications for AI practices (analytical comparison). Furthermore, we contrasted the centralized legislative approach in the EU with the decentralized approach in the US, highlighting each system's unique challenges and benefits.

The EU has proactively regulated AI, establishing a comprehensive regulatory framework prioritizing data protection and responsible AI development. General Data Protection Regulation (GDPR), a landmark piece of legislation, sets stringent standards for data collection, processing, and

Table 2. Criteria for responsible innovation

RI Dimensions	Key elements	References	Tools	References
Anticipation	Identifying potential impacts, risks, and uncertainties	Stilgoe et al. (2013)	Scenario thinking, value mapping, ideation for business modelling, translating vision into mission, game theory/perspective, and crowdsourcing are all valuable tools and approaches for businesses to strategize and make informed decisions.	Long et al. (2020)
	Engaging with a wide range of stakeholders	Stilgoe et al. (2013)		
	Understanding the dynamics influencing the formation of the innovation is essential for innovators.	Burget et al. (2017)		
Reflexivity	Reflecting on the values and assumptions that underpin the innovation is crucial, as it helps anticipate unintended consequences that may arise.	Stilgoe et al. (2013)	Formal evaluations, third party critical appraisal, informal (self) assessment culture, knowledge-concept-process mechanisms, and empowered and open communication are all important components of effective organizational learning and development.	Long et al. (2020)
	Considering the social, cultural, and political contexts in which the innovation is developed and used	Stilgoe et al. (2013)		
	Involving stakeholders early in the process is crucial for successful outcomes.	Wickson & Carew (2014)		
Inclusion	Ensuring that the innovation is developed and used in a way that is inclusive and participatory	Stilgoe et al. (2013)	Crowdsourcing via software, living lab structures, collaborative business modelling, partnerships, consultancy of experts, focus groups, and integrating views and opinions are all valuable methods for gathering diverse perspectives and generating innovative ideas in the context of business innovation and development.	Long et al. (2020)
	Engaging with diverse stakeholders and considering their perspectives and needs throughout the innovation process	Stilgoe et al. (2013)		
	Compelling of stakeholders for the purpose of substantively better decision-making and mutual learning	Wickson & Carew (2014)		
Responsiveness	Developing flexible and adaptable governance arrangements that can respond to changing circumstances and emerging ethical and social concerns	Owen et al. (2013); Lubberink et al. (2017).	Customizing or mainstreaming, preventing organizational inertia, adjusting/withdrawing innovation, and monitoring the external environment post-introduction of innovation are all important strategies for managing the implementation of innovative ideas and ensuring their success in the marketplace.	Long et al. (2020)
	Engaging with a wide range of stakeholders to ensure that potential issues are identified and addressed in a timely and effective manner	Stilgoe et al. (2013)		
Knowledge Management	Managing the various types of knowledge that are relevant to the innovation process, including both explicit and implicit knowledge	Owen et al. (2013); von Schomberg (2012)	Learning management systems, document management systems, web content management systems, decision support systems, knowledge repositories	Maican & Lixandroiu (2016); Gupta et al. (2022); Gottschalk et al. (2023)
	Ensuring that the best available evidence informs the innovation process, like engaging in different activities to obtain the necessary knowledge, and that stakeholders are able to make informed decisions about the development and use of innovations	Lubberink et al. (2017)		

usage, ensuring that individuals retain control over their personal information. Building upon GDPR, the EU advanced its regulatory framework by introducing the Data Governance Act (2021). This act was designed to bolster data governance, facilitate data sharing, and support the cultivation of responsible AI. In June 2023, the EU unveiled a revised version of the act, which broadened the scope to encompass a more comprehensive array of AI systems and reinforced a risk-based regulatory approach. Furthermore, it augmented the mandates for transparency and accountability while intensifying the antidiscrimination provisions, thereby setting a more robust standard for AI practices within the EU. Although these mandates are not exclusively AI-focused, they hold significant implications for the development and deployment of AI technologies. The Digital Services Act aims to regulate online platforms by introducing new requirements, such as conducting risk assessments, implementing transparency measures, and addressing illegal content. These requirements will significantly impact AI-powered platforms, such as those that use AI for content moderation or targeted advertising. The Digital Markets Act (DMA) aims to ensure fair competition in the digital market by imposing obligations on large online platforms' gatekeepers, which will significantly impact large AI companies such as Google and Meta, as they are considered gatekeepers under the DMA.

AI regulation in the United States is currently a patchwork of state laws and regulations. There is no federal law that regulates AI explicitly, and the laws that do exist vary from state to state. This patchwork approach to AI regulation has some advantages and disadvantages. On the one hand, it allows states to experiment with different approaches to regulating AI and to tailor their laws to the specific needs of their residents. On the other hand, it can create uncertainty for businesses operating in multiple states and can make it difficult for consumers to understand their rights. Table 3 gives examples of laws in different US states.

AI and Sustainability

Definition of Sustainable AI

Van Wynsberghe (2021) defines sustainable AI as "a movement to foster change in the entire life cycle of AI products (i.e., idea generation, training, re-tuning, implementation, governance) towards greater ecological integrity and social justice" (p. 213). Bolte et al. (2022) drew from Van Wynsberghe (2021) to define sustainable AI in two dimensions: AI for sustainability, which involves using AI to achieve the United Nations' sustainable development goals (SDGs), and sustainability of AI, which focuses on the environmental impacts of creating and utilizing AI technologies.

A comprehensive literature review made by Nishant et al. (2020) reveals that research on AI for sustainability is hindered by (1) excessive reliance on historical data in machine learning models, (2) uncertain human behavioral responses to AI-based interventions, (3) increased cybersecurity risks, (4) negative impacts of AI applications, and (5) difficulties in measuring the effects of intervention strategies. Sustainability is regarded as the triple bottom line (Elkington, 1998) of balancing the three components of economy, environment, and society, which align with the SDGs. Academic researchers such Yong et al. (2020) argue that these three aspects hold equal importance for a business's success. This section investigates the relationship between AI and sustainability.

Opportunities and Challenges for AI for Sustainability

AI and Environment. AI has the potential to influence the environment in several areas positively. Gupta et al. (2023) provide compelling evidence of AI's positive influence on sustainable entrepreneurship. Their extensive review highlights AI's capacity to contribute to environmental and economic goals, particularly in developing nations. For instance, it can improve resource management by enhancing energy efficiency, optimizing water usage, and facilitating waste management (Ahmad et al., 2021). AI can also help mitigate climate change by reducing greenhouse-gas emissions, improving climate predictions, and enhancing disaster response (Saggar & Nigam, 2023). Also, AI can contribute to biodiversity conservation by monitoring species, restoring habitats, reducing marine pollution,

Table 3. Some examples of AI laws in the EU and the US

EU Regulation (law/description)		US Regulation (states/law/description)		
General Data Protection Regulation (GDPR) (2016)	Comprehensive data protection law designed to give individuals control over their personal data and simplify the regulatory environment for international business.	California	California Consumer Privacy Act (2018)	Grants consumers more control over their personal data, requires businesses to be transparent about how they collect and use data, and establishes a private right of action for consumers.
Regulation on a European approach for Artificial Intelligence (AI Act) (2021)	The AI Act categorizes applications of AI into four levels of risk: unacceptable risk, high risk, limited risk and minimal or no risk.		The Bolstering Online Transparency Act (BOT) (2022	Requires online businesses to disclose to users whether they use automated decision-making tools (ADTs) and to provide users with the opportunity to opt out of ADT-based decisions.
Digital Services Act (DSA) (2022)	Regulates online services, including social media platform, online marketplaces, and app stores.	Illinois	Illinois AI Video Interview Act (2021)	Regulates the use of AI-powered video interviews in the hiring process, requiring employers to notify applicants of AI use, obtain their consent, and provide them with access to their interview data.
Digital Markets Act (DMA) (2022)	Aims to ensure fair competition in the digital market by imposing obligations on large online platform gatekeepers.	Indiana	Bill 5 Consumer data protection (2023)	Prohibits businesses from collecting, using, or disclosing personal data without the consent of the individual, and establishes a privacy regulator to enforce the law.
Data Governance Act (2023)	Aims: (1) To increase the availability of data for reuse; (2) To promote the fair and responsible use of data; (3) To increase trust in data	Maine	Data Privacy and Protection Act, HP 1270 (2023)	Establishes a comprehensive framework for data privacy protection in the United States, including requirements for data minimization, data security, and data breach notification.
		Pennsylvania	HB49	The proposed registry would require businesses using artificial intelligence systems to provide their contact details, the AI system's purpose and type, as well as a consent statement for the information to be stored by the Department of State.

improving vegetation classification, enhancing agriculture, and monitoring forests (Nishant et al., 2020). However, AI also negatively impacts the environment. Energy-intensive model training and power-consuming data centers can increase energy consumption (Strubell et al., 2020). Additionally, AI can generate e-waste (Contreras-Koterbay, 2020).

AI and Society. Both positive and negative societal alterations are possible as an outcome of AI. Let’s examine how it influences sectors such as health care and education, which serve as examples of AI’s widespread impact. In health care, AI can aid in diagnostics, treatment planning, and drug discovery, leading to better patient outcomes (Lee & Yoon, 2021). Yet privacy concerns with patient data, potential biases in AI algorithms influencing treatment recommendations (Lian et al., 2021), and unequal access to AI-powered health care remain significant obstacles despite these advancements (Kumar et al., 2021). In education, AI can facilitate personalized learning in education, thereby improving student outcomes and experiences (Luckin & Cukurova, 2019). Conversely, one of the negative aspects of AI in education is the "digital divide," which exacerbates inequalities between students with access to advanced technology and those without access. In regions like Africa, the educational divide is pronounced due to structural challenges and disparities among business operators, as Kazim (2021) detailed. While initiatives such as the African Union's 2063 strategy aim to address this, the role of responsibly implementing AI to help bridge these gaps is significant. Yet overreliance on AI may reduce human interaction in education (M. U., 2023).

Moving from specific sectors to a more general perspective, some concerns include the potential malicious use of AI, especially in the military (Ayamga et al., 2021), the negative impact of fake news on the mental health of some people and their reputations (Bachura et al., 2022), and existing biases in algorithms contributing to adverse outcomes in areas such as e-justice (Fryer, 2020).

AI and Economy. *The Economist* (2017) proclaimed, "The world's most valuable resource is no longer oil, but data." According to Verhezen (2020), AI and algorithms will significantly change the competitive landscape. As a result of digitization, the economy is shifting from "financial capitalism" to "data capitalism" (p. 61); businesses and their boards need to alter their operational and strategic approaches to flourish in new ecosystems characterized by personalized services as integral components of digital-services strategies. The widespread adoption of AI technologies has the potential to impact the economy significantly both negatively and positively.

1. Employment and workforce: AI has the potential to transform the workforce by automating tasks, increasing productivity, and creating new job opportunities in AI-related fields (Hunt et al., 2022). Yet job loss due to automation and the widening skills gap are concerns that need to be addressed (Georgieff & Hyee, 2022).
2. Economic growth and productivity: AI can improve efficiency and productivity across industries, contributing to economic growth (PwC, 2018). On the other hand, AI may hamper economic growth and exacerbate income (Puaschunder, 2020).
3. Businesses: AI positively alters human resource management within all phases: sourcing, hiring, and training (Vrontis et al., 2022). Also, by adopting AI in business-to-business marketing, Chen et al. (2022) found seven positive outcomes: efficiency improvements, accuracy improvements, better decision-making, customer relationship improvements, sales increases, cost reductions, and risk reductions. Conversely, AI could contribute to market monopolization through businesses' exclusive ownership of original data sources (Rikap, 2022).
4. Innovation and research: AI can spur innovation and the development of new products/services, accelerate research and development processes, and improve collaboration and information sharing (Guo et al., 2023).
5. Financial services and fintech: AI can improve risk assessment, fraud detection, and trading, as well as enhance customer service and personal finance management (Boustani, 2022). However, AI may also increase systemic risk in financial markets and contribute to financial exclusion for vulnerable populations (Bookstaber, 2017).
6. Agriculture and food industry: AI can optimize farming practices, increase crop yields, reduce food waste, improve supply-chain efficiency, and maximize land and water use (Bachmann et al., 2022). Despite these benefits, AI-driven farming may exacerbate existing inequalities in agriculture, and overreliance on AI may reduce resilience to unforeseen challenges (Gwagwa et al., 2021).

Best Practices for Responsible AI Development

Businesses must adopt best practices that consider AI systems' environmental, social, and economic impacts to promote their responsible development. Some of these best practices include:

1. Aligning AI development with the SDGs: some of the most widely recognized frameworks used by businesses include the Global Reporting Initiative (Vigneau et al., 2015), the Sustainability Accounting Standards Board (Rodriguez et al., 2017), the Task Force on Climate-Related Financial Disclosures (Chua et al., 2022), and the United Nations Global Compact (Orzes et al., 2018).
2. Promoting collaboration between AI developers, policymakers, and other stakeholders: collective impact is a practical framework to facilitate multi-stakeholder collaboration in sustainable AI development (Kania & Kramer, 2011; Chirumalla et al., 2022). This framework comprises five fundamental terms: establishing a common agenda, establishing shared measurement systems, engaging in mutually reinforcing activities, sustaining continuous communication, and having support organizations that serve as a backbone. Another framework is the Cynefin framework, which helps stakeholders address and select appropriate strategies for collaboration based on the problem's characteristics (Snowden & Boone, 2007). Numerous tools and resources can also facilitate multi-stakeholder collaboration in AI and sustainability. For instance, Stakeholder Circle[2] can assist in prioritizing stakeholders based on their importance and influence on the project. Platforms like Slack, Microsoft Teams, Basecamp, or Partnership Proposition Canvas also enhance communication, resource sharing, and project management among stakeholders.

DISCUSSION

The rapid advancements in AI are significantly reshaping the business world, creating a mix of opportunities and challenges. Plekhanov et al. (2022) note that digital transformation introduces complex strategic challenges, including the need for organizational awareness of AI principles, particularly in sustainability (Van Wynsberghe, 2021). This is exemplified by Demdoum et al. (2021), who observed a limited focus on environmental considerations in southeastern Algeria, reflecting a global trend of inadequate management of AI's environmental impact (Kar et al., 2022). There's a growing necessity for more effective governmental and consumer actions to promote sustainable AI practices.

Given these complexities, a comparison with existing frameworks can offer further insights. Scholars such as Mikalef et al. (2022), Dignum (2019), and Trocin et al. (2023) have documented the opportunities, challenges, and principles for RAI, and this study advances knowledge in this domain by providing a framework for implementing AI responsibly. From an international organization standpoint, OECD Principles on AI (2019) offer high-level, values-based principles for RAI, emphasizing benefits to people and the planet, transparency, and accountability. The European Commission's Ethics Guidelines for Trustworthy AI (2019) identify seven trustworthiness requirements, ranging from human oversight to societal well-being (HLEGAI, 2019). From a scholar's standpoint, Nylén (2021) provides a valuable framework focused on digital innovation strategy, emphasizing user experience, value proposition, digital evolution scanning, skills, and improvisation. Similarly, Correani et al. (2020) emphasize the importance of defining the scope of digital transformation, highlighting data's critical role in supporting transformed activities, tasks, and services that create value for customers.

In contrast to these frameworks, the proposed integrative framework does not focus on one approach (i.e., users). It offers a comprehensive perspective by delving deeper into AI's technical, legal, and sustainable aspects, potentially rendering it versatile and adaptable across various sectors. This breadth of analysis enables this study to cater to a diverse readership audience that includes data analysts, due to its technical depth, and legal and managerial policymakers, who may derive value from its implications for governance and strategic planning.

The strength of the proposed framework also resides in its potential generalizability across countries or regions. While the legal dimension may vary across jurisdictions due to the variety of AI-related laws and regulations, the underlying principles of responsible AI remain consistent.

Within this context, organizations must be aligned with local and international legislation to ensure the usefulness of implementation. Thus, adopting a comprehensive and integrative framework into the digital strategy is crucial to navigating AI challenges and ensures that organizations remain committed to fairness, accountability, transparency, and security as they innovate and scale. This study fosters awareness about RAI by highlighting ethical and legal considerations, encouraging stakeholder engagement, providing an integrative framework for responsible practices, and guiding diverse stakeholders toward ethical AI implementation.

Having outlined the strengths of the RAI framework, it is relevant to explore the policy implications of the current study, which are designed to benefit a broad spectrum of stakeholders in the field of AI, particularly businesses, developers, and policymakers:

- Businesses: the RAI framework serves as a comprehensive guide for companies to integrate AI responsibly, embodying the principles of responsible innovation (Stilgoe et al., 2013). It can enhance competitive advantage, improve customer trust, and mitigate AI deployment risks like biases or privacy violations. A primary implication recommends establishing an RAI assessment analogous to the IT Governance Assessment Process delineated by Peterson (2004) to thoroughly evaluate the framework's dimensions and subdimensions. For instance, it is crucial to ensure that technical challenges, such as quantization error, are mitigated or resolved by providing adequate education to the team and, where necessary, implementing techniques like QEBVerif as a quantization error-bound verification method (Zhang et al., 2023). Within this context, Zhu et al. (2023) developed a multi-strategy relation extraction model to reduce noise in nonstructured teaching resources for online education, which aligns with our RAI framework's emphasis on responsibly addressing technical challenges in AI deployment.
- Developers: AI developers can use the RAI framework as a blueprint for creating AI systems that are inherently responsible and aligned with ethical standards. While the technical dimension of the framework provides specific guidelines on principles like fairness, transparency, and safety, it's essential to recognize that the technical dimension alone is insufficient for RAI. Developers are encouraged to consider their work's broader ethical, social, and organizational implications. This comprehensive approach, which goes beyond mere technical solutions, can lead to the creation of AI systems that are more trustworthy, socially responsible, and aligned with human values.
- Policymakers: policymakers can draw valuable insights from the RAI framework in creating regulatory environments that foster responsible AI innovation and safeguard public interests. This is particularly relevant considering the varying approaches to AI regulation, as seen in the EU's recent updates to the AI Act and the diverse state-level regulations in the US. The RAI framework's principles provide a comprehensive basis for policymakers to navigate these differing legal landscapes, guiding AI development toward applications that are innovative, ethical, and beneficial to society across different jurisdictions.

Additionally, our study highlights the importance of shared responsibility among stakeholders. In line with Peterson's (2004) definition of IT governance as a distribution of decision-making rights and responsibilities, our framework advocates for "fruitful collaboration" (Sartori & Theodorou, 2022, p. 1) among various stakeholders, including policymakers, developers, and consumers, to effectively execute the framework. This perspective is consistent with the implications drawn by González-Tejero et al. (2023), who emphasize the need to build upon existing links between researchers, organizations, and governments. They argue for the development of principles to ensure the sustainable use of technologies and the implementation of infrastructures and systems that support the development of entrepreneurship in the digital-information revolution. Their findings reinforce our call for collaborative approaches in AI governance, underlining the significance of multi-stakeholder engagement in fostering responsible and sustainable AI practices. Furthermore, transparency in AI applications is a crucial policy implication, where regulatory bodies might mandate companies to comprehensively disclose the nature, purpose, and methods of their AI deployments, ensuring adherence to RAI principles.

CONCLUSION

In an era where AI rapidly transforms multiple domains and sectors, adopting and deploying RAI dimensions are more critical than ever. This study contributes to the field by presenting an integrated and comprehensive framework for RAI that not only encompasses technical principles such as accountability, privacy, transparency, safety, fairness, and autonomy but also extends to legal compliance, responsible innovation management, and alignment with SDGs. RIM is crucial, as it operationalizes ethical AI practices within corporate culture. Incorporating elements like anticipation and reflexivity ensures that organizations proactively identify and adapt to potential AI impacts, fostering ethical decision-making and inclusive stakeholder engagement. In parallel, the legal dimension is indispensable for navigating the complex legalities surrounding AI and safeguarding against potential ethical transgressions. While the RIM and legal dimensions play foundational roles in embedding responsible practices for AI, it's important to emphasize that all framework dimensions, including the technical and sustainability dimensions, are integral and interdependent. This research's primary scientific contribution lies in synthesizing these diverse dimensions into a cohesive framework, thereby offering a multifaceted approach to RAI that has not been extensively explored in existing literature that can be adopted globally. This study also serves as a valuable resource for stakeholders in AI for businesses seeking to navigate the complexities of RAI development and deployment, encouraging responsible use of AI technologies.

While the framework sets a foundational structure for RAI, it acknowledges the challenges in its implementation. The need for rigorous enforcement mechanisms and transparent accountability measures is emphasized, highlighting the practical aspects of applying the framework in real-world scenarios. Additionally, its global applicability and the requirement for customization according to varying legal jurisdictions underscore its versatility and adaptability. Despite these significant strides, it should be noted that the study has limitations in that it primarily focuses on business applications of AI and does not encompass the full spectrum of AI technologies, such as military applications.

This study paves the way for future academic research in AI and holds significant implications for the practical development and regulation of AI technologies. Comparative analysis could show how AI adoption varies across regions and its consequences. Developing indicators for each framework dimension can be helpful to assessment and evaluation instruments. Longitudinal studies observing changes over time may facilitate understanding the evolving nature of AI and its repercussions. Furthermore, an important direction for future research involves empirically applying our RAI framework in specific sectors, such as the technology industry, to test its principles and adaptability in real-world scenarios. This sector-specific application could provide deeper insights into our framework's practical utility and effectiveness. In regard to regulatory implications, the comprehensive nature of our RAI framework offers a blueprint for shaping future legislation and policy decisions in AI. It underscores the need for adaptive regulatory measures to keep pace with AI's rapid evolution, ensuring ethical, transparent, and inclusive practices are maintained as technology advances. This forward-looking approach is crucial for navigating the changing landscape of AI and ensuring its responsible evolution, both in development and regulation.

REFERENCES

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status quo, challenges and opportunities. *Journal of Cleaner Production*, *289*, 125834. doi:10.1016/j.jclepro.2021.125834

Alneyadi, S., Sithirasenan, E., & Muthukkumarasamy, V. (2016). A survey on data leakage prevention systems. *Journal of Network and Computer Applications*, *62*, 137–152. doi:10.1016/j.jnca.2016.01.008

Alsuwat, E., Solaiman, S., & Alsuwat, H. (2023). Concept drift analysis and malware attack detection system using secure adaptive windowing. *Computers, Materials & Continua*, *75*(2), 3743–3759. Advance online publication. doi:10.32604/cmc.2023.035126

Alwan, A. A., Ciupala, M. A., Brimicombe, A. J., Ghorashi, S. A., Baravalle, A., & Falcarin, P. (2022). Data quality challenges in large-scale cyber-physical systems: A systematic review. *Information Systems*, *105*, 101951. doi:10.1016/j.is.2021.101951

Atlam, H. F., & Wills, G. B. (2020). IoT security, privacy, safety and ethics. In M. Farsi, A. Daneshkhah, A. Hosseinian-Far, & H. Jahankhani (Eds.), Digital twin technologies and smart cities. Springer. doi:10.1007/978-3-030-18732-3_8

Ayamga, M., Akaba, S., & Nyaaba, A. A. (2021). Multifaceted applicability of drones: A review. *Technological Forecasting and Social Change*, *167*, 120677. doi:10.1016/j.techfore.2021.120677

Bachmann, N., Tripathi, S., Brunner, M., & Jodlbauer, H. (2022). The contribution of data-driven technologies in achieving the sustainable development goals. *Sustainability (Basel)*, *14*(5), 2497. doi:10.3390/su14052497

Bachura, E., Valecha, R., Chen, R., & Rao, H. R. (2022). The OPM data breach: An investigation of shared emotional reactions on Twitter. *Management Information Systems Quarterly*, *46*(2), 881–910. doi:10.25300/MISQ/2022/15596

Bhatore, S., Mohan, L., & Reddy, Y. R. (2020). Machine learning techniques for credit risk evaluation: A systematic literature review. *Journal of Banking and Financial Technology*, *4*(1), 111–138. doi:10.1007/s42786-020-00020-3

Boar, B. H. (1997). *Strategic thinking for information technology: How to build the IT organization for the information age*. John Wiley & Sons, Inc.

Bolte, L., Vandemeulebroucke, T., & Van Wynsberghe, A. (2022). From an ethics of carefulness to an ethics of desirability: Going beyond current ethics approaches to sustainable AI. *Sustainability (Basel)*, *14*(8), 4472. doi:10.3390/su14084472

Bookstaber, R. (2017). *The end of theory: Financial crises, the failure of economics, and the sweep of human interaction*. Princeton University Press., doi:10.1515/9781400884964

Bosu, M. F., & MacDonell, S. G. (2019). Experience: Quality benchmarking of datasets used in software effort estimation. *ACM Journal of Data and Information Quality*, *11*(4), 1–38. doi:10.1145/3328746

Boustani, N. M. (2022). Artificial intelligence impact on banks clients and employees in an Asian developing country. *Journal of Asia Business Studies*, *16*(2), 267–278. doi:10.1108/JABS-09-2020-0376

Brundage, M., Avin, S., Clark, J., Toner, H., Eckersley, P., Garfinkel, B., Dafoe, A., Scharre, P., Zeitzoff, T., Filar, B., Anderson, H., Roff, H., Allen, G. C., Steinhardt, J., Flynn, C., Éigeartaigh, S., Beard, S., Belfield, H., Farquhar, S., … Amodei, D. (2018). *The malicious use of artificial intelligence: Forecasting, prevention, and mitigation*. https://arxiv.org/ftp/arxiv/papers/1802/1802.07228.pdf

Burget, M., Bardone, E., & Pedaste, M. (2017). Definitions and conceptual dimensions of responsible research and innovation: A literature review. *Science and Engineering Ethics*, *23*(1), 1–19. doi:10.1007/s11948-016-9782-1 PMID:27090147

Burnham, K., & Anderson, D. (2002). *Model selection and multimodel inference: A practical information-theoretic approach* (2nd ed.). Springer-Verlag.

Ceicyte, J., & Petraite, M. (2018). Networked responsibility approach for responsible innovation: Perspective of the firm. *Sustainability (Basel)*, *10*(6), 1720. doi:10.3390/su10061720

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2022). AI and digitalization in relationship management: Impact of adopting AI-embedded CRM system. *Journal of Business Research*, *150*, 437–450. doi:10.1016/j.jbusres.2022.06.033

Chen, L., Jiang, M., Jia, F., & Liu, G. (2022). Artificial intelligence adoption in business-to-business marketing: Toward a conceptual framework. *Journal of Business and Industrial Marketing*, *37*(5), 1025–1044. doi:10.1108/JBIM-09-2020-0448

Chirumalla, K., Reyes, L. G., & Toorajipour, R. (2022). Mapping a circular business opportunity in electric vehicle battery value chain: A multi-stakeholder framework to create a win–win–win situation. *Journal of Business Research*, *145*, 569–582. doi:10.1016/j.jbusres.2022.02.070

Chua, W. F., James, R., King, A., Lee, E., & Soderstrom, N. (2022). Task force on climate-related financial disclosures (TCFD) implementation: An overview and insights from the Australian Accounting Standards Board Dialogue Series. *Australian Accounting Review*, *32*(3), 396–405. doi:10.1111/auar.12388

Colagrossi, A., Pesce, V., Silvestrini, S., Gonzalez-Arjona, D., Hermosin, P., & Battilana, M. (2023). Sensors. In V. Pesce, A. Colagrossi, & S. Silvestrini (Eds.), *Modern spacecraft guidance, navigation, and control* (pp. 253–336). Elsevier. doi:10.1016/B978-0-323-90916-7.00006-8

Contreras-Koterbay, S. (2020). In anxious anticipation of our imminent obsolescence. In C. Neill (Ed.), *Lacanian perspectives on Blade Runner 2049* (pp. 167–187). Palgrave Macmillan Cham. doi:10.1007/978-3-030-56754-5

Correani, A., De Massis, A., Frattini, F., Petruzzelli, A. M., & Natalicchio, A. (2020). Implementing a digital strategy: Learning from the experience of three digital transformation projects. *California Management Review*, *62*(4), 37–56. doi:10.1177/0008125620934864

Cui, H., Zhang, H., Ganger, G. R., Gibbons, P. B., & Xing, E. P. (2016). GeePS: Scalable deep learning on distributed GPUs with a GPU-specialized parameter server. In *Proceedings of the eleventh European conference on computer systems* (pp. 1–16). ACM. doi:10.1145/2901318.2901323

Dąbrowska, J., Almpanopoulou, A., Brem, A., Chesbrough, H., Cucino, V., Di Minin, A., Giones, F., Hakala, H., Marullo, C., Mention, A. L., Mortara, L., Nørskov, S., Nylund, P. A., Oddo, C. M., Radziwon, A., & Ritala, P. (2022). Digital transformation, for better or worse: A critical multi-level research agenda. *R & D Management*, *52*(5), 930–954. doi:10.1111/radm.12531

De Haes, S., & Van Grembergen, W. (2009). An exploratory study into IT governance implementations and its impact on business/IT alignment. *Information Systems Management*, *26*(2), 123–137. doi:10.1080/10580530902794786

De Laat, P. B. (2021). Companies committed to responsible AI: From principles towards implementation and regulation? *Philosophy & Technology*, *34*(4), 1135–1193. doi:10.1007/s13347-021-00474-3 PMID:34631392

De Vynck, G., Lerman, R., & Tiku, N. (2023, February 16). Microsoft's AI chatbot is going off the rails. *The Washington Post*. https://www.washingtonpost.com/technology/2023/02/16/microsoft-bing-ai-chatbot-sydney/

Demdoum, Z., Meraghni, O., & Bekkouche, L. (2021). The application of green accounting according to activity-based costing for an orientation towards a green economy: Field study. *International Journal of Digital Strategy, Governance, and Business Transformation*, *11*(1), 1–15. doi:10.4018/IJDSGBT.20210101.oa3

Diakopoulos, N., Friedler, S., Arenas, M., Barocas, S., Hay, M., Howe, B., ... & Zevenbergen, B. (2017). Principles for accountable algorithms and a social impact statement for algorithms. *FAT/ML.*

Dignum, V. (2019). *Responsible artificial intelligence: How to develop and use AI in a responsible way*. Springer. doi:10.1007/978-3-030-30371-6

Eitel-Porter, R. (2021). Beyond the promise: Implementing ethical AI. *AI and Ethics*, *1*(1), 73–80. doi:10.1007/s43681-020-00011-6

Elkington, J. (1998). Accounting for the triple bottom line. *Measuring Business Excellence*, *2*(3), 18–22. doi:10.1108/eb025539

European Commission (EC). (2023). *Artificial intelligence act*. https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/698792/EPRS_BRI(2021)698792_EN.pdf

Firlej, M., & Taeihagh, A. (2021). Regulating human control over autonomous systems. *Regulation & Governance*, *15*(4), 1071–1091. doi:10.1111/rego.12344

Floridi, L., & Cowls, J. (2022). A unified framework of five principles for AI in society. In S. Carta (Ed.), *Machine learning and the city: Applications in architecture and urban design* (pp. 535–545). Wiley. doi:10.1002/9781119815075.ch45

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—an ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*(4), 689–707. doi:10.1007/s11023-018-9482-5 PMID:30930541

Fryer, D. (2020). Race, reform, & progressive prosecution. *The Journal of Criminal Law & Criminology*, *110*(4), 769–802. https://www.jstor.org/stable/48595414

Georgieff, A., & Hyee, R. (2022). Artificial intelligence and employment: New cross-country evidence. *Frontiers in Artificial Intelligence*, *5*, 832736. doi:10.3389/frai.2022.832736 PMID:35620279

Giovanola, B., & Tiribelli, S. (2022). Beyond bias and discrimination: Redefining the AI ethics principle of fairness in healthcare machine-learning algorithms. *AI & Society*, *38*(2), 549–563. doi:10.1007/s00146-022-01455-6 PMID:35615443

González-Tejero, C. B., Ribeiro-Navarrete, B., Cano-Marin, E., & McDowell, W. C. (2023). A systematic literature review on the role of artificial intelligence in entrepreneurial activity. *International Journal on Semantic Web and Information Systems*, *19*(1), 1–16. doi:10.4018/IJSWIS.318448

Gottschalk, S., Yigitbas, E., Nowosad, A., & Engels, G. (2023). Continuous situation-specific development of business models: Knowledge provision, method composition, and method enactment. *Software & Systems Modeling*, *22*(1), 47–73. doi:10.1007/s10270-022-01018-9

Goujard, C. (2023, March 31). Italian privacy regulator bans ChatGPT. *Politico*. https://www.politico.eu/article/italian-privacy-regulator-bans-chatgpt/

Gunkel, D. J. (2018). The other question: Can and should robots have rights? *Ethics and Information Technology*, *20*(2), 87–99. doi:10.1007/s10676-017-9442-4

Guo, X., Li, M., Wang, Y., & Mardani, A. (2023). Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. *Journal of Business Research*, *163*, 113868. doi:10.1016/j.jbusres.2023.113868

Gupta, B. B., Gaurav, A., Panigrahi, P. K., & Arya, V. (2023). Analysis of artificial intelligence-based technologies and approaches on sustainable entrepreneurship. *Technological Forecasting and Social Change*, *186*, 122152. doi:10.1016/j.techfore.2022.122152

Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2022). Artificial intelligence for decision support systems in the field of operations research: Review and future scope of research. *Annals of Operations Research*, *308*(1-2), 215–274. doi:10.1007/s10479-020-03856-6

Gwagwa, A., Kazim, E., Kachidza, P., Hilliard, A., Siminyu, K., Smith, M., & Shawe-Taylor, J. (2021). Road map for research on responsible artificial intelligence for development (AI4D) in African countries: The case study of agriculture. *Patterns (New York, N.Y.)*, *2*(12), 100381. doi:10.1016/j.patter.2021.100381 PMID:34950903

Halder, S., Attili, V. S. P., & Gupta, V. (2022). Information privacy assimilation: An organizational framework. *International Journal of Digital Strategy, Governance, and Business Transformation*, *12*(1), 1–17. doi:10.4018/IJDSGBT.313954

HLEGAI, European Commission. (2019). *Ethics Guidelines for Trustworthy AI*. https://ec.europa.eu/digital-single-market/en/news/ethicsguidelines-trustworthy-ai

Hunt, W., Sarkar, S., & Warhurst, C. (2022). Measuring the impact of AI on jobs at the organization level: Lessons from a survey of UK business leaders. *Research Policy*, *51*(2), 104425. doi:10.1016/j.respol.2021.104425

Iansiti, M., & Lakhani, K. R. (2020). *Competing in the age of AI: Strategy and leadership when algorithms and networks run the world.* Harvard Business Review Press. https://hbr.org/2020/01/competing-in-the-age-of-ai

IDC. (2023, March 7). *Worldwide spending on AI-centric systems forecast to reach $154 billion in 2023, according to IDC*. https://www.idc.com/getdoc.jsp?containerId=prUS50454123

Jabbar, H., & Khan, R. Z. (2014). Methods to avoid over-fitting and under-fitting in supervised machine learning (comparative study). *Computer Science*, *Communication and Instrumentation Devices*, *70*, 978–981. doi:10.3850/978-981-09-5247-1_017

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389–399. doi:10.1038/s42256-019-0088-2

Johnson, D. G. (2015). Technology with no human responsibility? *Journal of Business Ethics*, *127*(4), 707–715. doi:10.1007/s10551-014-2180-1

Kania, J., & Kramer, M. (2011). Collective impact. *Stanford Social Innovation Review*, *9*(1), 36–41.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. doi:10.1016/j.bushor.2018.08.004

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production*, *376*, 134120. doi:10.1016/j.jclepro.2022.134120

Kazim, F. A. (2021). Digital transformation in communities of Africa. *International Journal of Digital Strategy, Governance, and Business Transformation*, *11*(1), 1–23. doi:10.4018/IJDSGBT.287100

Kearns, G. S., & Sabherwal, R. (2006). Strategic alignment between business and information technology: A knowledge-based view of behaviors, outcome, and consequences. *Journal of Management Information Systems*, *23*(3), 129–162. doi:10.2753/MIS0742-1222230306

Khther, R. A., & Othman, M. (2013). Cobit framework as a guideline of effective IT governance in higher education: A review. *International Journal of Information Technology Convergence and Services*, *3*(1), 21–29. doi:10.5121/ijitcs.2013.3102

Koch, S., & Altinkemer, K. (2021). A value framework for technology potentials: Business adoption of emotion detection capabilities. *International Journal of Digital Strategy, Governance, and Business Transformation*, *11*(1), 1–13. doi:10.4018/IJDSGBT.302636

Kou, G., Shi, Y., & Wang, S. (2011). Multiple criteria decision making and decision support systems—Guest editor's introduction. *Decision Support Systems*, *51*(2), 247–249. doi:10.1016/j.dss.2010.11.027

Kumar, A., Alaraj, M., Rizwan, M., & Nangia, U. (2021). Novel AI based energy management system for smart grid with RES integration. *IEEE Access : Practical Innovations, Open Solutions*, *9*, 162530–162542. doi:10.1109/ACCESS.2021.3131502

Larsson, S. (2020). On the governance of artificial intelligence through ethics guidelines. *Asian Journal of Law and Society*, *7*(3), 437–451. doi:10.1017/als.2020.19

Larsson, S., & Heintz, F. (2020). Transparency in artificial intelligence. *Internet Policy Review*, *9*(2). Advance online publication. doi:10.14763/2020.2.1469

Lee, D., & Yoon, S. N. (2021). Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges. *International Journal of Environmental Research and Public Health*, *18*(1), 271. doi:10.3390/ijerph18010271 PMID:33401373

Lian, J., Freeman, L., Hong, Y., & Deng, X. (2021). Robustness with respect to class imbalance in artificial intelligence classification algorithms. *Journal of Quality Technology*, *53*(5), 505–525. doi:10.1080/00224065.2021.1963200

Lin, Y., Hu, Q., Liu, J., & Duan, J. (2015). Multi-label feature selection based on max-dependency and min-redundancy. *Neurocomputing*, *168*, 92–103. doi:10.1016/j.neucom.2015.06.010

Long, T. B., Blok, V., Dorrestijn, S., & Macnaghten, P. (2020). The design and testing of a tool for developing responsible innovation in start-up enterprises. *Journal of Responsible Innovation*, *7*(1), 45–75. doi:10.1080/23299460.2019.1608785

Lubberink, R., Blok, V., Van Ophem, J., & Omta, O. (2017). Lessons for responsible innovation in the business context: A systematic literature review of responsible, social and sustainable innovation practices. *Sustainability (Basel)*, *9*(5), 721. doi:10.3390/su9050721

Luckin, R., & Cukurova, M. (2019). Designing educational technologies in the age of AI: A learning sciences-driven approach. *British Journal of Educational Technology*, *50*(6), 2824–2838. doi:10.1111/bjet.12861

M. U. E. (2023). The beneficial and harmful aspects of artificial intelligence in the educational process. *Horizon: Journal of Humanity and Artificial Intelligence, 2*(5), 603–606. https://univerpubl.com/index.php/horizon/article/view/1774

Maican, C., & Lixandroiu, R. (2016). A system architecture based on open source enterprise content management systems for supporting educational institutions. *International Journal of Information Management*, *36*(2), 207–214. doi:10.1016/j.ijinfomgt.2015.11.003

Mikalef, P., Conboy, K., Lundström, J. E., & Popovič, A. (2022). Thinking responsibly about responsible AI and "the dark side" of AI. *European Journal of Information Systems*, *31*(3), 257–268. doi:10.1080/0960085X.2022.2026621

Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence*, *1*(11), 501–507. doi:10.1038/s42256-019-0114-4

Mkrttchian, V., & Voronin, V. (2021). Digitalization of lifecycle management of domestic Russian tour products based on problem-oriented digital twins-avatars, supply chain, 3D-hybrid, federated, and coordinated blockchain. *International Journal of Digital Strategy, Governance, and Business Transformation*, *11*(1), 1–13. doi:10.4018/IJDSGBT.20210101.oa2

Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. *Journal of Business Ethics*, *167*(2), 209–234. doi:10.1007/s10551-019-04407-1

Mutasa, S., Sun, S., & Ha, R. (2020). Understanding artificial intelligence based radiology studies: What is overfitting? *Clinical Imaging*, *65*, 96–99. doi:10.1016/j.clinimag.2020.04.025 PMID:32387803

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, *53*, 102104. doi:10.1016/j.ijinfomgt.2020.102104

Nylén, D., & Holmström, J. (2015). Digital innovation strategy: A framework for diagnosing and improving digital product and service innovation. *Business Horizons*, *58*(1), 57–67. doi:10.1016/j.bushor.2014.09.001

OECD. (2019). *OECD AI Principles overview.* https://oecd.ai/en/ai-principles

Orzes, G., Moretto, A. M., Ebrahimpour, M., Sartor, M., Moro, M., & Rossi, M. (2018). United Nations Global Compact: Literature review and theory-based research agenda. *Journal of Cleaner Production*, *177*, 633–654. doi:10.1016/j.jclepro.2017.12.230

Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI governance: Identifying best practices and potential barriers and outcomes. *Information Systems Frontiers*, *25*(1), 123–141. doi:10.1007/s10796-022-10251-y PMID:35464171

Peterson, R. (2004). Crafting information technology governance. *Information Systems Management*, *21*(4), 7–22. doi:10.1201/1078/44705.21.4.20040901/84183.2

Plekhanov, D., Franke, H., & Netland, T. H. (2022). Digital transformation: A review and research agenda. *European Management Journal*. Advance online publication. doi:10.1016/j.emj.2022.09.007

Puaschunder, J. M. (2020). Revising growth theory in the artificial age: Putty and clay labor. *Archives of Business Research*, *8*(3), 65–107. doi:10.14738/abr.83.7871

PwC. (2018). *Sizing the prize: PwC's global artificial intelligence study: Exploiting the AI revolution*. https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html

Qiang, V., Rhim, J., & Moon, A. (2023). No such thing as one-size-fits-all in AI ethics frameworks: A comparative case study. *AI & Society*. Advance online publication. doi:10.1007/s00146-023-01653-w

Ramasastry, A. (2015). Corporate social responsibility versus business and human rights: Bridging the gap between responsibility and accountability. *Journal of Human Rights*, *14*(2), 237–259. doi:10.1080/14754835.2015.1037953

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action. *MIT Sloan Management Review*. https://sloanreview.mit.edu/projects/reshaping-business-with-artificial-intelligence/

Rikap, C. (2022). The expansionary strategies of intellectual monopolies: Google and the digitalization of healthcare. *Economy and Society*, *52*(1), 1–27. doi:10.1080/03085147.2022.2131271

Rodriguez, A., Cotran, H., & Stewart, L. S. (2017). Evaluating the effectiveness of sustainability disclosure: Findings from a recent SASB study. *The Bank of America Journal of Applied Corporate Finance*, *29*(2), 100–108. doi:10.1111/jacf.12237

Royakkers, L., Timmer, J., Kool, L., & Van Est, R. (2018). Societal and ethical issues of digitization. *Ethics and Information Technology*, *20*(2), 127–142. doi:10.1007/s10676-018-9452-x

Saggar, A., & Nigam, B. (2023). Maximising net zero in energy-intensive industries: An overview of AI applications for greenhouse gas reduction. *Journal of Climate Change*, *9*(1), 13–23. doi:10.3233/JCC230003

Sartori, L., & Theodorou, A. (2022). A sociotechnical perspective for the future of AI: Narratives, inequalities, and human control. *Ethics and Information Technology*, *24*(1), 4. doi:10.1007/s10676-022-09624-3

Schiff, D. S., Rakova, B., Ayesh, A., Fanti, A., & Lennon, M. (2020). *Principles to practices for responsible AI: Closing the gap*. arXiv. https://doi.org//arXiv.2006.0470710.48550

Schmidt, A. L., & Van der Sijde, P. (2022). Disruption by design? Classification framework for the archetypes of disruptive business models. *R & D Management*, *52*(5), 893–929. doi:10.1111/radm.12530

Schneider, G. (2022). Legal challenges of AI supported legal services: Bridging principles and markets. *The Italian Law Journal*, *8*, 243–291.

Sethi, T. S., & Kantardzic, M. (2017). On the reliable detection of concept drift from streaming unlabeled data. *Expert Systems with Applications*, *82*, 77–99. doi:10.1016/j.eswa.2017.04.008

Silva, L. M. D., Bitencourt, C. C., Faccin, K., & Iakovleva, T. (2019). The role of stakeholders in the context of responsible innovation: A meta-synthesis. *Sustainability (Basel)*, *11*(6), 1766. doi:10.3390/su11061766

Snowden, D. J., & Boone, M. E. (2007). A leader's framework for decision making. *Harvard Business Review*, *85*(11), 68–76. PMID:18159787

Stilgoe, J., Owen, R., & Macnaghten, P. (2013). Developing a framework for responsible innovation. *Research Policy*, *42*(9), 1568–1580. doi:10.1016/j.respol.2013.05.008

Strubell, E., Ganesh, A., & McCallum, A. (2020). Energy and policy considerations for modern deep learning research. *Proceedings of the AAAI Conference on Artificial Intelligence*, *34*(09), 13693–13696. doi:10.1609/aaai.v34i09.7123

Tabakhi, S., & Moradi, P. (2015). Relevance–redundancy feature selection based on ant colony optimization. *Pattern Recognition*, *48*(9), 2798–2811. doi:10.1016/j.patcog.2015.03.020

Tarafdar, M., Beath, C. M., & Ross, J. W. (2019). Using AI to enhance business operations. *MIT Sloan Management Review*, *60*(4). https://sloanreview.mit.edu/article/using-ai-to-enhance-business-operations/

The Economist. (2017, May 6). *Regulating the internet giants: The world's most valuable resource is no longer oil, but data*. https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data

Tian, H., & Tian, J. (2021). The mediating role of responsible innovation in the relationship between stakeholder pressure and corporate sustainability performance in times of crisis: Evidence from selected regions in China. *International Journal of Environmental Research and Public Health*, *18*(14), 7277. doi:10.3390/ijerph18147277 PMID:34299728

Trocin, C., Mikalef, P., Papamitsiou, Z., & Conboy, K. (2023). Responsible AI for digital health: A synthesis and a research agenda. *Information Systems Frontiers*, *25*(6), 2139–2157. doi:10.1007/s10796-021-10146-4

Van Wynsberghe, A. (2021). Sustainable AI: AI for sustainability and the sustainability of AI. *AI and Ethics*, *1*(3), 213–218. doi:10.1007/s43681-021-00043-6

Verhezen, P. (2020). What to expect from artificial intelligence in business: How wise board members can and should facilitate human–AI collaboration. In M. Y. Kuznetsov & M. I. Nikishova (Eds.), *Challenges and opportunities of corporate governance transformation in the digital era* (pp. 61–90). IGI Global. doi:10.4018/978-1-7998-2011-6.ch004

Vetter, T. R., & Mascha, E. J. (2017). Bias, confounding, and interaction: Lions and tigers, and bears, oh my! *Anesthesia and Analgesia*, *125*(3), 1042–1048. doi:10.1213/ANE.0000000000002332 PMID:28817531

Vigneau, L., Humphreys, M., & Moon, J. (2015). How do firms comply with international sustainability standards? Processes and consequences of adopting the global reporting initiative. *Journal of Business Ethics*, *131*(2), 469–486. doi:10.1007/s10551-014-2278-5

von Schomberg, R. (2012). Prospects for technology assessment in a framework of responsible research and innovation. In M. Dusseldorp & R. Beecroft (Eds.), *Technikfolgen abschätzen lehren*. VS Verlag für Sozialwissenschaften. doi:10.1007/978-3-531-93468-6_2

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *International Journal of Human Resource Management*, *33*(6), 1237–1266. doi:10.1080/09585192.2020.1871398

Wang, J., Shan, Z., Gupta, M., & Rao, H. R. (2019). A longitudinal study of unauthorized access attempts on information systems: The role of opportunity contexts. *Management Information Systems Quarterly*, *43*(2), 601–622. Advance online publication. doi:10.25300/MISQ/2019/14751

Wang, X., & Cheng, Z. (2020). Cross-sectional studies: Strengths, weaknesses, and recommendations. *Chest*, *158*(1), S65–S71. doi:10.1016/j.chest.2020.03.012 PMID:32658654

Wendelken, A., Danzinger, F., Rau, C., & Moeslein, K. M. (2014). Innovation without me: Why employees do (not) participate in organizational innovation communities. *R & D Management*, *44*(2), 217–236. doi:10.1111/radm.12042

West, M., Kraut, R., & Ei Chew, H. (2021). *I'd blush if I could: Closing gender divides in digital skills through education*. UNESCO. doi:10.54675/RAPC9356

Wickson, F., & Carew, A. L. (2014). Quality criteria and indicators for responsible research and innovation: Learning from transdisciplinarity. *Journal of Responsible Innovation*, *1*(3), 254–273. doi:10.1080/23299460.2014.963004

Wirtz, B. W., Weyerer, J. C., & Kehl, I. (2022). Governance of artificial intelligence: A risk and guideline-based integrative framework. *Government Information Quarterly*, *39*(4), 101685. doi:10.1016/j.giq.2022.101685

Wu, S. P. J., Straub, D. W., & Liang, T. P. (2015). How information technology governance mechanisms and strategic alignment influence organizational performance. *Management Information Systems Quarterly*, *39*(2), 497–518. doi:10.25300/MISQ/2015/39.2.10

Yimer, A. H. (2021). Challenging the challenges of e-government: The Ethiopian context. *International Journal of Digital Strategy, Governance, and Business Transformation*, *11*(1), 1–12. doi:10.4018/IJDSGBT.286772

Yong, J. Y., Yusliza, M. Y., Ramayah, T., Chiappetta Jabbour, C. J., Sehnem, S., & Mani, V. (2020). Pathways towards sustainability in manufacturing organizations: Empirical evidence on the role of green human resource management. *Business Strategy and the Environment*, *29*(1), 212–228. doi:10.1002/bse.2359

Zhang, Y. (2023). Analysis on the Development Strategy of Hainan's Sports Tourism Informatization in the Digital Era. *International Journal on Semantic Web and Information Systems*, *19*(1), 1–18. doi:10.4018/IJSWIS.325788

Zhang, Y., Song, F., & Sun, J. (2023). QEBVerif: Quantization error bound verification of neural networks. In C. Enea & A. Lal (Eds.), *Computer aided verification* (pp. 413–437). Springer. doi:10.1007/978-3-031-37703-7_20

Zhu, Z., Lin, H., Gu, D., Wang, L., Wu, H., & Fang, Y. (2023). MusREL: A utility-weighted multi-strategy relation extraction model-based intelligent system for online education. *International Journal on Semantic Web and Information Systems*, *19*(1), 1–19. doi:10.4018/IJSWIS.329965

Zins, C. (2007). Conceptual approaches for defining data, information, and knowledge. *Journal of the American Society for Information Science and Technology*, *58*(4), 479–493. doi:10.1002/asi.20508

ENDNOTES

[1] https://openai.com/safety-standards
[2] https://www.stakeholdermapping.com/stakeholder-circle-methodology/