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Institutional Theory (IT) and Diffusion of Innovation (DOI): A Theoretical Approach on Artificial Intelligence (AI)

Joel Ferreira Reis[1], Luiz Pereira Pinheiro Junior[1]

[1] Universidade Positivo, Business School, Curitiba, PR, Brazil

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ABSTRACT

Objective: this theoretical essay explores the adoption of artificial intelligence (AI) in organizations through the integrated lens of institutional theory (IT) and diffusion of innovation (DOI) theory. IT elucidates how coercive, normative, and mimetic pressures drive organizational conformity, while DOI categorizes adopters into innovators, followers, and traditionalists, emphasizing perceived innovation attributes. **Methods:** by synthesizing these frameworks, the study provides a comprehensive understanding of how institutional forces and adopter profiles collectively shape AI. **Results:** key findings reveal that AI adoption is influenced by regulatory compliance, industry benchmarks, and competitive imitation, with varying adoption rates depending on organizational readiness and sectoral demands. The study identifies gaps in current research, particularly the lack of integration between macro-level institutional pressures and micro-level adoption behaviors. **Conclusions:** it proposes a future research agenda to examine sector-specific barriers, ethical implications, temporal dynamics, and the role of digital infrastructure in AI institutionalization. Contributions include a novel theoretical framework that bridges structural and behavioral perspectives, offering actionable insights for policymakers and managers navigating AI adoption.

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Corresponding author:
Luiz Pereira Pinheiro Junior
Universidade Positivo, Business School
Rua Prof. Pedro Viriato Parigot de Souza, n. 5300,
Cidade Industrial, CEP 81280-330, Curitiba, PR, Brazil

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INTRODUCTION

The adoption of innovative technologies, particularly artificial intelligence (AI), is reshaping organizational and societal dynamics (Dwivedi, 2025). To understand this phenomenon, two theoretical approaches institutional theory (IT) and the diffusion of innovation (DOI) theory provide complementary perspectives. IT, as proposed by Scott (2014), examines how institutional pressures (coercive, normative, and mimetic) drive organizations toward isomorphism, ensuring legitimacy and compliance with societal expectations. Meanwhile, DOI, developed by Rogers (2003), focuses on the innovation-decision process, categorizing adopters into innovators, early adopters, early majority, late majority, and laggards, while emphasizing perceived attributes such as relative advantage and compatibility. Despite their individual strengths, few studies integrate these theories to analyze AI adoption, leaving a gap in understanding how institutional pressures interact with adopter profiles across different sectors.

A critical limitation in the literature is the lack of research combining IT and DOI to explore AI adoption. While IT explains why organizations conform to institutional norms, DOI elucidates how innovations spread based on adopter characteristics. Janssen et al. (2022) highlight the role of explainable AI in government decision-making, yet their study does not examine how institutional pressures shape adoption patterns. Similarly, Dwivedi et al. (2021) provide a multidisciplinary perspective on AI challenges but do not integrate institutional and diffusion factors. This disconnect underscores the need for a unified framework that bridges structural influences (IT) and perceptual drivers (DOI).

Empirical studies in sectors such as healthcare, finance, and logistics have applied IT and DOI separately. Research on blockchain adoption (Hartley et al., 2022) and cloud computing (Trope, 2014) reveals how coercive and mimetic pressures influence technology uptake. Chaudhury and Bharati (2008) used DOI to analyze IT outsourcing in SMEs, finding that perceived competitive advantage accelerates adoption. However, these studies do not explore how institutional forces interact with adopter profiles — for example, whether early adopters are more resistant to coercive pressures or if laggards align more with normative expectations. This gap is particularly evident in emerging markets and is amplified by Gartner's (2025) projection that AI adoption will enter mainstream institutionalization by 2026, with 60% of organizations reaching the systematic stage of AI maturity. The AI Maturity Model underscores how rapid technological advancement (e.g., generative AI) is compressing traditional innovation timelines, forcing organizations to reconcile institutional compliance with agile adoption. This acceleration aligns with our framework's emphasis on mimetic pressures in hypercompetitive sectors (e.g., finance adopting AI-driven analytics 2.5x faster than healthcare), while also revealing new tensions between DOI adoption stages and institutional path dependencies.

Recent advancements in AI governance further highlight the need for an integrated approach. Janssen et al. (2020) argue that data governance is critical for trustworthy AI, while Matheus et al. (2020) emphasize transparency in smart cities. However, these studies focus on institutional enablers (e.g., open data policies) without addressing how adopter profiles moderate their effectiveness. For example, do innovators in government AI projects respond differently to transparency-by-design principles (Janssen et al., 2017) compared to late majority adopters? Similarly, Pinheiro and Torres (2022) analyze South American AI initiatives but do not link them to DOI adopter categories. These omissions suggest a broader theoretical gap: how do institutional pressures differentially influence innovators versus laggards in AI adoption?

Another underexplored area is the role of digital transparency in AI diffusion. Matheus and Janssen (2020) propose that open government data enhances accountability, yet their framework does not incorporate DOI's innovation attributes (e.g., observability, trialability). Would AI solutions with higher observability, such as public-facing chatbots, diffuse faster under normative pressures? Conversely, would complex AI systems (e.g., predictive policing algorithms) face resistance due to low compatibility, even under coercive mandates? These questions remain unanswered, pointing to a second gap: the absence of studies examining how DOI's innovation attributes mediate institutional pressures in AI adoption.

The practical implications of this gap are significant. Rodrigues et al. (2024) show that AI adoption in supermarkets varies by task automation level, but their study does not assess whether isomorphic pressures explain these differences. Similarly, Shao et al. (2023) explore IoT integration in e-government but overlook how adopter profiles affect implementation. Without a combined IT-DOI lens, policymakers and managers lack actionable insights into which institutional levers (e.g., regulations, professional standards) most effectively accelerate AI uptake among different adopter groups.

This article addresses these gaps through a theoretical essay that integrates IT and DOI to analyze AI adoption (Dwivedi et al., 2021; Limongi & Marcolin, 2024). Our objectives are threefold: (1) to synthesize IT's institutional pressures with DOI's adopter profiles, (2) to propose a framework explaining their interaction in AI adoption, and (3) to identify sector-specific barriers and facilitators. By doing so, we contribute to both literature and practice. For academia, we offer a novel theoretical lens bridging macro-level pressures (IT) and micro-level adoption (DOI). For practitioners, we provide guidance on tailoring AI strategies to institutional contexts and adopter readiness.

The article first reviews IT and DOI, emphasizing isomorphism and adopter categories. Next, it analyzes applied studies in blockchain, cloud computing, and IT outsourcing to contextualize the theories. It then proposes a research agenda for AI adoption integrating IT and DOI. Finally, it discusses implications for future empirical work.

By combining these theories, we advance a holistic understanding of AI diffusion — one that accounts for why organizations adopt AI (institutional legitimacy) and how they do so (adopter-driven processes). This integration is timely, as AI's rapid evolution demands frameworks that reconcile structural constraints with behavioral diversity. Matheus et al. (2023) note that digital transparency alone cannot ensure AI adoption; it must align with stakeholders' innovation perceptions. Our study thus responds to calls for multidisciplinary AI research (Dwivedi et al., 2021) while offering actionable insights for governments and firms navigating AI's complexities.

THEORIES

Institutional theory — IT

Institutional theory (IT) emerged as an important field in the study of organizations, particularly in the 1940s, with the initial formulations by Selznick (1949). Selznick introduced the notion that organizations are not merely technical systems but also social systems deeply influenced by institutional norms and values. This pioneering approach was followed by contributions from Meyer and Rowan (1977), who observed that organizations adopt formal structures not only for efficiency but also to meet societal expectations, a phenomenon they described as 'rational myths.' They argued that organizational formality often serves to ensure legitimacy rather than to optimize performance.

IT has been fundamental in understanding how organizations interact with their institutional structures. It offers a sociological perspective, contrasting with more technical and economic approaches that often focus on operational efficiency. North (1990), one of the leading theorists of institutional economics, expands this understanding by emphasizing that institutions, such as formal and informal norms and rules, shape economic behavior and development over time. According to North (1990), "institutions are the rules of the game in a society ... that structure human interaction" (p. 3), highlighting the intersection between economic and social dimensions.

IT has diversified into several branches, one of the most well-known being the neoinstitutional approach promoted by DiMaggio and Powell (1983), who introduced the concept of institutional isomorphism. They argued that organizations within an organizational field tend to become more similar over time due to coercive, normative, and mimetic pressures. These pressures arise from various sources, such as government regulations (coercive pressure), professional standards (normative pressure), and the tendency of organizations to imitate others that appear more successful (mimetic pressure).

Additionally, the economic branch of IT, as discussed by authors such as North, focuses on how institutions affect efficiency and innovation within markets. The sociological branch examines how institutions influence organizational norms and behaviors. Scott (2014), for example, argues that "institutions consist of cognitive, normative, and regulatory structures that provide stability and meaning to social behavior" (p. 33). This definition shows how institutions not only regulate but also shape the cognition and identity of organizations.

In recent decades, IT has been applied to examine a range of modern organizational phenomena, including globalization, digitalization, and sustainability. Scott (2014) observes that "institutional processes are constantly evolving, shaped by global, technological, and political forces" (p. 219). This view reflects the contemporary relevance of the theory, especially as organizations face new challenges related to sustainability and social responsibility.

A significant current debate involves how organizations respond to external pressures to adopt sustainable and innovative practices. The theory suggests that compliance with environmental norms is often not just a matter of efficiency but also a response to social expectations and the pursuit of legitimacy. In this context, the theory has proven useful in explaining why many companies adopt ecological practices, even when these do not result in direct financial benefits.

Recent research explores the intersection of IT and AI in organizational contexts. Scholars argue that new institutionalism provides a valuable framework for understanding the role of AI in organizations, highlighting concepts such as legitimacy, environment, and isomorphism (Rudko et al., 2024). AI technologies are reshaping fields and institutions, while existing institutional infrastructures influence the pace and scope of AI-induced change (Larsen, 2021). In educational environments, the integration of AI reveals institutional inequalities and normative behaviors, stimulating the development of a critical theory of AI to analyze schools (Toncic, 2021). The application of IT to the production and consumption of algorithmic media offers insights into the evolving role of algorithms in media systems (Napoli, 2014). These studies collectively emphasize the need for a deeper theoretical understanding of the institutional significance of AI and its impact across various sectors, including business, education, and media.

Chandler and Hwang (2015) explore organizational adoption strategies at the microfoundations level of IT, emphasizing how internal learning processes influence organizations' responses to institutional pressures. Meanwhile, Dacin et al. (2002) provide an analysis of institutional change dynamics, addressing how organizations adapt their practices in the face of external and internal pressures, contributing to a deeper understanding of institutional transformations. These studies reinforce the importance of considering both micro and macro levels in the analysis of organizational adaptation and legitimacy, central themes in the application of IT to the adoption of new technologies such as AI.

DOI — Diffusion of innovation theory

The diffusion of innovation (DOI) theory was proposed by Everett Rogers in 1962 (Rogers, 1962) in his classic work *Diffusion of Innovations*. It seeks to explain how, why, and at what rate new ideas and technologies spread across societies and organizations. The origins of this theory date back to the early 20th century, when sociologists and anthropologists began investigating how technological innovations, such as the use of fertilizers and new seeds, spread among agricultural communities (Rogers, 2003).

Rogers (2003) argues that diffusion is "the process by which an innovation is communicated through certain channels over time among the members of a social system" (p. 5). This implies that the adoption of an innovation is not just an individual decision based on utility but also a social process influenced by cultural and structural factors. According to Rogers, the adoption of an innovation follows a pattern, categorizing individuals into five groups: innovators, early adopters, early majority, late majority, and laggards.

DOI applies to a wide range of disciplines, including marketing and consumer behavior, economics, and innovation management (Goldenberg et al., 2001; Lamey et al., 2021; Tidd & Bessant, 2020). In marketing, for example, the concept of the product life cycle is closely tied to the diffusion of innovations, with each phase of the cycle corresponding to different levels of adoption.

The economic branch of the theory focuses on the impact of innovation on economic growth. According to Schumpeter (1934), innovation is the engine of economic development, as new technologies create cycles of growth and creative destruction. In the organizational context, Moore (1991) expanded the theory by proposing the concept of 'crossing the chasm,' which suggests that many innovations fail to transition from early adopters to the early majority, a critical point for the mass acceptance of new products.

From a sociological perspective, the theory also examines how social networks, norms, and cultural roles affect the adoption of innovation. Rogers (2003)highlights that "interpersonal communication is one of the most effective ways to influence the adoption of an innovation" (p. 204). Thus, innovations tend to spread more rapidly when there are opinion leaders who influence other members of the community.

In recent years, DOI has been widely applied in high-tech and digital innovation contexts. The adoption of disruptive technologies, such as artificial intelligence, blockchain, and the internet of things (IoT), has been a focus of recent studies. According to Tidd and Bessant (2020), digitalization has significantly accelerated innovation diffusion cycles, creating challenges and opportunities for companies that need to keep pace with technological change.

A strong contemporary debate is related to the role of organizational culture in the adoption of innovations. Researchers such as Gopalakrishnan and Kovoor-Misra (2021) argue that "an organization's culture can act as a facilitator or barrier to the adoption of innovations, depending on its openness to change" (pp. 224-232). This reflects the importance of understanding the internal context of organizations, not just the external forces that promote innovation.

DOI provides a framework for understanding the adoption of AI in various fields. In healthcare, AI applications in endourology are still primarily research-based, with potential for stone disease detection, outcome prediction, and procedure optimization (Monga et al., 2024). The adoption of AI in manufacturing and healthcare industries is driven by economic factors and promises increased productivity and cost reduction (Rupp, 2020). Cultural considerations are crucial when implementing AI-based health technologies, such as breast cancer screening, to ensure rapid diffusion in society (Bhattacharya et al., 2020). In academic libraries, staff perceptions of AI and their self-defined adopter categories influence the diffusion of this emerging technology (Lund et al., 2020). To facilitate the appropriate adoption of AI, key strategies include developing training programs, creating adequate data infrastructure, ensuring transparency, and adopting innovations within continuous quality improvement frameworks (Monga et al., 2024).

DISCUSSION — THEORETICAL APPLICATION AND INTEGRATION IT AND DOI

To understand the adoption of AI in organizations, this chapter proposes an integrated analysis of IT and DOI. Although both theories address the dissemination of practices and technologies, they do so from complementary perspectives. IT focuses on institutional pressures — such as norms, regulations, and social expectations — that shape organizational decisions, while DOI provides a detailed view of the process by which innovation spreads among different adopter groups, from innovators to laggards (Chandler & Hwang, 2015; Rogers, 2003).

By combining these approaches, it is possible to explore not only the external factors that legitimize and encourage the use of AI but also the pace and patterns of adoption among organizations, influenced by both institutional factors and innovation dynamics. In this way, the joint analysis of the theories allows for a more comprehensive understanding of the challenges and opportunities that AI brings to organizational contexts, highlighting how organizations balance institutional pressures and innovation strategies in adopting this disruptive technology.

The combined application of DOI and IT offers a rich perspective for analyzing the adoption of emerging technologies in sectors such as blockchain in supply chains. Hartley et al. (2022) investigate the intentions to adopt this technology in supply chains, showing that while DOI elucidates adoption patterns among different organizational profiles, IT highlights the institutional pressures that guide or limit this adoption. In this context, institutional factors such as legitimacy and the need to comply with industry standards directly influence blockchain adoption, as companies seek to align with regulatory standards that foster trust and security in the use of this technology. Simultaneously, DOI complements the analysis by addressing the perceived gains in efficiency and security provided by blockchain in supply chain management.

Carvalho et al. (2017) discuss how IT and DOI contribute to a more integrated view of innovation, considering the interactions between social, institutional, and technological factors. IT, applied to a sociotechnical context, helps to understand how established norms and values shape innovation dynamics at both organizational and social levels, emphasizing the role of institutional structures in facilitating or restricting the development of new technologies. DOI, in turn, explores how innovations propagate in these systems, highlighting the role of social networks and interpersonal communication. This integrated approach is especially relevant for technologies that affect both technical and social aspects in organizations, such as those involving multiple stakeholders and requiring widespread acceptance for consolidation and expansion.

Bui (2015) reviews innovation diffusion theories and examines the interaction between DOI and IT to explain both the adoption and legitimization of emerging technological practices. Scott proposes that institutions operate through normative, regulatory, and cognitive structures, which exert substantial pressures on organizations. The combination of these theories is particularly applicable in highly regulated sectors, such as healthcare and finance, where the introduction of technologies like AI depends on both the perception of value and adherence to established norms and regulations. Thus, the joint application of DOI and IT allows for a detailed analysis of how organizations balance the pursuit of innovation with the need for legitimacy and institutional compliance, maximizing the effectiveness of technologies in specific contexts.

Redmond (2003) explores the relationship between innovation, diffusion, and institutional change, offering an analysis of how new technologies and innovative practices integrate into and transform the institutional environment. Redmond's approach considers that the diffusion of an innovation occurs not only due to its intrinsic utility but also through a process of adaptation to the existing institutional environment, where established norms, values, and structures influence and sometimes resist change. He suggests that DOI and IT act interdependently: while DOI explains how an innovation spreads among different types of adopters, IT provides insights into the structural and institutional forces that facilitate or hinder this process. In this sense, the institutional changes accompanying the adoption of a new technology can profoundly alter the organizational context, reconfiguring patterns of legitimacy and compliance.

The combined application of IT and DOI in technology contexts such as cloud computing offers a broad panorama for understanding the factors driving the adoption of this technology across various sectors. In Trope's (2014) study on the adoption of cloud computing by South African companies, it is observed that institutional factors — such as regulatory pressures and the need for compliance with industry standards — are decisive for companies to implement cloud computing. DOI complements this analysis by identifying adopter profiles and the perception of benefits and risks of the technology, contributing to the understanding of the dynamics of acceptance and resistance among companies of different sizes and sectors.

Another example of the combined application of IT and DOI in cloud computing adoption is found in Sastararuji et al.'s (2021) study on small and medium-sized enterprises (SMEs). Using an integrated approach with IT, DOI, and the TOE (technology, organization, and environment) model, the authors identify determining factors for the adoption of cloud-based accounting solutions, such as regulatory environment pressures, organizational support, and the need for continuous innovation. These studies show that the adoption of cloud technology depends not only on its technical or economic efficiency but also on how the technology aligns with institutional norms and expectations of legitimacy and security in the organizational environment, as these organizations balance the pursuit of innovation with the need to meet established standards.

Pinheiro et al. (2020) explore the adoption of cloud computing in the public sector, proposing a model that classifies governments as leaders, followers, or laggards based on their level of engagement and maturity in adopting this technology. Using an integrated perspective of DOI and IT, the authors identify that cloud adoption in government is strongly influenced by institutional pressures, such as security and data protection regulations, as well as social demands for transparency and efficiency. Leading governments tend to adopt the cloud proactively, serving as institutional models for other government entities, while followers and laggards show greater resistance due to normative and cultural constraints. DOI contributes to understanding how cloud innovation spreads among different types of government organizations, while IT helps to understand the specific institutional barriers that affect the speed and manner of adoption, emphasizing the importance of legitimacy and compliance in the public sector.

The combined application of DOI and IT provides a useful framework for understanding the adoption of RFID (radio frequency identification) technology in supply chains. Jie and Sia (2011) analyze the assimilation process of RFID among supply chain participants in China, revealing that the adoption of the technology is influenced by both institutional pressures and the perception of innovation. IT highlights the regulatory and normative forces driving companies to adopt RFID to meet industry standards and expectations, while DOI explores the factors motivating companies to adopt the technology based on its perceived benefits, such as greater efficiency and accuracy in inventory control. In the Chinese context, where there is strong government pressure to modernize supply chain infrastructure, the study shows that companies seeking institutional legitimacy are more inclined to integrate RFID to demonstrate compliance with efficiency and safety standards in the sector.

Chaudhury and Bharati (2008) apply DOI to analyze the adoption of this practice among small and medium-sized enterprises, highlighting the importance of innovation factors and institutional pressures. DOI explains how the perception of competitive advantages, such as cost reduction and access to specialized expertise, encourages SMEs to adopt IT outsourcing, while IT emphasizes the role of institutional pressures, including the need to keep up with industry trends and meet customer and stakeholder expectations. In competitive markets, SMEs feel pressure to align with the practices of larger companies that outsource their IT services, leading to a process of mimetic isomorphism. This scenario illustrates how efficiency and innovation pressures combine with institutional pressures, driving SMEs to adopt IT outsourcing as a means of legitimization and adaptation to market dynamics.

The application of DOI and IT in contexts such as the halal industry shows how these theoretical approaches can offer new insights in areas with cultural and religious specificities. Elbardan (2023) explores how the adoption of halal technologies is influenced by both the need for legitimacy in meeting religious and cultural requirements and the dissemination of innovative practices in the sector. IT helps to explain how specific norms and certifications in halal culture impose standards to be followed by companies seeking to serve this market. At the same time, DOI contributes to understanding how halal technologies spread based on the perceived quality and religious compliance these practices bring to consumers. This integrated perspective allows for an analysis of how institutional and innovation factors work together to consolidate halal technology in a sector heavily influenced by cultural legitimacy.

In the field of HR, the adoption of analytics for people management also illustrates the applicability of DOI and IT in emerging areas of organizational innovation. Ioakeimidou et al. (2023) investigate how the analytical maturity of organizations in human resources (HR) is shaped by both the need to align with institutional standards and the pursuit of competitive advantages promoted by the adoption of analytics. IT reveals that organizations adopting HR analytics often respond to regulatory and normative pressures, such as increased transparency and efficiency in talent management. On the other hand, DOI explains the process by which companies adopt this practice based on the perception that the use of advanced data can enhance strategic HR decisions, attracting and retaining talent more effectively. In this way, the theories explore and validate new fields of application, demonstrating how innovation and the need for institutional legitimacy drive the transformation of practices in sectors such as halal and HR, each with its cultural and operational specificities.

THEORETICAL FRAMEWORK: INTEGRATING DOI AND IT IN AI ADOPTION RESEARCH

Artificial intelligence (AI) has established itself as a transformative technology across various sectors, driving significant changes and redefining traditional processes. In the context of Industry 4.0, AI emerges as a central pillar, integrating cyber-physical systems and promoting intelligent automation in production chains. As highlighted by Nascimento and Bellini (2018), AI has been crucial in optimizing industrial operations, from predictive maintenance to supply chain management, enabling greater efficiency and cost reduction. Additionally, the ability to analyze large volumes of data in real time has facilitated faster and more assertive decision-making, solidifying AI as an indispensable tool for organizational competitiveness.

In the healthcare sector, AI has revolutionized diagnostics, treatments, and medical data management. Dwivedi et al. (2021) emphasize that machine learning algorithms have been used to identify patterns in medical exams, such as X-rays and MRIs, increasing diagnostic accuracy and reducing human errors. Furthermore, AI has been employed in the development of personalized medications and the prediction of disease outbreaks, contributing to a more proactive approach in healthcare. These applications not only improve the quality of care but also reduce operational costs and expand access to high-quality medical services.

In academia and research, AI has played an increasingly significant role, both in knowledge production and in the review and publication of scientific articles. Garrido (2023) notes that AI tools have been used to assist in peer review, identifying plagiarism and inconsistencies in texts, as well as suggesting improvements in writing. However, the use of these technologies also raises ethical concerns, such as the authorship of AI-generated works and the potential loss of human criticality in the evaluation process. Limongi (2024) reinforces the importance of establishing clear guidelines for the ethical and responsible use of AI in scientific research, ensuring integrity and transparency in academic processes.

In the innovation sector, AI has been a catalyst for the development of new products, services, and business models. Mariani et al. (2023) conduct a systematic review that demonstrates how AI has been applied to identify market trends, predict consumer demands, and accelerate innovation processes. Companies have used AI algorithms to analyze customer feedback and propose product improvements, as well as to explore new market opportunities. This ability to innovate rapidly and in a data-driven manner is crucial for companies seeking to remain competitive in a dynamic global landscape.

AI has also impacted sectors such as education, finance, and entertainment, redefining practices and creating new opportunities. In education, for example, intelligent tutoring systems have personalized learning, adapting to the pace and individual needs of students. In the financial sector, AI algorithms are used for risk analysis, fraud detection, and investment management. In entertainment, AI has been employed in the creation of personalized content, such as movie and music recommendations, as well as in the production of artistic works and digital games. These applications illustrate the versatility of AI and its potential to transform multiple sectors, provided its use is guided by ethical and responsible principles, as highlighted by Limongi and Marcolin (2024).

Institutional theory and diffusion of innovation theory offer valuable theoretical lenses for understanding how artificial intelligence (AI) has been adopted and legitimized across various sectors. Institutional theory, which emphasizes the importance of norms, regulations, and social pressures in shaping organizational practices, helps explain how AI has become a standard in sectors such as industry, healthcare, and education. As Nascimento and Bellini (2018) highlight, the integration of AI into Industry 4.0 occurs not only due to its technical efficiency but also because of competitive pressure and the pursuit of legitimacy in an environment where technological innovation is highly valued. Additionally, Garrido (2023) points out that, in the academic context, the adoption of AI tools for article review and publication reflects an adaptation to institutional expectations of speed and precision, even as it raises ethical issues that need to be regulated.

On the other hand, the diffusion of innovation theory, proposed by Everett Rogers, explains how AI spreads and is adopted across different sectors, considering factors such as relative advantage, compatibility, complexity, trialability, and observability. Dwivedi et al. (2021) and Mariani et al. (2023) emphasize that the rapid adoption of AI in sectors such as healthcare and innovation occurs due to its ability to offer superior solutions compared to traditional methods, such as more accurate diagnostics and accelerated innovation processes. However, the diffusion of AI also faces barriers, such as technical complexity and the need for training, topics addressed by Limongi and Marcolin (2024) when discussing the importance of AI literacy to ensure its ethical and effective adoption. Thus, the combination of these two theories allows for an understanding not only of how AI diffuses but also of how it becomes institutionalized, shaping and being shaped by the social and organizational structures in which it is embedded.

The combination of IT and DOI in the studies presented offers a broad and contextualized analysis of technology adoption across different sectors, elucidating how institutional pressures and adopter profiles influence these processes. In the isomorphism strand of IT, coercive, normative, and mimetic pressures manifest differently depending on the characteristics of each sector. For example, the adoption of blockchain in the Chinese supply chain, analyzed by Jie and Sia (2011), is motivated both by coercive pressures from the government, which seeks to modernize the sector, and by normative pressures that encourage companies to comply with safety and efficiency standards. Similarly, in the cloud computing sector, Trope (2014) highlights that regulatory compliance and industry expectations drive South African companies to adopt the technology, often in a mimetic manner, seeking to replicate the success of other companies and consolidate their position in the market.

In DOI, the categories of innovators, followers, and laggards help identify how different types of organizations respond to these innovations. Studies such as those by Chaudhury and Bharati (2008) on IT outsourcing and Ioakeimidou et al. (2023) on HR analytics reveal that innovative companies tend to adopt these practices first, motivated by the pursuit of competitive advantages and the potential to optimize operations and strategic decisions. Followers and laggards, on the other hand, align more slowly, being influenced by the practices of innovators and pressured by institutional changes that make these innovations gradually more necessary. In the case of outsourcing, for example, SMEs that initially resist using this strategy end up adopting it to keep up with industry practices, encouraged by the success observed in pioneering companies.

Finally, in specific sectors such as the halal industry and RFID use, both IT and DOI allow for the observation of a similar dynamic of adaptation to innovation, with important variations depending on the cultural and regulatory context. In the case of halal technologies (Elbardan, 2023), normative and coercive pressures stemming from cultural and religious standards create a unique institutional environment in which companies adopt innovation to meet these expectations and gain legitimacy among consumers and certifying bodies. In contrast, in the RFID sector, Chinese companies studied by Jie and Sia (2011) adopt the technology influenced both by regulatory pressure and by observing the efficiency benefits among early adopters, especially in a competitive and transforming environment.

These studies, taken together, highlight how IT and DOI, by considering isomorphism and adopter profiles, offer an in-depth analysis of innovation dynamics across diverse sectors, demonstrating the balance between institutional pressures and the willingness to adopt innovations according to organizational profiles.

Table 1. DOI + IT coercive.

Adopter profile (DOI)	Sectoral context	Research question	References
Innovators	AI in highly regulated sectors (e.g., healthcare, finance, government)	How do pioneering AI adopters in regulated sectors navigate coercive pressures and leverage legitimacy for innovation?	Jie and Sia (2011); Pinheiro et al. (2020); Janssen et al. (2022); Rodrigues et al. (2024); Shao et al. (2023)
Followers	Regulatory compliance in traditional industries	How do follower organizations align their AI practices with regulatory expectations without being first movers?	Trope (2014); Chaudhury and Bharati (2008); Matheus and Janssen (2020); Janssen et al. (2020); Limongi (2024)
Traditionalists	Legally mandated AI adoption	How do resistant organizations cope with legal AI requirements and what are their implementation challenges?	Sastararuji et al. (2021); Elbardan (2023); Matheus and Janssen (2020); Toncic (2021); Rudko et al. (2024)

Note. Developed by the authors.

The three tables presented in this research organize a study agenda that analyzes the adoption of AI in organizations by combining IT and DOI. Each table represents a dimension of IT isomorphism — coercive, normative, and mimetic — and relates these institutional pressures to DOI adopter profiles (innovators, followers, and traditionalists). This allows for an understanding of how different types of institutional pressure and organizational characteristics affect the decision to adopt innovative technologies such as AI.

In the first table, the coercive isomorphism dimension highlights how regulatory and legal pressures drive organizations to adopt AI, especially in sectors such as healthcare and finance. Innovative companies adopt AI proactively to comply with standards, while follower and traditional companies respond gradually to these demands, facing specific compliance barriers.

The second table, based on normative isomorphism, explores the influence of norms and professional standards on the adoption of AI. In this context, innovators typically align with industry standards to gain legitimacy, whereas followers and traditionalists adapt their practices as market norms evolve.

Table 2. DOI + IT normative.

Adopter profile (DOI)	Sectoral context	Research question	References
Innovators	AI and professional standards (e.g., banking, education, healthcare)	To what extent do innovative organizations leverage AI to align with professional norms and gain strategic advantage?	Hartley et al. (2022); Ioakeimidou et al. (2023); Limongi and Marcolin (2024); Mariani et al. (2023); Monga et al. (2024)
Followers	AI compliance with evolving sectoral regulations	How do follower organizations adopt AI to meet normative standards and follow industry leaders?	Carvalho et al. (2017); Bui (2015); Shao et al. (2023); Matheus et al. (2021); Rodrigues et al. (2024)
Traditionalists	AI implementation in conservative/regulatory-bound industries	What challenges do traditionalist organizations face in aligning AI practices with established professional expectations?	Elbardan (2023); Sastararuji et al. (2021); Matheus and Janssen (2020); Garrido (2023); Toncic (2021)

Note. Developed by the authors.

The third table explores mimetic isomorphism, where the adoption of AI is influenced by the imitation of practices from successful companies. Innovators set trends in the sector, creating adoption patterns that followers and traditionalists attempt to replicate to reduce uncertainties and compete in the market.

Table 3. DOI + IT mimetic.

Adopter profile (DOI)	Sectoral context	Research question	References
Innovators	AI as strategic benchmarking	How do innovative firms establish AI usage as an industry benchmark and stimulate mimetic adoption?	Redmond (2003); Pinheiro et al. (2020); Mariani et al. (2023); Dwivedi (2025)
Followers	Mimetic adoption in competitive environments	What drives follower firms to mimic early AI adopters and adopt best practices?	Trope (2014); Hartley et al. (2022); Ioakeimidou et al. (2023); Rodrigues et al. (2024)
Traditionalists	Late adoption and resistance	How do laggard firms respond to industry-wide AI adoption and what strategies mitigate perceived risks?	Chaudhury and Bharati (2008); Jie and Sia (2011); Garrido (2023); Rudko et al. (2024)

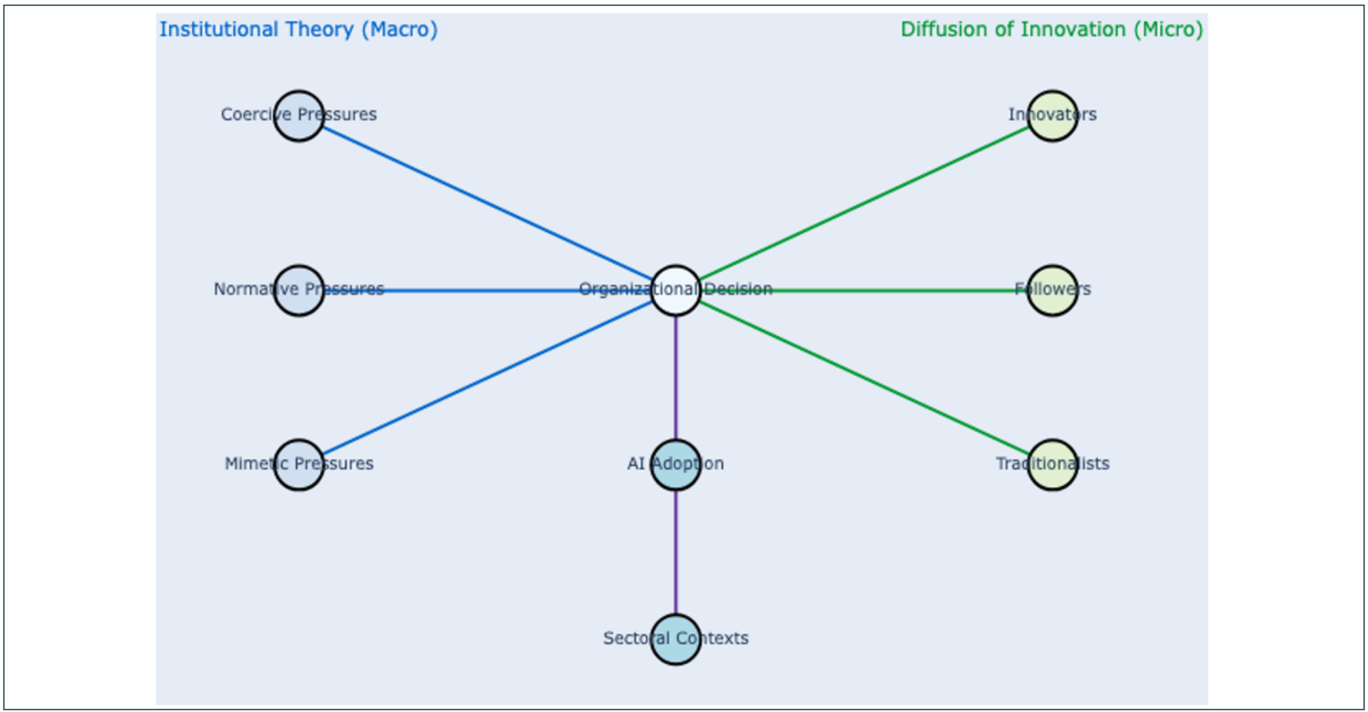
Note. Developed by the authors.

Together, the three tables structure a comprehensive analysis of how institutional pressures and adoption profiles shape the introduction of AI in different organizational contexts, serving as a foundation for future studies on the impact of these variables on the diffusion of technology.

Figure 1 presents an integrative framework for understanding AI adoption by organizations, combining insights from institutional theory (IT) and diffusion of innovation (DOI) (DiMaggio & Powell, 1983; Rogers, 2003). On the macro level, institutional pressures — coercive (e.g., regulations like GDPR), normative (industry standards), and mimetic (peer imitation) — shape organizational decisions, as highlighted by recent studies on AI governance (Dwivedi et al., 2021; Janssen et al., 2020). These forces align with Scott's (2014) institutional pillars, demonstrating how external legitimacy drives AI adoption, particularly in sectors like healthcare and finance, where compliance and benchmarking are critical (Hartley et al., 2022; Nascimento & Bellini, 2018).

On the micro level, the DOI framework explains heterogeneous adoption rates through adopter categories: innovators (early adopters like tech startups), followers (mainstream firms), and traditionalists (resistant laggards) (Monga et al., 2024; Rogers, 2003). Recent research emphasizes that organizational readiness and perceived benefits mediate these dynamics, as seen in studies on AI in SMEs (Chaudhury & Bharati, 2008) and public sectors (Matheus et al., 2023). The interplay between macro-level pressures and micro-level actor behavior underscores the 'chasm' between early and late adopters (Moore, 1991), which is particularly relevant for AI technologies requiring significant resource investment (Mariani et al., 2023).

The framework's outcome — AI institutionalization — varies by sector, reflecting contextual barriers and enablers. For instance, in healthcare, coercive pressures dominate (e.g., HIPAA compliance), while in finance, mimetic imitation of algorithmic trading prevails (Elbardan, 2023; Larsen, 2021). This aligns with North's (1990) institutional change theory, where path dependence and sectoral norms shape technology assimilation. Recent critiques also highlight ethical considerations, such as transparency-by-design (Janssen et al., 2017) and AI literacy (Limongi & Marcolin, 2024), which further modulate institutionalization.



Source: Developed by the authors.
Figure 1. DOI + IT and AI.

The synthesis of IT and DOI addresses gaps in innovation research, as noted by Carvalho et al. (2017) and Chandler and Hwang (2015), by bridging structural constraints (macro) with agency-driven adoption (micro). For example, AI adoption in smart cities (Matheus et al., 2020) reflects both policy mandates (IT) and local stakeholder engagement (DOI). This multilevel perspective is critical for policymakers and managers navigating AI's disruptive potential (Dwivedi, 2025; Gopalakrishnan & Kovoor-Misra, 2021).

The framework invites future research on AI-induced field change (Larsen, 2021), particularly how emerging technologies like generative AI (Dwivedi, 2025) disrupt institutional logics. Studies on blockchain (Hartley et al., 2022) and IoT (Shao et al., 2023) suggest similar patterns, reinforcing the need for dynamic models that account for technological evolution and societal impact (Tidd & Bessant, 2020). By integrating recent empirical findings — such as the role of explainable AI in government (Janssen et al., 2022) or ethical AI in academia (Limongi, 2024) — this framework offers a robust lens for analyzing AI's institutionalization across diverse contexts.

FINAL CONSIDERATIONS

This theoretical essay has explored the integration of institutional theory (IT) and diffusion of innovation (DOI) theory to analyze the adoption of artificial intelligence (AI) in organizations. By synthesizing these frameworks, we have provided a comprehensive understanding of how institutional pressures (coercive, normative, and mimetic) and adopter profiles (innovators, followers, and traditionalists) shape AI diffusion across sectors. The findings highlight that AI adoption is not merely a technical decision but a complex interplay of social, institutional, and perceptual factors. This integrated approach bridges macro-level structural influences with micro-level behavioral dynamics, offering a robust lens for future research and practice (DiMaggio & Powell, 1983; Rogers, 2003).

One critical insight is the role of coercive pressures in highly regulated sectors like healthcare and finance, where compliance with legal standards drives AI adoption (Janssen et al., 2020). However, gaps remain in understanding how these pressures interact with organizational readiness and ethical considerations, particularly in emerging markets. Future studies could investigate how coercive mandates, such as GDPR or HIPAA, influence the pace and scope of AI adoption among traditionalists, who may face unique implementation challenges (Elbardan, 2023; Sastararuji et al., 2021). Additionally, research could explore the unintended consequences of regulatory pressures, such as stifling innovation or exacerbating inequalities in resource-limited settings (Limongi & Marcolin, 2024).

Normative pressures, rooted in professional standards and industry expectations, also play a pivotal role in AI adoption. For instance, innovators in banking and education often leverage AI to align with evolving norms and gain strategic advantages (Hartley et al., 2022). Yet, the mechanisms by which normative pressures diffuse across sectors remain underexplored. Future research could examine how professional networks and certification bodies (e.g., IEEE, ISO) shape AI adoption among followers, particularly in conservative industries like manufacturing or agriculture (Mariani et al., 2023). Comparative studies across cultures could further reveal how normative expectations vary and influence AI institutionalization (Gopalakrishnan & Kovoor-Misra, 2021).

Mimetic isomorphism, driven by the imitation of successful peers, is another key driver of AI adoption, especially in competitive environments (Redmond, 2003). While innovators set benchmarks, followers often mimic these practices to reduce uncertainty. However, the conditions under which mimetic adoption leads to sustainable innovation versus superficial compliance are unclear. Future studies could analyze the role of transparency and observability in mimetic processes — for example, how public-facing AI applications (e.g., chatbots) accelerate adoption compared to opaque systems like predictive policing algorithms (Matheus & Janssen, 2020). Case studies of failed mimetic adoption could also yield insights into risk mitigation strategies (Chaudhury & Bharati, 2008).

The intersection of IT and DOI also raises questions about sector-specific barriers. For example, healthcare's reliance on explainable AI contrasts with finance's emphasis on algorithmic efficiency (Dwivedi et al., 2021; Janssen et al., 2022). A promising research avenue is to develop sector-specific frameworks that account for these differences, leveraging tools like Gartner's AI Maturity Model to assess institutional readiness (Rodrigues et al., 2024). Similarly, studies could explore how AI adoption varies between public and private sectors, given differing institutional logics (Pinheiro et al., 2020).

Another underexplored area is the temporal dimension of AI adoption. While DOI outlines stages of innovation diffusion, IT emphasizes path dependence and institutional inertia (North, 1990). Future research could investigate how these temporal dynamics interact — for instance, whether rapid AI advancements compress traditional diffusion timelines or create dissonance with entrenched institutional practices (Larsen, 2021). Longitudinal studies tracking AI adoption in real time, such as in smart cities or Industry 4.0 initiatives, could provide valuable insights (Matheus et al., 2023).

Ethical and societal implications also warrant deeper examination. As AI becomes institutionalized, issues like bias, accountability, and human–AI collaboration emerge (Limongi, 2024). Future studies could explore how institutional pressures mediate ethical AI adoption — for example, whether normative standards for fairness outperform coercive regulations in promoting responsible AI (Janssen et al., 2017). Interdisciplinary collaborations with ethicists and policymakers could further enrich this line of inquiry (Tidd & Bessant, 2020).

The role of digital infrastructure in enabling AI adoption is another critical frontier. Research could assess how data governance frameworks (e.g., FAIR principles) interact with institutional pressures to facilitate or hinder AI diffusion (Janssen et al., 2020). Case studies of countries with advanced digital infrastructure (e.g., Estonia) versus developing nations could reveal inequities and inform policy recommendations (Shao et al., 2023). The rapid evolution of AI technologies, such as generative AI, demands adaptive theoretical frameworks. Future research could extend this study by integrating emerging theories like technology-organization-environment (TOE) or dynamic capabilities theory to capture AI's disruptive potential (Dwivedi, 2025). Experiments testing the proposed framework in real-world settings, such as AI-driven supply chains or public sector automation, could validate its applicability and refine its constructs (Hartley et al., 2022).

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Authors

Joel Ferreira Reis
Universidade Positivo, Business School
Rua Prof. Pedro Viriato Parigot de Souza, n. 5300, Cidade Industrial, CEP 81280-330, Curitiba, PR, Brazil
joelfreis@gmail.com

Luiz Pereira Pinheiro Junior
Universidade Positivo, Business School
Rua Prof. Pedro Viriato Parigot de Souza, n. 5300, Cidade Industrial, CEP 81280-330, Curitiba, PR, Brazil
luiz.junior@up.edu.br

Authors' contributions

1st author: conceptualization (equal), data curation (equal), formal analysis (equal), funding acquisition (equal), investigation (equal), methodology (equal), project administration (equal), resources (equal), validation (equal), visualization (equal), writing - original draft (equal), writing - review & editing (equal).

2nd author: conceptualization (equal), data curation (equal), formal analysis (equal), investigation (supporting), methodology (equal), project administration (equal), resources (equal), software (equal), supervision (equal), validation (equal), visualization (equal), writing - original draft (equal), writing - review & editing (equal).