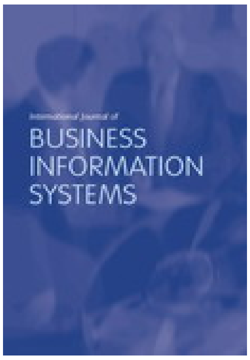

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Exploring artificial intelligence adoption among Italian firms: the AI readiness level

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Exploring artificial intelligence adoption among Italian firms: the AI readiness level

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Abstract: This study presents the first comprehensive analysis of artificial intelligence (AI) adoption among Italian firms, with a particular focus on the emerging impact of generative AI. Drawing upon the diffusion of innovations theory and the technology-organisation-environment (TOE) framework, we surveyed 237 managers from an Italian business school to examine their perspectives on both predictive/analytical AI and generative AI implementation. Our findings revealed varying levels of adoption and identified a significant gap in organisational AI readiness assessment tools. In response, we developed the AI readiness level (AIRL) framework, grounded in the TOE model, to evaluate AI maturity and guide strategic planning. This framework enables organisations to assess their AI capabilities, align initiatives with business objectives, and address key barriers such as skills shortages and data quality concerns. The study's limitations include the Italian context and specific executive sample. Future research should expand the sample size, diversify industries, and use randomised sampling.

Keywords: artificial intelligence; generative AI; Italian firms; AI readiness level; AIRL; DOI theory; TOE framework; technology adoption; innovation diffusion; AI implementation; digital transform.

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1 Introduction

The business environment has recently undergone profound changes, propelled by technological advancements in fields such as artificial intelligence (AI), particularly generative AI, data analytics, robotics, digital media, cloud computing and social technologies. These digital innovations are reshaping organisations' foundational and operational structures, ushering in an era marked by increased innovation, efficiency and competitive advantage (Akter et al., 2022; Almanasra, 2024; Ayoko, 2021; Bharadwaj et al., 2013).

The recent surge in popularity of transformer-based large language models (LLMs), a cornerstone of generative AI, highlights AI's growing importance in maintaining business competitiveness (Raiaan et al., 2024; Zhao et al., 2023). Generative AI's capabilities extend beyond enhancing operational efficiency; it plays a crucial role in improving customer interactions, building brand loyalty, and facilitating proactive risk management and strategic planning (Agrawal et al., 2019; Borges et al., 2021). However, integrating AI into business processes presents several challenges, including ethical concerns, the need for workforce upskilling and retraining, and the establishment of robust data governance frameworks to protect sensitive information (Ashok et al., 2022; Bostrom and Yudkowsky, 2018; Pant et al., 2024).

The significant implications of AI necessitate a comprehensive examination of its role across various industries, with particular emphasis on generative AI technologies (Mungoli, 2023), analysing both their benefits and challenges (Bharadiya, 2023). Understanding AI adoption rates and their driving factors is essential for assessing industries' readiness for an AI-driven future (IBM, 2022, 2023; Maslej et al., 2024).

In this context, alongside global reports from consultancy firms, numerous studies have explored AI adoption within enterprises. The literature encompasses surveys and case studies examining enterprise adoption and management of AI, with increasing attention to generative AI applications (Magoulas and Swoyer, 2020). Research indicates that AI adoption in enterprises is gaining momentum, offering the potential for increased revenue, reduced costs and improved efficiency (Enholm et al., 2022). However, organisations face challenges in assessing their readiness for AI implementation, particularly regarding the complexities of generative AI technologies. Jöhnk et al. (2021) propose five categories of AI readiness factors and corresponding indicators to guide decision-making in the adoption process. Despite AI's strategic opportunity, only a small percentage of organisations have extensively incorporated it into their processes (Siddique, 2018). To address this gap, Siddique (2018) suggests a seven-component framework for building enterprise AI capability, supported by case studies from various industries. Davenport (2021) emphasises the importance of creating and implementing an effective AI strategy, taking a pragmatic yet positive approach to its long-term potential. This principle becomes paramount when dealing with generative AI systems, whose emergent adoption paths often transcend conventional monitoring frameworks, exposing organisations to concrete risks of information leaks. Given that enterprise AI adoption remains in its early stages, as evidenced by the literature, organisations should assess their implementation readiness and develop comprehensive strategies to harness AI's potential, particularly considering the transformative impact of generative AI.

Among the literature on AI readiness at the firm level, we focus our attention on the study by Alsheibani et al. (2018), which examines AI adoption rates and influencing factors in Australian organisations. Their research aims to provide a comprehensive understanding of AI implementation across the country. It utilises two established theoretical frameworks: innovation diffusion theories, which explain how organisations adopt and implement innovations, and the technology-organisation-environment (TOE) framework, which identifies factors influencing AI adoption at the organisational level within the Australian context. To the best of our knowledge, there is a lack of studies focused on the Italian context, specifically regarding the AI readiness level (AIRL) of Italian organisations.

Addressing this gap in the literature and following the theoretical approach commonly used in AI adoption studies, such as Alsheibani et al. (2018), we develop our research based on the diffusion of innovations (DOI) theory and the TOE framework. The DOI theory, articulated by Rogers (2003), serves as the primary theoretical lens for this study. By mapping the attributes of the surveyed organisations to the categories defined by Rogers, this study aims to identify patterns and typical characteristics of early AI adopters within the Italian context.

Furthermore, based on the findings of this exploratory study, our research aims to develop a framework to assess the AIRL of these organisations, grounding it in the TOE framework (Tornatzky and Fleischer, 1990). The AIRL framework measures AI adoption and maturity within organisations, covering stages from initial awareness to full integration and optimisation, including the incorporation of generative AI technologies.

The research employed a convenience sampling method, targeting executive MBA alumni from an Italian business school. Participants comprised graduates who responded to an online survey. Whilst acknowledging the inherent limitations of convenience sampling, (e.g., Alessi and Martin, 2010; Schonlau et al., 2009), the study collected 237 valid responses, providing diverse perspectives on AI's anticipated role, including generative AI, in shaping organisational strategies.

Our research reveals a diverse spectrum of AI adoption among Italian businesses, ranging from innovators to cautious laggards. This varied landscape aligns with the DOI theory, reinforcing our theoretical foundation. We observed increasing investments in AI technologies, particularly in generative AI applications, indicating progression through the innovation adoption phases. Pioneering organisations are demonstrating AI's value and encouraging wider acceptance. The findings underscore AI's crucial role in the Italian corporate environment – not merely for operational efficiency but as a catalyst for innovation, competitive advantage and sustained growth – with generative AI playing an increasingly significant role. However, our analysis exposed a critical need for a more precise evaluation tool to assess organisational AI readiness. This insight led to the development of the AIRL framework, grounded in the TOE model (Tornatzky and Fleischer, 1990). The AIRL framework addresses limitations identified in our initial study, bridging the gap between empirical findings and practical business needs. By connecting our AI adoption research with the AIRL framework, we have created a refined tool for assessing and facilitating AI integration in corporate settings, including the adoption of generative AI technologies. This approach enhances both theoretical understanding of AI adoption and provides organisations with a practical roadmap for navigating AI integration, directly addressing the need for more precise evaluation tools in the adoption process.

This paper comprises five key sections. The following section establishes the theoretical foundation, culminating in our research questions. Section 3 outlines the methodological approach, including data collection processes, sample characteristics and analytical techniques. Section 4 presents our key findings on AI adoption patterns in Italian organisations and introduces the AIRL framework. Finally, Section 5 concludes the paper by discussing theoretical and managerial implications, reflecting on the AIRL framework's contributions, acknowledging study limitations and proposing future research directions.

2 Theoretical framework

2.1 Integrating AI within organisations

The evolution of AI in the business world is marked by significant achievements and occasional setbacks, reflecting an ever-progressing field (Dwivedi et al., 2021). AI's origins trace back to the 1950s, but its substantial economic impact began in the 1980s with the introduction of expert systems. However, the technological limitations of that era hindered sustained progress, leading to a temporary decline. The late 1990s and early 2000s witnessed a resurgence fuelled by the internet's expansion and substantial advancements in machine learning and data analytics. These developments broadened AI's utility to include customer relationship management and business analytics (Zhang and Lu, 2021). Today, generative AI is advancing rapidly, with technologies like OpenAI's GPT and o1, Google's Gemini and Anthropic's Claude demonstrating sophisticated capabilities in language and coding. Generative AI, in particular, is transforming the landscape with its potential to disrupt business models and strategies across various sectors (Gozalo-Brizuela and Garrido-Merchan, 2023).

AI's development has established it as a critical focus for contemporary businesses, driven by the proliferation of big data and the development of advanced algorithms and rapidly expanding computing infrastructure (Mikalef and Gupta, 2021). Tools such as chatbots and conversational agents, exemplified by ChatGPT, are now commonplace, enhancing stakeholder engagement and operational efficiency across numerous industries (Gkinko and Elbanna, 2023).

The widespread adoption of AI, particularly generative AI, in both private and public sectors has attracted the attention of scholars and industry experts alike (Almanasra, 2024). The significant impact of AI on organisational structures, operational processes and workforce dynamics has led to extensive academic inquiry, particularly concerning its effects on workplace productivity and management (Dwivedi et al., 2023; Hillebrand et al., 2025; Raisch and Krakowski, 2021; Soulami et al., 2024). Until late 2022, AI's use in business processes was primarily confined to large corporations with the data and financial resources to develop machine learning applications and the necessary technical infrastructure. This scenario changed dramatically with the launch of OpenAI's ChatGPT, the first widely accessible chatbot based on a pre-trained, generative neural network. This innovation democratised access to generative AI, enabling billions of users to benefit from its capabilities and making AI's impact on business and society a critical area of interest for management researchers (Linkon et al., 2024; Murire, 2024; Noy and Zhang, 2023; Peres et al., 2023).

2.2 The DOI theory

From a theoretical perspective, this study draws on the DOI theory developed by Rogers (2003). Rogers provides a comprehensive framework for understanding how new ideas and technologies, such as AI and generative AI, spread through cultures and industries (Alyoubi and Yamin, 2024; Rogers, 2003). According to Rogers, innovations diffuse through a population in different stages: innovators, early adopters, early majority, late majority and laggards. Each category exhibits distinct characteristics and attitudes towards adopting innovations. Innovators are risk-takers willing to embrace uncertainty, whilst early adopters, often opinion leaders, assess and validate innovations for others. The early and late majority are more cautious, with the late majority adopting primarily due to social pressure. Laggards are the most resistant, being rooted in tradition and past practices (Rogers, 1983).

In the context of AI, early adopters are forward-thinking organisations that quickly recognise the transformative potential of AI technologies, including generative AI, and strategically invest in integrating them into their operations (Alsheibani et al., 2018; Gómez and Palomas, 2024). These organisations gain a competitive advantage by using AI to enhance efficiency, drive innovation and improve decision-making processes (Haenlein and Kaplan, 2019). Moreover, they play a crucial role in bridging the gap between innovators and the majority of the market. Their proactive approach establishes industry standards and influences others to follow suit, accelerating the overall adoption of AI technologies across different sectors. The success and feedback of these early adopters significantly influence the perception and subsequent adoption of AI in the broader market. This underscores the importance of strategic foresight and a willingness to embrace cutting-edge technologies to maintain a competitive advantage in today's rapidly evolving technological landscape (Borges et al., 2021; Westerman et al., 2014).

2.3 The TOE framework

The TOE framework emerges as a comprehensive model for understanding the complex interplay of factors influencing technology adoption within organisations (Tornatzky and Fleischer, 1990). Originating in the 1990s with the works of Tornatzky and Fleischer, the TOE framework delineates three key contextual dimensions – technological, organisational and environmental – that collectively shape an organisation's technology adoption and implementation strategies. It emphasises that technology adoption is not merely a function of the technology's intrinsic attributes but also results from the complex interplay between these three contextual elements.

The technological context pertains to the current technologies used within the organisation as well as those accessible in the broader market. It considers the characteristics of the technology being evaluated, with factors such as relative advantage (perceived benefits over existing options), compatibility (fit with organisational norms and existing infrastructure), complexity (ease of use and understanding), trialability (opportunity for experimentation) and observability (visibility of positive outcomes) being crucial in shaping adoption decisions (Rogers, 2003; Tornatzky and Fleischer, 1990). Moreover, recent studies highlight the importance of perceived usefulness and perceived ease of use, underscoring their roles as key determinants within the technological domain (Oliveira and Martins, 2011; Venkatesh et al., 2003). In the case of generative AI, these factors are particularly significant due to its advanced capabilities and potential transformative impact.

The organisational context focuses on internal factors that influence an organisation's readiness to adopt new technologies. These factors include organisational size, structure (e.g. centralised or decentralised decision-making), culture (e.g. openness to change, risk tolerance), top management support and resource availability (financial, human and technological). The presence of technology champions is also a crucial component that can drive successful adoption (Kuan and Chau, 2001; Zhu et al., 2003). Furthermore, organisational learning capacity and absorptive capacity play vital roles in determining an organisation's ability to assimilate and utilise new knowledge, thereby enhancing its capability to leverage technology for competitive advantage (Cohen and Levinthal, 1990; Zahra and George, 2002). When adopting generative AI, these organisational factors become even more pertinent.

Lastly, the environmental context encompasses external forces that shape an organisation's technology adoption decisions. It includes the broader industry environment, market conditions, competitive pressures, regulatory requirements and the availability of external technological support (Baker, 2012; Zhu et al., 2003). Moreover, this context captures the influence of institutional factors, such as coercive, mimetic and normative pressures, which can drive organisations to conform to industry standards and practices (DiMaggio and Powell, 1983; Teo et al., 2003). Understanding these external dynamics is crucial for organisations navigating complex ecosystems, particularly when considering the adoption of generative AI technologies.

The TOE framework has been extensively explored through empirical studies, demonstrating its broad applicability across diverse business contexts (Shahadat et al., 2023). This robust framework has been effectively utilised to analyse factors influencing technology adoption in various sectors and regions. For instance, Zhu et al. (2003) employed the TOE framework to investigate the adoption of electronic business practices among European firms, revealing key facilitators and barriers unique to different national settings (Zhu et al., 2003). Similarly, Premkumar and Roberts (1999) applied the TOE framework to examine how organisational characteristics influence the adoption of new information technologies in rural small businesses (Premkumar and Roberts, 1999). These studies exemplify the framework's capacity to address both broad and specific organisational contexts.

In addition to these empirical inquiries, the TOE framework has been the subject of numerous literature reviews that consolidate and critique its theoretical and practical implications. These reviews serve not only to validate the framework but also to refine and extend its utility. For example, Baker (2012) provides a comprehensive review of the TOE framework, offering insights into its evolution and application across various studies (Baker, 2012). Oliveira and Martins (2011) focus more specifically on analysing the framework's effectiveness within the context of IT adoption (Oliveira and Martins, 2011). These literature reviews are vital as they synthesise large volumes of empirical evidence, thereby enhancing our understanding of the TOE framework's versatility and adaptability in addressing the complex dynamics of technology adoption, including emerging technologies like AI.

2.4 Integration of diffusion theory within the TOE framework

Rogers' DOI theory complements the TOE framework, offering a comprehensive approach to understanding innovation adoption in organisations. The DOI theory identifies three primary predictors of adoption: leadership characteristics, particularly openness to change; internal organisational dynamics, including structure, complexity, formalisation, connectivity, resources and size; and external organisational factors, such as receptivity to new systems. Rogers (2003) also emphasises the importance of technological characteristics (innovation attributes) in influencing decision-makers. Notably, he positions leadership characteristics as an integral component of the organisation's internal environment, aligning with the TOE framework's structure.

The TOE framework builds upon these concepts by systematically examining the interplay between internal organisational characteristics, external organisational factors and technological attributes. This integration enables a more nuanced understanding of how various factors influence the adoption and DOI within organisational settings, particularly when examining advanced technologies such as generative AI.

By integrating insights from both the DOI theory and the TOE framework, researchers and practitioners can develop a more comprehensive understanding of the innovation adoption process (Amini and Jahanbakhsh Javid, 2023; Basloom et al., 2022). This integrated approach considers both individual and organisational factors that drive or hinder technology adoption, providing a robust theoretical foundation for examining the complex dynamics of innovation diffusion in contemporary business environments.

2.5 Research objectives

Recognising the increasing significance of AI in contemporary organisations, this study pursues two interconnected research objectives. First, it examines AI technology adoption patterns in Italian organisations through the lens of DOI theory. This involves analysing the characteristics of organisations leading in AI adoption and comparing these characteristics with Rogers' innovator and early adopter profiles.

The second objective focuses on developing and validating the AIRL framework. This framework aims to provide a structured approach for evaluating organisational AI maturity and guiding strategic planning for AI implementation. It measures AI capabilities across different stages of adoption whilst addressing implementation barriers such as skills gaps and data quality. The AIRL framework integrates three crucial factors – technology, organisation and environment – to create a comprehensive assessment tool.

The overarching aim is to establish a thorough evaluation method and tool that enables organisations to better understand and enhance their AI readiness, whilst simultaneously contributing to both theoretical knowledge and practical implementation guidance in the field of AI adoption.

3 Methodology

3.1 Research design and sample

This research employs two distinct approaches: an exploratory study and the development of the AIRL framework based on the exploratory survey results. The AIRL framework is grounded in the TOE framework and inspired by NASA's 9-level technology readiness level (TRL) scale. This novel framework provides a comprehensive assessment of AI adoption and maturity within organisations.

Given the nascent stage of AI integration, particularly generative AI, in Italian enterprises, an exploratory approach was selected to investigate various aspects of AI adoption comprehensively. This approach enables a broad examination, providing insights that can guide future, more targeted studies.

The sample for this study comprises 237 MBA graduates from an Italian business school. All participants hold senior managerial positions within their respective organisations, ensuring that the responses reflect informed perspectives on AI adoption and integration at a strategic level.

A significant proportion of respondents were general managers (37.1%), followed by those in marketing/sales (14.8%) and operations (12.7%). This distribution underscores the strategic and operational insights provided by the respondents, ensuring that the data reflects high-level perspectives on AI implementation within their organisations.

Regarding the geographical representation of the organisations surveyed, they spanned the entire nation of Italy and included a diverse range of sizes, from small to medium-sized enterprises. This diverse sample provides a robust foundation for understanding the landscape of AI adoption across various organisational contexts.

Data were collected using an online questionnaire distributed to the selected MBA graduates. The questionnaire was designed to provide a comprehensive view of AI adoption, with a focus on generative AI applications, across different sectors and organisational levels. It included questions on:

- The current state of AI adoption within their organisations.
- Specific areas or departments where AI, particularly generative AI, is being implemented.
- The perceived impact of AI on organisational strategy and future work.
- Challenges and barriers encountered in AI adoption.
- Strategic planning and intentions regarding AI integration.

The questionnaire employed a combination of closed-ended and open-ended questions, enabling both quantitative analysis and qualitative insights.

Based on the findings from the exploratory study, a framework for assessing organisations' AIRL was developed. The AIRL framework is established on the TOE framework and is inspired by NASA's 9-level TRL scale. It is designed to evaluate the extent of AI adoption and maturity within organisations, with particular attention to generative AI technologies. The AIRL framework encompasses a comprehensive spectrum of stages, ranging from initial awareness of AI technologies to their complete integration and optimisation within organisational processes. This structured approach enables organisations to identify their current position in the AI adoption journey, facilitate strategic planning and allocate resources more effectively. Ultimately, the AIRL measure provides insights into how deeply AI technologies, particularly generative AI, are embedded within an organisation's operational and strategic layers, enhancing the potential for successful AI deployment and maximising the associated benefits.

4 Results

4.1 Main findings of the exploratory study

The main findings from the exploratory research provide a comprehensive and informed perspective on AI adoption and integration, with a particular focus on generative AI, among Italian enterprises.

4.1.1 Levels of AI engagement, objectives for AI adoption and AI applications

The engagement levels with AI varied among the surveyed organisations. Many organisations were primarily end-users of AI technologies, whilst a notable proportion was still in the exploratory phase of AI adoption. Interestingly, 36.7% of respondents indicated that their organisations had not yet implemented AI solutions, suggesting a cautious approach towards AI adoption as organisations continue to evaluate the potential benefits and challenges, particularly those associated with generative AI.

The primary objectives for adopting AI were focused on improving internal operations (32.3%), enhancing customer experience (25.4%) and mitigating risks (15.2%). These goals reflect a pragmatic approach to leveraging AI for tangible business improvements, emphasising efficiency, customer satisfaction and risk management.

The study identified several typical AI applications, including fraud and security measures, natural language processing (NLP) and computer vision. There was also significant interest in AI for content creation and experimentation, indicating that organisations are exploring a broad spectrum of AI capabilities, particularly those offered by generative AI technologies. This diversity in application underscores the versatility of AI technologies in addressing various business needs.

4.1.2 Investment trends and experimentation with generative AI

Investment in AI technologies has shown a positive trend, with most organisations either maintaining or increasing their AI spending over the past 12 months. This commitment to AI investment underscores the strategic importance that organisations place on AI as a catalyst for future growth, innovation and competitive advantage. The anticipation that this trend will continue reflects a long-term vision where AI is integral to business strategy and operational efficiency.

Alongside the general AI investment trends, the study revealed that many organisations are actively exploring generative AI. However, full-scale implementation of generative AI is virtually non-existent. Whilst generative AI's potential to revolutionise business processes and models is broadly recognised, significant concerns about ethical issues, data quality and reliability persist. These concerns underscore the need for novel frameworks that assist managers in implementing technology that interacts with users, requiring them to experiment and adopt an agile approach (McAfee et al., 2023). Moreover, it implies the need for robust regulatory frameworks to ensure that generative AI technologies are implemented in ethical, reliable and beneficial ways for all stakeholders involved.

4.1.3 Leveraging generative AI for creativity

Regarding creativity, respondents generally view AI as beneficial for fostering creativity and generating new ideas. Nonetheless, opinions vary regarding AI's overall impact on human creativity. Some express concerns that AI, particularly generative AI, could diminish human creativity if not appropriately managed. This dichotomy highlights the necessity for a balanced approach to AI integration – one that leverages AI to augment human creativity rather than replace it. Ensuring that AI serves as a tool to enhance creative processes can enable the maintenance of human ingenuity's unique value whilst benefiting from AI's capabilities.

4.1.4 Challenges in AI adoption: organisational obstacles and critical considerations on workforce impact

The study reveals various challenges and obstacles that organisations face in adopting AI, particularly generative AI.

Several significant challenges emerged as barriers to effective AI adoption. The most pressing issue identified was the availability of skilled personnel, pointing to a critical gap in AI expertise within organisations. This shortage underscores the urgent need for investment in education and training to develop a workforce capable of leveraging AI technologies, including those related to generative AI. Moreover, strategic clarity and access to high-quality data were major concerns. Organisations need a clear vision and robust data management practices to integrate AI successfully. Furthermore, securing senior management commitment and demonstrating the financial benefits of AI are crucial for obtaining the necessary resources and support for AI initiatives. Without senior leadership commitment and a clear return on investment, AI projects may struggle to gain traction.

In addition to the specific challenges of AI adoption, the study identified several broader organisational obstacles. Budget constraints, lack of skills, cultural resistance and data quality issues were all significant barriers. These obstacles highlight the need for a holistic approach to AI integration. Organisations must invest in skills development and strategic planning whilst fostering a culture that embraces change. Effective change management is essential to overcome resistance and ensure a smooth transition to AI-enhanced operations. Addressing these organisational obstacles is crucial for unlocking AI's full potential and achieving meaningful business outcomes.

4.1.5 The impact of AI on the workforce

Opinions among respondents were mixed, reflecting the complex and multifaceted nature of AI's influence on employment. Many expressed uncertainties about AI's future effects on jobs and work processes. Whilst some anticipated that AI would create new job roles and augment existing ones, others were concerned about job displacement and the need for new skill sets, particularly in relation to generative AI technologies. This uncertainty underscores the importance of proactive workforce planning and development. Organisations must prepare for the potential shifts in job roles and skill requirements by investing in reskilling and upskilling initiatives. By doing so, they can help mitigate the risks of job displacement and ensure that employees are equipped to thrive in an AI-driven workplace.

4.2 The AIRL framework

From our analysis of AI adoption patterns and challenges among Italian organisations emerged the AIRL framework. This framework builds upon two foundational elements: NASA's TRL scale (Héder, 2017; Olechowski et al., 2020) and the TOE framework (Tornatzky and Fleischer, 1990). Whilst the TRL scale provides a systematic approach to evaluating technology maturity, the TOE framework offers crucial insights into how technological, organisational and environmental factors collectively influence technology adoption within organisations.

The integration of the TOE framework is particularly significant as it ensures our assessment considers not only technological readiness but also organisational capabilities and environmental contexts. This universal approach recognises that successful AI adoption depends on the interplay between an organisation's technical infrastructure, its internal capabilities, culture and its external operating environment. This theoretical foundation enables the AIRL framework to provide a more nuanced and comprehensive evaluation of an organisation's AI readiness, including readiness for generative AI.

4.2.1 Framework structure and levels of AI readiness

The AIRL framework comprises nine progressive levels, each representing a distinct stage in an organisation's AI journey. These levels reflect an organisation's growing sophistication in AI adoption and implementation, from initial awareness to industry leadership. Each level incorporates considerations from all three TOE dimensions, ensuring a balanced assessment of technological capability, organisational readiness and environmental adaptation.

The progression begins with the foundation phase (levels 1–2), where organisations first recognise AI's potential and begin educational initiatives. Level 1 (awareness) represents organisations that acknowledge AI's importance but have not yet taken concrete steps, whilst level 2 (interest) indicates active engagement in understanding AI's potential applications and benefits, including those of generative AI.

The development phase (levels 3–4) marks the transition from theoretical understanding to practical implementation. Organisations at level 3 (experimenting) conduct pilot projects and assess their readiness across technological, organisational and environmental dimensions. At level 4 (operational), organisations successfully implement AI in specific areas, demonstrating measurable impact whilst addressing challenges in each TOE dimension.

The integration phase (levels 5–6) represents a significant advancement in AI maturity. Organisations at level 5 (strategic) have integrated AI into their overall strategy, whilst level 6 (transformative) indicates fundamental business model transformation through AI. This phase particularly emphasises the organisational dimension of the TOE framework, as it requires significant cultural and structural changes, particularly when incorporating generative AI technologies.

The leadership phase (levels 7–9) represents the highest levels of AI maturity. Organisations at these levels not only excel in AI implementation but also contribute to the broader AI ecosystem. Level 7 (collaborative) involves active engagement in AI partnerships and knowledge sharing. Level 8 (ethical) focuses on establishing robust governance frameworks, ensuring ethical implementation of AI, including generative AI. Level 9 (leading) represents organisations setting industry standards and driving innovation.

4.2.2 The four-quadrant classification

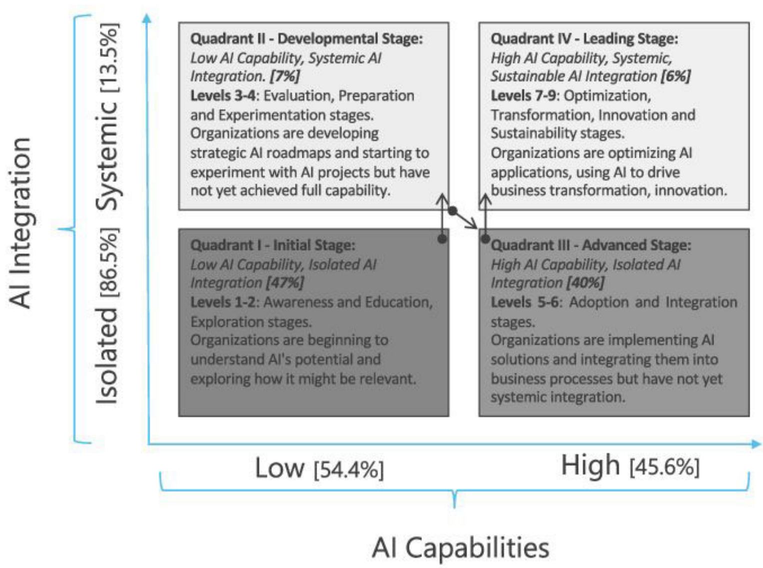
To make this framework more accessible and actionable, we developed a four-quadrant classification system based on two critical dimensions: AI capability and AI integration. We have measured these dimensions using specific questions in our exploratory study. As illustrated in Figure 1, this classification provides a visual representation of how organisations position themselves in their AI journey. The quadrants effectively map to different combinations of AIRL levels, offering a simplified yet comprehensive view of an organisation's AI maturity.

The initiating quadrant, representing organisations with low capability and isolated integration, typically corresponds to AIRL levels 1–2. These organisations are beginning their AI journey, focusing primarily on building awareness and understanding, including initial explorations of generative AI.

The implementing quadrant (levels 3–4) comprises organisations that have begun systematic integration despite relatively low capabilities, demonstrating their commitment to AI adoption. This may include pilot projects involving generative AI applications.

Organisations in the strategising quadrant (levels 5–6) possess advanced AI capabilities but have not yet achieved full integration across their operations. The most advanced organisations fall into the Transforming quadrant (levels 7–9), characterised by both high capability and systemic integration. These organisations typically lead their industries in AI innovation and best practices, often pioneering the use of generative AI technologies.

Figure 1 AIRL of Italian organisations' AI capabilities and integration (see online version for colours)



4.2.3 Application of the framework to Italian companies

Based on the exploratory study we developed to understand the situation regarding AI in Italian organisations, we know that many organisations (118) are implementing AI, but not on a large scale, suggesting selective or department-specific AI projects rather than organisation-wide integration. A significant number of responses (87) indicate that AI is not being implemented at all, suggesting that a substantial proportion of organisations are either in the early stages of considering AI or have yet to find a compelling use case, perhaps due to uncertainties around generative AI.

Some organisations (23) are progressing towards large-scale AI implementation but have not yet fully achieved this goal. A smaller group of organisations (9) reported that they are implementing AI on a large scale and integrated across the business. This suggests a more advanced stage of AI adoption, where AI technologies are embedded in multiple aspects of the organisation's operations. Therefore, we can state that for 86.5%, integration is isolated, whilst for 13.5%, the level is systemic.

Moreover, the distribution of AI experience levels among the surveyed organisations is categorised into four levels. A significant proportion of the organisations examined (30%) have been engaged with AI for over a year, indicating substantial experience and possibly integration of AI into their operations or product offerings. This group likely has a deeper understanding of AI's challenges and opportunities, including those associated with generative AI, and may have already realised tangible benefits or identified specific areas for improvement.

Another segment of organisations (15.6%) is in the early stages of AI adoption, with experience ranging from six months to one year. These organisations have progressed beyond the initial exploration phase and may be implementing AI solutions at a larger scale, developing use cases or evaluating the impact of their initial AI projects.

A slightly larger proportion of the sample (17.7%) includes organisations new to AI with less than six months of experience. These organisations are likely in the exploration or pilot phase, testing AI solutions to understand how AI can benefit their operations, products or services. Their engagement level suggests a cautious approach, focusing on learning and experimentation, possibly with generative AI technologies.

The largest group of respondents (36.7%) indicated that their organisations have not yet implemented any AI solution. This result could indicate several possibilities: they are still in the planning or consideration phase, evaluating potential AI opportunities and challenges; they may lack the resources, expertise or strategic direction needed for AI adoption; or they may not see AI as suitable for their current needs or goals.

Our research reveals a distinctive distribution of Italian organisations across these quadrants, providing valuable insights into the current state of AI adoption in Italy. The largest segment (47%) falls within the initiating quadrant, indicating that many Italian organisations are still in the early stages of their AI journey. This finding suggests significant potential for growth and development in AI adoption across the Italian business landscape, particularly in the realm of generative AI.

A smaller but significant proportion (40%) occupies the Strategising quadrant, demonstrating strong AI capabilities but room for improvement in integration. The relatively small percentages in the implementing (7%) and transforming (6%) quadrants suggest that whilst some organisations have achieved advanced AI implementation, there is considerable opportunity for progression across the spectrum, including the adoption of generative AI technologies.

The AIRL framework serves as more than just a diagnostic tool; it provides organisations with a roadmap for advancing their AI capabilities and integration. By understanding their current position within this framework, organisations can develop targeted strategies for improvement, allocate resources more effectively and benchmark their progress against industry peers. Moreover, the framework's grounding in the TOE theory ensures that organisations consider all crucial aspects of AI adoption – technological readiness, organisational capability and environmental factors – in their strategic planning.

The framework's value extends beyond individual organisational assessment. It contributes to our understanding of industry-wide AI adoption patterns and challenges, enabling the identification of common barriers and success factors. This broader perspective enables organisations to learn from others' experiences and make more informed decisions about their AI initiatives, including those involving generative AI.

As AI technologies continue to evolve and reshape business landscapes, the AIRL framework provides a structured approach for organisations to assess, plan and execute their AI strategies. Its comprehensive nature, grounded in established theoretical frameworks and empirical research, makes it a valuable tool for organisations at any stage of their AI journey.

5 Discussion

This study makes several important contributions to both theory and practice in the field of AI adoption and organisational readiness, with particular emphasis on the emerging role of generative AI technologies. Through our comprehensive analysis of Italian organisations' AI adoption patterns and the development of the AIRL framework, we have advanced the understanding of how organisations can effectively navigate the challenges of AI integration, including those posed by generative AI.

5.1 Theoretical contributions

Our research extends existing theoretical frameworks in several significant ways. First, by applying the DOI theory to AI adoption, particularly focusing on generative AI, in Italian organisations, we provide new insights into how this transformative technology spreads through organisational landscapes. Our findings validate Rogers' (2003) adoption categories in the AI context, with innovators and early adopters representing approximately half of our sample. This significant proportion aligns with and expands upon previous research (Lund et al., 2020; Raman et al., 2024), highlighting these groups' crucial role in driving AI adoption within Italian organisations, whilst revealing adoption patterns unique to AI technologies, particularly generative AI, that extend beyond traditional innovation models.

The second theoretical contribution of this study is the development of the AIRL framework, which represents a significant advancement in technology adoption models. By integrating the systematic approach of NASA's TRL scale with the comprehensive perspective of the TOE framework, we have created a novel tool that addresses the specific challenges of AI adoption, including those related to generative AI. The AIRL framework's innovation lies in its ability to:

1. Provide a nuanced, multi-level assessment of AI readiness that extends beyond binary adoption models.
2. Integrate technological, organisational and environmental factors specific to AI adoption.
3. Offer a structured approach to evaluating both AI capabilities and integration levels.
4. Account for the ethical and governance dimensions of AI implementation, particularly regarding generative AI.

Our empirical findings from Italian organisations have revealed a clear pattern in AI adoption that aligns with but also extends current theoretical understanding. The discovery that 47% of organisations are in the 'Initiating quadrant' whilst 40% are in the 'Strategising quadrant' suggests a more complex adoption pattern than previously theorised, highlighting the importance of considering both capability development and integration processes in technology adoption models, particularly regarding generative AI technologies.

Furthermore, our research contributes to the theoretical discourse on organisational change in the context of AI adoption. The AIRL framework's emphasis on progressive stages of adoption, from awareness to leadership, provides a theoretical foundation for understanding how organisations transform through AI integration. This aligns with recent work by Baier et al. (2024) on organisational redesign for AI implementation whilst extending it through a more structured assessment approach that includes considerations for generative AI.

5.2 Managerial implications

Our findings have significant implications for practitioners. The AIRL framework provides managers with a practical tool for:

1. Assessing their organisation's current AIRL, including readiness for generative AI.
2. Identifying specific areas requiring development.
3. Planning strategic initiatives for advancing AI capabilities.
4. Benchmarking against industry peers.
5. Making informed decisions about resource allocation.

The empirical evidence from our study of Italian organisations offers valuable insights for managers. The finding that many organisations have strong AI capabilities but struggle with integration (40% in the Strategising quadrant) suggests that managers should focus not only on developing technical capabilities but also on organisational integration strategies, particularly when implementing generative AI solutions.

Our research specifically highlights the crucial role of management in successful AI adoption. The data indicate that whilst technical challenges exist, organisational and cultural factors often present more significant barriers to AI implementation. This underscores the need for managers to:

- Develop comprehensive change management strategies.
- Invest in workforce development and training, particularly in skills related to generative AI.
- Create clear governance frameworks for AI implementation.
- Foster a culture of innovation and experimentation.
- Balance rapid adoption with ethical considerations, particularly regarding generative AI technologies.
- Ensure alignment between AI initiatives and business objectives.

To support practitioners in implementing these findings, we have developed an interactive assessment tool (AIRL Assessment Tool, 2024) that operationalises the AIRL framework. This tool enables organisations to systematically evaluate their AI maturity across technological, organisational and environmental dimensions through a structured questionnaire. The assessment provides a comprehensive analysis that includes:

1. a numerical AIRL score (1–9) with corresponding maturity level description
2. precise positioning within the capability-integration matrix through an interactive quadrant visualisation
3. tailored strategic recommendations with supporting rationale based on the organisation's current state.

This practical instrument enables managers to bridge the gap between theoretical understanding and actionable strategy, offering concrete guidance for advancing their organisation's AI capabilities and integration. The tool is particularly valuable for strategic planning as it not only diagnoses current AI readiness but also provides a clear roadmap for progression to higher maturity levels.

6 Conclusions

Our research advances the field of AI adoption through several distinctive contributions that bridge theoretical understanding and practical implementation. By extending the DOI theory to AI adoption, we reveal unique patterns specific to AI technologies, highlighting the crucial role of innovators and early adopters in driving organisational AI transformation. The development of the AIRL framework represents a significant advancement in understanding and facilitating AI adoption by integrating NASA's TRL scale with the TOE framework, providing a nuanced, multi-level assessment that extends beyond binary adoption models. Our empirical analysis of Italian organisations reveals both progress and challenges in AI adoption, with many organisations still in early stages of implementation, particularly in the 'Initiating' and 'Strategising' quadrants. This distribution suggests significant opportunities for growth and development, particularly in embracing generative AI technologies. The operationalisation of our framework through an interactive assessment tool enables organisations to systematically evaluate their AI readiness and receive tailored strategic recommendations, effectively bridging the gap between academic understanding and practical implementation.

Whilst our study provides valuable insights, several limitations should be acknowledged. First, our sample was limited to Italian organisations and specifically to MBA graduates, which may affect the generalisability of our findings. Second, the cross-sectional nature of our study captures only a snapshot of AI adoption at a specific point in time. Third, whilst our framework encompasses generative AI, the rapid evolution of this technology may introduce new considerations not fully captured in our current model.

Future research could address these limitations and extend our findings in several ways:

- Longitudinal studies: tracking organisations' progression through AIRL levels over time, particularly in relation to the adoption of generative AI technologies.

- Cross-cultural comparisons: validating the AIRL framework across different national contexts to assess its applicability in varying cultural and economic environments.
- Industry-specific applications: examining how the framework applies in different sectors, considering the unique challenges and opportunities of generative AI in each industry.
- Ethical implications: investigating how organisations balance AI adoption with ethical considerations, particularly focusing on data privacy, intellectual property and the ethical use of generative AI.
- Impact assessment: measuring the relationship between AIRL levels and organisational performance metrics, such as innovation outcomes, operational efficiency and competitive advantage.

As AI technologies continue to evolve, particularly in the realm of generative AI, frameworks that can systematically assess and guide organisational readiness become increasingly vital. Future research building upon these foundations will be crucial in advancing both theoretical understanding and practical implementation of AI technologies in organisational contexts, ultimately enabling organisations to harness the benefits of AI whilst mitigating associated risks.

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Declarations

All authors declare that they have no conflicts of interest.

References

Agrawal, A., Gans, J.S. and Goldfarb, A. (2019) 'Exploring the impact of artificial intelligence: prediction versus judgment', *Information Economics and Policy*, Vol. 47, pp.1–6, DOI: 10.1016/j.infoecopol.2019.05.001.

AIRL Assessment Tool (2024) [online] https://claude.site/artifacts/e2bb9fb1-7824-49ed-ad30-d8bd13e6d858 (accessed 7 January 2024).

Akter, S., Michael, K., Uddin, M.R., McCarthy, G. and Rahman, M. (2022) 'Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics', *Annals of Operations Research*, Vol. 308, No. 1, pp.7–39, DOI: 10.1007/s10479-020-03620-w.

Alessi, E.J. and Martin, J.I. (2010) 'Conducting an internet-based survey: benefits, pitfalls and lessons learned', *Social Work Research*, Vol. 34, No. 2, pp.122–128, DOI: 10.1093/swr/34.2.122.

Almanasra, S. (2024) 'Applications of integrating artificial intelligence and big data: a comprehensive analysis', *Journal of Intelligent Systems*, Vol. 33, No. 1, p.20240237, DOI: 10.1515/jisys-2024-0237.

Alsheibani, S., Cheung, Y. and Messom, C. (2018) 'Artificial intelligence adoption: AI-readiness at firm-level', *PACIS 2018 Proceedings*, p.37 [online] https://aisel.aisnet.org/pacis2018/37 (accessed 30 October 2024).

Alyoubi, B.A. and Yamin, M.A.Y. (2024) 'Investigating the role of diffusion of innovation theory, environmental pressure and organisational capabilities towards adoption of digital technologies', *International Journal of Business Information Systems*, Vol. 46, No. 1, pp.32–55, DOI: 10.1504/ijbis.2024.138555.

Amini, M. and Jahanbakhsh Javid, N. (2023) 'A multi-perspective framework established on diffusion of innovation (DOI) theory and technology, organization and environment (TOE) framework toward supply chain management system based on cloud computing technology for small and medium enterprises', *International Journal of Information Technology and Innovation Adoption*, Vol. 11, pp.1217–1234 [online] https://ssrn.com/abstract=4340207 (accessed 30 October 2024).

Ashok, M., Madan, R., Joha, A. and Sivarajah, U. (2022) 'Ethical framework for artificial intelligence and digital technologies', *International Journal of Information Management*, Vol. 62, p.102433, DOI: 10.1016/j.ijinfomgt.2021.102433.

Ayoko, O.B. (2021) 'Digital transformation, robotics, artificial intelligence and innovation', *Journal of Management and Organisation*, Vol. 27, pp.831–835, DOI: 10.1017/jmo.2021.64.

Baier, P., DeLallo, D. and Sviokla, J.J. (2024) 'Your organisation isn't designed to work with GenAI', *Harvard Business Review*, 26 February [online] https://hbr.org/2024/02/your-organization-isnt-designed-to-work-with-genai.

Baker, J. (2012) 'The technology-organisation-environment framework', in Dwivedi, Y.K., Wade, M.R. and Schneberger S.L. (Eds.): *Information Systems Theory: Explaining and Predicting Our Digital Society*, Springer New York, Vol. 1, pp.231–245, DOI: 10.1007/978-1-4419-6108-2_12.

Basloom, R.S., Mohamad, M.H.S. and Auzair, S.M. (2022) 'Applicability of public sector reform initiatives of the Yemeni government from the integrated TOE-DOI framework', *International Journal of Innovation Studies*, Vol. 6, No. 4, pp.286–302, DOI: 10.1016/j.ijis.2022.08.005.

Bharadiya, J.P. (2023) 'The impact of artificial intelligence on business processes', *European Journal of Technology*, Vol. 7, No. 2, pp.15–25, DOI: 10.47672/ejt.1488.

Bharadwaj, A., El Sawy, O.A., Pavlou, P.A. and Venkatraman, N. (2013) 'Digital business strategy: toward a next generation of insights', *MIS Quarterly*, Vol. 37, No. 2, pp.471–482 [online] http://www.jstor.org/stable/43825919 (accessed 2 December 2024).

Borges, A.F., Laurindo, F.J., Spínola, M.M., Gonçalves, R.F. and Mattos, C.A. (2021) 'The strategic use of artificial intelligence in the digital era: systematic literature review and future research directions', *International Journal of Information Management*, Vol. 57, p.102225, DOI: 10.1016/j.ijinfomgt.2020.102225.

Bostrom, N. and Yudkowsky, E. (2018) 'The ethics of artificial intelligence', in *Artificial Intelligence Safety and Security*, pp.57–69, Chapman and Hall/CRC, Boca Raton.

Cohen, W.M. and Levinthal, D.A. (1990) 'Absorptive capacity: a new perspective on learning and innovation', *Administrative Science Quarterly*, Vol. 35, No. 1, pp.128–152, DOI: 10.2307/2393553.

Davenport, T.H. (2021) 'Enterprise adoption and management of artificial intelligence', *Management and Business Review*, Vol. 1, No. 1, pp.165–172, DOI: 10.1177/2694105820210101025.

DiMaggio, P.J. and Powell, W.W. (1983) 'The iron cage revisited: institutional isomorphism and collective rationality in organisational fields', *American Sociological Review*, Vol. 48, No. 2, pp.147–160, DOI: 10.2307/2095101.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T. and Williams, M.D. (2021) 'Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities and agenda for research, practice and policy', *International Journal of Information Management*, Vol. 57, p.101994, DOI: 10.1016/j.ijinfomgt.2019.08.002.

Dwivedi, Y.K., Kshetri, N., Hughes, L., Slade, E.L., Jeyaraj, A., Kar, A.K. and Wright, R. (2023) 'So what if ChatGPT wrote it?' Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy', *International Journal of Information Management*, Vol. 71, p.102642, DOI: 10.1016/ j.ijinfomgt.2023.102642.

Enholm, I.M., Papagiannidis, E., Mikalef, P. and Krogstie, J. (2022) 'Artificial intelligence and business value: a literature review', *Information Systems Frontiers*, Vol. 24, No. 5, pp.1709–1734, DOI: 10.1007/s10796-021-10186-w.

Gkinko, L. and Elbanna, A. (2023) 'The appropriation of conversational AI in the workplace: a taxonomy of AI chatbot users', *International Journal of Information Management*, Vol. 69, p.102568, DOI: 10.1016/j.ijinfomgt.2022.102568.

Gómez, J. and Palomas, S. (2024) 'The returns of early adoption of information technologies: order of adoption or level of adoption advantages?', *MIS Quarterly*, pp.1047–1076, DOI: 10.25300/MISQ/2024/17125.

Gozalo-Brizuela, R. and Garrido-Merchan, E.C. (2023) *ChatGPT is Not All You Need. A State of the Art Review of large Generative AI Models*, arXiv preprint arXiv:2301.04655.

Haenlein, M. and Kaplan, A. (2019) 'A brief history of artificial intelligence: on the past, present and future of artificial intelligence', *California Management Review*, Vol. 61, No. 4, pp.5–14, DOI: 10.1177/0008125619864925.

Héder, M. (2017) 'From NASA to EU: the evolution of the TRL scale in public sector innovation', *The Innovation Journal*, Vol. 22, No. 2, pp.1–23 [online] https://innovation.cc/all-issues/volume22-issue2 (accessed 2 December 2024).

Hillebrand, L., Raisch, S. and Schad, J. (2025) 'Managing with artificial intelligence: an integrative framework', *Academy of Management Annals*, Vol. 19, No. 1, pp.343–375, https://doi.org/ 10.5465/annals.2022.0072.

IBM (2022) *IBM Global AI Adoption Index* [online] https://www.ibm.com/downloads/cas/ (accessed 30 October 2024).

IBM (2023) *IBM Global AI Adoption Index* [online] https://www.multivu.com/players/English/ 9240059-ibm-2023-global-ai-adoption-index-report/ (accessed 30 October 2024).

Jöhnk, J., Weißert, M. and Wyrtki, K. (2021) 'Ready or not, AI comes – an interview study of organisational AI readiness factors', *Business & Information Systems Engineering*, Vol. 63, No. 1, pp.5–20, DOI: 10.1007/s12599-020-00676-7.

Kuan, K.K.Y. and Chau, P.Y.K. (2001) 'A perception-based model for EDI adoption in small businesses using a technology-organisation-environment framework', *Information & Management*, Vol. 38, No. 8, pp.507–521, DOI: 10.1016/S0378-7206(01)00073-8.

Linkon, A.A., Shaima, M., Sarker, M.S.U., Nabi, N., Rana, M.N.U., Ghosh, S.K., Rahman, M.A., Esa, H. and Chowdhury, F.R. (2024) 'Advancements and applications of generative artificial intelligence and large language models on business management: a comprehensive review', *Journal of Computer Science and Technology Studies*, Vol. 6, No. 1, pp.225–232, DOI: 10.32996/jcsts.2024.6.1.26.

Lund, B.D., Omame, I.M., Tijani, S. and Agbaji, D.A. (2020) 'Perceptions toward artificial intelligence among academic library employees and alignment with the diffusion of innovations' adopter categories', *College and Research Libraries*, Vol. 81, No. 5, pp.865–882, DOI: 10.5860/crl.81.5.865.

Magoulas, R. and Swoyer, S. (2020) *AI Adoption in the Enterprise 2020* [online] https://www.oreilly.com/radar/ai-adoption-in-the-enterprise-2020/ (accessed 2 December 2024).

Maslej, N., Fattorini, L., Perrault, R., Parli, V., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J.C., Shoham, Y., Wald, R. and Clark, J. (2024) *The AI Index 2024 Annual Report (AI Index Steering Committee, Issue*. S. University [online] https://aiindex.stanford.edu/wp-content/uploads/2024/05/HAI_AI-Index-Report-2024.pdf (accessed 2 December 2024).

McAfee, A., Rock, D. and Brynjolfsson, E. (2023) 'How to capitalise on generative AI', *Harvard Business Review*, Vol. 101, No. 6, pp.42–48.

Mikalef, P. and Gupta, M. (2021) 'Artificial intelligence capability: conceptualization, measurement calibration and empirical study on its impact on organisational creativity and firm performance?', *Information and Management*, Vol. 58, No. 3, p.103434, DOI: 10.1016/j.im.2021.103434.

Mungoli, N. (2023) 'Revolutionising industries: the impact of artificial intelligence technologies', *Journal of Electrical Electronics Engineering*, https://doi.org/10.1016/j.hybadv.2024.100277.

Murire, O.T. (2024) 'Artificial intelligence and its role in shaping organizational work practices and culture', *Administrative Sciences*, Vol. 14, No. 12, p.316, DOI: 10.3390/admsci14120316.

Noy, S. and Zhang, W. (2023) 'Experimental evidence on the productivity effects of generative artificial intelligence', *Science*, Vol. 381, No. 6654, pp.187–192, DOI: 10.1126/science.adh2586.

Olechowski, A.L., Eppinger, S.D., Joglekar, N. and Tomaschek, K. (2020) 'Technology readiness levels: shortcomings and improvement opportunities', *Systems Engineering*, Vol. 23, No. 4, pp.395–408, DOI: 10.1002/sys.21533.

Oliveira, T. and Martins, M.F. (2011) 'Literature review of information technology adoption models at firm level', *Electronic Journal of Information Systems Evaluation*, Vol. 14, No. 1, pp.110–121.

Pant, A., Hoda, R., Spiegler, S.V., Tantithamthavorn, C. and Turhan, B. (2024) 'Ethics in the age of AI: an analysis of AI practitioners' awareness and challenges', *ACM Trans. Softw. Eng. Methodol.*, Vol. 33, No. 3, DOI: 10.1145/3635715.

Peres, R., Schreier, M., Schweidel, D. and Sorescu, A. (2023) 'On ChatGPT and beyond: how generative artificial intelligence may affect research, teaching and practice', *International Journal of Research in Marketing*, Vol. 40, No. 2, pp.269–275, DOI: 10.1016/j.ijresmar.2023.03.001.

Premkumar, G. and Roberts, M. (1999) 'Adoption of new information technologies in rural small businesses', *Omega*, Vol. 27, No.4, pp.467–484, DOI: 10.1016/S0305-0483(98)00071-1.

Raiaan, M.A.K., Mukta, M.S.H., Fatema, K., Fahad, N.M., Sakib, S., Mim, M.M.J., Ahmad, J., Ali, M.E. and Azam, S. (2024) 'A review on large language models: architectures, applications, taxonomies, open issues and challenges', *IEEE Access*, Vol. 12, pp.26839–26874, DOI: 10.1109/ACCESS.2024.3365742.

Raisch, S. and Krakowski, S. (2021) 'Artificial intelligence and management: the automation-augmentation paradox', *Academy of Management Review*, Vol. 46, No. 1, pp.192–210, DOI: 10.5465/amr.2018.0072.

Raman, R., Mandal, S., Das, P., Kaur, T., Sanjanasri, J.P. and Nedungadi, P. (2024) 'Exploring university students' adoption of ChatGPT using the diffusion of innovation theory and sentiment analysis with gender dimension', *Human Behavior and Emerging Technologies*, Article ID 3085910, Vol. 2024, DOI: 10.1155/2024/3085910.

Rogers, E.M. (1983) *Diffusion of Innovations*, University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship, SSRN [online] https://ssrn.com/abstract=1496176 (accessed 15 October 2024).

Rogers, E.M. (2003) *Diffusion of Innovations*, 5th ed., Free Press, New York.

Schonlau, M., Van Soest, A., Kapteyn, A. and Couper, M. (2009) 'Selection bias in web surveys and the use of propensity scores', *Sociological Methods & Research*, Vol. 37, No. 3, pp.291–318, DOI: 10.1177/0049124108327128.

Shahadat, M.H., Nekmahmud, M., Ebrahimi, P. and Fekete-Farkas, M. (2023) 'Digital technology adoption in SMEs: what technological, environmental and organizational factors influence in emerging countries?', *Global Business Review*, DOI: 10.1177/09721509221137199.

Siddique, S.S. (2018) *The Road to Enterprise Artificial Intelligence: A Case Studies Driven Exploration*, PhD thesis, Massachusetts Institute of Technology.

Soulami, M., Benchekroun, S. and Galiulina, A. (2024) 'Exploring how AI adoption in the workplace affects employees: a bibliometric and systematic review', *Frontiers in Artificial Intelligence*, Vol. 7, p.1473872, DOI: 10.3389/frai.2024.1473872.

Teo, H-H., Wei, K.K. and Benbasat, I. (2003) 'Predicting intention to adopt interorganisational linkages: an institutional perspective', *MIS Quarterly*, pp.19–49, DOI: 10.2307/30036518.

Tornatzky, L.G. and Fleischer, M. (1990) *The Processes of Technological Innovation*, Lexington Books, Lexington, MA [online] https://books.google.it/books?id=EotRAAAAMAAJ (accessed 30 October 2024).

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003) 'User acceptance of information technology: toward a unified view', *MIS Quarterly*, pp.425–478, DOI: 10.2307/30036540.

Westerman, G., Bonnet, D. and McAfee, A. (2014) *Leading Digital: Turning Technology into Business Transformation*, Harvard Business Press, Boston, MA.

Zahra, S.A. and George, G. (2002) 'Absorptive capacity: a review, reconceptualization and extension', *Academy of Management Review*, Vol. 27, No. 2, pp.185–203, DOI: 10.2307/4134351.

Zhang, C. and Lu, Y. (2021) 'Study on artificial intelligence: the state of the art and future prospects', *Journal of Industrial Information Integration*, Vol. 23, p.100224, DOI: 10.1016/j.jii.2021.100224.

Zhao, W.X., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., Min, Y., Zhang, B., Zhang, J., Dong, Z., Du, Y., Yang, C., Chen, Y., Chen, Z., Jiang, J., Ren, R., Li, Y., Tang, X., Liu, Z. and Wen, J-R. (2023) *A Survey of Large Language Models*, ArXiv, abs/2303.18223.

Zhu, K., Kraemer, K. and Xu, S. (2003) 'Electronic business adoption by European firms: a cross-country assessment of the facilitators and inhibitors', *European Journal of Information Systems*, Vol. 12, No. 4, pp.251–268, DOI: 10.1057/palgrave.ejis.3000475.