AI IN BUSINESS: A VICTIM OF OVERREGULATION?

Assessing the Impact of AI Regulation on Business Adoption Rate

By
Alexandra Ion

Submitted to
Central European University - Private University

Department: Economics and Business

In partial fulfilment of the requirements for the degree of Master of Arts in Economic Policy in Global Markets

Supervisor: Yusaf Akbar

Vienna, Austria
2025

COPYRIGHT NOTICE

[1] Icon by Font Awesome.

AUTHOR'S DECLARATION

I, the undersigned, **Alexandra Ion**, candidate for the MA degree in Economic Policy declare herewith that the present thesis titled "AI in Business: A Victim of Overregulation. Assessing the Impact of AI Regulation on Business Adoption Rate" is exclusively my own work, based on my research and only such external information as properly credited in notes and bibliography. I declare that no unidentified and illegitimate use was made of the work of others, and no part of the thesis infringes on any person's or institution's copyright.

I also declare that no part of the thesis has been submitted in this form to any other institution of higher education for an academic degree.

Vienna, 09 June 2025

Alexandra Ion

ABSTRACT

The rapid advancement of AI technology presents both unprecedented opportunities and significant challenges. While businesses must act fast to leverage AI's benefits, governments face the challenge of mitigating associated risks, including transparency, bias, intellectual property concerns, and privacy issues. However, it is still unclear if regulation may enable or hinder the adoption of AI by businesses. This thesis examines the impact of regulatory frameworks on AI adoption in business by answering the question "How do differences in regulatory frameworks influence the integration of AI technologies in business? ". This question will be answered using a Difference-in-Differences approach, comparing France, an EU member state with an enforced AI policy, with the United Kingdom, which has a more hands-off approach and has yet to implement a dedicated AI regulation. The findings show that the business AI adoption rate is, on average, 35 percentage points lower when a policy exists. However, this evidence should be further analyzed in the years to come, as the policy has been implemented only for one year and long-term effects are expected. Balancing regulation and technological progress is critical to fostering economic growth, maintaining competitiveness, and addressing future societal challenges such as labor market shifts and the digital divide.

TABLE OF CONTENTS

List of Figures and Tables

LIST OF ABBREVIATIONS

AI – Artificial Intelligence

DID – Difference-in-Differences

DMA – Digital Markets Act

DSA – Digital Services Act

EU – European Union

GDPR – General Data Protection Regulation

UK – United Kingdom

CHAPTER ONE: INTRODUCTION

Throughout history, technological innovation has consistently transformed the way humanity lived and worked. From the invention of the wheel to the Industrial Revolution, and more recently, the era of computerization, each new technological advancement has unlocked great opportunities while simultaneously introducing significant challenges. Today, we stand at the dawn of another revolutionary shift: the rise of artificial intelligence (AI). In this thesis, AI is defined as

> a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments (European Union 2024).

While AI has been under development for decades, its true potential revealed itself to the public in 2023, when it became widely accessible. One year after, businesses already started to harness the potential of it to create value. As the recent McKinsey survey denotes, 65% of the respondents report their organizations actively integrating AI into regular operations in 2024, a nearly twofold increase in ten months. The results of the study also showed that confidence in the transformative power of AI remains strong, with three-quarters of participants anticipating it will drive profound or even disruptive changes across industries in the years to come. In the same survey it is also stated that AI is already delivering measurable advantages for organizations, driving cost reductions and boosting revenues in the departments where it is applied (McKinsey 2024). According to e Mauro and Sestino the applications of AI within business are many, ranging from supporting decision-making to process mining or automation. In their paper they indicate that AI solutions are mostly used to enhance already existing processes by transforming raw data into actionable insights, automating administrative and financial tasks, improving customer engagement via chatbots and digitalizing human resources management (De Mauro/ Sestino 2022). Owning to these capabilities, AI is widely recognized as a driver of business growth, boosting productivity, while optimizing workflows and lowering overall operational expenses.

However, despite the numerous benefits artificial intelligence offers to businesses, its adoption also entails significant risks, including concerns related to transparency, bias, intellectual property, and privacy (Heidt 2024; Kaminski 2023; Koshiyama et al. 2024). In response, governments and international organizations are increasingly considering how such risks can be addressed through legal and regulatory frameworks. The involvement of public authorities is particularly critical in addressing power asymmetries between corporations and individuals, ensuring that the deployment of AI systems does not infringe upon fundamental rights. Such oversight aims to restrict the use of AI to applications that do not harm the users, thereby reinforcing ethical standards and accountability in business practices.

One of the main challenges in regulating artificial intelligence lies in the limited empirical evidence on how such regulation affect business decision-making. Past regulatory interventions of the digital realm have shown unclear insights, and for this reason the literature remains ambiguous as to whether AI regulations act primarily as a deterrent, by increasing perceived compliance costs and complexity, or as an enabler, by fostering trust and providing clearer operational guidelines.

This thesis seeks to address this gap by investigating whether regulatory frameworks incentivize or hinder the adoption of AI technologies in the private sector. Specifically, it aims to answer the research question: *"How do differences in regulatory frameworks influence the integration of AI technologies in business?"*. To examine this, a Difference-in-Differences (DiD) approach is employed, statistically comparing the AI adoption rates of businesses in two countries: France and the United Kingdom (UK). France is used as a representative case of a regulated environments, as it is a member of the European Union (EU), which implemented the world's first comprehensive legal framework for AI, the Artificial Intelligence Act, in 2024. In contrast, the United Kingdom has historically favored a more laissez-faire approach to digital regulation and has not yet enacted a dedicated AI law.

Recognizing that public policy is not the only factor influencing AI adoption, the Difference-in-Differences model also incorporates three key covariates, which should account for additional technological and economic impacts: "Governance and Ethics", reflecting if the existing regulations and ethical framework of a country sufficiently support the implementation of AI in a manner that fosters trust and legitimacy; "Digital Capacity", measuring the robustness of national digital infrastructure and technological readiness; and "Innovation Capacity", assessing a country's support for research, entrepreneurship, and the translation of scientific insights into applied AI solutions (Shearer/ Stirling / Pasquarelli 2020, 135-137).

After conducting the analysis, the results indicate that, on average, AI adoption rates are 35 percentage points lower in countries where an AI regulatory framework is in place. However, these results should be interpreted with caution. The AI Act was implemented only recently in 2024 and it is reasonable to expect that the full effects of such comprehensive regulation may take longer to materialize. Short-term impacts may not capture the long-term behavioral and strategic adjustments businesses might make in response to new legal frameworks. However, addressing this research question early after the enforcement of the regulation is both timely and necessary, as understanding the influence of the policy on AI adoption is critical for achieving a balance between fostering innovation and mitigating associated risks.

The structure of this thesis is the following: Chapter 2 reviews the relevant academic literature, beginning with an examination of how previous regulatory frameworks targeting the digital domain have influenced business and the broader economy. It then turns to the existing research on the anticipated impact of the AI Act on business practices. Chapter 3 introduces the rationale for selecting France and the United Kingdom as case studies, providing an overview of their respective AI regulatory approaches and levels of AI adoption among businesses. Chapter 4 outlines the data sources and presents the variables employed in the empirical analysis. Chapter 5 details the research design and methodology used in the study, followed by Chapter 6, which presents the empirical findings. Finally, Chapter 7 offers policy recommendations derived from the results, with the aim of informing effective and innovation-friendly AI regulation. The last Chapter presents the conclusion and an insight into future possible research based on the results of this thesis.

CHAPTER TWO: LITERATURE REVIEW

This chapter will situate this thesis and its topic within the existing scientific literature. First, as the AI Act is a newly implemented regulatory framework, direct empirical evidence on its impact is limited. Therefore, the first section of this chapter is giving an insight into the research about previous similar regulatiory frameworks within the European Union to provide a broader context. In the second part an overview will be given over current scholarly predictions regarding how AI regulation might influence the willingness of businesses to implement this technology.

2.1. Impact of previous EU digital regulations on businesses and the economy

Before analyzing the potential effects of new AI regulations, it is valuable to consider the impact on business decisions of past digital policies to better understand the likely outcomes. The European Union has a well-established history of regulating emerging technologies, as demonstrated by frameworks such as the General Data Protection Regulation (GDPR), the Digital Services Act (DSA), or the Digital Markets Act (DMA). Moreover, the EU remains the only governing body to introduce comprehensive intergovernmental legislation specifically targeting artificial intelligence. This positions the EU as a unique case for evaluating regulatory influence on national businesses.

In the literature, regulations are seen as essential for how businesses react to emerging technologies. According to the study conducted by Fredrik Erixon, Oscar Guinea, Erik van der Marel, and Elena Sisto, productivity differences among services firms across both developed and developing countries cannot be fully explained by conventional economic indicators. While firm-level attributes such as size and capital intensity, along with industry characteristics, account for part of the variation, a substantial portion remains unaccounted for. Consequently, this study suggests that broader structural factors, such as regulatory quality, are also key drivers. Moreover, even when regulatory frameworks appear similar across countries, their impacts can vary significantly due to differences in market structure (Erixon et. al 2022, 14). This insight will be important for the choice of the control and treatment group in this thesis, as the countries assigned to one of the groups need to have similar market and economy structures, in order isolate only the effect of the AI regulatory framework.

Returning back to Erixon's et. al study, it has slightly a negative outlook on policies, as its results find that regulatory restrictions in digital trade and technologies tend to limit firms' ability to effectively adopt digital solutions (Erixon et. al 2022, 14). Because of these findings, the authors of the study raise concerns regarding the European Commission's impact assessments and the adequacy of its economic analysis related to the new digital regulations. They argue that critical economic dimensions such as technology diffusion, access to digital service, and innovation are largely overlooked, despite their fundamental importance to national productivity and long-term economic growth (Erixon et. al 2022, 3-6).

Additionally, the study finds that either the distributional effects of these regulations nor the new costs for businesses associated with them have received sufficient attention. Because of that smaller economies and firms are likely to carry a disproportionate share of the regulatory burden. Also, countries that have concentrated their resources on advancing their digital sectors may be particularly vulnerable. Within the European Union for instance, exposure to these impacts varies widely. Northen European nations, typically small, open, and highly competitive, are expected to be among the most significantly affected by these new obligations. Similarly, Central and Eastern European countries could face adverse outcomes, especially due to the increased risk of smaller firms being marginalized or excluded from key markets (Erixon et. al 2022, 3-6).

Lastly, two key factors outlined in the study are particularly relevant for this thesis, as they inform the selection of control variables for the Difference-in-Differences regression model. According to the authors, the distribution of regulatory costs across EU countries is primary shaped by: (1) the industrial and economic structure of each country, and (2) the nature of its existing regulatory environment. The fist factor relates to national factor endowments, such as access to data and digital competencies, which firms leverage to gain comparative advantages in production, marketing and trade. Countries with more developed digital capacities may therefore be more exposed to regulatory impacts (Erixon et. al. 2022, 2-3). Taking these factors in consideration, the statistical model in this thesis will include variables such as "Digital Capacity" and "Innovation Capacity", in order to account for their effect on business AI adoption.

The second factor indicated by the study concerns the current level of regulatory restrictiveness, which varies significantly across both member states and sectors. This variation influences how new digital regulations will be absorbed and contributes to the uneven distribution of associated economic costs throughout the European Union (Erixon et. al. 2022, 2-3). These finding of the study, motivated the choice of the variable "Governance and Ethics" as a cofounder in the statistical model of this thesis.

Similarly, the study by Carl Frey and Giorgio Presidente "Privacy Regulation and Firm Performance: Estimating the GDPR Effect Globally" is assessing a negative impact of EU's regulation on businesses. The findings of this study show that after the General Data Protection Regulation (GDPR) was introduced by the European Union in May 2018, firms subject to the regulation experienced an average decline of 8% in profits and 2% in sales. Notably, these negative outcomes were concentrated among small and medium-sized enterprises (SMEs), while no measurable impact on sales or profits was observed for large technology firms as Facebook or Google. According to their study, the GDPR can influence firm performance through two primary channels. First, compliance with the regulation imposes direct costs on companies, as they are required to implement GDPR-compliant technologies and processes. For instance, enabling EU residents to access, amend, delete, or transfer their personal data necessitates the development or acquisition of appropriate IT systems. These adjustments can be financially significant: PwC reports that some firms allocate over 10 million euros annually to meet compliance obligations (PwC 2021). Second, the regulation may negatively impact e-commerce activity, thereby reducing sales. GDPR restricts the sharing of user data with third parties unless explicit user consent is obtained. Since valid consent must be affirmative, the process of collecting user data becomes more costly and less efficient, potentially limiting firms' ability to leverage personal data for commercial purposes. Furthermore, users themselves may face a form of "consent fatigue", which could discourage engagement and lead to a decline in online transactions.

Interesting for this thesis is also the limitations section of these study, as the following points might coincide also with the results regarding the new AI Act. Moreover, it also shows that even if the outcomes of the statistical model are indicating a negative effect, the regulation might bring also incentives for companies to adopt AI, that are just either not captured by the model or need more time to become evident. Thus, according to the authors the interpretation of their results requires caution. Firstly, some of the negative outcomes observed may come from transitional costs during the initial phase of adoption, implying that the long-term effects of the GDPR could be less severe. Secondly, should the GDPR framework gain broader international acceptance and move toward becoming a de facto global norm, firms catering to the EU market may no longer face a competitive disadvantage. Thirdly, it is important to acknowledge that the study does not evaluate benefits for individuals in terms of enhanced data privacy and protection are not reflected in the economic estimates presents (Frey/Presidente 2024).

Lastly, Kati Suominen (2022), researcher at the Center for Strategic and International Studies, estimated as well high costs for European firms due to EU's digital policies, such as the Digital Services Act (DSA) and Digital Markets Act (DMA), the Data Act, the Artificial Intelligence Act, and the Media Freedom Act. This study has thus identified a range of operational and compliance-related cost increases faced by technology firms and their customers following the implementation of these digital policies. According to it, U.S. digital service providers operating in Europe are estimated to have incurred compliance costs and fines totaling between $22 billion and $50 billion. In addition, these firms are likely to experience long term losses, potentially amounting to hundreds of billions of dollars, due to restrictions in the use of proprietary data, which hinder their ability to innovate, develop new services, and provide integrated digital solutions to European businesses and consumers (Suominen 2022).

Also, European firms that rely in U.S digital services are affected as well, with cost increases estimated at approximately 5%, translating to an aggregate burden of around €71 billion. The authors of the study state further that beyond direct financial implications, European consumers are impacted both as end-users of U.S. technologies and indirectly through goods and services embedded with those technologies, such as Internet of Things (IoT) products. Moreover, broader dynamic effects are anticipated, including a slowdown in digital transformation among European firms, reduced export competitiveness, and the deepening of digital divides, particularly between large corporations and smaller enterprises. The study concludes these developments not only challenge the competitiveness of European businesses but also adversely affect U.S digital providers' access to the European market and their broader commercial relationships with European clients (Suominen 2022).

In summary, the existing literature on the impact of the EU's digital regulatory frameworks and their economic impact on businesses indicates that previous European Union regulations concerning the digital realm have frequently been associated with increased compliance costs, a slowdown of digital transformation processes, and missed economic opportunities for business within EU member states. These consequences, driven by current regulatory frameworks, disproportionately affect smaller national companies. As a result, these firms may struggle to keep pace with technological advancements. This trend risks consolidation innovation within larger corporations, granting them near-monopolistic control over the development and application of new technologies. Consequently, they may also influence the purposes for which these innovations are used and determine their accessibility, thereby indirectly shaping consumer experiences and choices.

2.2. Existing studies on the AI Act and its influence on AI business adoption

Although the insights about digital regulations, which have been described in the previous subchapter, are essential for understanding the broader impact of policy on AI adoption, this thesis aims to focus more specifically on the AI regulation and its implications for the business landscape, because in this case it is not clear yet its precise impact on business. Even though public use of artificial intelligence is still in its early stage, the European Union has already introduced a comprehensive legislative framework, the AI Act, which entered into force on the 1st of August 2024.

However, there is a debate in the literature if regulating AI is having a positive or negative effect on AI business adoption rates. On one side, the AI Act would undoubtedly offer advantages to businesses, particularly by fostering digital trust. In one of its reports, Mckinsey states that measures such as improving the transparency and explainability of AI systems can strengthen this trust, ultimately contributing to improved business outcomes, Firms that successfully build digital trust are more likely to achieve annual growth rates of 10% or higher in both revenue and earnings before interest and taxes (EBIT) (Grennan/Kremer/ Zipparo 2022). Further, the study by Barbara Prainsack and Nikolaus Forgó brings three solid arguments, which show that the AI Act has a lot of potential in fostering the adoption of this new technology: first, clear regulation that defines what technology developers and providers may and may not do fosters legal certainty and predictability, supporting rather than hindering innovation. It is ambiguity and insufficient public investment, not regulation itself, that tends to obstruct technological progress. Second, not all innovation inherently benefits society. In fact, some recent innovations have exacerbated challenges such as climate change and inequality. A more systematic evaluation of who benefits from innovation, and at whose expense, is increasingly necessary, especially in sectors like healthcare, where technological advances hold great promise but vary in societal value. And third, the narrative that the EU lags behind China and the US due to stringent regulation oversimplified the issue. Structural factors such as the lack of an integrated digital market and inadequate public investment in AI capabilities and talent are far more significant barriers to European leadership in this field (Prainsack/ Forgó 2024).

However, on the other side, there are significant implementation challenges, especially concerning the AI Act's reliance on harmonized technical standards. A study conducted by the OECD highlights that the current timelines for adopting these standards are largely unrealistic for most organizations, particularly small and medium-sized enterprises (SMEs). The issue which raises serious feasibility concerns, is that the AI Act's high-risk requirements will become applicable as early as August 2026, but in reality, the adoption of a single technical standard can take six to twelve months. Nevertheless, the European standardization bodies CEN and CENELEC are currently working on approximately 35 technical standards to support the Act's implementation, a volume that may overwhelm many smaller firms (Ebel/ Jäck/ Kilian 2025).

Beyond the challenges of timing, according to OECD also the financial burden associated with compliance is substantial. Implementing the AI Act through harmonized standards could lead to significant recurring costs. For SMEs, annual compliance expenses are estimated to begin at approximately €200.000, with far higher figures projected for larger enterprises. This considerable number and complexity of the standards pose a serious challenge for firms with limited financial and human resources, especially as these companies must not only purchase the standards but also interpret and operationalize them. This often necessitates additional investments in specialized personnel with the expertise to manage technically demanding compliance processes (Ebel/Jäck/ Kilian 2025).

Furthermore, OECD also recognizes the disparity in resources, which is reflected in the unequal influence exerted during the standard-setting process itself. SMEs and startups are significantly underrepresented in the committees responsible for drafting these technical standards. In contrast, large multinational corporations play a dominant role in shaping the regulatory landscape. This imbalance risks producing standards that primary benefit the interests and capacities of well-established firms, many of which are headquartered outside the EU, potentially hindering innovation and raising entry barriers for local players. Without inclusive stakeholder representation, there is a genuine concern that these standards may fail to reflect the practical needs and values of a diverse European economy (Ebel/ Jäck/ Kilian 2025). It is precisely this imbalance, between regulatory ambition and practical feasibility, that this thesis seeks to investigate.

As the literature in this section indicates, because the AI Act is still in its early stages, it is unclear if its effects on businesses are expected to reflect those of previous regulatory initiatives. We also do not know yet, if smaller firms are likely to be disproportionately burdened by the harmonized standards, which may limit their ability to compete on the market, which could further strengthen the dominance of multinational corporations, allowing them to shape the direction of technological development and exert greater influence over the market.

2.3. Gaps in the current research and how this study contributes

As outlined in the related literature above, the economic implications of regulating digital technologies are generally viewed with concern, particularly due to the high compliance costs imposed on domestic firms. Especially smaller and local enterprises often bear a disproportionate share of this regulatory burden. However, when considering implementing an AI regulatory framework one should also think about the economic the responsible and standardized adoption of AI technologies brings. Firms involved in developing these systems face significant reputational and financial risks when their products fail to perform reliably. For example, the occurrence of "hallucinations", instances in which AI systems generate false or illogical information, has led to public scrutiny and, in some cases, substantial financial losses in market value for leading generative AI companies. These examples highlight the importance of regulation not just as a burden, but as a framework for safeguarding quality, trust, and long-term economic viability. Overall, the risks introduced by AI can be mitigated by thoughtfully designed regulation which guides firms toward responsible and safe deployment practices.

Despite the importance of this issue, there remains a notable gab in the academic literature regarding the specific impact of regulation on AI adoption at the firm level. In particular, it is unclear whether regulatory initiatives serve as a deterrent to adoption, due to anticipated costs and complexity, or as an enabler, by fostering trust and creating clearer operational guidelines. This ambiguity reflects an interesting area in need of empirical investigation. This thesis seeks to address that gap by exploring whether recent and upcoming AI regulations influence firms' willingness and ability to adopt AI technologies. Specifically, it examines whether such regulations act as a constraint on innovation or as a driver for structured, trustworthy AI integration within business environments.

Chapter Three: France vs. UK: similar economies diverge on AI regulation

To empirically investigate the impact of regulation on firms' adoption of artificial intelligence, this thesis employs a Difference-in-Differences analysis. Because of the parallel trend assumption, this method requires two comparable cases that differ primarily in the independent variable, in this case, the presence or absence of an AI regulatory framework. Since the focus of this study is on the European Union's regulatory approach to AI, France is selected as the treatment group. To serve as a control group, the United Kingdom is chosen due to its high degree of comparability to France across several key indicators.

According to Statista, the population of France stands at approximately 68.25 million, while the UK has a slightly higher population of 68.27 million (Statista 2024 a. 2025). Economically, both countries are considered mid-sized advanced economies. For 2024, France's GDP is estimated at €3.18 trillion, and the UKs at €3.59 trillion (Statista 2024 b., d.), with both nations recording in the same year an annual GDP growth rate of around 1% (Statista 2024 c., e.). In terms of AI adoption, the two countries are similarly positioned. The Government AI Readiness Index (2024) assigns France a score of 79.36, closely followed by the UK at 78.88, indicating near-parity in public sector preparedness for AI integration (Cirri/ Crampton/ Fuentes/ Gonzalo/ Hankins/ Striling/ Sulamaan 2024, 18).

An additional factor supporting this comparison is the UKs prior membership in the European Union until its formal exit in 2020. This shared regulatory history makes the UK a particularly relevant counterfactual for evaluating the potential effects of EU AI regulation on business behavior.

However, it is important to mention that UK is not the only possible option as a control group. For example, Switzerland could as well be considered as an alternative, as it also does not have an AI regulation in place so far and is economically and demographically very similar to some EU countries, such as the Netherlands. However, an analysis of this pair of countries has been excluded for this thesis, as there is no publicly available data for the two countries regarding the AI adoption by business until 2025.

3.1. AI regulation

Nevertheless, the two countries, France and UK, have very different approach in terms of regulating AI. In the case of France, the primary legislative framework for regulating AI is the EU AI Act. The AI Act is the European Union's landmark legislation establishing the world's first comprehensive legal framework for artificial intelligence. Officially adopted as Regulation (EU) 2024/1689, it aims to promote the development and use of trustworthy AI while safeguarding fundamental rights, health, and safety across EU. As the European Commission describes it, the Act takes a risk-based approach, classifying AI systems into four categories: unacceptable risk (banned entirely), high risk (subject to strict regulatory requirements), limited risk (requiring transparency), and minimal or no risk (subject to no regulation). The AI Act is foreseeing that high-risk AI systems, such as those used in critical infrastructure, law enforcement, employment, or healthcare, must meet rigorous standards related to data quality, transparency, human oversight, and cybersecurity before entering the EU market. In addition to regulating AI applications, the Act sets obligations for general-purpose AI models, particularly those with systemic risks, It introduces transparency and copyright-related requirements, with further guidance to be provided through a Code of Practice coordinated by the EU's newly established AI Office, The AI Act is part of a broader strategy that includes initiatives like the AI Innovation Package and the AI Pact, designed to support early adoption, industry engagement, and coordinated implementation, While the regulation aims to mitigate the risks of AI, it also seeks to position Europe as a global leader in ethical and human-centric AI development (European Commission).

Besides that, like many other countries, France has committed itself to advancing artificial intelligence, with the COVID-19 pandemic further accelerating both the conceptual development and practical application of AI across multiple sectors. President Emmanuel Macron has identified AI as a strategic priority for his administration, aiming to position France as a global leader in the field. Together with these ambitions, the French government has also taken proactive steps to anticipate and address the regulatory challenges posed by AI technologies (Duflot 2024, 38).

France's national AI strategy was first introduced in 2017, coinciding with the beginning of President Macron's first term in office. Known as the National Strategy for Artificial Intelligence, it is embedded within the broader France 2030 initiative, a long-term economic investment plan with a total budget of €100 billion, including €40 billion in co-financing from the European Union. The strategy's core objective is to safeguard and reinforce France's economic, technological, and political sovereignty in the AI domain. Within this framework, €1.5 billion has been specifically allocated for the formulation and implementation of national AI policy (Duflot 2024, 38).

In order to address the risks that come with the use of AI, French National Assembly has engaged in discussion around the development of an ethical charter on artificial intelligence, with the ambitious goal of integrating it into the Preamble of the French Constitution. Such a move would grant the charter a status above ordinary legislation, aligning it with the legal weight of the Universal Declaration of Human Rights (Duflot 2024, 41).

The proposed charter aimed to establish, at the constitutional level, that AI cannot be granted legal personality. Within this framework, artificial intelligence is defined as an algorithm that evolves in its structure and learns beyond its initial programming. The charter outlined core principles AI systems must adhere to, such as subordination to human commands, and called for mandatory auditing and oversight to monitor AI's progression toward autonomous decision-making. However, despite initial momentum, the proposal was never adopted into the Constitution and appears to have been set aside (Duflot 2024).

In addition to promoting ethical governance, the French government also seeks to enhance the global competitiveness of its AI sector by leveraging voluntary standardization as a policy tool. By shaping standards proactively, France aims to create favorable conditions for the development and international recognition of reliable and trustworthy AI products and services. This strategy is intended not only to reinforce the domestic AI ecosystem but also to position French stakeholders as leaders in global AI governance and innovation (OECD 2022).

Lastly, in alignment with the goals outlined in France's national AI strategy, particularly the emphasis on ethical, transparent, and trustworthy use of AI, Cedric Villani's influential AI policy report proposed the creation of a legally structured ethics body to foster public dialogue on digital and AI-related issues. This recommendation led to the establishment of the Pilot National Digital Ethics Committee (CNPEN) in early 2020. Initially tasked with exploring three core areas of AI ethics, the committee's mandate is expected to expand progressively, reflecting its growing role in shaping ethical oversight in the digital domain (European Commission 2021).

On the other hand, the UK strategy regarding regulating AI is much more hands-off. As of now, according to the AI Watch, the United Kingdom does not have a unified or comprehensive legal framework dedicated exclusively to artificial intelligence. Rather, the country has adopted a principles-based, sector-specific regulatory model, allowing existing regulatory bodies to apply and interpret AI-related rules within their respective domains. This non-legislative strategy has been praised for its flexibility, enabling regulators to adapt more easily to the rapid pace of AI innovation (White&Case 2025).

Nonetheless, recent policy developments signal a gradual move towards formalized and binding regulation. In the July 2024 King's Speech, the government announced plans to introduce statutory obligations for developers of advanced AI systems. Accompanying this, the establishment of the AI Safety Platform aims to assist business in identifying and managing AI-related risks. Looking ahead, comprehensive AI legislation is expected in 2025, which will likely formalize currently voluntary arrangements and confer independent oversight upon the AI Safety Institute (White&Case 2025).

In parallel, a number of targeted policy efforts, such as the AI Action Plan, the Technology working Group's findings, and ongoing consultations on copyright law, point to increasing regulatory activity in key sectors, including finance, data protection, and intellectual property (White&Case 2025). These developments make the UK a suitable control group for this study, as the available data has not yet been influenced by binding AI-specific regulatory measures.

3.2. AI business adoption

As this thesis analyses the impact of policies on the AI adoption by business, it is useful to look into the business landscape in both countries, to be more precise how far they have come implementing technologies that rely on artificial intelligence.

Despite the vat potential, artificial intelligence still presents challenges for widespread adoption within French companies. As of 2024, fewer than half of businesses in France had invested in AI technologies, significantly below the global average of 72% according to Le Monde (Madeline 2025). In response, the French government launched the second phase of its AI strategy in 2022, aimed at accelerating AI integration across sectors and enhancing national competitiveness. The France 2030 investment plan, mentioned in the previous subchapter, foresees €2.5 billion has been specifically allocated to support the development and deployment of AI technologies. The overarching objective is to embed AI throughout the value chain, enabling French enterprises to innovate, modernize operations, and expand their presence in global markets. Programs such as AI Booster are central to this effort, offering targeted support to more than 200 small and medium-sized enterprises (SMEs) and mid-sized firms. These initiatives are designed to help businesses streamline operations, improve competitiveness, and advance their digital transformation. To reinforce its position in the global AI arena, France is also investing heavily in human capital. Public funding totaling €560 million will be directed toward strengthening the country's AI education infrastructure, particularly through the enhancement of national centers of excellence and the expansion of AI training programs. These efforts aim to aim to attract, train, and retain talent, while boosting the productivity and capabilities of the domestic AI workforce (Madeline 2025).

In the case of the United Kingdom, AI adoption among businesses has been gradually increasing since late 2023, though overall uptake remains moderate. As of September 2024, 15% of UK businesses reported actively using AI technologies, up to 5 percentage points from the previous year. Among larger firms (those with 250 or more employees), adoption is significantly higher at 30%. The primary motivation cited for AI adoption is to improve business operations, reported by 40% of users (Office for Nation Statics 2024).

Despite this growth, the majority of businesses (80%) are not planning to adopt AI in the immediate future. Only 10% reported intentions to implement AI within the next three months, a figure that remains largely unchanged from earlier in 2024. Among larger business, this number rises slightly to 13%. The main barriers to adoption include the difficulty identifying relelevant business use cases (6%), the lack of in house AI expertise (6%) and the cost concerns (6%). However, 81% of businesses stated they had not encountered any active barriers or had not yet attempted to adopt AI at all (Office for National Statistics 2024).

These similar profiles make France and the UK particularly suitable for comparison in this thesis. Both countries exhibit relatively low adoption rated of the AI technology. However, while France reflects a policy-driven approach with limited business uptake, the UK illustrated a more gradual, market-led trajectory, distinguished by comparatively higher levels of user engagement despite the overall low adoption. Both countries face challenges related to skills, costs, and clarity of business use cases, but differ in how policy and market dynamics shape the adoption landscape. Based on these insights, a meaningful analysis can be conducted on how regulation may influence AI adoption across varying national contexts.

CHAPTER FOUR: DATA

4.1. Data sources: Description and justification

To carry out the Difference-in-Differences (DiD) analysis, it is essential to obtain data for both the treatment and control groups during periods before and after the intervention, in this case, the enforcement of AI-related policy in 2024. For this purpose, the dataset used in the analysis was curated by Atharva Soundankar, Junior Data Analyst at Manasvi Tech Solutions in India, and is publicly available on the platform Kaggle.

The dataset captures the expanding influence of AI-generated content across various sectors, for instance journalism, retail, healthcare or finance. It provides a broad overview of public sentiment, engagements trends, economic impact and regulatory developments. As the use of AI-generated content becomes increasingly widespread, this dataset offers a robust foundation for examining trends in adoption, identifying potential biases, and projecting future developments. According to the author its relevance extends to data analysis, business strategists and research in the field of machine learning, making it particularly well-suited for the aims of this thesis.

The dataset was compiled through a systematic process, drawing on publicly available sources including institutional reports and data bases from organizations such as Stanford University (AI Index Report, which provides annual insights into AI adoption and technological advancement), the Massachusetts Institute of Technology (Technology Review, offering critical analyses of AI's impact on media, business and innovation), the OECD (Digital Economy Outlook, highlighting AI-driven transformations in global markets) and Statista. Additional data was sourced from official government publications. To ensure accuracy and analytical rigor, the data was cleaned, structured and validated by the original author. According to the author, the resulting dataset is designed to support academic research, inform business intelligence efforts, and aid the development of AI applications by providing a reliable reflection of current trends in the field.

However, this core dataset has certain limitations, particularly in its ability to capture the full range of factors that influence besides policy AI adoption in businesses. Many of these factors are essential for inclusion as confounders in the Difference-in-Differences (DiD) model to ensure a robust causal analysis. Academic literature highlights several such variables. For example, a recent study by Youngsoo Kim, Victor Blazquey, and Taeyeon Oh (2024) addresses this topic by exploring the determinants of generative AI adoption in Korean firms. The authors apply the Unified Theory of Acceptance and Use of Technology (UTAUT) model to examine key factors influencing technology acceptance and usage behavior. Their study, based on survey responses from 300 employees across both large corporations and SMEs, shows several important findings. First, the perceived ease of use and compatibility of AI systems with existing processes significantly increases firms' willingness to adopt the technology. Second, social influence, particularly support from colleagues and managers, positively affects behavioral intention towards adoption. Finally, demographic characteristics such as age and work experience also play a role in shaping employees' perception of AI and their likelihood of using it (Blazquey/ Oh/ Youngsoo 2024). These findings indicate the importance of interacting behavioral, organizational, and demographic variables into a comprehensive analysis of AI adoption, variables which are not included in the core data set.

Additional supporting evidence for factors which influence adoption, is provided by the study conducted by Heidi Heimberger, Djerdj Horvart and Frank Schultmann, which examines the current state of research on artificial intelligence adoption from a production perspective. The authors conducted a systematic literature review of scholarly work published between 2010 and 2014, focusing specifically on AI adoption within production environments. By applying a rigorous selection process, they identified and analyzed a sample of studies that contribute directly to understanding of AI implementation in production settings. Their review highlights 35 factors that play a significant role in shaping AI adoption in this context. These factors are organized into a conceptual framework, several components of which are directly relevant to the empirical analysis in this thesis. These include the availability of a skilled workforce, access to data, the presence of ethical guidelines, managerial support, IT infrastructure, investment capacity, education and training, regulatory frameworks, data storage solutions, and a culture of innovation (Heimberger/ Horvart/ Schultmann 2024).

To incorporate the factors identified in the literature as confounders in this analysis, this thesis draws on data from the Government AI Readiness Index, developed by Oxford Insights. Launched in 2021, the index has become a widely recognized benchmarking tool for assessing national preparedness to deploy AI technologies. It is now referenced by various national governments and major international institutions, including UNESCO and the G20, highlighting its credibility and relevance worldwide.

The most recent edition evaluates AI readiness of 188 countries, doing so in the context of increasing global complexity, including changing citizen expectations, economic uncertainty, climate challenges, and growing social inequality. The 2024 index is based on 40 indicators across 10 dimensions, structured within three main pillars: Government, Technology and Data and Infrastructure. These dimensions capture both the institutional and technical capacity required to implement AI effectively.

At its core, the index analyses how well-prepared are governments to deploy AI. By offering a comprehensive, data driven view of national readiness, the index provides insights that not only support general evidence-based policymaking but also align closely with the control variables needed for the Difference-in-Differences analysis in this thesis, which will be explained next in more detail.

4.2. Key variables

This thesis uses a Difference-in Differences (DiD) framework to examine the effect of regulatory policies on the adoption of artificial intelligence in business. To operationalize this analysis, a set of key variables has been selected based on both data availability and relevance in the academic literature.

The independent variable is the AI Adoption Rate (%) sourced from the core dataset compiled by Atharva Soundankar. This variable directly captures the proportion of businesses adopting AI over time and serves as the primary indicator of AI integration at the national level.

To control for additional factors that influence AI adoption, several confounders will be included: “Governance and Ethics” which captures the extent to which regulations and ethical frameworks are enforced in a country, “Digital Capacity” which reflects the level of digital infrastructure and technological preparedness of the country and “Innovation Capacity” which reflects a country’s ability to foster research and development, support entrepreneurship, and translate scientific advances into technological real-life applications. These variables collectively aim to control for the structural, economic and technological conditions that may influence national AI adoption trends independently of regulatory intervention.

While a variety of further contextual factors may influence AI adoption such as human capital, data representativeness, infrastructure, data availability or a country’s strategic vision regarding AI, only a subset of these variables were included in the DiD regression model. This decision rests on the foundational principle in causal inference: for a variable to qualify as a confounder, it must be associated both with the treatment assignment (which country receives the policy) and the outcome of interest (AI adoption).

According to the literature, all the previous mentioned factors would meet these criteria. But as parsimonious models are usually more reliable, in this thesis the choice of confounders was not only based on the literature's indications but also by examining pre-treatment differences (before 2024) in the means between the treatment and the control groups. Statistically significant differences may suggest that a variable could be driving both treatment status and the outcome, and thus should be included in the regression in order to reduce omitted variable bias. For this reason independent-sample t-tests were conducted for each candidate confounder variable over the pre-treatment period (2021-2023).

The results indicate that only "Innovation Capacity" exhibited a statistically significant difference between France (M = 67.47) and the UK (M=75.37), with a t-statistic of -5.48 and a p-value well below conventional thresholds for significance. The other two included variables, "Governance and Ethics" and "Digital Capacity", showed noticeable differences in mean values but did not reach statistical significance at the 5% level, suggesting some potential for confounding in this context.

Chapter Five: The Difference-in Differences Model

5.1 Method

Since the influential work of Ashenfelter and Card (1985), the Difference-in Differences (DiD) method has become a widely adopted tool for estimating causal effects. The main concept involves observing two groups, one treatment group and one control group, across two time periods. The treatment group is exposed to a specific intervention during the second period, while the control group remains unaffected in both periods (Békés / Kézdi 2021, 620-635).

When the same units are tracked over time within each group, the DiD approach compares the change in outcomes for the treatment group with the change in outcomes for the control group. This "double differencing" helps eliminate biases in post-treatement comparison that might arise from permanent differences between the groups, as well as those resulting from time trends unrelated to the intervention. This method, therefore, provides a cleaner estimate of the treatmet effect by isolating it from confoundung factors (Békés/ Kézdi 2021, 620-635).

5.2. Assumptions for Difference-in-Differences

For the Difference-in-Differences approach to produce an unbiased and consistent estimate of the treatment effect, several assumtions must be met. First, the model must be correctly specified, meaning that the functional form and the included covriates acccurately capture the true underlying relationship in the data. Second, the error term is assumed to have an expected value of zero and must be independent of the explanatory variables; this ensures that the estimates are not biased due to omitted variable bias or endogeneity. Third, and most imprtant, the parallel trend assumption must hold. This assumption states that, in the absence of the treatement, the treatment and control groups would have followed similar trajectories over time. Only under this condition can any observed divergence in outcomes after the intevention be attributed to the treatment itself (Békés / Kézdi 2021, 620-635). On Figure 1. the parallel trend in AI Adoption Rate between France and the UK can be observed since 2022 until 2024, the year in which the treatment took place. Following 2024 there is a divergence in the trend, where the UK experiences a significant drop in adoption, while France shows an increase. This divergence might be explained either by the introduction of the policy, or by other global economic or technological factors. In order to isolate the causal effect of the policy, the DiD analysis is required.

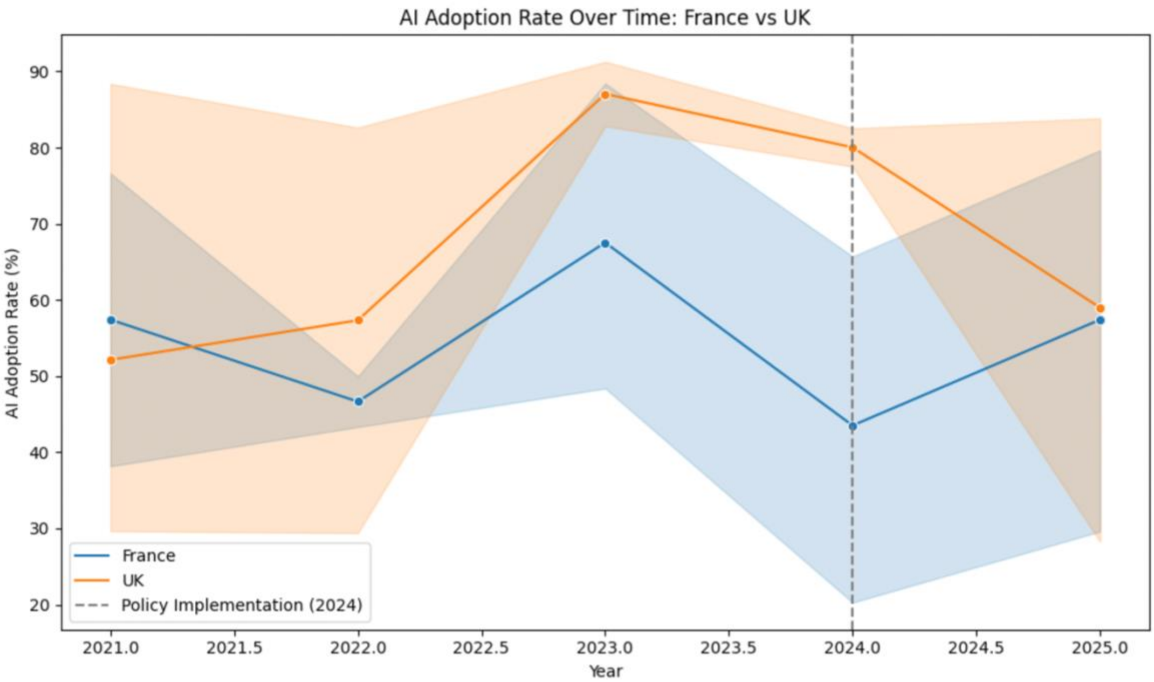

***Figure 1**: AI Adoption Rate Over Time*

5.3 The DiD model

In this thesis the outcome in the DiD approach is constructed by the following equation:

$$Y_{it} = \alpha + \beta P_{it} + \gamma T_{it} + \delta(P_{it} \cdot T_{it}) + \theta G_{it} + \mu I_{it} + \sigma D_{it} + \varepsilon_{it}$$

In this model specification, α represents the constant term, while ß captures the general time trend. The coefficient term γ accounts for the fixed effect specific to each group and δ denotes the treatement effect, the primary parameter of interest in the analysis. The coefficient terms θ, μ and σ are accounting for the effects on the AI adoption of the confounder variables "Government and Ethics" (G), "Innovation Capacity" (I) and "Digital Capacity" (D). The error term ε encompasses random, unobserved influences, including any bias introduced by omitted variables.

The binary variable P is a time indicator that equals 1 for observations in the post-treatement period (2024) after the AI Act was inplemented and 0 for observations in the pre-treatement period (2020-2023). Similarly, T is a group indicator, which takes the value 1 if the observation belongs to the treatement group, France, and 0 if it is from the control group, UK. The interactionterm (P ·T) identifies observations from the treatment group after the intervention, allowing us to isolate the causal impact of the treatment.

Chapter Six: Results and discussion

6.1 Difference-in-Differences regression output

To estimate the causal effect of the EU's AI Act on AI adoption by business, a Difference-in Differences (DiD) regression model was employed. The dependent variable is the AI adoption rate, with the interaction term (P ·T) capturing the treatement effect for France post-policy implementation relative to the UK, the control group, The model also controls for several instituional characteristics, including "Governance and Ethics", "Innovation Capacity" and "Digital Capacity". These factors are included because additional to the regulation, they also could have an individual effect on AI adoption.

The results of the OLS regression, estimated with robust standard errors (HC3), are summarized in Table 1.

***Table 1**: Difference-in-Differences Output*

	Coefficient	p-value
Intercept	-1549.2290	0.068
Treatement	92.3172	0.191
Post Policy	-62.3160	0.096
Treatement x Post Policy	-35.0719	0.089
Governance and Ethics	9.1175	0.008
Innovation Capacity	9.3729	0.212
Digital Capacity	1.1709	0.289

6.2. Interpretation of key coefficients

The coefficient of the interaction term (P ·T) is -35.07 and marginally significant at 10% level (p = 0.089). This suggests that, after controlling for country-level institutional capacity and industry structure, AI adoption in France was on average 35 percentage points lower post-policy compared to the control group UK. While the result is not conventionally significant at the 5% level, the direction of the effect raises the possibility that the policy may have had a dampening effect on AI adoption, or that the policy implementation was too short to capture a positive change. Moreover, it is important to mention, that before adding any confounders, the interaction coefficient is positive matching the direction of the divergence after 2024 observed on Figure 1. An explanation for the flip in the signs after including any confounder variable, could be that these variables are absorbing some of the variation that might otherwise have been attributed the policy.

Treatment and Post-Policy Main Effects

The "Post Policy coefficient (−62.32, $p = 0.096$) is negative and marginally significant, suggesting that all countries experienced a general decline in AI adoption after 2024, independent of treatment status. This could be attributed to external economic or regulatory shocks affecting AI diffusion globally.

The "Treatment" coefficient (92.32, $p = 0.19$) represents the baseline difference in AI adoption rates between treatment and control groups before the policy. Though positive, it is not statistically significant, implying that France did not significantly differ from the UK in their AI adoption rates prior to 2024, an argument that the parallel trend does hold.

Control Variables

Governance and Ethics

The coefficient for "Governance and Ethics" is positive and statistically significant (9.12, $p = 0.008$), indicating that a one-point increase in governance score is associated with a 9.1 percentage point increase in AI adoption, holding other factors constant. This supports the argument that strong ethical and regulatory institutions are critical enablers of AI deployment.

Innovation Capacity

The coefficient for “Innovation Capacity” coefficient (9.37) is positive but not statistically significant ($p = 0.212$). Although innovation infrastructure may be relevant for AI adoption, the lack of significance suggests that its effect is less robust in this sample or already captures by other correlated variables.

Digital Capacity

Similarly, “Digital Capacity” shows a small and statistically insignificant effect (1.17, $p = 0.289$), suggesting that digital infrastructure alone may not be sufficient to drive AI adoption once institutional quality is accounted for.

6.3. Limitations

Despite the fact that the DiD model in this thesis has been carefully designed, in order for it to account for all sources of variation or other factors which might bias the results, there are three limitations that must be addressed.

Firstly, a major constraint is the limited sample size. Since the AI Act has been implemented recently, there are relatively few post-policy observations available. On the one hand, this could lead to less accurate results, especially for the attempt to generalize the causal impact of the AI Act for all EU member states, or make it more difficult to detect the difference between groups. On the other hand, the lack of observations after the policy was enforced may not fully capture the long-term effects of the legislation on AI adoption.

Secondly, there is no publicly available dataset that provides information on internal business characteristics, such as company employees’ age, their work experience or digital skills, in the two countries. However, the literature identifies them as important factors impacting AI adoption, and the absence of these controls may limit the precision of the estimates.

Lastly, although in this thesis the results showed a negative relationship between regulating AI and adoption rates, it is important to acknowledge, as illustrated by the study conducted by Carl Frey and Giorgio Presidente discussed in the literature review, that the DiD model did not include any variable accounting for the societal impact of the Act. However, one of the primary objectives of the Act is to protect fundamental rights. In this light, the decrease in AI adoption may not represent an undesirable outcome, but it could reflect a necessary adjustment, whereby the businesses engaging in potential harmful or abusive AI practices are discouraged or removed from the market.

Chapter Seven: Policy recommendation

In this chapter two policy recommendations will be proposed designed to enhance the influence of EU's AI Act on business decisions, based on the results presented in the previous section. As the main results showed, French businesses have been adopting less AI after 2024, in compared to their counterparts in the United Kingdom, a trend that could have broader implications for the future economic development of France. This suggests that, probably to some extent, the uniform standards imposed by the AI Act have made business decision makers either reluctant regarding the expansion of their AI usage, or at least made them to postpone related investments.

One way in which this issue could be addressed, is by providing more clarity to business owners, regarding which specific provisions of the Act are relevant for their AI-related activities and how they should proceed to achieve compliance. This could be achieved either by establishing dedicated guidance channels that respond to business queries and offer clear and practical advice on the requirements or by offering tailored training programs, especially for smaller local companies, as the study by Carl Frey and Giorgio Presidente showed that these would be the most affected by new regulations, in order to help them understand, implement and align their operations with the standards of the Act. If the European Commission or the governments of the member states will take such actions, this will not only reduce uncertainty and lower compliance costs, but also foster greater confidence in the adoption of AI technologies across the business sector.

The second potential strategy for encouraging companies to adopt AI while maintaining effective regulation, would be to move towards a regulatory framework more similar to the approach planned to be implemented in the United Kingdom. This would involve adopting a principles-based, sector-specific model in which the standards of the AI Act are tailored to the specific needs and characteristics of each industry. This more flexible approach is better suited to the dynamic nature of AI technologies, as it allows regulation to adapt more easily to ongoing technological development. Furthermore, it acknowledges that the role and application of AI vary significantly across industries; a more tailored framework would therefore be between positioned to address sector-specific requirements and support innovation in a more targeted and effective manner.

As such, the EU could consider adopting a combined approach that builds on the strengths of both clear, harmonized standards and flexible, sector-specific guidance in order to achieve a balance between legal certainty and innovation readiness.

CHAPTER EIGHT: CONCLUSION

In summary, the Difference-in-Differences analysis conducted in this thesis provides partial evidence of a treatment effect resulting from EU's AI Act, implemented in 2024. The coefficient of the interaction term between treatment status and the post-policy period is negative and marginally significant, suggesting that AI adoption rates in France declined relative to the UK following the policy's implementation. While the effect does not reach the conventional 5% significance threshold, its direction implies that the policy's effect is negative within the short timeframe observed.

Importantly, among the institutional control variables, the "Governance and Ethics" index stands out as a strong predictor of AI adoption. The coefficient is positive and statistically significant, indicating that stronger ethical and governance frameworks are associated with greater levels of AI uptake. This finding underscores the importance of institutional quality in enabling the diffusion of emerging technologies, and the need of further research on the influence of regulatory frameworks and their quality on business.

In contrast, "Innovation Capacity" and "Digital Capacity" do not show statistically significant effects in this model, although their coefficients are positive. This may reflect either multicollinearity with other institutional variables or limitations in the measurement of their influence over this specific period.

The regression model does not indicate significant pre-policy differences in AI adoption between the treatment and control groups, which supports the parallel trend assumption underlying the DiD approach. Furthermore, the modest R-squared value suggests that while the model captures some important explanatory factors, a substantial portion of the variation in AI adoption remain unexplained, likely due to unobserved economic, political, or technological dynamics.

Looking ahead, it is evident that further research is needed in order to consolidate the results, and to determine if AI regulations indeed have a strong and statistically significant negative effect on businesses' decision to a adopt AI. Furthermore, considering the normative power of the European Union, it is possible, similar to the experience with GDPR, that the EU's AI Act could soon become, a prototype and source of inspiration for other countries seeking to ensure that AI is used in a manner that respects human rights. If this occurs, then the current decrease in AI adoption by business may no longer be as significant, as similar trend will emerge everywhere in the world at the same time.

This is why it is important that the existing AI regulations are designed in a responsible and efficient way. For that to materialize we should start monitoring the effect of such regulation as early as possible. Even if a general and evident decline in AI adoption by business will happened, proactive oversight could help to mitigate and limit its extent. Moreover, AI is evolving at a peace that outstrips traditional policy cycles, we simply do not have the time to wait three to four years to evaluate outcomes. Early outcomes, even if limited, can guide timely adjustments and ensure that regulation empowers innovation rather than holding it back.

Bibliography

Békés, Gábor/ Kézdi, Gábor (2021): Data Analysis for Business, Economics, and Policy. Cambridge, Cambridge University Press.

Blazquez, Victor/ Oh, Taeyeon/ Youngsoo, Kim (2024): Determinants of Generative AI System Adoption and Usage Behavior in Korean Companies: Applying the UTAUT Model. In: Behavioral sciences, Nr. 14, Vol: 1, 1035 - 1057.

Deloitte (2024): The impact of Generative AI on UK businesses: a deep dive. URL: https://www.deloitte.com/uk/en/issues/generative-ai/trust-in-generative-ai-uk.html. Last accessed: 15.05.2025.

De Mauro, Andrea/ Sestino, Andrea (2022): Leveraging Artificial Intelligence in Business: Implications, Applications and Methods. In: Technology analysis & strategic management, Vol. 34, Nr. 1, 16–29.

Duflot, Alain (2024): Artificial Intelligence in the French Law of 2024. In: *Legal Issues in the Digital Age*, Vol. 5, Nr. 1, 37–56.

Cirri, Giulia/ Crampton, Eddie / Fuentes Nettel, Pablo / Gonzalo, Grau / Hankins, Emma/ Stirling, Richard/ Sulamaan, Rahim (2024): Government Al Readiness Index 2024. Oxford Insights.

Ebel, Dominik/ Jäck, Linda/ Kilian, Robert (2025): Making digital regulation work – The crucial role technical standards play in implementing the EU AI Act. URL: https://oecd.ai/en/wonk/making-digital-regulation-work-the-crucial-role-technical-standards-play-in-implementing-the-eu-ai-act. Last accessed: 15.05.2025.

European Union (2024): Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). OJ L 1689. URL: https://eur-lex.europa.eu/eli/reg/2024/1689/oj. Lastly accessed: 8.06.2025.

Erixon, Fredrik/ Guinea, Oscar/ Van der Marel, Erik/ Sisto, Elena (2022): After the DMA, the DSA and the New AI regulation: Mapping the Economic Consequences of and Responses to New Digital Regulations in Europe. European Centre for International Political Economy (ECIPE).

European Commission: AI Act. URL: https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai. Last accessed: 15.05.2025.

European Commission (2021): France AI Strategy Report. URL: https://ai-watch.ec.europa.eu/countries/france/france-ai-strategy-report_en. Last accessed: 15.05.2025.

Frey, Carl Benedikt/ Giorgio Presidente (2024): Privacy Regulation and Firm Performance: Estimating the GDPR Effect Globally. In: Economic inquiry, Vol. 62, Nr. 3, 1074–1089.

Heidt, Amanda (2024): Intellectual property and data privacy: the hidden risks of AI. URL: https://www.nature.com/articles/d41586-024-02838-z. Lastly accessed: 07.06.2025.

Heimberger, Heidi/ Horvat, Djerdj/ Schultmann, Frank (2024): Exploring the Factors Driving AI Adoption in Production: A Systematic Literature Review and Future Research Agenda. In: Information technology and management, Vol. 8.

Kaminski, M. E. (2023): Regulating the risks of AI. In: Boston University Law Review, Vol. 103, Nr. 5, 1347-1411.

Koshiyama, Adriano et al. (2024): Towards Algorithm Auditing: Managing Legal, Ethical and Technological Risks of AI, ML and Associated Algorithms. In: *Royal Society open science*, Vol. 11, Nr. 5, 230859–34.

Grennan, Liz/ Kremer/ Andreas, Singla, Alex/ Zipparo, Peter (2022). Why businesses need explainable AI—and how to deliver it. McKinsey. URL: https://www.mckinsey.com/capabilities/quantumblack/our-insights/why-businesses-need-explainable-ai-and-how-to-deliver-it. Last accessed: 15.05.2025.

Madeline, Béatrice (2025): French businesses are slow to adopt AI. In: Le Monde. URL: https://www.lemonde.fr/en/economy/article/2025/02/08/french-businesses-are-slow-to-adopt-ai_6737924_19.html. Last accessed: 15.05.2025.

McKinsey (2024): The state of AI in early 2024: Gen AI adoption spikes and starts to generate value. URL: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai. Last accessed: 26.01.2025.

OECD (2022): AI STANDARDISATION INITIATIVE. URL: https://oecd.ai/en/dashboards/policy-initiatives/http:%2F%2Faipo.oecd.org%2F2021-data-policyInitiatives-27284. Last accessed: 15.05.2025.

Prainsack, Barbara/ Forgó/ Nikolaus (2024): New AI Regulation in the EU Seeks to Reduce Risk without Assessing Public Benefit. In: Nature medicine, Vol. 30 Nr. 5, 1235–1237.

PWC (2021): A privacy reset — from compliance to trust-building. Put privacy at the heart of all you do, compete better on customer trust. URL: https://www.pwc.com/us/en/services/consulting/cybersecurity-risk-regulatory/library/privacy-reset.html. Last accesed: 15.05.2024.

Office for National Statistics (2024): Business insights and impact on the UK economy. URL: https://www.ons.gov.uk/businessindustryandtrade/business/businessservices/bulletins/businessinsightsandimpactontheukeconomy/3october2024. Last accessed: 15.05.2025.

Shearer, Eleanor/ Stirling, Richard / Pasquarelli, Walter (2020): Government AI Readiness Index 2020. Oxford Insights.

Statista (2024 a.): Estimated population of the United Kingdom from 1871 to 2023. URL: https://www.statista.com/statistics/281296/uk-population/. Last accessed: 15.05.2025.

Statista (2024 b.): France: Gross domestic product (GDP) in current prices from 1987 to 2029. URL: https://www.statista.com/statistics/263575/gross-domestic-product-gdp-in-france/. Last accessed: 15.05.2025.

Statista (2024 c.): France: Real gross domestic product (GDP) growth rate from 2019 to 2029. URL: https://www.statista.com/statistics/263604/gross-domestic-product-gdp-growth-rate-in-france/. Last accessed: 15.05.2025.

Statista (2024 d.): Gross domestic product (GDP) in current prices of the United Kingdom (UK) from 1987 to 2029. URL: https://www.statista.com/statistics/263590/gross-domestic-product-gdp-of-the-united-kingdom/. Last accessed: 15.05.2025.

Statista (2024 e.): United Kingdom: Real gross domestic product (GDP) growth rate from 2019 to 2029. URL: https://www.statista.com/statistics/263613/gross-domestic-product-gdp-growth-rate-in-the-united-kingdom/. Last accessed: 15.05.2025.

Statista (2025): France: Total population from 2020 to 2030. URL: https://www.statista.com/statistics/263743/total-population-of-france/. Last accessed: 15.05.2025.

Suominen/ Kati (2022): Implications of the European Union's Digital Regulations on U.S. and EU Economic and Strategic Interests. Center for Strategic and International Studies (CSIS).

White & Case (2025): AI Watch: Global regulatory tracker - United Kingdom. URL:

https://www.whitecase.com/insight-our-thinking/ai-watch-global-regulatory-tracker-united-kingdom. Last accessed: 15.05.2025.