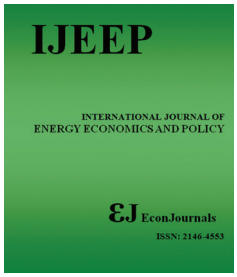

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The Impact of Countries' Artificial Intelligence Readiness Levels on New Business Establishment: Controlling for Energy Consumption, Economic Growth, Inflation, and Population

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ABSTRACT

This study empirically examines how a country's AI readiness level affects the establishment of new businesses while controlling for key macroeconomic variables such as energy consumption, economic growth, inflation, and population growth. It specifically highlights Kazakhstan, a country with significant potential for digital transformation and entrepreneurial development, to clarify the relationship between AI readiness indicators and new business startups at the national level. The analysis utilizes subcomponents of the AI preparedness ındex (AIPI) developed by the International Monetary Fund, which includes digital infrastructure, innovation and economic integration, human capital and labor market policies, and regulation and ethics indicators. The World Bank's "Starting a Business" index is used as a measure of new business establishments. By employing secondary data from various countries, hierarchical regression is applied to assess the additional explanatory power of AI-related indicators on new business formation in a stepwise fashion. The findings indicate that macroeconomic variables such as economic growth, energy consumption, inflation, and population growth have a statistically limited impact on the new business establishment index. In contrast, all sub-indices related to artificial intelligence readiness exert positive and significant effects on new business establishment. Notably, the dimensions of digital infrastructure and regulatory and ethical considerations demonstrate higher explanatory power and effect size. The results underscore that entrepreneurial activity is influenced not only by macroeconomic conditions but also by digital, technological, and institutional capabilities. Therefore, this study emphasizes that AI readiness has become a crucial structural component supporting new business establishment and offers important implications for digital transformation and entrepreneurship policies.

Keywords: Artificial Intelligence Readiness Index, Neural Networks, New Business Establishment, Energy Consumption, Economic Growth, Inflation, Population, Kazakhstans
JEL Classifications: O30, O57, C10, C21, C26

1. INTRODUCTION

Neural network applications, which were crucial for businesses in the 20th century, have further expanded in the 21st century and now form the basis of various artificial intelligence (AI) applications in business. Initially, neural networks were designed to mimic human intelligence in order to analyze and draw conclusions, but they have evolved to interpret the results of these analyses. AI, on the other hand, comprises a comprehensive suite of large-scale applications that facilitate human-centered information communication. While AI applications perform data analysis similar to neural networks, they are far more powerful as they enable human interaction and autonomously manage the analysis process. The rapid advancement in AI technologies has sparked a fundamental technological paradigm shift, transforming economic structures. AI not only fuels automation and boosts efficiency in production processes but also fundamentally reshapes innovation, labor market structures, and entrepreneurship dynamics. In this

context, variations in countries' AI development and adaptation capacities are becoming decisive factors in the emergence of new business models and the encouragement of new business establishments. This study aims to empirically explore the impact of a country's AI development level on the establishment of new business, while controlling for macroeconomic factors such as energy consumption, economic growth, inflation, and population. The significance of this study lies in its ability to examine the AI-entrepreneurship relationship at the national level within a multivariate framework, providing evidence-based insights for digital transformation and entrepreneurship policies.

The effects of artificial intelligence (AI) on economic transformation are primarily discussed in the context of productivity, labor markets, and income distribution. Acemoglu et al. (2022), in their analysis of AI and automation's impact on labor demand, found that technology creates new job opportunities while substituting certain tasks. Similarly, Acemoglu and Restrepo (2022) highlighted that task-based automation can increase wage inequalities, but this process is closely linked to institutional and technological capabilities. Aghion et al. (2017) considered AI a general-purpose technology with the potential to accelerate long-term economic growth, arguing that technological differences between countries can lead to divergent growth paths. In this context, AI is viewed as a strategic element that not only transforms existing economic structures but also facilitates the emergence of new economic actors. Artificial neural networks, particularly deep learning approaches, are the backbone of this transformation and they enable the processing of large-scale data and modeling complex economic processes. This algorithmic infrastructure allows firms to make more effective decisions in areas such as demand forecasting, production planning, pricing, and risk management; these advancements help lower barriers to entry and promote the establishment of new businesses. The AI preparedness ındex (AIPI), developed by the IMF to assess countries' levels of AI development - currently only presenting data for 2023 - is significant in this regard (IMF, 2026).

The impact of AI on innovation processes is another critical area of discussion in entrepreneurship literature. Cockburn et al. (2018) argue that AI acts as a "general-purpose technology" within innovation processes, accelerating the production of new knowledge and creating a conducive environment for entrepreneurial activities. Brynjolfsson and McAfee (2017) contend that AI transforms business economies of scale, reduces barriers to entry, and facilitates small-scale enterprises' access to global markets. This transformation is particularly important in countries with robust digital infrastructure, as it supports the rise of new business establishments.

Research on entrepreneurship has long emphasized the relationship between technological advancements and the formation of new businesses. Audretsch and Keilbach (2004) demonstrated that venture capital plays a crucial role in economic performance and that innovative capacity fosters the emergence of new firms. Audretsch and Thurik (2001) argued that, within the "new economy" framework, technological change is central to the transition from managed economies to entrepreneurial economies. This perspective provides a significant theoretical foundation for understanding AI's transformative impact on the entrepreneurial ecosystem.

The implications of digitalization and AI on entrepreneurship have only recently begun to be systematically explored. Nambisan et al. (2019) suggested that digital technologies have transcended spatial and organizational boundaries in entrepreneurial processes, accelerating the formation of new businesses. Obschonka and Audretsch (2020) pointed out that AI and big data have ushered in a new era in entrepreneurship research, particularly emphasizing how digital and technological capabilities at the national level shape entrepreneurial behavior. These studies indicate that advancements in AI can have both direct and indirect effects on the establishment of new businesses.

The development of new businesses at the country level is closely linked to the institutional structure and regulatory framework. Klapper et al. (2006) demonstrated that entry regulations can pose significant barriers to new firm entry, while Djankov et al. (2006) highlighted how regulatory quality affects economic growth and entrepreneurial performance. Wennekers et al. (2005) showed that the level of entrepreneurship varies depending on a country's stage of economic development, underscoring the importance of comparative analyses at the country level. In this context, collecting data on new business establishments in a comparable manner across countries is critical for maintaining methodological consistency in research studies.

The impact of AI-based technologies on economic structures, entrepreneurial dynamics, and business establishment processes has been extensively debated in recent years, both in developed and developing countries. Notably, the influence of structural elements such as digital infrastructure capacity, innovation ecosystems, human capital, and regulatory frameworks on entrepreneurial activities underscores the growing importance of comparative analyses at the country level. Within this context, it is emphasized that AI's impact on entrepreneurship involves not only technological transformations but also institutional and governance changes (Hamada et al., 2021). Kazakhstan has emerged as one of the leading countries in Central Asia in terms of digital transformation and the integration of AI-based technologies into its economic and institutional frameworks. The critical role of small and medium-sized enterprises (SMEs) in economic diversification, job creation, and sustainable growth has made the strengthening of the entrepreneurial ecosystem a strategic priority. Indicators show that Kazakhstan's level of AI readiness has potential for improvement, particularly in areas like digital infrastructure, innovation, economic integration, and regulatory frameworks. When examining the new business establishment index and its sub-indicators related to artificial intelligence, it becomes evident that the entrepreneurial environment is influenced not just by macroeconomic conditions but also by technological capacity and institutional structures (IMF, 2026; World Bank, 2026). Recent empirical studies indicate that artificial intelligence and advanced analytical methods significantly enhance the prediction of small business success, offering greater explanatory power compared to traditional approaches (Bekbolsynova et al., 2025).

Therefore, Kazakhstan serves as a meaningful and representative case for analyzing the relationship between artificial intelligence development and entrepreneurship at the country level.

This study incorporates various macroeconomic control variables to better isolate the effects of AI development on new business establishments. Energy consumption is included as a key control variable, reflecting the scale of economic activity and production capacity (Stern, 2000). Economic growth is closely linked to endogenous technological development processes and can stimulate entrepreneurial activity (Romer, 1990). The inflation rate, a measure of macroeconomic stability, affects investment and entrepreneurial decisions (Barro, 2013), while population growth rate indicates the size of the potential pool of entrepreneurs and the breadth of the market (Bloom et al., 2003).

For the empirical analysis, hierarchical regression was employed. This method allows for the gradual addition of independent variables to the model, helping to assess the additional explanatory power of AI development on new business creation (Cohen et al., 2003; Tabachnick and Fidell, 2019). Initial inclusion of the control variables enabled the separation of the impact of macroeconomic conditions; subsequently, the addition of the AI indicator highlights the unique contribution of technological capacity to entrepreneurship. This approach is widely recognized in multivariate analyses and provides a robust methodological framework (Hair et al., 2019). Overall, the study aims to make an original and empirical contribution to the literature on the impact of digitalization on new business formations by integrating insights from artificial intelligence, entrepreneurship, and economic transformation at the country level through a holistic approach.

2. LITERATURE REVIEW

The literature reviewed in this study encompasses both theoretical and empirical research which examined the effects of artificial intelligence (AI) technologies on economic structure, innovation processes, and entrepreneurial dynamics within a multidimensional framework. Studies focusing on the impact of AI on labor markets, wage structures, and productivity reveal the economic consequences of technological transformation. Meanwhile, research on entrepreneurship, digitalization, and corporate structure sheds light on the conditions under which new businesses are formed. Additionally, studies addressing macroeconomic factors such as energy consumption, economic growth, inflation, and population provide a contextual framework for understanding the economic environment in which entrepreneurial activities occur. Within this comprehensive literature, it appears that an isolated analysis of the impact of AI advancements on new business formation at the national level can only be effectively conducted through a holistic approach that considers technological capacity, corporate structure, and macroeconomic conditions together. Therefore, the studies presented below explain the AI-entrepreneurship relationship through both direct and indirect mechanisms, forming the theoretical background and empirical framework of this research.

Acemoglu et al. (2022) empirically examined the effects of AI technologies on employment and labor demand. Their study specifically aimed to reveal how AI transforms the job market in terms of professions and tasks. It utilized large-scale microdata obtained from online job postings in the United States to analyze changes in skill demands related to AI over time. Through this data, indicators of AI exposure were created at the profession-task level, and panel data regression techniques were applied. The findings indicate that the increase in AI-intensive tasks leads to employment growth in certain occupational groups while causing job losses in routine and automation-prone tasks. Moreover, AI was found to play a complementary role in some sectors by encouraging the emergence of new tasks; however, this effect is more pronounced in high-skilled professions. The study concludes that the effects of AI on the labor market are not uniform and that technological transformation creates both winners and losers.

Acemoglu and Restrepo (2022) investigated the role of automation and task-based technological change in increasing wage inequality in the United States. The primary objective of their research was to analyze, at the task level, the mechanisms through which technological progress affects employment and wage structures. The study employed comprehensive datasets containing occupational, task, and wage data from the US labor market, categorizing tasks vulnerable to automation versus those created by new technologies for analysis. Structural modeling and regression techniques were utilized to empirically evaluate the long-term effects of automation on wage distribution. The findings reveal that automation suppresses wages, particularly in occupations requiring moderate skills, while supporting wage increases in highly skilled and technology-complementary tasks. Additionally, the study found that the capacity of technological progress to create new tasks partially offsets the negative effects of automation, though this compensatory effect is not experienced equally across all occupational groups. The study concludes that task-based automation contributes to increasing wage inequality, a process influenced by organizational structure and skill distribution.

In their study, Aghion et al. (2017) explored the effects of artificial intelligence technologies on long-term economic growth using a theoretical framework. They aimed to uncover the role of artificial intelligence in the economic growth process and the mechanisms by which this technology alters growth dynamics. Instead of relying on an empirical dataset, the researchers used analytical models grounded in endogenous growth theories. Within this context, artificial intelligence was regarded as a general-purpose technology that enhances knowledge production and boosts the efficiency of research and development activities. The model's results indicate that artificial intelligence can increase the capacity for innovation by complementing human labor in research processes, which has a positive long-term impact on economic growth rates. However, the authors emphasize that the beneficial effects of artificial intelligence on growth do not occur automatically; institutional structure, education levels, and the capacity for technological adaptation play crucial roles in shaping this process. The study also highlights that the potential influences of artificial intelligence on income distribution and labor markets may hinder the equitable distribution of growth benefits across society.

Audretsch and Keilbach (2004) investigated the impact of entrepreneurial activities on economic performance through the lens of "entrepreneurship capital." The primary objective was to demonstrate how entrepreneurship serves as a critical factor of production, not only at the individual firm level but also in terms of regional and national economic performance. Their research utilized regional data collected in Germany, incorporating metrics such as new firm establishment rates, employment structure, and indicators of regional economic performance. Employing multivariate regression techniques for their empirical analyses, they tested the effects of entrepreneurial capital on regional growth and productivity. Their findings reveal that entrepreneurial capital has a statistically significant and positive impact on economic performance. Specifically, regions with a high concentration of new business establishments showed higher levels of economic growth and productivity. The study concludes that entrepreneurial activities accelerate knowledge diffusion, enhance innovation capacity, and, consequently, indirectly support economic performance.

Nambisan et al. (2019) examined how digital technologies transform innovation and entrepreneurship processes through a conceptual and holistic framework. Their main objective was to reveal how digital transformation reshapes the nature, scale, and organizational forms of entrepreneurial activities. Rather than relying on empirical data analysis, this research involved a systematic review of existing studies and the development of a conceptual model. The authors emphasize that digital platforms, big data, artificial intelligence, and algorithmic systems play a pivotal role in innovation processes. They argue that digital technologies have largely liberated entrepreneurial activities from spatial and temporal constraints, accelerated the emergence of new business models, and lowered barriers to entry. Furthermore, the study states that digital transformation enhances entrepreneurs' access to resources, expanding opportunities for experiential learning and scalability. The findings reveal that digital technologies have become a fundamental component of the entrepreneurial ecosystem, leading to innovation evolving into a more open, network-based, and platform-oriented structure.

Obschonka and Audretsch (2020) examined the transformative effects of artificial intelligence (AI) and big data technologies on entrepreneurial activities, arguing that a new era of entrepreneurship has begun. Their primary objective was to reveal how AI-powered data analytics and algorithmic systems reshape entrepreneurial processes and influence entrepreneurial behavior. Rather than relying on a single empirical dataset, the research evaluated existing empirical studies and developed a conceptual framework. The study emphasizes that AI and big data applications offer significant advantages to entrepreneurs in various processes, including opportunity identification, business idea development, resource allocation, and scaling. The authors argue that data-driven decision-making mechanisms reduce uncertainty and transform how entrepreneurs perceive risk. Furthermore, they state that AI-powered systems shift entrepreneurial activities away from reliance on individual intuition towards a more systematic and analytical approach. The findings indicate that artificial intelligence and big data create new opportunities in the entrepreneurial ecosystem at both individual and regional levels, fostering a supportive environment for the establishment of new businesses.

Klapper et al. (2006) empirically examined the impact of entry regulations on entrepreneurial activity and the establishment of new businesses at the country level. The primary aim of the study was to determine whether legal and administrative regulations regarding company formation pose an obstacle to entrepreneurship, and how this effect varies among countries. The research utilized a broad panel of countries with differing income levels, incorporating new firm entry rates, sector-level firm demographic data, and regulatory indicators from the World Bank. Panel data regression methods were employed to analyze the effects of entry regulations on entrepreneurship across different sectors and countries. The findings reveal that new business entries are significantly lower in countries with high bureaucratic costs and regulatory burdens in the company formation process. The negative impact of entry regulations on entrepreneurship is particularly pronounced in sectors that rely on external financing and possess high growth potential. The study concludes that regulatory barriers reduce competition and weaken market dynamism, highlighting that entry regulations serve as a deterrent to entrepreneurship and that institutional reforms are essential for encouraging the establishment of new businesses.

Djankov et al. (2006) examined the impact of economic regulations on economic growth within a comparative framework across countries. Their main objective was to identify the mechanisms through which entry regulations, ease of doing business, and legal-institutional regulations affect economic growth performance. The research used a panel dataset covering numerous countries from various income groups, including economic growth rates and indicators reflecting regulatory quality in the analysis. For empirical analysis, cross-country regression techniques were applied to test the relationship between the regulatory environment and economic growth. The findings show that excessive and complex regulations significantly hinder economic growth. The study indicates that capital accumulation and entrepreneurial activity are weaker in countries with particularly strict entry and operating regulations. Conversely, growth performance is higher in countries with more flexible and market-friendly regulatory frameworks. Additionally, the study reveals that regulatory quality indirectly affects the growth process through channels of financial development and investment.

Wennekers et al. (2005) examined the relationship between nascent entrepreneurship and the level of economic development in various countries. Their main objective was to investigate how entrepreneurship changes at different stages of economic development and to identify the structural factors that influence this relationship. The research utilized international comparative datasets that included countries with varying income and development levels, measuring entrepreneurship indicators through data from the global entrepreneurship monitor (GEM). For empirical analysis, cross-country regression techniques were applied to test the effects of per capita income level, labor market structure, and institutional factors on entrepreneurship. The findings indicate that entrepreneurship levels exhibit a non-

linear relationship with economic development; specifically, entrepreneurship rates tend to be relatively high in low- and high-income countries but lower in middle-income countries. This trend is attributed to the fact that paid employment becomes more attractive than self-employment at certain stages of economic development. The study also highlights that institutional structures and labor market conditions significantly influence entrepreneurial activity.

Stern (2000) analyzed the role of energy consumption in the macroeconomy of the United States from a long-term perspective. The study aimed to clarify the direction and nature of the relationship between energy consumption and economic growth within a multivariate framework. It involved long-term time series data for the U.S., incorporating energy consumption, capital, labor, and output variables into the analysis. Empirical analyses were performed using multivariate cointegration analysis and error correction models to determine the long-term relationships between these variables. The findings suggest that energy consumption is not merely a passive input in the economic growth process, but rather a fundamental and complementary element of production. Specifically, increases in energy use significantly impact output levels in the long run, and the relationship between energy and growth is bidirectional. Additionally, the study reveals that energy prices and technological advancements indirectly influence macroeconomic performance through energy demand.

Romer (1990) addressed the role of technological change in the economic growth process within the framework of endogenous growth theory. The primary objective of this study was to explain how technological progress emerges as a process determined by the dynamics of the economic system rather than as an external factor. The research does not rely on empirical data; instead, it theoretically explores the relationships among technological innovation, knowledge accumulation, and economic growth through analytical and mathematical models. The model identified research and development activities, human capital, and knowledge production as fundamental drivers of economic growth. The findings demonstrate that knowledge production generates increasing returns, which enable sustainable economic growth in the long term. Furthermore, the study emphasizes that technological innovations are driven by market incentives and institutional structures; thus, public policies and the investment environment play a crucial role in the growth process. The conclusions highlight that technological development is central to economic growth, and that a country's capacity for innovation is a critical factor in explaining growth disparities.

Barro (2013) investigated the relationship between inflation and economic growth from a long-term and comparative perspective. The main goal of the study was to assess the impact of inflation rates on economic growth performance and to determine whether this relationship is linear. The study utilized macroeconomic data from a broad sample of countries with varying income levels, including inflation rates and per capita economic growth rates in the analysis. Panel data regression techniques were employed to empirically test the effects of inflation on growth while controlling for other variables. The findings indicate that low and stable inflation rates have a limited effect on economic growth, whereas high and volatile inflation rates significantly harm economic growth. In particular, high inflation is shown to distort investment decisions, reduce capital accumulation, and lead to inefficiencies in resource allocation. The study also reveals that the impact of inflation on growth is more pronounced in developing countries.

Bloom et al. (2003) investigated how changes in population structure influence economic growth, focusing on the concept of the demographic opportunity window (or demographic dividend). The primary aim was to understand how declines in fertility and mortality rates affect the age structure of a population and the potential implications for economic performance. The research utilized long-term demographic and macroeconomic data from countries with varying levels of development, incorporating factors such as the proportion of the working-age population, dependency ratios, savings levels, and economic growth indicators. Through empirical analyses, including cross-country comparisons and regression techniques, the study examined the relationships between demographic structure and economic growth. The findings revealed that an increase in the share of the working-age population can accelerate economic growth, provided it is supported by suitable education, employment, and institutional policies. However, the study emphasized that demographic opportunities do not automatically lead to economic growth; factors such as labor market flexibility, investments in human capital, and macroeconomic stability significantly influence this relationship. The research also indicated that population growth rates and age structure indirectly affect entrepreneurial potential and capital accumulation.

The empirical literature exploring the relationship between energy consumption and economic growth provides an essential framework for understanding the indirect influences of macroeconomic conditions on entrepreneurship and new business establishment. In this context, Aidarova et al. (2024) and Abdibekov et al. (2024) analyzed the long-term relationships among energy consumption, production structure, and economic growth using panel ARDL and bounds test methodologies, discovering that energy use plays a statistically significant role in economic performance. Similarly, Baimagambetova et al. (2025) and Lukhmanova et al. (2025) examined the causal links between energy consumption and economic growth through panel causality and Toda-Yamamoto causality tests across various country groups and samples, demonstrating that energy consumption is a key macroeconomic factor influencing growth dynamics. Although these studies do not directly address artificial intelligence or entrepreneurship, their findings highlight the critical impact of energy consumption on economic structure, reinforcing the rationale for incorporating energy as a control variable in this study.

Current literature discusses the effects of artificial intelligence (AI) technologies on economic structure, employment, innovation, and entrepreneurship at different levels. However, findings regarding how these effects manifest at the country level and under various macroeconomic conditions remain limited. Notably, there is a lack of empirical studies investigating the impact of AI advancements on new business establishments while controlling

for key macroeconomic variables such as energy consumption, economic growth, inflation, and population. This gap highlights the need for a more systematic and comparative analysis of the unique contribution of technological capacity to entrepreneurship. Therefore, the following section of this study outlines the empirical model, the datasets utilized, and the analysis methodology developed to examine how countries' levels of AI advancement affect new business establishments. This approach aims to fill the identified gap in the literature through a theoretically grounded and methodologically consistent empirical framework.

3. METHOD

One significant advantage of hierarchical regression over multiple regression is its capacity to introduce independent variables (predictive variables) into the model in an order determined by theoretical or empirical assessments. This ordered approach allows for a clearer examination of the primary independent variable's effect. Hierarchical regression is a widely used method for analyzing the individual impact of each group of variables, which are added incrementally in the analysis. This method calculates the change in adjusted R-squared at each step, thereby measuring the increase in variation for the enhanced model (Pedhazur, 1997; Lewis, 2007). The method is especially valuable for models that include control variables, as it estimates the effect of the main independent variable independently from the control variable. Control variables are essentially fixed factors in relation to the research question. While these variables may not direct relevance to the research problem, omitting them can lead to misinterpretation of the findings.

4. DATA AND FINDINGS

The Starting a Business indicator is a part of the World Bank's Doing Business project, designed to measure how easy or difficult it is to formally establish a new business in an economy. The primary aim of this indicator is to objectively assess the number of procedures, completion time, costs, and minimum paid-in capital required for setting up a new limited liability company. This ensures comparability across over 190 countries. The World Bank's methodology is based on formal processes applicable in the largest business cities worldwide (World Bank, 2026).

This indicator uses a standardized business definition for each economy: A limited liability company that is 100% domestically owned, established with initial capital of 10 times its revenue, engaged in general commercial or manufacturing activities, and employing between 10 and 50 local employees within 1 month of its establishment. The measurement also considers two types of standard companies, differing only by the gender of their owners - one with five married women and the other with five married men. The index score is a simple average of the component indicators calculated for these two types of companies (World Bank, 2026).

The indicators include recording all the necessary procedures involved in the business establishment process. These procedures encompass the required approvals, licenses, permits, and legal registration processes. Furthermore, the time and cost associated with each procedure are calculated, and the information collected from experts such as local lawyers, notaries, and public officials during the data collection process is verified. The sequential nature of the processes, their simultaneous execution capability, and data consistency are rigorously examined, enhancing the international comparability of the methodology (World Bank, 2026).

In this context, the Starting a Business indicator offers a reliable foundation for understanding the entrepreneurial environment, identifying international best practices, and monitoring the impact of regulatory burdens on new business establishment.

With the information age, data and information technologies have rapidly integrated into our individual, social, and economic lives. In particular, the impact of these technologies on economic activities has become essential, primarily through their integration into information management. The initial adoption of information and communication technologies in business was facilitated by effective automation and information management. Subsequently, analytical methods, such as expert software and artificial neural networks that create models from data, emerged to yield effective results for businesses. Today, all these information management methods are encompassed under artificial intelligence, which has become an indispensable element, without alternatives or substitutes.

The artificial ıntelligence readiness ındex (AIPI), developed by the ınternational monetary fund (IMF), is a comparable indicator designed to measure countries' capacity to adopt artificial intelligence technologies and derive economic and social benefits from them. The index evaluates how countries adapt to artificial intelligence within a multi-dimensional framework and serves as an analytical reference for policymakers (IMF, 2026).

The AIPI is structured around four key dimensions that assess how effectively countries can utilize artificial intelligence: Digital infrastructure, human capital and labor market policies, innovation and economic integration capacity, and regulatory and ethical frameworks. These dimensions represent structural factors that significantly influence the adoption and spread of artificial intelligence (IMF, 2026). The indicators used in the index are standardized and calculated on a scale of 0-1 to ensure comparability between countries; higher scores indicate a greater level of AI readiness.

Recent analyses published by the IMF indicate that generative AI technologies, in particular, can have transformative effects on labor markets, productivity dynamics, and income distribution. In this context, differences in AIPI scores among countries suggest that the impact of AI on economic growth and employment may vary from one country to another (Cazzaniga et al., 2024). Consequently, AIPI is regarded as an important variable for controlling the structural preparedness levels of countries in empirical studies analyzing the macroeconomic impacts of artificial intelligence technologies.

This study focuses on the sub-indices of digital ınfrastructure, ınnovation and economic ıntegration, human capital and labor market policies, and regulation and ethics, rather than using the AI readiness index as a predictor for the New Business Establishment Index. This approach more clearly illustrates the impact of artificial intelligence and neural networks on the establishment of new businesses. Table 1 systematically summarizes the variables used in the study, providing brief descriptions and data sources. Since the AI readiness index data was published only for 2023, the study is limited to data from that year. The data was obtained from the following sources: https://www.imf.org/external/datamapper, https://data.worldbank.org, https://ourworldindata.org, and https://archive.doingbusiness.org/en/data (Access date: 01.11.2025).

In analyzing the research data, we first presented descriptive statistics to give an overview of the countries regarding the examined variables. In the second step, we examined the impact of the AI readiness indices on entrepreneurship, specifically the New Business Establishment Index, using hierarchical regression models. This step involved analyzing the influence of each sub-dimension of the AI readiness index on the establishment of new businesses separately.

Table 2 presents the descriptive statistics for the variables included in the study. The proximity of the mean and median values in the AI readiness index (AIPI), along with its subcomponents - digital ınfrastructure ındex (DII), Innovation and economic ıntegration ındex (IECII), human capital and labor market ındex (HCLMI), and regulation and ethics ındex (RETI) - indicates a balanced distribution of these variables across the sample. Additionally, the skewness and kurtosis values for these variables are within acceptable limits, suggesting that their distributions are relatively close to normal. Regarding the macroeconomic control variables, the distributions of GDP and population growth rate (POPGR) are statistically balanced. However, the significant range between the minimum and maximum values of the energy consumption (ENERGC) variable highlights diverse energy consumption dynamics among countries. Despite this, the skewness and kurtosis values for energy consumption indicate that its distribution is generally acceptable. One notable finding in the table pertains to the inflation variable (INFCP). The high skewness and kurtosis coefficients for inflation, compared to other variables, suggest that inflation rates exhibit an asymmetric distribution among countries. The presence of significantly high inflation values in some countries skews the distribution to the right. This finding is essential as it indicates that countries have a non-homogeneous structure in terms of inflation.

The impact of the digital ınfrastructure ındex on the new business establishment ındex was analyzed through hierarchical regression using two models (Table 3). The first model assessed only the effects of control variables on the digital ınfrastructure ındex (Model 1: $F = 1.490$, $P > 0.05$). According to this model, only inflation demonstrated a statistically significant effect on the new business establishment ındex at the 0.10 significance level, while the other variables showed no statistically significant effects. In Model II, the digital ınfrastructure ındex variable was included in the analysis. The model was again found to be statistically significant ($F = 9.607$, $P < 0.05$). Unlike the first model, inflation's effect became statistically insignificant in Model II. However, the digital ınfrastructure ındex had a significant effect ($\beta = 0.536$, $P < 0.05$). Thus, we observe that digital infrastructure positively influences the new business establishment ındex. The coefficient of determination in Model I was calculated at 0.041, while in Model II, it increased significantly to 0.230. Also, the change in R-squared was found to be statistically significant. This indicates that the control variables explain only 4.1% of the variability in the new business establishment ındex, but when the digital ınfrastructure ındex is included, the model explains 23% of this variability.

Table 1: Variable definitions and sources

Variable	Definition	Source
AIPI	AI preparedness index	https://www.imf.org/external/datamapper
DII	Digital infrastructure	https://www.imf.org/external/datamapper
IECII	Innovation and economic integration	https://www.imf.org/external/datamapper
HCLMI	Human capital and labor market policies	https://www.imf.org/external/datamapper
RETI	Regulation and ethics	https://www.imf.org/external/datamapper
GDP	GDP growth (annual %)	https://data.worldbank.org
ENERGC	Annual change in primary energy consumption (%)	https://ourworldindata.org/energy-production-consumption
INFCP	Inflation, consumer prices (annual %)	https://data.worldbank.org
POPGR	Population growth (annual %)	https://data.worldbank.org
SBS	Starting a business score	https://archive.doingbusiness.org/en/data

Table 2: Descriptive statistics findings for the variables

Statistics	Mean	Median	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
AIPI	0.4949	0.4895	0.15213	0.18	0.80	0.212	−0.908
DII	0.1163	0.1137	0.04819	0.02	0.21	0.097	−1.126
IECII	0.1201	0.1144	0.03400	0.03	0.19	0.055	−0.409
HCLMI	0.1277	0.1267	0.03279	0.03	0.20	−0.294	−0.159
RETI	0.1309	0.1337	0.04718	0.03	0.23	0.203	−0.648
GDP	3.0644	2.8876	2.55338	−5.53	10.16	0.040	0.518
ENERGC	0.9848	1.5472	5.08134	−19.47	15.57	−0.532	2.249
INFCP	8.3863	5.6491	9.57571	−1.04	53.86	2.959	9.350
POPGR	1.3713	1.2217	1.33059	−1.15	6.53	0.881	1.350
SBS	86.0879	87.8000	8.81130	52.50	100.00	−1.157	1.391

According to the f-squared values that express predictive power for both models, Model I, which includes only the control variables, has a predictive power of 4.3%, while Model II, which incorporates the Digital Infrastructure Index, has a predictive power of 29.9%. For both models, we examined the presence of multicollinearity among the independent variables using VIF coefficients and determined that no multicollinearity exists.

The effect of the ınnovation and economic ıntegration ındex on the new business establishment Index was assessed using hierarchical regression with two models (Table 4). In the first model (Model 1), only control variables (GDP, energy consumption, inflation, and population growth rate) were included, and the model was found to be statistically insignificant overall ($F = 1.490$; $P > 0.05$). Among the control variables, only inflation showed borderline significance at the 10% level, while the other variables were statistically insignificant. In the second model (Model 2), the ınnovation and economic ıntegration ındex (IECII) was added. This model proved to be statistically significant ($F = 6.087$; $P < 0.05$). The results of Model 2 indicated that the IECII variable has a positive and statistically significant effect on the new business establishment ındex ($\beta = 0.418$; $t = 4.837$; $P < 0.05$). This finding suggests that as countries enhance their innovation capacity and level of economic integration, the conditions for establishing new businesses improve. The insignificance of all control variables in Model 2 indicates that the explanatory power of the IECII is more dominant. Examining the model fit measures, the explained variance ratio (R^2) was 0.041 in Model 1, which increased to 0.184 in Model 2. This 0.141 increase in R^2 is statistically significant ($\Delta R^2 = 0.141$; $F = 23.394$; $P = 0.000$), revealing that the addition of the Innovation and economic ıntegration ındex significantly elevates the explanatory power regarding the variation in the new business establishment ındex. The f^2 values, indicating effect size, display a low effect size for Model 1 ($f^2 = 0.056$) and a near-moderate effect size for Model 2 ($f^2 = 0.225$). Additionally, the VIF values remaining within acceptable limits in both models confirms that there is no issue with multicollinearity among the independent variables.

The effects of the human capital and labor market policies index on the new business establishment index were analyzed in Table 5 using a two-stage modeling approach with hierarchical regression. In the first model (Model 1), only control variables - GDP, energy consumption, inflation, and population growth rate - were included. Overall, this model was found to be statistically insignificant ($F = 1.490$; $P > 0.05$). Among the control variables, only the inflation variable approached the 10% significance level, while the other control variables did not have a statistically significant effect on the new business establishment index. In the second model (Model 2), the human capital and labor market policies index (HCLMI) was added to the analysis. This model proved to be statistically significant ($F = 8.008$; $P < 0.05$). The results indicated that the HCLMI variable has a positive and statistically significant effect on the new business establishment index ($\beta = 0.469$; $t = 5.719$; $P < 0.05$). This finding suggests that the quality of human capital and the enhancement of labor market policies contribute positively to conditions for starting new businesses. Notably, all control variables in Model 2 became statistically insignificant, highlighting the significant explanatory power of HCLMI. When evaluating the model fit measures, the explained variance ratio (R^2) increased from 0.041 in Model 1 to 0.224 in Model 2. This 0.183 increase in R^2 is statistically significant ($\Delta R^2 = 0.183$; $F = 32.709$; $P = 0.000$), indicating that the inclusion of human capital and

Table 3: Hierarchical regression findings for the effect of the digital infrastructure index on the new business establishment index

Variable code	Model 1				Model 2			
	Beta	t	Significance	VIF	Beta	t	Significance	VIF
GDP	−0.117	−1.377	0.171	1.052	0.092	1.126	0.262	1.254
ENERGC	0.009	0.107	0.915	1.091	−0.006	−0.077	0.939	1.092
INFCP	−0.155	−1.872	0.063	1.001	−0.072	−0.964	0.337	1.033
POPGR	−0.045	−0.534	0.594	1.041	0.089	1.143	0.255	1.124
DII					0.536	6.356	0.000	1.328
F	1.490 (P>0.05)				9.607 (P<0.05)			
R^2	0.041				0.230			
ΔR^2					0.216 (F=40.397, *P*=0.000)			
f^2	0.043				0.299			

Table 4: Hierarchical regression findings for the effect of the innovation and economic integration index on the new business establishment index

Variable code	Model 1				Model 2			
	Beta	t	Significance	VIF	Beta	t	Significance	VIF
GDP	−0.117	−1.377	0.171	1.052	0.002	0.028	0.978	1.192
ENERGC	0.009	0.107	0.915	1.091	0.054	0.656	0.513	1.106
INFCP	−0.155	−1.872	0.063	1.001	−0.057	−0.712	0.478	1.052
POPGR	−0.045	−0.534	0.594	1.041	−0.016	−0.202	0.840	1.056
IECII					0.418	4.837	0.000	1.233
F	1.490 (P>0.05)				6.087 (P<0.05)			
R^2	0.041				0.184			
ΔR^2					0.141 (F=23.394, *P*=0.000)			
f^2	0.056				0.225			

Table 5: Hierarchical regression findings for the effect of the human capital and labor market policies index on the new business establishment index

Variable code	Model 1				Model 2			
	Beta	t	Significance	VIF	Beta	t	Significance	VIF
GDP	−0.117	−1.377	0.171	1.052	0.040	0.489	0.626	1.186
ENERGC	0.009	0.107	0.915	1.091	0.012	0.156	0.876	1.091
INFCP	−0.155	−1.872	0.063	1.001	−0.083	−1.094	0.276	1.029
POPGR	−0.045	−0.534	0.594	1.041	0.026	0.342	0.733	1.069
HCLMI					0.469	5.719	0.000	1.203
F		1.490 (P>0.05)				8.008 (P<0.05)		
R^2		0.041				0.224		
ΔR^2						0.183 (F=32.709. *P*=0.000)		
f^2		0.043				0.288		

Table 6: Hierarchical regression findings for the effect of the regulation and ethics index on the new business establishment index

Variable code	Model 1				Model 2			
	Beta	t	Significance	VIF	Beta	t	Significance	VIF
GDP	−0.117	−1.377	0.171	1.052	0.075	0.938	0.350	1.216
ENERGC	0.009	0.107	0.915	1.091	0.025	0.324	0.746	1.092
INFCP	−0.155	−1.872	0.063	1.001	−0.054	−0.722	0.471	1.047
POPGR	−0.045	−0.534	0.594	1.041	0.048	0.640	0.523	1.080
RETI					0.535	6.519	0.000	1.273
F		1.490 (P>0.05)				10.046 (P<0.05)		
R^2		0.041				0.265		
ΔR^2						0.225 (F=32.709, *P*=0.000)		
f^2		0.056				0.265		

labor market policy indices substantially enhances the model's explanatory power concerning the variation in the new business establishment index. The f^2 values, which measure effect size, indicate a low effect size for Model 1 ($f^2 = 0.043$) and a moderate to strong effect size for model 2 ($f^2 = 0.288$). Additionally, the VIF values remained within acceptable limits in both models, indicating no multicollinearity problem among the independent variables.

The effect of the regulation and ethics index on the new business establishment index was analyzed using a two-stage modeling approach with hierarchical regression, as shown in Table 6. In the first model (Model 1), only the control variables - GDP, energy consumption, inflation, and population growth rate - were included. This model was found to be statistically insignificant overall ($F = 1.490$; $P > 0.05$), with the effects of all control variables being statistically insignificant. In the second model (Model 2), the regulation and ethics index (RETI) was incorporated into the analysis. This model was statistically significant ($F = 10.046$; $P < 0.05$). The results indicated that the RETI variable has a positive and statistically strong effect on the new business establishment index ($\beta = 0.535$; $t = 6.519$; $P < 0.05$). This finding shows that an effective regulatory framework and strong ethical standards significantly enhance the conditions for establishing new businesses in countries. The insignificance of all control variables in Model 2 further underscores the dominant explanatory power of RETI. When examining the model fit measures, the explained variance ratio (R^2) was 0.041 in Model 1 and increased to 0.265 in Model 2. The increase of 0.225 in R^2 was statistically significant ($\Delta R^2 = 0.225$; $F = 32.709$; $P = 0.000$). This result demonstrates that adding the regulatory and ethical index significantly boosts the explanatory power concerning the variation in the new business establishment index. The f^2 values indicate a low effect size for Model 1 ($f^2 = 0.056$) and a medium-high effect size for Model 2 ($f^2 = 0.265$). Furthermore, the VIF values remained within acceptable limits in both models, confirming that there is no multicollinearity problem among the independent variables.

5. CONCLUSION AND RECOMMENDATIONS

This study examines how a country's readiness for artificial intelligence (AI) affects new business establishment, while accounting for key macroeconomic factors such as energy consumption, economic growth, inflation, and population growth. The findings indicate that although macroeconomic indicators have a limited direct effect on the new business establishment index, structural indicators related to artificial intelligence play a significant and explanatory role. This highlights the importance of recognizing that today's entrepreneurship is influenced not only by traditional macroeconomic conditions but also by digital and technological capacities.

Hierarchical regression analyses reveal that the sub-components of AI readiness significantly and positively impact new business establishment. Indices related to digital infrastructure, innovation and economic integration, human capital and labor market policies, as well as regulatory and ethical frameworks, each contribute to an increased explained variance in the model and strongly affect the new business establishment index. The fact that regulation, ethics, and digital infrastructure have higher explanatory power and effect size indicates that the entrepreneurial ecosystem is closely tied not only to technological capabilities but also to institutional and governance frameworks.

At the macro level, the findings suggest that today's entrepreneurs align their actions with the demands of the information age. New business establishments are mainly supported by digital infrastructure, innovation capacity, qualified human capital, and a predictable regulatory environment. This implies that the influence of artificial intelligence and related technologies on entrepreneurship is both direct and structural.

This study is a macro-level analysis conducted at the country level using secondary data. Future research should include micro-level studies that reflect the perspectives of entrepreneurs establishing new businesses or public administrators involved in business establishment processes in specific countries. Such studies would provide a more detailed understanding of the mechanisms underlying the observed relationships. Additionally, there is a significant need for the development of more detailed and comparable indicators that measure the intensity of artificial intelligence and artificial neural network usage at the business level, which would benefit both academic research and policy design.

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