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EL DISEÑO DE UN MODELO DE INTELIGENCIA ARTIFICIAL QUE AFINA LOS RESULTADOS DEL ANÁLISIS EN LA TOMA DE DECISIONES EN ECONOMÍA: EL CASO DEL CONSUMO FINAL DE ENERGÍA EN LA UE

(DESIGN OF AN ARTIFICIAL INTELLIGENCE MODEL THAT REFINES THE RESULTS OF ANALYSIS IN ECONOMIC DECISION MAKING: THE CASE OF FINAL ENERGY CONSUMPTION IN THE UE)

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ABSTRACT

The objective of this Final Degree Dissertation, entitled 'Design of an Artificial Intelligence model that refines the results of the analysis in economic decision making: the case of final energy consumption in the UE' is to shed light on the potential of Artificial Intelligence (AI) from a decision-maker perspective.

The study commences by establishing the bases of the traditional way of conducting data-driven decisions and discussing the various processes that exist. Additionally, it defines the limitations of these traditional approaches.

The subsequent section explores the novel AI approaches for the decision making process, first, it establishes the fundamental concepts of AI. Additionally, it clarifies the distinctions between AI and Machine Learning. Then, it dives into the process of making decisions using AI, proposing examples of techniques employed in different areas.

Having laid the groundwork, the research delves into the economic effects that arise from the integration of AI in businesses and international organizations, distinguishing between firm level, and microeconomic and macroeconomic level repercussions.

Lastly, a real-world case study in the European energy sector is presented, to compare the predictive performance of traditional methods with AI techniques.

Key words: Artificial Intelligence, data-driven decisions, economic effects, predictive performance.

RESUMEN

El objetivo de este Trabajo de Fin de Grado, titulado 'Diseño de un modelo de Inteligencia Artificial que afina los resultados del análisis en la toma de decisiones en economía: el caso del consumo final de energía en la UE', es arrojar luz sobre el potencial de la Inteligencia Artificial (IA) para el proceso de toma de decisiones.

El estudio comienza estableciendo las bases del enfoque tradicional para la toma de decisiones y analizando los procesos que existen. Además, se definen las limitaciones de estos enfoques tradicionales.

La siguiente sección explora los nuevos enfoques basados en IA. En primer lugar, se establecen los conceptos fundamentales de la IA. Además, se aclaran las diferencias entre IA y 'Machine Learning'. Luego, se profundiza en el proceso de toma de decisiones utilizando esta tecnología.

Habiendo sentado las bases, la investigación se adentra en los efectos económicos que surgen de la integración de la IA en empresas y organizaciones internacionales, diferenciando entre el nivel de la empresa y las repercusiones micro y macroeconómicas.

Por último, se presenta un estudio de un caso real en el sector energético europeo, para comparar el rendimiento predictivo de los métodos tradicionales con las técnicas novedosas de la IA.

Palabras clave: Inteligencia Artificial, decisiones basadas en datos, efectos económicos, rendimiento predictivo.

INTRODUCTION

In contemporary times, there exists a prevalent misconception regarding the potential impact of Artificial Intelligence (AI) implementation within the realm of business. Although AI holds numerous advantages, many individuals view it as a detrimental technology that will inevitably lead to significant job losses, as they believe that machines could perform all human activities better than us.

Furthermore, the recent emergence of AI technologies like ChatGPT and DALL E, particularly with the creation of realistic fake images and human-like text, has fuelled beliefs that AI has the capacity to develop self-consciousness or even bring the demise of humanity. These concerns have been amplified by the views expressed by influential figures such as Elon Musk and Stephen Hawking (Rory, 2014).

However, it is crucial to recognize that humans' lack of knowledge in a matter often compels us to rely on sensationalized newspaper headlines. This not only spread fear but also discourages us from embracing the revolution brought about by AI, thereby placing us at a disadvantage in the global business landscape.

Therefore, the objectives of this dissertation are as follows:

- To elucidate the fundamental functioning of AI algorithms, dispelling apprehensions and fostering confidence in its implementation within the business and national policy sphere.
- To present concrete data regarding the economic implications of AI, including its potential side effects. This information will facilitate the adaptation of national policies and provide a compelling justification for investments in AI at the business level.
- To offer guidance on how to effectively get useful information from raw data, to enhance the decision making process, based on objective evidence.
- To comprehend the limitations and advantages of current and novel AI methods. To better understand the performance distinctions of both for the decision making process, both in theoretical and practical means.

By pursuing these objectives, we aim to provide a comprehensive understanding of AI and its significance in the business world. Ultimately, this dissertation seeks to dispel unfounded fears, encourage informed decision-making, and empower organizations to harness the potential of AI for their strategic advantage.

METHODOLOGY

This study employs a comprehensive methodology to analyse the process of data-driven decision-making, with a specific emphasis on the potential implications of integrating Artificial Intelligence (AI). By combining the scientific method, historical descriptive analysis, and quantitative techniques, we investigate the impact of AI on decision making processes in the economic domain.

The research design begins with a comprehensive literature review. This involved an in-depth examination of existing research papers, books, and official online resources to establish a theoretical framework. By drawing insights from a wide range of sources, the literature review provides a solid foundation for understanding the key concepts, theories, and other concerns surrounding AI in the economic context.

This analysis relies on official documents from international organizations to ensure accuracy and credibility, such as the publications from the European Commission, the European Parliament, the Executive Office of the President of the US, or the World Intellectual Property Organization (WIPO). Apart from other publications from internationally well-known private organizations, such as Accenture, PricewaterhouseCoopers (PwC), BP p.l.c., or Google.

To understand the evolution of AI and its impact on economic decision making over time, the historical descriptive method was employed. This approach involved studying historical data, case studies, and real-world examples. The aim was to gain a historical perspective, identify patterns, and recognize trends in the application of AI within the economic domain. This includes firm-level decisions, as well as policy level.

Quantitative analysis played a crucial role in this research. Data collection involved gathering economic data from reliable sources such as Eurostat and the Organisation of Economic Co-operation and Development (OECD), to accomplish the comparison between traditional methods to make decisions, and novel methods.

Finally, we conducted an inference analysis to assess the predictive capabilities of conventional approaches versus emerging AI models in a real-world international trade scenario. The aim of this section is to provide tangible evidence to firms and international organizations, showcasing the information-gathering potential of this technology for anticipating future events.

1. FOUNDATIONS FOR DATA-DRIVEN DECISION MAKING

An effective decision making process based on objective observation is a crucial aspect of any public or private organization (Walton, 2020). Currently more than ever, with the emerge of viral fake news and the exponential growth in available data, the importance of integrating analysis tools for data handling has increased (Raghupathi & Raghupathi, 2021).

The primary aim of any data-driven decision is to process raw data to obtain useful information as efficiently as possible (Raghupathi & Raghupathi, 2021), which, in turn, facilitates decision-makers in identifying and addressing opportunities and threats (Haining et al., 2019).

Effective decisions imply a series of considerations, but probably the most important one concerns the amount of time required to give the response, as there exists an inherent trade-off between the quality of information and the timeliness of the decision (Walton, 2020). Since it is impossible to exhaustively enumerate all the preconditions necessary for an action to occur (Qualification problem) and all the consequences of an action (Ramification problem), regardless of the amount of time dedicated to analysing a problem (Dietterich, 2017).

Therefore, we invariably operate with incomplete, inadequate and low-quality information, resulting in an inaccurate representation of reality (Dietterich, 2017; Walton, 2020). Therefore, uncertainty, which is characterized as the absence of comprehensive knowledge or information concerning the probability or likelihood associated with future events or outcomes (Knight, 1921; as cited in Sniazhko, 2019), is an inevitable aspect of every decision making process.

In addition to the aforementioned challenge, another issue in decision making is the sensitivity of the system. If a system is excessively sensitive, it can result in a rise in false alarms, thereby needlessly consuming valuable organizational resources (Dietterich, 2017). While reducing the trigger sensitivity may result in the inability to detect potential significant impacts of ‘unknown unknowns’. It is prudent to consider that most real-world environments are not completely observable or statics over time (Russell & Norving, 2010), as hidden events could emerge. These unforeseen events can also be referred to as ‘Black Swans’ if they imply a significant impact on the overall economy (Taleb, 2008).

To increase even more the complexity degree, in a constantly evolving field, such as economics, these decisions need to be consistent throughout time, in other words, they need to address the current and future needs of the organization (Walton, 2020).

In light of these concerns, we feel that it is important to shortly delve into the evolution of data-driven decision making from its origins, exploring both the typical implementation process as well as the limitations that can arise from the use of current tools. Additionally, we will take a closer look at the concept of black swans, which can complicate the decision making process even further. By studying these factors in greater depth, we can gain valuable insights into how to make better, more informed business decisions in the future.

1.1. BACKGROUND OF DATA-DRIVEN DECISIONS

Data has long been a focal point of human interest in facilitating informed decision making processes. For instance, as early as 1753, James Lind wrote about preventive measures based on available data for scurvy, a condition commonly observed among sailors due to a deficiency in vitamin C (Boland et al., 2017). However, it was not until the advent of the Industrial Revolution in 1760 that descriptive analysis emerged as a viable tool for controlling manufacturing processes. By the 1920s, a greater emphasis was placed on this analysis to achieve cost savings through standardization and waste minimization, leading to the development of optimization functions (Gómez-Caicedo et al., 2022).

The analysis of the known knowns period started in 1958, when IBM published an article by Hans Peter Luhn, in which the term ‘business intelligence’ was first coined. Luhn described a model capable of performing extractive summarization (highlighting and auto-coding) documents to provide useful information (Brynjolfsson & Mcafee, 2017; Gómez-Caicedo et al., 2022). During this period, the primary focus of the new concept of AI was directed towards the development of methods for planning in fully observed worlds, or games with perfect information (Dietterich, 2017).

During the 1970s, a number of significant statistical advancements surfaced in the medical field. These included Archie Cochrane's endeavour to optimize health benefits given the finite resources available in the healthcare sector, first articulated in 1972 (Boland et al., 2017). Another notable development was the coinage of the term ‘meta-analysis’ as a statistical tool to aggregate results from independent studies, an achievement credited to Gene Glass in 1976 (Boland et al., 2017). Shortly thereafter, the first real-applications of expert systems were described, comprising rule-based machines designed to emulate the decision making process of domain experts. This is the case of the Nippon Steel Corporation’s blast furnace controller (Yui et al., 1989; as cited in Duan et al., 2019).

The latter approach underwent further refinement in the 1990s with the addition of visual information tools, such as graphs and charts, to support decision-makers (Gómez-Caicedo et al., 2022).

In 1980, the data-driven decision making process saw a notable advancement, commonly referred to as the ‘unknown knowns’ period. During this time, researchers began addressing uncertain knowns that they had intuited, meaning that they began exploring the potential for making predictions. This development first emerged within the medical field, where investigations into various variables led to uncertain inferences being made in order to improve disease diagnosis (Dietterich, 2017).

Between 1990 and 2000, organizations recognized the need for predictive analysis to go beyond the descriptive analysis previously employed. During the first decade of the 2010s, the emergence of organizational data warehouses gave rise to new economic theories for leveraging the vast amounts of data at their disposal (Gómez-Caicedo et al., 2022).

Certain authors have suggested that we have now entered into a new phase in the race against uncertainty, the so-called ‘unknown unknowns’ exploration. This involves grappling with unmodeled variables within the world that have not yet been fully accounted for (Dietterich, 2017).

1.2. DEALING WITH UNCERTAINTY

When confronted with uncertainty, there are typically two fundamental approaches that are often considered: uncertainty reduction and uncertainty coping. The uncertainty reduction approach encompasses several techniques such as information gathering, proactive collaboration, and networking, with information gathering being the most widely employed strategy. Proactive collaboration aims to mitigate external uncertainties through vertical integration, control mechanisms, or contractual agreements. In contrast, the uncertainty coping approach involves various techniques, including but not limited to, imitation, flexibility, reactive collaboration, and others (Sniazhko, 2019).

At the international level, information gathering, and reactive collaboration are often the preferred strategies to cope with uncertainty (Sniazhko, 2019). This information gathering is generally discussed in statistical and econometric fields (Lotfi & El Bouhadi, 2021), and the expected value for getting more information is always positive, if the information is not misleading (Russell & Norving, 2010).

To ensure avoidance of fraudulent data, it is crucial to rely on the aggregate numbers provided by big data, rather than individual instances. In the current era, data is abundant and seemingly endless (Senn-Kalb & Mehta, 2023), presenting an opportunity for harnessing its potential. However, extracting valuable insights from this data is the key to its effective utilization. This has prompted the emergence of different statistical analysis approaches, such as descriptive, predictive, prescriptive, and discovery or wisdom analysis, each offering varying levels of analytical depth (Raghupathi & Raghupathi, 2021).

Descriptive analysis involves summarizing the data as it is, without attempting to make any predictions or recommendations (Raghupathi & Raghupathi, 2021). This approach has been closely linked to the econometrics literature (Gómez-Caicedo et al., 2022), and can be a valuable tool for gaining a better understanding of the data at hand.

The next phase in the analysis of data is predictive analysis, which seeks to make proactive decisions in advance of potential changes (Raghupathi & Raghupathi, 2021). According to Athey and Imbens (2019), there are two main approaches to reach forehanded conclusions from data. The first approach assumes that the data is generated by a specific stochastic data model, which means that the data follows a particular probability distribution. The second approach, on the other hand, uses algorithmic models and considers the data mechanism to be unknown. In other words, the algorithmic model does not assume any specific probability distribution for the data, but rather tries to identify patterns and relationships in the data using various mathematical techniques.

The field of economics and statistics has traditionally focused on the former approach, which involves developing a modelling methodology and establishing confidence intervals (Athey & Imbens, 2019). However, in this stage, it is important to pause and consider the true meaning of confidence intervals. In traditional statistics, as well as in modern econometrics, confidence intervals represent a primary method for quantifying uncertainty. However, it is crucial to comprehend that a confidence interval does not correspond to the probability of the defined variable occurring in the real observed world - a commonly asked question in practical applications. Instead, it reflects the confidence that the parameter estimated from the data fits the underlying distribution of the population from which the data were sampled (Murphy, 2022).

In other words, a confidence interval is a range of values within which the true population parameter is expected to fall with a specified degree of confidence, typically 95% or 99%. The confidence level denotes the likelihood of obtaining such an interval in repeated sampling. Instead, to accurately measure the probability of an estimated value occurring in observed data, it is necessary to utilize Bayesian credible intervals, often used in the ML approach (Murphy, 2022).

Prescriptive analysis is a method that employs business knowledge models to provide decision-makers with the most effective solutions (Raghupathi & Raghupathi, 2021). The primary objective is to provide clear comprehension of the various results that may emerge from different courses of action (Yalcin et al., 2022). Conversely, discovery analysis aims to recognize new possibilities in terms of markets, products, and strategies (Raghupathi & Raghupathi, 2021).

Furthermore, in order to overcome limitations of human cognition and potential biases resulting from personal interests, various decision making methods have been developed.

As reported by Yalcin et al. (2022), the most frequently utilized methods include Fuzzy Analytic Hierarchy Process (Fuzzy AHP), Best-Worst Method (BWM), and Analytic Network Process (ANP). Fuzzy AHP ranks alternatives based on degrees of truth rather than solely on numerical criteria (WIPO, 2019). BWM involves the selection of the most important factors by consulting with experts. ANP, on the other hand, attempts to weigh factors (Y) to obtain the best possible output (X). Additionally, less common econometric models such as Capital Asset Model (CAPM) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) are also employed (Lotfi & El Bouhadi, 2021).

However, the primary challenge with the human approach lies in the fact that practical techniques, such as predictive and prescriptive analysis, tend to be less developed in the econometrics literature, despite their apparent importance in the decision making literature (Yalcin et al., 2022). What leads decision-makers to rely heavily on personal judgement, rather than objective data analysis. In support of this view, a study conducted in 2003 found that approximately 80% of decision-makers depend on their own judgement rather than statistical analysis (Haley, 2003; as cited in Sniazhko, 2019; Haining et al., 2019).

1.3. STANDARDISED PROCESS OF MAKING DATA-DRIVEN DECISIONS

In order to address the absence of a standardised decision making process across organizations, a comprehensive literature review was conducted to establish a common course of action, encompassing two primary workflows. The first approach, the exploratory approach, is implemented when there is limited prior knowledge about the matter being considered, while the second approach is applied when there is an existing understanding of the underlying structure.

1.3.1. Exploratory approach

When confronted with an unfamiliar environment, the agent must acquire knowledge about its functioning to facilitate informed decision making (Russell & Norving, 2010).

To ascertain the underlying structure, a three-step procedure is employed, encompassing descriptive analysis, dependency analysis, and conceptualization of the structure. The initial stage involves the implementation of a ‘sense loop’ to generate useful descriptive information from raw data (Haining et al., 2019). This process encompasses techniques like Extract, Transform, and Load (ETL) for data processing (Raghupathi & Raghupathi, 2021). And thereafter, the descriptive analysis phase per se, which summarizes the pre-processed data to get useful information to use in the next step. However, it is important to note that data pre-processing remains a significant challenge, often consuming up to 80% of the work time for AI researchers and data scientists (Lee et al., 2019).

This stage has become increasingly important in recent years (Raghupathi & Raghupathi, 2021), given the exponential growth in the amount of available data, about 40% each year, estimated to reach about 163 trillion gigabytes by 2025 (Senn-Kalb & Mehta, 2023). Moreover, humans now consume over five times as much information as they did in 1986 (Forte, 2022).

The second stage of our workflow involves a dependency analysis, through which we obtain patterns from the transformed data (Raghupathi & Raghupathi, 2021). This enables the validation of hypotheses through real-world observations (Géron, 2019).

Upon validating the hypotheses, the workflow proceeds to the third and final stage, which involves conceptualizing the structure of the matter. This stage allows for the development of causal assumptions based on a world model, facilitating informed decision making (Pearl & Mackenzie, 2020).

The field of international trade illustrates the pattern. Despite a gradual growth in international trade over time, it was not until the period spanning from 1850 to 1913 that it truly flourished, ultimately accounting for 8% of the world's GDP in the latter year (O’Rourke et al., 2007). Consequently, it became imperative for governments to assume control over these capital flows to avert national income losses, and facilitate well-informed decision-making. In 1913, the first global Nomenclature for goods was approved, which involved the classification of goods into five major groups and the filtration of the 186 most representative items (Juárez Allende, 2022). This step could be understood as the data pre-processing stage, wherein the world's available products were refined to a mere 186. Subsequently, in 1922, following the implementation of this nomenclature, the International Bureau of Commercial Statistics conducted the primary analysis (descriptive analysis) and interpretation (dependency analysis) (Friedenberg, 1968). This provided policy makers with necessary information for informed decisions regarding international trade.

1.3.2. Sense-Response process loop

Once a comprehensive model of the subject matter is established, the subsequent stage is referred to as the Sense-Response process loop (Haining et al., 2019). This approach serves as a vital framework for businesses and decision-makers, empowering them to make well-informed decisions by leveraging the wealth of available data. The Sense-Response process loop comprises six distinct stages, which collectively aid organizations in the collection, analysis, and strategic implementation of data to enhance their operational efficiency and effectiveness.

The first stage, after the descriptive and dependency analysis discussed above, is the predictive analysis of historical data. This stage involves using historical data to predict future outcomes. By analysing historical data, organizations can identify potential opportunities and threats. This stage is critical in determining the direction an organization should take (Raghupathi & Raghupathi, 2021). Therefore, we need to codify forehand the historical states of the target variable, along with other environmental factors and time; the initial state from which we start the analysis, and a goal in mind (Russell & Norving, 2010).

The second stage entails conducting a comprehensive discovery analysis, which involves the identification of both opportunities and threats derived from the data. This analysis aims to unveil potential opportunities while remaining vigilant in detecting and addressing potential threats (Raghupathi & Raghupathi, 2021; Haining et al., 2019).

The third stage is the proposal elaboration. In this stage, the opportunity or thread is defined, and its importance is justified (Duan et al., 2019). A possible methodology to leverage the opportunity or solve the problem is also proposed (Raghupathi & Raghupathi, 2021), as long as the possible available actions to the decision agent, and its sequence to reach the goal (Russell & Norving, 2010). This stage requires an induction approach to generate a hypothesis from observable evidence, followed by a deduction process to draw conclusions from the hypothesis. A causal model is elaborated to solve the identified problem or leverage the detected opportunity (Pearl & Mackenzie, 2020).

The fourth stage involves the selection of the next project. Agents engage in a process of posing relevant questions to ascertain the priority among the developed proposals, considering the limited availability of resources (Duan et al., 2019). Typically, this entails assigning a cost to each contemplated course of action. (Russell & Norving, 2010). This stage plays a crucial role in determining the subsequent project based on organizational requirements and resource constraints (Brynjolfsson & Mcafee, 2017).

The fifth stage is the prescriptive analysis of the alternatives. This stage involves determining the most optimal course of action to improve the likelihood of achieving the desired outcome. Once the team has determined the optimal solution, they must provide stakeholders with a comprehensive report that includes conclusions, scope, and limitations of the recommended action (Raghupathi & Raghupathi, 2021; Walton, 2020).

The sixth and final stage is the response. This stage represents the culmination of the sense-response process loop, which refers to the actions taken to respond to changes and includes resource management. Workers often play a pivotal role in the availability of resources; hence, persuading them to pursue collective goals is the final step in each iteration of this process loop (Brynjolfsson & Mcafee, 2017; Haining et al., 2019).

In conclusion, the Sense-Response Process Loop empowers organizations to leverage available data for informed decision-making, optimizing operations and enhancing their bottom line.

1.4. LIMITATIONS OF CURRENT METHODS

The primary challenge encountered by humans in the process of decision making is attributed to cognitive limitations. Human beings are often unable to effectively process extensive and ever-increasing volumes of data, particularly when operating under constantly changing circumstances (Duan et al., 2019; Forte, 2022; Walton, 2020). This is further compounded by a cognitive bias that leads us to confirm previously held beliefs rather than expand our knowledge into new domains, which are often the sources of true improvements (Taleb, 2008).

Biased decisions may arise as well, when researchers selectively choose variables for their study, instead of relying on established statistical measures (Athey & Imbens, 2019).

Even if the researcher follows a statistical approach, such as in the econometrics field, before conducting any statistical modelling analysis there are several restrictions that are difficult to be met in real cases, such as the assumptions of linearity, independence, homoscedasticity, and normality for a simple linear regression model (Raghupathi & Raghupathi, 2021). Beyond statistical limitations, other econometric models have other assumptions, such as market efficiency, but in reality, human behaviour is influenced by rumours and false information, rather than rational principles (Lotfi & El Bouhadi, 2021).

Consequently, traditional models are unable to make highly accurate out-of-sample predictions, thus limiting the real-world applications of these methods (Athey & Imbens, 2019). Rather than seeing the big picture, we are left with only a precise but incomplete piece of the reality (Taleb, 2008).

2. NOVEL MODELS FOR DATA-DRIVEN DECISION MAKING

As stated by a number of experts, the utilization of ML in decision theory involves the implementation of strategies, that enable the identification of the optimal course of action from an array of already available alternatives (Murphy, 2022). However, we will take into consideration for this section a wider definition provided by the European Commission AI expert group, which defines the decision theory ML-driven, as a group of ‘techniques (that) allow to perform the reasoning on the data from the coming sensors’ (AI HLEG & European Commission, 2019, p. 4). These operations include making logical deductions, creating plans and schedules, conducting extensive searches within solution sets, and optimizing multiple potential solutions to a problem (AI HLEG & European Commission, 2019).

That being said, the main advantage of applying ML tools for decision making comes from its capacity to reduce uncertainty, through the gathering information approach (Sniazhko, 2019). Mainly because of the potential to provide rapid and cost-effective solutions through its ability to generate accurate predictions and responses (Davenport et al., 2019; Haining et al., 2019). For example, in 2017, IBM demonstrated the predictive power of AI models by achieving a precision rate of over 77% in predicting weather forecasts over a one-to-three-day period (ForecastWatch, 2018).

However, although AI is indeed renowned for its predictive capabilities (Szczepaniuk & Szczepaniuk, 2022), it encompasses a broader range of applications, including information gathering, risk management, and alternative selection models that we will discuss after understanding the meaning of AI and ML.

2.1. UNDERSTANDING THE MEANING OF ARTIFICIAL INTELLIGENCE

The concept of Artificial Intelligence (AI) was initially introduced by John McCarthy in 1955 (Brynjolfsson & Mcafee, 2017). While various interpretations exist, the European Commission provides a comprehensive definition of AI as ‘systems that display intelligent behaviour, by analysing their environment and taking actions to achieve specific goals’ (European Commission, 2018, p. 1). Nonetheless, this definition requires knowing what ‘intelligent behaviour’ means. Generally, it refers to the capacity of machines to execute cognitive processes resembling those of humans, including learning, comprehension, logic, and interaction with their environment (Turing, 2004).

In essence, AI machines possess the capability to autonomously emulate the behaviours of a rational agent by perceiving their surroundings via sensors. Acting upon this perception, a rational agent aims to attain optimal expected outcomes based on objective performance functions, derived from past and present environmental knowledge and potential actions (Kühl et al., 2022).

2.1.1. Classification of AI

Beyond its definition, the predominant classification method used to differentiate AI machines is based on their range of capabilities, resulting in a distinction between narrow and general-purpose AIs (AI HLEG & European Commission, 2019).

Narrow AIs are designed to address a specific task rather than multitasking. This type of AI represents the prevalent technology in commercial-use nowadays (Duan et al., 2019). On the other hand, Artificial General Intelligence (AGI), also called general-purpose AI, strives to emulate the breadth of human capabilities, encompassing a wide array of activities (AI HLEG & European Commission, 2019; European Parliament, 2023). The ultimate objective of these general AIs is to possess the capacity to solve complex problems in unfamiliar and unstructured environments, going beyond pre-defined scenarios (Gobble, 2019).

However, the aforementioned classification alone does not provide a comprehensive understanding of the capabilities of this technology. To gain further insight, we will utilize the classification proposed by Duan, Edwards and Dwivedi (2019), which distinguishes the following AI techniques (among which, some belong to the ML branch): rule-based inference, semantic linguistic analysis, Bayesian networks, artificial neural networks, similarity measures, and others.

Rule-based inference seeks to replicate expert knowledge by computing decisions at each stage of the process. Initially, this task was performed by humans, but now it is increasingly carried out autonomously using methods such as classification regression trees or rule mining.

Semantic linguistic analysis aims to comprehend information directly from human language. An impressive example of this is the development of advanced natural language processing (NLP) models like Chat GPT (see OpenAI, 2023).

Bayesian networks rely on probabilistic inference. They learn the most probable associations between nodes, which represent relationships among selected variables, through data revision. In fact, this property is also leveraged on a larger scale in some machine learning algorithms, enabling them to discover hidden patterns within each layer of interconnected neurons (Géron, 2019).

Similarity measures encompass various techniques for determining the proximity of variables. Some examples include k-means clustering and support vector machines (Duan et al., 2019).

Furthermore, there are other algorithms such as frame-based representation and genetic algorithms. Frame-based representation offers a richer knowledge structure using frames rather than rules, although it can be more challenging to interpret. Genetic algorithms, on the other hand, simulate the process of Darwinian natural selection, ultimately leading to the emergence of the most optimal solution by making small mutations and adopting the ones that work best (Duan et al., 2019; Russell & Norving, 2010).

2.1.2. Machine Learning as a powerful tool for economics

In the realm of disciplines beyond technology, such as economics, it is not uncommon for the concepts of AI and Machine Learning (ML) to be erroneously interchanged, despite their fundamental distinctions (Kühl et al., 2022).

However, while AI covers all the machines that display any intelligent behaviour, ML algorithms just represent those machines that had learn to perform this intelligent behaviour, through observable examples by themselves. Rather to include those machines that follow a rule-based approach previously codified by human experts (Brynjolfsson & Mcafee, 2017; Géron, 2019). Therefore, Machine Learning is recognized as a distinct subfield within the broader field of Artificial Intelligence, rather than being synonymous.

This innovative technique is the reason why AI became so popular in the 1990s, after the so-called second ‘AI winter’ period, from 1974 to 1993 (Duan et al., 2019; WIPO, 2019), characterized by significant scepticism. This was largely due to the challenges of efficiently ensemble Bayesian networks needed to work under uncertainty conditions (Russell & Norving, 2010).

Common classification of ML techniques includes supervised, semi-supervised, unsupervised, and reinforcement learning (Géron, 2019). There are others, such as generative adversarial networks, but for the purpose of this study, the above four are sufficient.

Supervised learning strives to ensure the robustness of fitting on an independent test set by minimizing the differences between predicted and observed outcomes, which is useful for classification and prediction tasks (Géron, 2019). This process requires the provision of labelled data, which entails providing the model with the expected results for incoming inputs (Schmidt et al., 2020; as cited in Enholm et al., 2021).

In contrast, unsupervised learning does not involve providing the system with a target output. Instead, the algorithm is tasked with identifying relationships among the variables in the provided data (e.g., covariates). This process entails clustering the data and identifying the variables that best explain the data, which can be interpreted as a form of dimensionality reduction (Géron, 2019). Unsupervised learning has numerous applications, including fraud detection and system failure prediction, or even new patterns recognition (see Kirillov et al., 2023).

Reinforcement learning strives to optimize long-term outputs by minimizing penalties and maximizing rewards through iterative input sequences based on machine-chosen actions. Its primary objective is to maximize long-term performance by minimizing overall penalties and maximizing overall rewards (Russell & Norving, 2010).

Among the numerous coding techniques for ML algorithms, artificial neural networks have been a transformative force in the AI landscape over the past decade. Therefore, it is important to understand the basics of its simplest form, supervised ML based on artificial neural networks.

This algorithm is composed of units, so-called neurons, or nodes, that are divided into several layers. The units of each layer are connected to all the next layer's nodes through direct links. That being said, the first layer has to have as many units as variables we want to input into our system. The middle layers are where the calculations to generate output are made, by changing the weights of each link, based on our chosen layer's activation function (e.g., ReLU, Softmax…), and a Gradient Descent using the resulting error between predicted and actual values throughout each iteration. At the top of the algorithm, we find the output layer, where each node represents each of the desired outputs we want to get from the system (Géron, 2019; Russell & Norving, 2010). For instance, if the goal is to predict a single value, the final layer would have one neuron. In a classification task with categories A and B and their respective percentages, the last layer would comprise two neurons.

The main advantage ML provides in economic analysis is that, rather than estimating a single model based on defining principles, this technology is able to estimate and compare many alternative models at once, providing it with empirical data (Athey & Imbens, 2019). This marks a departure from the previous reliance on human-coded knowledge in AI systems (Domingos, 2015; as cited in Agrawal et al., 2019). Enabling machines to autonomously learn and continually evolve, marking a significant shift in their capacity for self-improvement (Kühl et al., 2022).

2.2. THE USE OF ML FOR ENHANCED DECISIONS

The implementation of ML into the decision making process is perceived as a mean of improving current decision making tools, rather than a complete displacement of the old methods (Trajtenberg Manuel, 2019). As the ultimate goal is to achieve a competitive advantage regardless of the analytic means (Muñoz-Hernandez et al., 2016; as cited in Gómez-Caicedo et al., 2022).

In this regard, the economic sector that has made significant progress in the development of artificial intelligence is referred to as business analytics. However, it is worth noting that in the 1990s, there was a prior effort to incorporate AI into the economic field through an econometric lens, which ultimately proved unsuccessful (Hornik et al., 1989; White, 1992; as cited in Athey & Imbens, 2019). Business analytics refers to the systematic examination of data in order to derive insights that can facilitate and improve informed decision making within a specific time frame (Gómez-Caicedo et al., 2022; Raghupathi & Raghupathi, 2021).

According to Wullianallur Raghupathi and Viju Raghupathi (2021), the field of business analytics comprises models, methods, and tools. Models are the key component of business analytics, where statistical methods, data mining, domain models (such as ROI, net present value, or Monte Carlo Model), and AI, particularly ML, are utilized to generate decision-making support based on data. Methods refer to how the data is visualized and presented in numerical outputs, while tools encompass the programs (such as Tableau, and SPSS) and programming languages (such as Python and R) used to interact with the data to obtain the desired results.

Despite the potential of AI applications in business analytics, its full potential is yet to be realized as the dominant analytical approach in business analytics remains to be descriptive analysis, as opposed to predictive or prescriptive approaches (Gómez-Caicedo et al., 2022), where AI has more practical applications (Athey & Imbens, 2019).

Moreover, in contemporary times, there have been notable instances where econometric knowledge has been effectively combined with the benefits of AI. Notably, a prominent example involves the modelling of consumer behaviour in three distinct stages, encompassing the decision of whether to purchase a product from a specific category, the selection of a preferred item within the chosen category, and determining the optimal quantity to be purchased. In this context, econometric techniques are employed to model these stages, which are then refined further by the application of AI algorithms that enhance the predictive accuracy of consumer actions (Wan et al., 2017; as cited in Athey & Imbens, 2019).

Following the completion of a concise literature review, it has been identified several crucial areas related to decision-making, that can benefit from the implementation of this new technology. As previously discussed, these areas include information gathering, risk management, and alternative selection. In the subsequent discussion, we will examine the primary coding approaches that can be utilized to address these problems and find appropriate solutions.

2.2.1. Information gathering

To begin with information gathering, it is important to remember that it is a crucial step in reducing uncertainty. There are three main approaches that can be employed in this regard, namely summarization techniques, predictions, and fault detections. Extractive summarization, first proposed by Hans Peter Luhn in 1958, is an algorithm that mimics the process of highlighting important information from a document. Abstractive summarization, on the other hand, seeks to comprehend the meaning of the text and extract insights from it (Brynjolfsson & Mcafee, 2017). Both of these techniques can benefit from machine learning (ML) algorithms based on Natural Language Processing (NLP), such as the Chat GPT model (OpenAI, 2023).

In terms of predictions, several approaches have been developed, as this is a primary focus area for AI technology. ML techniques such as traditional regression methods (e.g., linear, logistic regression) can be utilized (Szczepaniuk & Szczepaniuk, 2022). More complex techniques, such as Hidden Markov Models (HMM), can also be employed for decision making purposes. HMM aims to identify what could happen next based on what has been observed in a given time state as they rely on Bayesian inference (Dietterich, 2017; Murphy, 2022). However, it has limitations in predicting hidden states that are unforeseen for the model (Szczepaniuk & Szczepaniuk, 2022).

Other approaches include Credal Networks, which are advantageous over commonly used Bayesian Networks as they do not require precise probabilities and instead use sets of probability distributions consistent with the available data evidence (Dietterich, 2017). Finally, fault detection applications of AI have been discussed in various research papers with apparently good results (Enholm et al., 2021; Szczepaniuk & Szczepaniuk, 2022).

2.2.2. Risk management

Regarding risk management, the objective is to either maximize the expected outcome or minimize potential risks in the worst-case or most uncertain scenario. One possible approach to achieve this objective is through the use of an outlier detector, such as a Support Vector Machine (SVM) trained to reduce the upper limit of the generalization error, which tends to occur where the greatest unexpected results arise (Szczepaniuk & Szczepaniuk, 2022). In other words, this approach involves identifying the hyperplane that reduces the differences between predicted and actual results.

Another approach involves minimizing the results for the worst-case scenario, which can be achieved through the use of Markov Decision Processes (MDP). This model involves generating predictions based on an MDP model, then selecting the validation policy that maximizes the expected results in the worst-case scenario (e.g., the 10% worst outcomes) (Dietterich, 2017).

2.2.3. Course of action selection

However, the most relevant advantage in decision making process automatization comes from the possibility of being able to evaluate and select alternatives in an autonomous way, in other words, elaborate a prescriptive analysis.

In this matter, we could identify two major groups: heuristics and metaheuristics optimization algorithms. The main difference between them lies in their approach. While heuristics rely on intuitive judgments and rules based on experience, metaheuristics are inspired by natural processes (Szczepaniuk & Szczepaniuk, 2022).

On the first hand, heuristics optimization algorithms use domain knowledge to find the most optimal solution. Techniques under this umbrella include the Monte Carlo Tree Search (MCTS) and Fuzzy logic. The Monte Carlo Tree Search (MCTS) algorithm operates on the principle of randomly selecting moves in a game and subsequently evaluating the outcome. The algorithm updates the search tree after each iteration based on the results, thereby improving the decision making process. The key advantage of MCTS is that it relies on the available evidence rather than on the known model itself. A notable example of MCTS's effectiveness is its successful integration with a deep neural network in the AlphaGo algorithm, which defeated the top masters of the game (Dietterich, 2017).

While the Fuzzy logic, Fuzzy logic, also known as Fuzzy AHP, which was discussed in the traditional approach methods, offers a similar benefit of handling degrees of truth, but in an autonomous manner. This capability has been widely applied in various fields, including decision making processes, to improve the accuracy of evaluations (Szczepaniuk & Szczepaniuk, 2022).

On the other hand, certain metaheuristic optimization algorithms incorporate techniques based on evolutionary genetics theory, ant colony optimization, bee swarms, and other natural processes (Szczepaniuk & Szczepaniuk, 2022; WIPO, 2019). These methods utilise nature-inspired processes to efficiently find the most optimal solution, rather than randomly trying different paths, which could take a considerable amount of time (Szczepaniuk & Szczepaniuk, 2022).

Furthermore, within this prescriptive analysis approach, there are specific algorithms of interest designed to facilitate decision making based on policy heterogeneity. One such algorithm is a simple regression tree, that is truncated to shift optimization rules from assessing predictive accuracy, to evaluating the heterogeneity of the effects for each of its branches. This algorithm operates in the following manner, the data is divided into two halves, with the first half utilized to create a model capable of predicting the desired output, while the other half is used to estimate the policy effects on each leaf of the tree (the final nodes). Subsequently, the second regression tree is evaluated based on the effects of heterogeneity in all the leaves (Athey & Imbens, 2019).

As we have demonstrated, the capabilities of AI extend beyond predictive analysis, as it has the potential to perform various decision making processes autonomously, which were once exclusively performed by humans (Manyika, Chui, et al., 2017). This feature of AI presents a significant opportunity for organizations and nations to significantly enhance their efficiency by facilitating the rapid proposal of highly accurate solutions.

2.3. KEY ADVANTAGES OF ML METHODS

ML methods are progressively acknowledged as the only feasible alternative to human intelligence in the realm of decision making (Haining et al., 2019). This is partly attributed to their capacity to emulate human behaviour and even address certain limitations, inherent in our current analytical methods, offering potential enhancements.

One such limitation is time period restrictions, as the world is constantly evolving new changes appear, and the traditional methods take time to be reconfigured. In this vein, ML has the capacity to flexibly incorporate newly available data and to dynamically refine its solution, to adapt its model to the latest data (Lotfi & El Bouhadi, 2021), as online ML methods could be constantly updated with new available data (Géron, 2019), as well as faster responses comparing to traditional analytical methods (Dietterich, 2017).

Shifting focus to the AI way to deal with the challenge of inaccurate world modelling, it is true that the initial progress in this field was primarily limited to well-defined games due to the absence of certainty in real-world problems. Nonetheless, recent advancements have been made in more complex games, such as poker, which involves imperfect information. Notably, the ML system known as Libratus managed to defeat four of the world's top ten players in 2017, despite the inherent uncertainties of the game (Dietterich, 2017). The key takeaway is that, unlike traditional rule-based approaches, ML relies on discovering patterns from data, and thus, working with a fixed and perfect model of the world is less necessary (Géron, 2019).

In relation to the issues of ‘Black Swans’ discussed in the first section of this document, it is important to note that while the associated uncertainty cannot be measured by traditional social science approaches (Taleb, 2008), ML models have demonstrated the ability to detect some common triggers of financial crises and predict them ahead of time (Géron, 2019; Lotfi & El Bouhadi, 2021). Consequently, ML has found numerous applications in the field of autonomous fault detection (Enholm et al., 2021).

Moreover, when handling uncertainty, a fundamental difference is observed between the traditional statistical approach employed by economists and the ML approach. In the former approach, the parameter is considered an unknown fixed constant, while the data is considered random. On the other hand, the Bayesian approach commonly used in inference ML models, considers the data as fixed (as it is known), while the parameter is treated as random (since it is unknown) (Murphy, 2022).

In contrast to human capabilities, machines can improve their performance as more data is provided, often generating insights that may not be immediately apparent to human reasoning (Szczepaniuk & Szczepaniuk, 2022). Moreover, as ML could be trained on almost any form of data, hence they have an unprecedented potential for extracting valuable insights from increasingly large amounts of unstructured data, including natural language and body expressions, which traditional methods may struggle to process (Lotfi & El Bouhadi, 2021; Szczepański, 2019).

Moreover, in order to address the issue of human bias that may arise from the use of hand selection methods in variable studies, machine learning (ML) experts have adopted the use of sparsity to select variables that are more explanatory, rather than making assumptions. In essence, experts in the field of machine learning recognize that the sparsity of data is what gives it its informative value. Therefore, in order to get rid of useless data, to simplify the problem calculations, they try to eliminate those variables that add less sparsity to the data set (Athey & Imbens, 2019).

Another advantage of utilizing AI, as opposed to statistical modelling, lies in the fact that they follow the evidence brought from huge amounts of data (Haining et al., 2019). This approach requires fewer stringent assumptions to be fulfilled in order to be inferred properly to the rest of the population, in contrast to statistics and econometrics (Athey & Imbens, 2019).

Moreover, the success of AI in practical applications stems from its reliance on a diverse array of algorithms, each with its unique advantages for different types of data. Some of the techniques employed include bagging results, model averaging, and ensemble methods (Géron, 2019). We have something similar in econometrics, using averages and mixture models, however these techniques could just emerge similar algorithms, hence the final outcome resulted in a poorer prediction of the reality (Athey & Imbens, 2019). Moreover, AI can even integrate specialized algorithms that focus on different aspects of the decision making process, interconnected through nodes to solve complex problems (WIPO, 2019).

2.4. LIMITATIONS OF NOVEL AI METHODS

In regard to the challenges associated with ML and decision-making, one critical factor to consider is the transparency of the AI model (Walton, 2020). Many individuals, including experts, view these models as black boxes (Duan et al., 2019), producing results without any clear explanation of their underlying processes.

Despite the lack of complete interpretability of the human mind, humans are still able to communicate and explain their ideas using cause-and-effect language (Pearl & Mackenzie, 2020). In this way, we assume transparency in our own decision making processes when our cause-and-effect explanations make sense to us.

In contrast, the AI decision making process is based on Bayesian networks, which rely on correlation rather than causal inference. This makes it challenging for humans to understand the decision making process in the same way as we do with human-made decisions (Pearl & Mackenzie, 2020).

From a technical standpoint, Bayesian networks are built upon probabilistic calculations based on Bayes' theorem (Russell & Norving, 2010):

$$P(action \mid effect) = \frac{P(effect \mid action) * P(action)}{P(effect)}$$

However, this formulation can yield correlations that may appear valid but lack meaningful interpretation from a human perspective (Pearl & Mackenzie, 2020). Apart from the ethical concerns that could imply (Dietterich, 2017).

Understanding the significance of logical reasoning over mere correlations requires acknowledging prevalent misconceptions in analysing correlations. Judea and Dana (2018) identified three types of junctions that contribute to these misconceptions: chain junction, fork junction, and collider junction.

The first type, chain junction, occurs when a produces b and when b is detected, c is activated. This leads to a high correlation between a and c, but there is no direct causation between the two. A classic example of a chain junction is the relationship between fire, smoke, and alarm.

The second type, fork junction, occurs when b produces a and c, such as in the case of the relationship between shoe size, age of a child, and reading ability. When I child is older, it generally has a bigger foot size, and greater capability to read. However, there is no direct causation between shoe size and reading ability.

The third type, collider junction, occurs when a and c produce b in the same way, which could lead to the mistaken belief that each one has a negative correlation. An example of this type of junction is the relationship between talent and beauty contributing to an actor's success, where some famous actors have talent while others are just handsome.

In all these cases, the correlation between a and c may suggest a causal relationship, but in reality, there is no causation at all. Henceforth, it is crucial to explore novel techniques for designing algorithms that leverage causal models, given that machine learning algorithms currently prioritize predictive accuracy over the establishment of causation.

Moreover, other important AI-related issues include an elevated risk of cyberattacks, potential errors in the model of the world utilized by the AI, misspecified goals, and other errors that may be attributed to human operators (Dietterich, 2017). Therefore, new initiatives such as the EU's 'Destination Earth' program, aim to model the world, in this case, to measure potential environmental changes brought about by human activities (European Commission, 2021a).

Moreover, machines are often based solely on predictions, and in some cases, additional analyses such as average treatment effects or knowledge of other structural parameters could be beneficial (Athey & Imbens, 2019). In this vein, other authors suggest that even though the analysis of big data enables the ability to predict, it doesn't enable the ability to judge, as many other variables are involved in the latter (Agrawal et al., 2019).

Additionally, most ML algorithms are designed to propose a single solution rather than a range of possibilities, and they typically work with only one perspective of the data. By adopting a multiple perspectives approach, it is possible to develop a high-performing system that is less data-dependent, as exemplified by the successful implementation of GPT-4, which utilizes both textual and visual data for training (Dietterich, 2017; OpenAI, 2023).

In addition to the above technical issues related to AI's applications in decision making, there are ethical concerns that have emerged. These concerns address the potential harm that AI can cause to human rights and well-being (Evas, 2020). Public and private organizations have recognized these concerns, leading to the creation of documents on the topic.

Initially, the topics covered by these documents were broad, but as Fjeld et al. (2020) noted, they have begun to converge into eight key principles. These principles, ranked in order of prevalence, from most to least common, are fairness and non-discrimination, privacy, and accountability (tied in prevalence), transparency and explain-ability, safety and security, professional responsibility, and human control of technology and promotion of human values (tied in prevalence).

Fairness and non-discrimination were centred around unbiased data representation and inclusivity. Privacy and accountability were the next most common principles. Privacy refers to an individual's right to privacy and control over their personal data, while accountability pertains to measuring the impact of AI and implementing new regulations if necessary.

Transparency and explain-ability are related to the interpretability of AI outcomes and an individual's right to know when they are interacting with AI. Safety and security focus on the predictability of AI outputs and the risks of algorithms being compromised by third parties. Professional responsibility pertains to the professionalism of AI developers and the creation of accurate algorithms over the long run.

Finally, the principle of human control of technology and promotion of human values. This principle emphasizes the importance of human decision making in critical situations and the need to prioritize human values and well-being in AI development.

3. BIG CHALLENGES OF AI IN ECONOMICS

In the upcoming section, we will analyse the economic consequences of AI, focusing on its micro and macroeconomic impacts, as well as firm-level impacts. The former provides information for policymakers at the national and supranational levels, while the latter is targeted at entrepreneurs, managers, and business owners.

In this sense, it is pertinent to acknowledge our choice to investigate the economic ramifications of AI rather than solely focusing on ML. The main reason is the lack of specific data pertaining exclusively to ML systems, as within the economic domain, these terms are frequently employed interchangeably. Therefore, in this section, we have opted to employ the broader terminology of AI within this section.

Nevertheless, prior to delving into the justifications, we present the following table as a concise summary of the overall economic impacts of AI. This will offer the reader a broader perspective on the potential economic challenges associated with the adoption of AI.

Table 3.1.- Challenges of AI in economics resume

Advantages	Disadvantages
National, sectorial and firm income growth	Increased wealth gap between countries
Enhanced quality and personalization of products and services	Increased disparity in digitalization and benefits among companies
Increased labour productivity	Disproportionate impact on individuals with lower education levels
Long-term job gains	Short-term job losses due to automation
Improved profitability for enterprises	Challenges related to personal privacy rights and intellectual property rights
Contributions towards reducing environmental footprint	

Note: Based on data from our literature review

In short, it seems that AI holds the potential for significant economic advantages. Nevertheless, it is accompanied by certain drawbacks, particularly pertaining to disparities, displacement of employment, and the safeguarding of fundamental rights.

3.1. MICRO AND MACROECONOMIC LEVEL

All over the world, AI is positioning itself as a key factor for economic development and competitiveness. In fact, there is a consensus about the expected gross domestic product (GDP) boost brought about by AI's implementation of around 14% from the period of 2019 to 2030, which represents $15.7 trillion (USD) (Bughin et al., 2019; Gillham et al., 2018). In other words, this is currently a major commercial opportunity (Rao & Verweij, 2017).

The overall income growth primarily stems from two factors: heightened consumption driven by improved product quality and customization, and increased labour productivity, particularly in the initial years (Gillham et al., 2018). Conversely, alternative viewpoints suggest that the benefits will arise from cost reductions achieved through optimized utilization of production factors, and enhanced quality control measures (Szczepański, 2019).

Moreover, the above calculous does not consider the income from AI's trade surplus (Agrawal et al., 2019), nor the allocation of displaced workers into higher value-added activities, as the routines tasks will be outperformed by AIs (Enholm et al., 2021; Szczepański, 2019), therefore the benefits could be even higher.

On the other hand, with regard to anticipated changes in sector profitability, it is projected that by 2030, all sectors of the economy will experience a gain of at least 10%, however not all the sectors will experience the same rises (Gillham et al., 2018).

At the forefront, Gillham et al. (2018) suggest that health, education and public services will experience the greatest impact, with a boost of gains of about 21%, this is mainly due to the personalization and time savings unlocked due to the AI's implementation. Furthermore, the healthcare system will be enhanced by AI's implementation by optimization of hospital workflows, improving the allocation of human and material resources, advancements in disease detection, and the aid in the discovery of new medicines (European Commission, 2021a).

In the second place, we find retail, wholesale, accommodation, and food services. All of them with a 15% gains boost (Gillham et al., 2018). In fact, currently, 70% of AI's benefits come from the wholesale sector, especially from Customer Relationship Management (CRM) and Enterprise Risk Management (ERM) systems (Evas, 2020).

Lastly, within the third place, transportation, financial and professional services emerge. With an expected gains boost of 10% (Gillham et al., 2018). This could be the result of being at the forefront of AI's implementation, in the case of the logistics sector (BCG, 2018; as cited in Szczepański, 2019). This enables them to take advantage not only of autonomous vehicles and route optimization but also of optimizing multimodal transportation (European Commission, 2021a). For instance, during the 1991 Persian Gulf crisis, the utilization of an AI algorithm by U.S. forces revolutionized logistics planning. This cutting-edge technology facilitated the efficient management of a fleet comprising 50,000 vehicles, accomplishing in a matter of hours what previously required several weeks of manual effort (Russell & Norving, 2010).

AI-powered transportation systems can accurately anticipate customer orders and pre-ship goods, as demonstrated by Amazon's advanced AI algorithms (Davenport et al., 2019). These innovations result in faster and more lucrative deliveries, enhancing overall efficiency and profitability (Agrawal et al., 2019).

3.1.1. Productivity gains

Productivity plays a vital role in micro and macroeconomic analysis, especially for the latter, as it directly influences a nation's living standards (Mankiw, 2021). In this sense, numerous studies provide substantial evidence supporting the notion that AI contributes significantly to national productivity enhancements.

For instance, research indicates that AI has the potential to augment baseline productivity by 26.08% in the year 2035 (Purdy & Daugherty, 2017). Moreover, other studies forecast an annual productivity growth increase ranging from 0.8 to 1.4%, equivalent to a mean increase of 22% by 2035 (Manyika, Chui, et al., 2017). This sharply contrasts with the previously exaggerated claims of a 40% boost in labour productivity, which were based on first inflated expectations of the technology (Purdy & Daugherty, 2017; as cited in Castro & New, 2016).

This potential solution addresses the prevailing decline in labour productivity experienced in modern times. OECD data reveals a deceleration in aggregate labour productivity growth rate within the G7 group, decreasing from 9.99% (1995-2005) to 3.41% (2005-2015) [1]. Similar trends are observed in other advanced economies from an average of 2.7% (1996-2006) to 1.0% (2006-2016) (Furman & Seamans, 2019). Additionally, in 28 other OECD countries, the same tendency occurs, with the annual growth rate declining

[1] The OECD numbers come from annual data across the G-7 countries (OECD, 2023b). Composed of Canada, France, Germany, Italy, Japan, the United States, and the United Kingdom (see Table 3.1).

from 2.3% (1995-2004) to 1.1% (2005-2015) (Agrawal et al., 2019). Hence, this productivity decline has not only affected developed countries but has also become evident in emerging and developing nations (Agrawal et al., 2019).

3.1.2. Inequalities between countries

The proliferation of AI brings numerous advantages; however, it is not devoid of drawbacks. One notable disadvantage is the widening gap between countries. Rao and Verweij (2017) observed that the projected global benefits of AI by 2030 will primarily accrue to the United States and China (around 70%), with China alone contributing over 45% of the overall impact. In contrast, Europe is estimated to account for approximately 16% of these benefits.

This phenomenon can be attributed, not to a lack of capital resources, but rather to the scarcity of skilled workers in the Information and Communication Technology (ICT) sector in Europe (European Commission, 2018), which hinders Europe's progress in AI research and development (Evas, 2020). Additionally, countries such as China, and the United States have a comparatively larger workforce engaged in activities that are partially technically automatable (Manyika, Chui, et al., 2017), as well as the largest internal markets in terms of GDP (OECD, 2023a). Therefore, they could experience more benefits from the AI implementation due to productivity and demand gains (Gillham et al., 2018).

Furthermore, when examining the situation in developing nations, the uneven distribution of AI's benefits on a global scale becomes even more apparent. Latin America, Africa, and various non-developed Asian markets, including Oceania (grouped with Africa and other non-developed regions in the study), are collectively estimated to represent a mere 11% of the projected AI GDP gains (Rao & Verweij, 2017). What highlights the limited access and potential economic gains from AI in these regions compared to developed countries.

Various studies further support this notion, indicating that countries with advanced AI capabilities have the potential to achieve an additional 20 to 25% in net economic benefits compared to their current state. On the other hand, developing countries may only capture approximately 5 to 15% of these benefits (Bughin et al., 2019). his significant disparity suggests that the potential economic gains from AI are disproportionately skewed towards developed nations, exacerbating the existing global economic gap.

Another aspect to consider is the impact of AI on manufacturing. As noted by Szczepański (2019), the introduction of AI in manufacturing processes may lead to certain manufacturers choosing to produce goods in their home countries rather than in underdeveloped nations. This shift could result in a flow of income from underdeveloped regions to already developed countries. Consequently, strengthening the gap between countries even more.

3.1.3. Labour market

The societal implications of AI, particularly its potential impact on unemployment, have attracted considerable attention and concern. The contentious nature of this subject further contributes to the diverse array of opinions regarding its impact. In essence, three primary schools of thought emerge regarding how the integration of AI will shape the employment landscape: pessimistic, neutral, and optimistic perspectives.

Advocates of the pessimistic stance posit that AI automation will result in the elimination of more jobs than it will create. Conversely, proponents of the optimistic outlook contend that AI, akin to past technological revolutions, will engender increased wealth and a multitude of employment opportunities (Manyika, Chui, et al., 2017). However, as acknowledged by Szczepański (2019), the most feasible scenario is that in the short and possibly medium term, the negative impact on jobs will be more pronounced, while in the longer term, job creation will ultimately outweigh the initial job destruction. Therefore, in order to shed light on the unemployment implications of AI, it is essential to examine the available data.

Overall, estimations suggest that 32% of jobs will undergo significant changes due to AI implementation (OECD, 2018; as cited in Szczepański, 2019), while just 10% will become highly dependent on AI (Gillham et al., 2018). That being said, the large majority of the impacted jobs, around two-thirds of them, are expected to be unskilled positions, whereas skilled jobs are anticipated to benefit the most from the implementation of AI (Gillham et al., 2018; Szczepański, 2019).

However, the impact of AI on the job market goes beyond mere changes in job roles. Based on projections, it is estimated that by 2030, AI will result in a transition to new occupational categories affecting approximately 14% of global jobs, which corresponds to around 326 million workers worldwide, assuming a rapid adoption of automation (Manyika, Lund, et al., 2017).

However, the discussion about job losses or gains is about to be discussed. Nonetheless, as an introductory overview, to know whether AI will lead to such outcomes, it is crucial to consider both the speed of AI implementation and workers' adaptation, as well as the elasticity of consumer demand.

3.1.3.1. Job losses

When considering job loss, there are two main perspectives that lead to completely distinct conclusions: one that focuses on measuring entire automatable jobs, and another that assesses the automatable skills within tasks rather than entire positions. To show these discrepancies depending on the chosen approach, while some studies indicate that 47% of jobs in the United States are at high risk of automation (Frey & Osborne, 2017; as cited in Furman & Seamans, 2019), skill-based analysis estimates that only 9% of US jobs are truly at risk, as more than 70% of their tasks can be automated (Arntz et al., 2015; as cited in Gillham et al., 2018).

Besides, even from a logical standpoint, the approach focusing on specific tasks is more sensible, as most AI systems are specialized in particular tasks, rather than possessing general intelligence. An example of this is the utilization of machine learning vision for the detection of cancer cells, which aids healthcare professionals in reviewing critical cases rather than entirely replacing them (Brynjolfsson & Mcafee, 2017).

Therefore, following the task or skill-based perspective, the studies expect that approximately 60% of jobs involve 30% of automatable tasks, while less than 5% of jobs could be fully automated (Manyika, Lund, et al., 2017). These percentages ages are higher in those jobs that require less education level, specifically, it is expected an automation of 44% of the roles that require an education level lower than high school. While the corresponding percentage age for job roles requiring a bachelor's degree is expected to be as low as 1% (Artnz, et al., 2016; as cited in EOP US, 2016).

Moreover, some empirical studies suggest a tendency of disappearing of the middle-skill class in favour of the low-skill and high-skill, which brings a more fragmented and polarised society (Frank et al., 2019).

Nevertheless, it is challenging to measure the global effects accurately, as these figures not only depend on the country but also on the industry. Consequently, countries such as the United States and Europe have a range of jobs at high risk of automation, varying from 23% to 76%, while in Asia, the range is 11% to 29% (Gillham et al., 2018).

Based on the aforementioned analysed data, it can be concluded that negative side-effects in the labour market will occur if workers fail to adapt promptly to the changes brought about by AI. It is crucial for individuals to be able to adjust or preserve their work in response to the advancements in AI technology (Furman & Seamans, 2019).

3.1.3.2. Job gains

When considering job gains, it is widely accepted that enhanced productivity resulting from AI can lead to expanded employment opportunities, despite a decrease in the amount of labour required per unit of output. This is because the enhanced productivity resulting from AI can lead to reduced working hours, while increased earnings for workers and lowered prices for products. Consequently, if demand is elastic enough, families' consumption expenditure could increase, especially in the service sector (Arntz et al., 2015, as cited in Agrawal et al., 2019; Gillham et al., 2018; EOP US, 2016).

As organizations accumulate more capital, through increased productivity and families' expenditure, they may also increase their demand for labour in non-automated tasks, to further leverage the economic expansion. This virtuous cycle of productivity growth, rising consumption expenditure, and increased labour demand have the potential to generate sustained economic growth and create more employment opportunities (Arntz et al., 2015, as cited in Agrawal et al., 2019; Gillham et al., 2018; EOP US, 2016).

Furthermore, although AI is capable of self-learning patterns hence solving problems previously just made by humans (Enholm et al., 2021), not all the tasks within a job will be automatable (Davenport et al., 2019), and in many other tasks, humans will still have a comparative advantage in terms of costs or efficiency (Agrawal et al., 2019; Furman & Seamans, 2019).

Moreover, according to historical data, it can be postulated that the introduction of new technology drives general job creation in the long term. While In the short term, technology-related occupations can help mitigate job losses resulting from the displacement of outdated methods (Frank et al., 2019; Manyika, Lund, et al., 2017; EOP US, 2016).

Not only historical data, but rather recent examples of robots in various industries demonstrate that although the implementation of industrial robots may lead to the loss of manufacturing jobs, this can be offset by the creation of service-related jobs (Dauth et al., 2017; as cited in Furman & Seamans, 2019). This suggests that the effects of job losses in one industry can be mitigated by employment growth in other industries (Agrawal et al., 2019).

Lastly, it is noteworthy that jobs are constantly evolving, and new ones are constantly emerging. A notable study conducted in 2011 in the United States revealed that novel occupations constituted 0.56% of annually created jobs (Jeffrey Lin, 2011; as cited in Manyika, Lund, et al., 2017). Looking ahead to 2030, it is anticipated that 8-9% of the labour force will be engaged in entirely new employment opportunities (Manyika, Lund, et al., 2017).

3.1.3.3. Changes in sectors

Following the context of sector distinctions, it is important to note that not all sectors will witness similar reductions in working hours, thereby leading to an anticipated transformation of the job market in the years ahead.

As shown before, this analysis will be based on the capabilities of the machine's approach proposed by Manyika, Chui, et al. (2017). In the study 18 human capabilities were identified and evaluated. The results indicate that machines outperform humans in recognizing known patterns, optimization and planning for objective outcomes under multiple constraints, retrieving information from vast sources, navigating objects autonomously, and collecting and processing data.

Therefore, manual and repetitive tasks such as transportation, switchboard operations, filing clerical work, and travel agency services, as well as basic computational tasks like assembly line work, are highly susceptible to automation (Gillham et al., 2018; EOP US, 2016). This is further corroborated by the prevalence of AI-related patents in industries characterized by such tasks, including transportation, human-computer interaction, entertainment, industry and manufacturing, and banking (WIPO, 2019), which strengthens the case for automation in these sectors.

Indeed, certain pilot projects have already been implemented in public administrations to automate traditional document review and classification processes typically carried out by clerks (European Commission, 2021a). But also at the private level, conversational intelligent agents, such as Siri or Alexa, could now do tasks previously reserved for clerks, such as making calls, composing texts, and scheduling meetings through voice commands (Enholm et al., 2021).

On the other hand, there are job roles that cannot be automated due to machines' limitations in certain areas. Machines struggle with tasks involving the creation of novel action patterns, adaptation to constantly changing environments, fostering creativity, and understanding and generating social and emotional sentiments (Duan et al., 2019; Manyika, Chui, et al., 2017). But above all of them, the most important feature the machines are not capable to mimic at the moment is the intention of doing something rather than minimising a parameter (Pearl & Mackenzie, 2020), which difficult its applications for roles with high responsibilities.

As a result, service sectors that demand advanced social and emotional skills, as well as cognitively demanding jobs that rely on logical reasoning and jobs requiring creativity without a clearly defined objective, are less likely to be automated. Examples of such jobs include healthcare, technology, financial services, education, scientific research, innovation, and entrepreneurship (Brynjolfsson & Mcafee, 2017; Davenport et al., 2019; Manyika, Chui, et al., 2017; Manyika, Lund, et al., 2017).

However, other sources suggest that elderly care services, despite their reliance on high emotional skills, could be automated through the use of robotics (European Commission, 2021a). Hence, when referring to ‘highly social and emotional jobs,’ we are mainly considering roles related to children or healthcare.

In summary, the future workforce will primarily focus on tasks that involve persuading people to achieve common goals, determining the next problems to tackle (Brynjolfsson & Mcafee, 2017; Davenport et al., 2019), and jobs with high emotional involvement. Conversely, less time will be dedicated to predictable physical tasks and data-centric activities, as machines already outperform humans in these areas (Manyika, Lund, et al., 2017).

Therefore, by 2030 just 30% of the tasks will be low-digital repetitive jobs, while the higher-skilled workers are expected to increase from 40% to more than 50% of the total job market, particularly in digital sectors. Hence we could expect a drop in salaries for low-skilled workers in favour of higher ones (Bughin et al., 2019).

3.2. FIRM-LEVEL

AI is widely recognized as a vital element for gaining and sustaining a competitive edge in the business realm (Lee et al., 2019). Studies project that, on average, AI adoption could boost firms' cashflow by 16% by 2030 (Bughin et al., 2019). Therefore, this section aims to delve into the potential impact of AI implementation at the organizational level, unravelling the transformative possibilities it holds.

According to a comprehensive literature review conducted by Enholm et al. (2021), insightful findings have emerged regarding the impact of AI across various firm-level dimensions, categorized as first and second order effects.

Within the realm of first order effects, three key categories have surfaced: process efficiency, insight generation, and business process transformation. Notably, AI has demonstrated remarkable potential in enhancing process efficiency by generating significant gains in productivity, mitigating, or eliminating human errors, achieving precision in task execution, and reducing risks associated with human operators.

Notably, the above seen increase in 2035's baseline productivity level, from 22% to 26% (Manyika, Chui, et al., 2017; Purdy & Daugherty, 2017), will have significant impacts on companies. This extraordinary productivity growth is primarily attributed to the anticipated automation of approximately 30% of the total enterprises' working hours by 2030 (Manyika, Lund, et al., 2017).

To illustrate this reduction in practical terms, let's consider two real-world cases. First, JPMorgan implemented an AI-driven system capable to review commercial loan contracts, resulting in a significant reduction in time and effort. As a result, the task previously requiring 360,000 hours could be completed in a matter of seconds with the new system. Second, Udacity implementation of an AI algorithm, which led to a 54% improvement in the sales team's acceptation rate while simultaneously serving twice the number of customers (Brynjolfsson & Mcafee, 2017; Davenport et al., 2019).

Another cost reduction AI example, is the cases of Digital Equipment Corporation and DuPont, both achieved respectively annual cost reductions of $40 million and $10 million (Russell & Norving, 2010).

Moreover, according to Küpper et al. (2018), it is expected that AI will reduce business costs by as much as 20%. Accounting workforce productivity for 70% of this reduction costs. While the remaining 30% will come from waste reduction and defect elimination, as algorithms could identify new ways to minimize or even eliminate both issues through pattern recognition and automated quality control systems (Szczepański, 2019).

On the other hand, coming back to Enholm's first order effects, the AI generation of insights through AI has led to elevated decision making quality and agility (further discussed in the section 'sense-response process loop').

Moving on to second order effects, the literature review highlights five significant trends that have been directly influenced by AI. These encompass the creation and refinement of products and services, increased company profitability, enhanced market effectiveness, elevated customer satisfaction, improved environmental and social sustainability performance, and the potential for corporate reputation decline resulting from widespread workforce reductions due to automation.

Therefore, the AI-driven CRM (Customer Relationship Management) systems forementioned will have a significant impact on the firms' revenues, especially for consumer segmentation (Agrawal et al., 2019), as this leads to better products and services refinement. Notably, in major e-commerce firms, AI-driven recommendation engines are estimated to contribute between 30 to 40% of sales (Bughin et al., 2018).

Moreover, in the realm of environmental and social responsibility, empirical studies suggest that energy costs and resource consumption can be significantly reduced through AI, positioning it as a key player in addressing pollution and waste (Toniolo et al., 2020). Leveraging this environmental advantage, businesses can incorporate AI into their advertising campaigns to attract an increasingly eco-conscious consumer, while reducing its costs.

An illustrative example of AI's power in reducing energy costs is Google's data centre. By implementing an AI algorithm in 2016 that utilized existing sensor data, Google achieved a 40% reduction in energy consumption compared to levels achieved by human experts (Evans & Gao, 2016). Furthermore, AI projects have demonstrated impressive results even without extensive sensor investments. For instance, an AI project aimed at detecting faults in thermal power plants revealed a 44% reduction in the number of sensors required for water wall pipe leakage detection and a 55% reduction in turbine engine failure detection (Khalid et al., 2021; as cited in Szczepaniuk & Szczepaniuk, 2022).

3.2.1. Competition changes

The adoption of AI could potentially create inequalities among companies of different sizes, resulting in unfair competition in the market. This could ultimately lead to a reduction in innovation, as quasi-monopolies may form in certain sectors (Furman & Seamans, 2019). This phenomenon can be attributed, in part, to larger companies possessing greater financial resources and a larger customer base, thus granting them access to a wider pool of data (Agrawal et al., 2019) and resources to invest in their own AI infrastructure, thereby creating a competitive advantage over smaller companies (Brynjolfsson & Mcafee, 2017; European Commission, 2018; Lee et al., 2019).

According to Bughin et al. (2019), early companies adopters (AI adopters in 2022-2024), will experience a rise of 122% in their 2030 cash flow. In contrast, 2030's AI adopters will experience a mere cashflow rise of 10%. While those companies that fail to adopt AI by 2030 may experience a decline of 23% in their cash flow due to intensified competition. Which is translated into a wider technological gap between small and big companies.

As such, to ensure healthy competition and foster innovation, public initiatives have been implemented to encourage the integration of AI among small and medium-sized enterprises (SMEs). One such initiative, proposed by the European Commission, is the creation of 'Digital Innovation Hubs,' which can provide SMEs with the necessary resources to test and adopt AI technology (European Commission, 2018).

Moreover, other private tendencies limit the necessity for self-build ML infrastructure, given cloud services provided by companies such as Google, Amazon, Microsoft and Salesforce, among others. Which coupled with the fact that by using certain Machine Learning techniques, such as fine-tuning, which allows good models to be trained on as little as 100 data records, the gap between large and small companies becomes smaller (Davenport et al., 2019).

3.2.2. Legal concerns

Lastly, another essential factor influencing individual agents is the legal implications associated with AI. It is imperative for homeowners to have a comprehensive understanding of their rights, while enterprises must ensure compliance with relevant regulations to avoid any violations.

Although there is currently no well-established legal framework for AI, the European Union (EU) has taken the lead in its development (Evas, 2020). Notably, on May 11th, 2023, the EU's Internal Market Committee and Civil Liberties Committee collaboratively endorsed a preliminary negotiation plan for the proposed AI Act by the European Commission (European Parliament, 2023). Therefore, we will use this regulation as a legal framework for future regulations in other countries as well.

While this regulation aims to promote certain fundamental rights, it also imposes limitations that impact other rights, such as the freedom to conduct business, freedom of art and science, and aspects of intellectual property rights, as acknowledged by the European Commission (European Commission, 2021a).

The AI Act introduces six key prohibitions that have direct implications for the aforementioned rights:

1. The act restricts the use of real-time and post-remote biometric identification in publicly accessible spaces, even in cases of emergencies such as kidnapping or terrorist attacks.
2. Emotion recognition technologies are limited in their application in law enforcement, border management, workplaces, and educational institutions.
3. Indiscriminate scraping of biometric data from social media or secure cameras for the purpose of creating facial recognition databases is prohibited.
4. Biometric categorization systems utilizing sensitive characteristics, such as socioeconomic status or gender, also face restrictions.
5. Recommender systems employed by social media platforms fall under the category of high-risk AI, hence face limitations as well.
6. Partial publication of copyrighted content used for training AI databases is subject to restrictions.

Moreover, it should be noted that exceptions to these rules are made for research activities and open-source AI projects (European Parliament, 2023). The implementation of these prohibitions has the potential to mitigate the negative consequences associated with this technology, thereby safeguarding the interests of families.

However, as stated by Sam Altman, CEO of OpenAI, AI companies will strive to comply with European regulations. Failure to do so may result in the termination of operations within the EU territory (Waters et al., 2023), therefore falling behind those countries that have access to this technology. A recent example illustrating this scenario is Bard, an AI language model developed by Google, which was introduced in February 2023 (Pichai, 2023), and is available in over 180 countries and territories. Notably, Bard is not accessible in any EU member states (Google, 2023), due to stringent data protection regulations imposed by the European authorities (POEU, 2022).

Therefore, it is crucial to foster collaboration between governments and enterprises in order to find mutually beneficial solutions that do not detriment any of the stakeholders involved in the economy. By working together, we can strike a balance between technological advancements and safeguarding the interests of all parties involved.

4. A PRACTICAL IMPLEMENTATION OF AI MODEL APPLIED TO ENERGY FINAL CONSUMPTION IN THE EU

In the preceding sections, our analysis relied on information from diverse scientific publications. Nonetheless, we aim to delve deeper by conducting our own models' comparative study from scratch, scrutinizing both conventional predictive analysis methods utilized by economists and emerging AI models.

To achieve this, our focus is on studying energy consumption among European states. We have developed multiple models capable of predicting a country's annual energy consumption based on the added value of each economic sector. Our deepening objective is to uncover valuable insights and contribute to the advancement of predictive analysis in the business domain.

We have opted to utilize public sector data from Eurostat, due to its publicly accessible nature, as opposed to relying on datasets from private corporations. Additionally, we have drawn inspiration from various public AI initiatives, such as the German Federal Government's successful implementation of AI in the health and customs fields (European Commission, 2021b). Based on these examples, we are confident that we can further expand the application of AI to various other public sectors within national economies, such as the energy sector.

4.1. JUSTIFICATION OF THE ENERGY SECTOR SELECTION

The European Union (EU) is heavily reliant on imported fossil fuels, particularly from Russia, which accounted for nearly 40% of the EU's total energy consumption in 2021 (BP p.l.c., 2022). This heavy dependence raises concerns about energy security and the EU's vulnerability to geopolitical events, especially in the wake of the recent Ukrainian invasion.

Consequently, the EU is compelled to transition to renewable energy sources before 2030 (European Commission, 2022), in order to tackle its lack of fossil fuels. However, while renewables represent the medium-long-term solution, there is an urgent need for immediate measures, as the energy situation in Europe is anticipated to deteriorate in the forthcoming years.

To grasp the gravity of this situation, it is crucial to recognize the significance of US assistance in meeting the EU's energy demands. Presently, the US serves as the EU's primary alternative to Russian energy sources, particularly in terms of petroleum. And, although Norway has emerged as a key leader in natural gas exports to the EU, surpassing Russia's exports in the third quarter of 2022, the US again remains a significant player in this arena (Yanatma, 2023).

Currently, all available gas supplies from the US are being directed to the EU. However, once China's Covid-19 restrictions are lifted, its energy market will require the same level of energy as before. Consequently, there will be no new suppliers to the US liquefied natural gas (LNG) system until 2026 when plans are underway to invest in new LNG projects in collaboration with the French energy group Engie S.A. (de Luna, 2022).

Considering these factors, there is a pressing need for swift energy-saving policies at least until we could rely heavily on renewables. This is where the power of AI comes into play. AI has the ability to not only reduce energy consumption, as demonstrated by Google's success in this area (Evans & Gao, 2016), but also accurately forecast energy requirements based on various factors, such as expectations of economic growth. This could potentially lead to energy importation savings at the EU level, as better predictions are made, the need for a larger safety stock to deal with unexpected prediction fluctuations disappears.

4.2. GOAL OF THE ANALYSIS

In this document section, our objective is to demonstrate the superior results of AI algorithms in comparison to traditional methods for predictive analysis, a crucial information gathering technique discussed earlier. Furthermore, we shed light on the vast potential AI algorithms hold within the realm of international business. By embracing these cutting-edge tools, international organizations can unlock unprecedented opportunities, revolutionizing their decision making processes and gaining a competitive edge in today's dynamic and rapidly evolving world.

On the other hand, the objective of this concrete analysis is to create a model able to predict the final energy consumption of a country (dependent variable) with the least error possible, using as the predictors (independent variables) the value added of each sector from its national economy. In fact, we try to develop a unified model capable of functioning effectively across all 28 member countries that constituted the European Union in 2019.

From an economic analysis standpoint, and based on our earlier discussion on causation, solely considering the aggregate increment in the value of all final products generated by each sector of the national economy, without considering any other relevant predictor variable such as the total national population, may give the impression that these data alone are insufficient to make accurate predictions.

However, the purpose of this analysis is to achieve good predictions even without perfect information. As in many other real examples, access to precise information is not possible.

4.3. DATA BASE INFORMATION

For this study, we have used official European Union website countries' records, from Eurostat (ESS, 2023; Eurostat, 2023). Specifically, two databases were employed: 'final energy consumption' (sdg_07_11) and 'gross value added and income by A*10 industry' (namq_10_a10).

As defined by Eurostat, the 'final energy consumption' measures the energy utilized by end users in a country, for example, industries, transportation, and households. However, it excludes non-energy purposes of energy sources (such as chemical production), internal energy sector consumption, and energy losses during its transformation and distribution.

On the other hand, in the 'gross value added and income by A*10 industry' we found the value added for each sector of the economy, the 'A*10' comes from a breakdown of the industries found in 'NACE Rev. 2' into 10 industries.

Table 4.1.- A*10 breakdown of NACE Rev. 2.

Seq. No	NACE Rev. 2 sections	Description
1	A	Agriculture, forestry and fishing
2	B, C, D and E	Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; water supply; sewerage, waste management and remediation activities
2a	*C*	*of which: Manufacturing*
3	F	Construction
4	G, H and I	Wholesale and retail trade; repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities
5	J	Information and communication
6	K	Financial and insurance activities
7	L	Real estate activities
8	M and N	Professional, scientific and technical activities; administrative and support service activities
9	O, P and Q	Public administration and defence; compulsory social security; education; human health and social work activities
10	R, S, T and U	Arts, entertainment and recreation, repair of household goods and other services

Note: European Commission, 2010, p. 9.

As per Eurostat, the acronym NACE (Nomenclature générale des Activités économiques dans les Communautés Européennes) functions as a comprehensive framework for classifying economic activities. Specifically, NACE Rev 2 finds extensive application in the realms of statistical analysis and diverse disciplinary domains.

The study focuses on the European Union's 28 member countries of 2019, comprising Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and the United Kingdom. Data from 2000 to 2021 were examined for all countries, except for the United Kingdom, where the most recent data available is from 2019 in both datasets.

The main reason to include the UK is to provide the model with a wider range of examples, enhancing the overall predictive capabilities of the model.

The final database we have been working on consists of 614 non-null entries, with 70% used for training the models and 30% for testing their performance, both of them randomly selected [2]. In other words, the evaluations of the error in predictions are based on the error of non-seen instances rather than using the same data as in the training phase. This error is measured in units of the final energy consumption with the root mean squared error (RMSE) metrics.

It includes 13 columns, that comprise 11 variables from namq_10_a10, 1 from sdg_07_11, and an additional column representing the corresponding years of the data. In the following table, there is a descriptive analysis of the main characteristics for each of the numerical variables used, in which we have not included years, as this is considered a categorical-ordinal variable (see Table 4.2). However, the number of columns will fluctuate in each model, due to the removal of columns that exhibit incongruity, as determined through our statistical analysis.

Furthermore, the data is presented in annual figures, with the value added of each sector expressed in million euros at current prices, and the final energy consumption expressed in million tonnes of oil equivalent.

[2] We have utilized for the data splitting process the 'train_test_split' module from the scikit-learn library.

That being said, our aim is to calculate the total energy consumption of a country, by analysing the national value added by each sector. Hence, the final consumption will be considered as the dependent variable, while the value added, and years will serve as the independent variables in our analysis.

4.4. STATISTICAL INFERENCE PREDICTION MODELS

In order to achieve optimal predictor selection for multiple linear regression and address collinearity concerns, a correlation analysis was undertaken utilizing the Pearson correlation coefficient (r) (see Table 4.3). The formula employed in this analysis is as follows:

$$r = \frac{[n(\sum xy) - \sum x \sum y]}{\sqrt{[n(\sum x^2) - (\sum x)^2}} * [n(\sum y^2) - (\sum y)^2]$$

Notably, the Pearson correlations revealed strong linear associations between the dependent variable and all independent variables, indicating a high likelihood of achieving good performance in the multilinear regression model.

Table 4.4.- Correlations of the independent variables with 'Final energy consumption'.

Independent variables	Correlation
Agriculture, forestry and fishing	0.8521
Industry (except construction)	0.9580
Manufacturing	0.9459
Construction	0.9281
Wholesale and retail trade, transport, accommodation and food service activities	0.9615
Information and communication	0.9159
Financial and insurance activities	0.9052
Real estate activities	0.9357
Professional, scientific and technical activities; administrative and support service activities	0.9309
Public administration, defence, education, human health and social work activities	0.9425
Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies	0.9572

Note: Analysis based on data from Eurostat, 2023.

On the other hand, collinearity is a concern in regression models when predictor variables are highly correlated, diminishing their statistical significance. It inflates estimator variance, biases predictor variable decisions, and expands confidence intervals. Addressing collinearity is crucial for accurate and reliable model outcomes.

In our example, we have found that the risk of collinearity is very high among the independent variables, as our Pearson correlations are high along the dataset. This problem is particularly evident in the following cases.

Table 4.5.- Collinearity issues detection.

Correlation	**Variable 1**	**Variable 2**
0.9972	Manufacturing	Industry (except construction)
0.9809	Real estate activities	Wholesale and retail trade, transport, accommodation and food service activities
0.9803	Public administration, defence, education, human health and social work activities	Wholesale and retail trade, transport, accommodation and food service activities
0.9818	Public administration, defence, education, human health and social work activities	Real estate activities
0.9933	Public administration, defence, education, human health and social work activities	Professional, scientific and technical activities; administrative and support service activities

Note: Analysis based on data from Eurostat, 2023.

After careful consideration, we made the decision to remove the value-added columns pertaining to ‘Manufacturing’, ‘Real estate activities’, and ‘Public administration, defence, education, human health, and social work activities’. This choice was driven by the stronger correlations observed between the remaining variables and the dependent variable. Additionally, the ‘Manufacturing category is already encompassed within the 'Industry (except construction)' column, as per its definition. Therefore, the codes eliminated from Table 4.1 were ‘C’, ‘L’ and ‘O, P and Q’, leaving us with just 9 of the 12 first predictors.

Subsequent to the elimination of the initial variables, we proceeded with the actual inference analysis. For this purpose, we employed multilinear regression analysis to discern relationships between variables. In this case our 'y' is the 'Final energy consumption', while each 'x' will be our independent annual value-added sectors, while our 'ε' will be 0, as we will evaluate our models on concrete values, rather a range of ±ε.

$$y = b0 + b1(x') + b2(x'') + \cdots + bp(x^p) + \varepsilon$$

Our workflow encompassed the utilization of the integrated Excel data analysis tool for conducting regression analysis. To enhance our predictive model, we followed the conventional approach of testing the null hypothesis significance for each individual independent variable at a confidence level of 0.95.

Moreover, to adhere to the ceteris paribus principle, we systematically removed one variable at a time, eliminating the variable having the highest p-value, as if the p-value is greater than 0.05, we do not have enough statistical evidence to dismiss the absence of a relationship between the dependent variable 'Final energy consumption' and these predictors. That being said, Table 4.6 shows the first multiple linear regression model (in the 'Coefficients' column) as well as the P-values for each predictor (see Table 4.6).

That being said, variables eliminated on each round, as well as justification for its elimination, are the following: 'Financial and insurance activities - K' (see P-value Table 4.6), 'Professional, scientific and technical activities; administrative and support service activities - M and N' (see P-value Table 4.7), 'Information and communication - J' (see P-value Table 4.8), and 'Construction - F' (see P-value Table 4.9).

This process resulted in the creation of five distinct multilinear models, each representing a different adjustment to the data frame created in each iteration. Among these models, only the final one provided statistical evidence, with a 0.95 confidence level, to reject the null hypothesis that there is no relationship between the target variable 'Final energy consumption' and all the 5 remaining independent variables (see Table 4.10).

The latter model resulted in the following coefficients for each variable. However, it is crucial to note that no scaling was implemented, leading to seemingly small coefficients due to the significant range disparity between the predictor values and the predicted value.

Table 4.11.- Coefficients of multilinear regression model 5.

Predictors (except the intercept)	Coefficients
Intercept	16683.65
Year	-8.2822
Agriculture, forestry and fishing	0.0006
Industry (except construction)	0.0003
Wholesale and retail trade, transport, accommodation and food service activities	0.0002
Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies	-0.0005

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

As previously discussed, the goal of this analysis was to compare the error between the traditional models, represented by the multilinear regression analysis, and the following ML prediction models. Therefore, prior to discussing the results, we need to conduct the AI analysis.

4.5. ML PREDICTION MODELS

For this section, we have utilized Python programming language, specifically the 'Sklearn' and 'XGBoost' libraries, to implement our AI algorithms. We have used the preconfigured parameters provided by these libraries, as they achieved an accurate model performance without any hyperparameters fine-tuning.

Our battery of ML algorithms includes AdaBoost, Bagging, Bayesian Ridge, Decision Tree, Elastic Net, Extra Trees, Gradient Boosting, Huber Regressor, K-Nearest Neighbors, Lasso, Linear Regression, Random Forest, RANSAC Regressor, Ridge, SGD Regressor, and XGBoost.

In other to compare the traditional and novel predictive methods in the same conditions, we have created the above seen 16 algorithms for each of the 5 data bases resulting from the elimination of variables in each iteration of the aforementioned traditional workflow.

Moreover, it is crucial to highlight that prior to training our models, we meticulously scaled each predictor variable using Gaussian distributions for numerical columns, while assigning values to each year, as they are considered categorical ordinal figures. This approach ensured optimal training results and enhanced the reliability of our models.

$$Gaussian\ f(x) = \frac{1}{\sigma\sqrt{(2\pi)}} * e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

To apply this statistical formula in a systematic way using code, we have relied on the ‘PowerTransformer’ module from the ‘sklearn.preprocessing’ module. Our scaler has used the method ‘yeo-johnson’ from the first module. In practice, the ‘yeo-johnson’ method is a technique used for transforming non-normal distributions to approximately follow a Gaussian distribution. This scaler is used for each of the numerical independent variables’ columns used to predict the ‘Final energy consumption’ while establishing a correct model to transform the predictors of the training data (fit_transform). Subsequently, the same transformation is applied to the predictors of the testing data (transform).

For the years column, as it is considered a categorical, ordinal feature, we have codified it using another approach. Instead of Gaussian distributions, we have created dichotomous (0/1 variables) columns for each of the unique years contained in the years’ column. For this process, we have utilized ‘get_dummies’ method from Pandas library.

Finally, for the evaluation of these models, we have used the root for the ‘mean_squared_error’ method from the ‘sklearn.metrics’ module. Thereafter, a dictionary for the algorithms was created, composed of the algorithm name as the key item, followed by the corresponding method as the value, for each of the 16 above-mentioned algorithms.

Thereafter, we created a new data frame with the observed results. In order to accomplish this, we have trained each of the 16 methods using the scaled predictors data, and the training dependent variable data. Secondly, we have measured the root mean squared error, using the model we have just created, the predictions of the testing data, and the actual values. The results were unified in a data frame, with the first column indicating the name of the algorithm from the dictionary key item and the RMSE associated in the following column.

4.6. RESULTS OF BOTH MODELS

The results are discussed in terms of the established evaluation metrics, in this case, we have chosen the Root Mean Squared Error (RMSE), which measures the average prediction error in the same units as the observed data. RMSE was chosen over other percentage age metrics like Mean Absolute Percentage age Error because the latter is not appropriate for data with a small scale (Jierula et al., 2021), such as our objective variable.

In the traditional multilinear regression model, we have found that the less independent variables we had, the fewer error we observed in the testing data. Dropping down from a RMSE of ±210.24 for the 9 predictors' model to ±122.02 for the 5 predictors' model, an error reduction of 42%. This, considering the figures range of the predicted variable, from 4 to 2254, is an impressive result. This great performance is mainly due to the high correlation above seen.

Therefore, it appears that the current approaches aimed at enhancing the model's ability to generalize beyond the training data have proven effective. In addition to the advantages associated with a more simplified model.

However, when comparing these figures with those obtained from AI algorithms, we truly understand the potential of this technology in the business field. For example, the same linear regression applied by an AI model achieved an error of ±30.13 for the 9 predictors' data frame, while reaching a similar error for the 5 predictors' data frame.

Table 4.13.- The top 5 best predictive performance models.

Model	Number of predictors	RMSE
Extra Trees	7	3.55
Extra Trees	8	3.69
Extra Trees	9	3.80
Extra Trees	5	4.01
XGBoost	8	4.07

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

Although, by applying other AI approaches, we reach almost perfect predictions for the testing data, reaching a predictive error as little as ±3.55 for the Extra Trees model with

7 predictors, which supposes a reduction of the prediction error of more than 97%, compared to the best linear regression model's RMSE.

Based on the observations presented in Table 4.12, it can be inferred that the primary disparities among the models are not contingent on the number of variables analysed, but rather on the specific methodology employed (see Table 4.12). In light of this, the subsequent table will provide a comprehensive summary of the average performance achieved by each approach.

Table 4.14.- Ranking of the top predictive methods.

Models	Average RMSE
Extra Trees	3.84
XGBoost	4.38
Gradient Boosting	4.97
Random Forest	5.66
Bagging	5.70
Decision Tree	7.53
AdaBoost	7.82
K-Nearest Neighbors	17.33
Lasso	30.81
Ridge	30.85
Bayesian Ridge	30.89
SGD Regressor	31.26
Elastic Net	31.33
Huber Regressor	35.86
RANSAC Regressor	43.98
Multiple Linear Regressor	225.87

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

The analysis reveals that the top five methods yield comparable results, with variations of less than 2 units. However, it is crucial to note that these findings do not imply that these methods will exhibit the same level of performance across different datasets. The selection of the appropriate ML method for each instance depends on numerous factors, and there is no universally optimal algorithm for every problem.

CONCLUSIONS

In today's data-driven era, information holds immense potential for reducing uncertainty. With the exponential growth of available data, it becomes increasingly important to harness its power for measuring progress and gaining insights into unforeseen future events.

Throughout history, economists and statisticians within the field of economics have developed decision models based on objective data and well-defined workflows. Surprisingly, however, many decision-makers still heavily rely on intuition rather than leveraging numerical evidence to inform their choices.

Recognizing this gap, we have developed two distinctive workflows to enable data-driven decision-making: the exploratory approach and the sense-response loop. The exploratory approach aims to unravel the intricacies of unknown phenomena, while the sense-response loop empowers proactive action based on predicted opportunities and threats.

Yet, despite these advancements, certain limitations in current data analysis techniques have been identified, particularly their suboptimal predictive power, which can lead to subpar data-driven decisions. In contrast, machine learning techniques have emerged as a promising alternative, offering superior predictive performance in significantly shorter time frames. In our practical case, we observed a remarkable 97% reduction in prediction errors when comparing traditional methods with novel machine learning-based approaches.

These advancements hold the potential to revolutionize how organizations gather information, manage risks, and select courses of action. However, the implementation of such technologies brings both advantages and challenges to the forefront of economic dynamics.

On the positive side, widespread adoption of machine learning is expected to drive income growth at the national, sectoral, and firm levels. This growth will be fuelled by enhanced labour productivity, improved product and service quality, and personalized offerings. Additionally, machine learning is anticipated to contribute to reducing environmental footprints and result in long-term job gains.

Conversely, the downsides must also be considered. The disparity between countries, companies, and workers with varying educational backgrounds is a prominent concern. Short-term job losses due to automation pose another challenge, as do issues surrounding personal privacy rights and intellectual property rights.

Overall, we firmly believe that machine learning stands as one of the most promising tools available today to elevate decision making outcomes in both public and private organizations. Taking action to foster its adoption is crucial, otherwise, we could find ourselves lagging behind countries and enterprises that have embraced this transformative technology.

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ANNEX I

Table 3.0.1.- G-7's annual labour productivity growth.

Year	Annual growth	Growth in constant figures
1995	0.921956	100
1996	1.052419	101.0524
1997	1.268007	102.3338
1998	1.099907	103.4593
1999	1.267701	104.7709
2000	1.5384	106.3827
2001	0.314755	106.7175
2002	0.293534	107.0308
2003	0.62595	107.7008
2004	1.151085	108.9405
2005	0.958843	109.985
2006	0.978981	111.0618
2007	0.713684	111.8544
2008	-0.31924	111.4973
2009	-2.10935	109.1455
2010	1.190151	110.4445
2011	0.581199	111.0864
2012	0.449296	111.5855
2013	0.473181	112.1135
2014	0.658845	112.8521
2015	0.780255	113.7327

Note: Adapted from OECD, 2023b.

Table 4.0.2.- Descriptive analysis of numerical data in the training database.

	Energy	A	B, C, D and E	C	F	G, H and I	J	K	L	M and N	O, P and Q	R, S, T and U
Mean	405	74088	816535	670238	243108	798875	214299	221548	472475	454087	789335	141445
Standard Error	26	4653	61617	52411	17416	54910	16391	16313	38732	36657	59234	11547
Median	186	35172	357580	272129	91578	295901	68580	82199	139284	108293	292495	40786
Standard Deviation	534	96383	1276229	1085543	360716	1137316	339487	337885	802226	759262	1226873	239162
Range	2250	403992	7824393	6784477	1795694	5157618	1636307	1609201	3417198	3761454	6277820	1142559
Minimum	4	658	7407	6643	2326	10602	1743	1540	2372	2646	6390	1111
Maximum	2254	404650	7831800	6791120	1798020	5168220	1638050	1610741	3419570	3764100	6284210	1143670
Count	429	429	429	429	429	429	429	429	429	429	429	429
Kurtosis	2.6287	1.8975	8.0284	9.6253	2.4618	1.6134	3.7134	3.8279	2.7360	3.6944	3.2519	3.7219
Skewness	1.8623	1.7382	2.6600	2.8849	1.8734	1.7114	2.1358	2.1061	2.0323	2.1438	2.0362	2.1401

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

Table 4.0.3.- Correlation analysis of numerical data in the training database.

	Energy	*A*	*B, C, D and E*	*C*	*F*	*G, H and I*	*J*	*K*	*L*	*M and N*	*O, P and Q*	*R, S, T and U*
Energy	1	0.8521	0.9580	0.9459	0.9281	0.9615	0.9159	0.9052	0.9357	0.9309	0.9425	0.9572
A	0.8521	1	0.7738	0.7590	0.8534	0.8893	0.7663	0.7548	0.8273	0.8053	0.8479	0.8265
B, C, D and E	0.9580	0.7738	1	0.9972	0.8879	0.9351	0.9102	0.8958	0.9222	0.9222	0.9243	0.9692
C	0.9459	0.7590	0.9972	1	0.8605	0.9130	0.8844	0.8659	0.8991	0.9013	0.9035	0.9558
F	0.9281	0.8534	0.8879	0.8605	1	0.9735	0.9539	0.9369	0.9573	0.9487	0.9611	0.9392
G, H and I	0.9615	0.8893	0.9351	0.9130	0.9735	1	0.9547	0.9536	0.9809	0.9679	0.9803	0.9742
J	0.9159	0.7663	0.9102	0.8844	0.9539	0.9547	1	0.9598	0.9718	0.9776	0.9689	0.9371
K	0.9052	0.7548	0.8958	0.8659	0.9369	0.9536	0.9598	1	0.9561	0.9507	0.9430	0.9429
L	0.9357	0.8273	0.9222	0.8991	0.9573	0.9809	0.9718	0.9561	1	0.9783	0.9818	0.9692
M and N	0.9309	0.8053	0.9222	0.9013	0.9487	0.9679	0.9776	0.9507	0.9783	1	0.9933	0.9486
O, P and Q	0.9425	0.8479	0.9243	0.9035	0.9611	0.9803	0.9689	0.9430	0.9818	0.9933	1	0.9566
R, S, T and U	0.9572	0.8265	0.9692	0.9558	0.9392	0.9742	0.9371	0.9429	0.9692	0.9486	0.9566	1

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

Table 4.6.- Inference analysis model 1 (9 variables).

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	16403.3918	1599.9992	10.2521	0.0000	13258.3665	19548.4172	13258.3665	19548.4172
Year	-8.1426	0.7956	-10.2344	0.0000	-9.7065	-6.5787	-9.7065	-6.5787
A	0.0006	0.0002	3.5014	0.0005	0.0003	0.0010	0.0003	0.0010
B, C, D and E	0.0003	0.0000	14.7623	0.0000	0.0002	0.0003	0.0002	0.0003
F	0.0001	0.0001	1.9075	0.0571	0.0000	0.0003	0.0000	0.0003
G, H and I	0.0002	0.0001	3.7467	0.0002	0.0001	0.0003	0.0001	0.0003
J	-0.0001	0.0001	-0.8807	0.3790	-0.0002	0.0001	-0.0002	0.0001
K	0.0000	0.0001	0.3811	0.7033	-0.0001	0.0002	-0.0001	0.0002
M and N	0.0000	0.0000	0.7208	0.4715	0.0000	0.0001	0.0000	0.0001
R, S, T and U	-0.0005	0.0001	-3.8406	0.0001	-0.0008	-0.0003	-0.0008	-0.0003

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

Table 4.7.- Inference analysis model 2 (8 variables).

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	16414.7658	1598.0923	10.2715	0.0000	13273.5105	19556.0212	13273.5105	19556.0212
Year	-8.1480	0.7947	-10.2531	0.0000	-9.7100	-6.5859	-9.7100	-6.5859
A	0.0006	0.0002	3.9072	0.0001	0.0003	0.0009	0.0003	0.0009
B, C, D and E	0.0003	0.0000	15.8043	0.0000	0.0002	0.0003	0.0002	0.0003
F	0.0001	0.0001	1.8716	0.0620	0.0000	0.0003	0.0000	0.0003
G, H and I	0.0002	0.0000	4.6300	0.0000	0.0001	0.0003	0.0001	0.0003
J	-0.0001	0.0001	-0.8036	0.4221	-0.0002	0.0001	-0.0002	0.0001
M and N	0.0000	0.0000	0.6862	0.4929	0.0000	0.0001	0.0000	0.0001
R, S, T and U	-0.0005	0.0001	-3.8585	0.0001	-0.0008	-0.0003	-0.0008	-0.0003

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

Table 4.8.- Inference analysis model 3 (7 variables).

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	16287.9497	1586.3736	10.2674	0.0000	13169.7504	19406.1491	13169.7504	19406.1491
Year	-8.0855	0.7890	-10.2484	0.0000	-9.6363	-6.5347	-9.6363	-6.5347
A	0.0006	0.0002	3.8714	0.0001	0.0003	0.0009	0.0003	0.0009
B, C, D and E	0.0003	0.0000	15.8946	0.0000	0.0002	0.0003	0.0002	0.0003
F	0.0001	0.0001	1.7792	0.0759	0.0000	0.0003	0.0000	0.0003
G, H and I	0.0002	0.0000	5.1824	0.0000	0.0001	0.0003	0.0001	0.0003
J	0.0000	0.0001	-0.4879	0.6259	-0.0002	0.0001	-0.0002	0.0001
R, S, T and U	-0.0005	0.0001	-3.9170	0.0001	-0.0008	-0.0003	-0.0008	-0.0003

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

Table 4.9.- Inference analysis model 4 (6 variables).

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	16400.6922	1568.0383	10.4594	0.0000	13318.5539	19482.8305	13318.5539	19482.8305
Year	-8.1416	0.7798	-10.4400	0.0000	-9.6744	-6.6087	-9.6744	-6.6087
A	0.0006	0.0001	5.0951	0.0000	0.0004	0.0009	0.0004	0.0009
B, C, D and E	0.0003	0.0000	16.0933	0.0000	0.0002	0.0003	0.0002	0.0003
F	0.0001	0.0001	1.7252	0.0852	0.0000	0.0002	0.0000	0.0002
G, H and I	0.0002	0.0000	5.6168	0.0000	0.0001	0.0003	0.0001	0.0003
R, S, T and U	-0.0005	0.0001	-3.8975	0.0001	-0.0008	-0.0003	-0.0008	-0.0003

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

Table 4.10.- Inference analysis model 5 (5 variables).

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	16683.6533	1563.0751	10.6736	0.0000	13611.2918	19756.0149	13611.2918	19756.0149
Year	-8.2822	0.7774	-10.6541	0.0000	-9.8102	-6.7542	-9.8102	-6.7542
A	0.0006	0.0001	4.8079	0.0000	0.0003	0.0008	0.0003	0.0008
B, C, D and E	0.0003	0.0000	16.1487	0.0000	0.0002	0.0003	0.0002	0.0003
G, H and I	0.0002	0.0000	9.9591	0.0000	0.0002	0.0003	0.0002	0.0003
R, S, T and U	-0.0005	0.0001	-3.9163	0.0001	-0.0008	-0.0003	-0.0008	-0.0003

Note: Analysis based on data from ESS, 2023; Eurostat, 2023.

Table 4.12.- Ranking of predictive models analysed.

Order	Method	Model	Number of Variables	RMSE (Test)
1	AI algorithm	Extra Trees 3	7	3.55
2	AI algorithm	Extra Trees 2	8	3.69
3	AI algorithm	Extra Trees 1	9	3.80
4	AI algorithm	Extra Trees 5	5	4.01
5	AI algorithm	XGBoost 2	8	4.07
6	AI algorithm	XGBoost 5	5	4.09
7	AI algorithm	XGBoost 1	9	4.10
8	AI algorithm	Extra Trees 4	6	4.17
9	AI algorithm	XGBoost 3	7	4.39
10	AI algorithm	Gradient Boosting 1	9	4.52
11	AI algorithm	Bagging 5	5	4.57
12	AI algorithm	Gradient Boosting 2	8	4.59
13	AI algorithm	Gradient Boosting 3	7	4.61
14	AI algorithm	Random Forest 5	5	5.14
15	AI algorithm	XGBoost 4	6	5.25
16	AI algorithm	Gradient Boosting 5	5	5.30
17	AI algorithm	Bagging 1	9	5.56
18	AI algorithm	Random Forest 3	7	5.62
19	AI algorithm	Random Forest 1	9	5.63
20	AI algorithm	Random Forest 2	8	5.68
21	AI algorithm	Gradient Boosting 4	6	5.80
22	AI algorithm	Bagging 2	8	5.94
23	AI algorithm	Bagging 3	7	6.02
24	AI algorithm	Random Forest 4	6	6.24
25	AI algorithm	Bagging 4	6	6.42
26	AI algorithm	Decision Tree 5	5	7.05
27	AI algorithm	Decision Tree 3	7	7.23
28	AI algorithm	AdaBoost 1	9	7.29
29	AI algorithm	AdaBoost 5	5	7.48
30	AI algorithm	Decision Tree 2	8	7.60
31	AI algorithm	Decision Tree 1	9	7.80
32	AI algorithm	Decision Tree 4	6	7.96
33	AI algorithm	AdaBoost 3	7	7.97
34	AI algorithm	AdaBoost 2	8	8.07
35	AI algorithm	AdaBoost 4	6	8.29
36	AI algorithm	K-Nearest Neighbours 2	8	16.61
37	AI algorithm	K-Nearest Neighbours 1	9	16.69
38	AI algorithm	K-Nearest Neighbours 3	7	16.84
39	AI algorithm	K-Nearest Neighbours 4	6	17.92
40	AI algorithm	K-Nearest Neighbours 5	5	18.57
41	AI algorithm	Linear Regression 1	9	30.13
42	AI algorithm	Ridge 1	9	30.24
43	AI algorithm	Bayesian Ridge 1	9	30.56
44	AI algorithm	Lasso 1	9	30.63

45	AI algorithm	SGD Regressor 5	5	30.68
46	AI algorithm	SGD Regressor 4	6	30.70
47	AI algorithm	SGD Regressor 1	9	30.72
48	AI algorithm	Lasso 3	7	30.81
49	AI algorithm	Lasso 4	6	30.81
50	AI algorithm	Lasso 5	5	30.81
51	AI algorithm	Bayesian Ridge 4	6	30.87
52	AI algorithm	Bayesian Ridge 5	5	30.88
53	AI algorithm	Ridge 5	5	30.97
54	AI algorithm	Ridge 4	6	30.97
55	AI algorithm	Lasso 2	8	30.98
56	AI algorithm	Linear Regression 3	7	30.98
57	AI algorithm	Ridge 3	7	30.99
58	AI algorithm	Linear Regression 5	5	31.03
59	AI algorithm	Linear Regression 4	6	31.03
60	AI algorithm	Bayesian Ridge 3	7	31.05
61	AI algorithm	Bayesian Ridge 2	8	31.09
62	AI algorithm	Ridge 2	8	31.10
63	AI algorithm	Linear Regression 2	8	31.16
64	AI algorithm	Elastic Net 1	9	31.24
65	AI algorithm	Elastic Net 4	6	31.28
66	AI algorithm	Elastic Net 2	8	31.36
67	AI algorithm	Elastic Net 3	7	31.39
68	AI algorithm	Elastic Net 5	5	31.40
69	AI algorithm	SGD Regressor 3	7	31.81
70	AI algorithm	SGD Regressor 2	8	32.41
71	AI algorithm	Huber Regressor 1	9	35.32
72	AI algorithm	Huber Regressor 5	5	35.34
73	AI algorithm	Huber Regressor 4	6	35.89
74	AI algorithm	Huber Regressor 2	8	36.35
75	AI algorithm	Huber Regressor 3	7	36.38
76	AI algorithm	RANSAC Regressor 1	9	39.12
77	AI algorithm	RANSAC Regressor 4	6	43.54
78	AI algorithm	RANSAC Regressor 2	8	44.36
79	AI algorithm	RANSAC Regressor 3	7	45.42
80	AI algorithm	RANSAC Regressor 5	5	47.45
81	Traditional	M. Linear regression 5	5	122.02
82	Traditional	M. Linear regression 4	6	203.34
83	Traditional	M. Linear regression 1	9	210.24
84	Traditional	M. Linear regression 3	7	215.51
85	Traditional	M. Linear regression 2	8	223.88

Note: Analysis based on data from ESS, 2023; Eurostat, 2023

ANNEX II

En la actual era impulsada por los datos, la información juega un papel crucial en la reducción de la incertidumbre inherente a cualquier decisión. Al obtener información sobre eventos futuros imprevisibles, podemos obtener una ventaja competitiva sobre otros actores.

A lo largo de la historia, los economistas y estadísticos han desarrollado modelos de toma de decisiones basados en datos objetivos y flujos de trabajo bien definidos en el campo de la economía. En general, hemos observado una evolución desde los primeros análisis puramente descriptivos hacia el análisis predictivo que surgió en la década de 1990. Actualmente, estamos avanzando hacia la predicción de lo que denominamos "incógnitas desconocidas", es decir, eventos imprevisibles que aún escapan a nuestro conocimiento.

Sin embargo, muchos responsables de la toma de decisiones aún confían en gran medida en la intuición en lugar de aprovechar la evidencia numérica para respaldar sus elecciones.

Para abordar esta brecha, hemos delineado dos enfoques clave para la toma de decisiones: el "enfoque exploratorio", que se utiliza para analizar fenómenos novedosos y no estudiados, y el "proceso de estímulo-respuesta", que se aplica a situaciones en las que entendemos claramente el funcionamiento del tema en cuestión.

El primero es un proceso de tres pasos que aglutina el análisis descriptivo, análisis de dependencia y la conceptualización de la estructura de la materia a tratar.

Por su parte, el segundo consta de seis partes. Primero, el análisis predictivo basado en datos históricos, con el objetivo de tomar decisiones proactivas. A continuación, se lleva a cabo un análisis de descubrimiento, cuyo propósito es identificar posibles oportunidades y amenazas futuras a partir de las predicciones. En base a estos hallazgos, se formulan propuestas adecuadas para abordar los problemas o aprovechar las oportunidades identificadas. Seguidamente, se evalúan estas propuestas y se selecciona el orden de prioridad de los distintos descubrimientos identificados, teniendo en cuenta los recursos disponibles de la empresa. En la quinta etapa, se realiza un análisis prescriptivo de las diferentes alternativas propuestas, donde se estudia la mejor línea de acción posible para alcanzar el objetivo establecido. Por último, encontramos la etapa de respuesta, donde se asignan los recursos capitales y humanos necesarios para lograr los objetivos planteados.

Sin embargo, a pesar de estos avances por parte de estadísticos y economistas, se han identificado ciertas limitaciones en las técnicas actuales de análisis de datos, especialmente dado el deficiente rendimiento de los análisis predictivos tradicionales en el mundo real. Esto puede ser una de las principales causas subyacentes de la preferencia de la intuición por parte de los tomadores de decisiones.

En contraste, las técnicas de aprendizaje automático han surgido como una alternativa prometedora, ofreciendo un rendimiento predictivo significativamente superior. En nuestro caso práctico, observamos una notable reducción del 97% en los errores de predicción al comparar los métodos tradicionales con los enfoques novedosos basados en el aprendizaje automático.

Otro punto importante de nuestro trabajo es el reconocimiento del funcionamiento de esta tecnología, así como la diferenciación de los conceptos comúnmente confundidos de IA y ML. La IA es una tecnología que consiste en un conjunto de algoritmos que capacitan a una máquina para realizar tareas similares a las humanas. Sin embargo, cabe destacar que la mayor parte de algoritmos tan solo son capaces de realizar una única tarea, en lugar de las múltiples tareas que puede realizar una persona.

Por otro lado, no todas las máquinas inteligentes poseen la capacidad de aprender patrones por sí mismas. Esta habilidad sólo la poseen los algoritmos de ML, los cuales suelen ser entrenados mediante diferentes enfoques. En líneas generales, estos enfoques incluyen el aprendizaje supervisado, en el cual se utilizan ejemplos del resultado deseado a modo de entreno; el aprendizaje no supervisado, donde se busca la forma óptima de solventar problemas sin proveer al algoritmo de unos ejemplos previos; y el aprendizaje por refuerzo, que implica aprender a partir de recompensas y castigos anteriormente codificados.

Estos algoritmos de ML se componen de distintas capas de nodos conectados entre sí, que intentan simular el funcionamiento del cerebro humano. Aunque en la práctica, lejos de conferir a las máquinas la capacidad de razonar por sí mismas, esta estructura permite llegar a un resultado óptimo en base a correlaciones y patrones encontrados en los datos suministrados con anterioridad.

Estos avances tienen el potencial de revolucionar la forma en que las organizaciones recopilan información, gestionan riesgos y toman decisiones. Para ilustrar estos conceptos, hemos proporcionado varios ejemplos documentados de casos reales que demuestran la aplicación práctica de las técnicas de IA.

Sin embargo, la implementación de estas tecnologías conlleva tanto ventajas como desafíos en la dinámica económica mundial. En términos de ventajas, se espera que la adopción generalizada de la IA impulse el crecimiento de los ingresos a nivel nacional, sectorial y empresarial. Se estima que el Producto Interno Bruto (PIB) global aumente en un 14%. En cuanto a estimaciones sectoriales, se espera un crecimiento de al menos el 10% en todos los sectores económicos, mientras que las empresas pueden anticipar un aumento promedio del flujo de efectivo del 16%.

Este crecimiento se atribuye al incremento del consumo final, impulsado por las mejoras en la calidad y personalización de productos y servicios. Además, para 2035, se espera que la IA eleve los niveles de productividad internacional base entre un 22% y un 26%. Esto será más evidente en las naciones desarrolladas, las cuales han experimentado una desaceleración en el crecimiento de la productividad en los últimos años.

Además, se anticipa que el aprendizaje automático contribuirá a reducir el impacto ambiental, al encontrar formas de reducir el consumo energético y de recursos.

Además de su impacto económico, se anticipa que el aprendizaje automático también contribuirá a abordar los desafíos ambientales al encontrar formas de reducir el consumo de energía y recursos. Por otra parte, la irrupción de esta tecnología, como en anteriores revoluciones, resultará en ganancias laborales a largo plazo.

Sin embargo, junto con estas ventajas, es importante considerar los posibles aspectos negativos. Una preocupación destacada es la disparidad entre países, empresas y trabajadores con diferentes niveles educativos. Se espera que los mayores beneficios de la IA se concentren en las naciones desarrolladas, con China y Estados Unidos liderando y capturando aproximadamente el 70% de estos beneficios a nivel global. Asimismo, se observan diferencias significativas entre las empresas que adoptan la IA tempranamente y aquellas rezagadas, con aumentos respectivos del 122% y del -23% en sus flujos de efectivo.

Además, las diferencias entre los niveles educativos también son notables. Se estima que el 44% de los trabajos que requieren educación inferior a la escuela se verán automatizados, mientras que para aquellos que requieren un título universitario, este porcentaje desciende por debajo del 1%.

Otro desafío es la pérdida de empleo a corto plazo debido a la automatización. Se espera que haya importantes cambios en el mercado laboral, con una transición de trabajos que implican tareas repetitivas hacia trabajos que demandan perfiles con mayores conocimientos técnicos y habilidades emocionales.

Aunque a largo plazo se espera un aumento en la creación de empleo, el tiempo necesario para adaptarse a las nuevas exigencias del mercado laboral podría generar altos niveles de desempleo en las primeras etapas de implementación de esta tecnología. Además, también se deben abordar cuestiones relacionadas con la privacidad personal y los derechos de propiedad intelectual.

En la sección final de este documento, profundizamos en las ventajas de la IA frente a los métodos tradicionales, mediante la realización de un estudio para un caso real en el sector energético europeo. Dado el importante impacto que la invasión ucraniana ha supuesto en esta industria, pretendemos evaluar alguna de las ventajas que la IA puede ofrecer en este contexto.

En particular, nuestro estudio se enfoca en el desarrollo de un modelo predictivo, que estima el consumo final nacional anual de energía, para los 28 estados miembros que conformaban la Unión Europea en 2019, utilizando los valores anuales esperados del valor añadido de cada sector, en cada una de sus respectivas economías nacionales.

Para evaluar la precisión de nuestras predicciones, empleamos la métrica del error cuadrático medio (RMSE). Los resultados demuestran una notable mejora al emplear técnicas de IA, con un RMSE de ±3,55, frente al ±122 logrado con los métodos tradicionales. Esto representa una reducción del error de predicción superior al 97%, lo que pone de relieve la superioridad de nuestro enfoque innovador basado en IA.

Como conclusión, creemos firmemente que la IA se posiciona como una de las herramientas actuales más prometedoras para mejorar los resultados de la toma de decisiones, tanto en organizaciones públicas como privadas. Tomar medidas para fomentar su adopción es crucial, de lo contrario podríamos quedarnos rezagados frente a países y empresas que ya hayan adoptado esta tecnología transformadora.