Evaluating the integration of artificial intelligence technologies in defense activities and the effect of national innovation system performance on its enhancement

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Evaluating the integration of artificial intelligence technologies in defense activities and the effect of national innovation system performance on its enhancement[1]

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Abstract

This paper employs graph theory to assess the extent of integration of artificial intelligence (AI) technologies within defense activities and investigates how the performance of the national innovation system (NIS) influences this integration. The analysis utilizes data from 33 countries with defense industries, observed from 1990 to 2020. Empirical findings indicate that the United States (U.S.) leads globally, with a significant gap between the U.S. and other countries. NIS performance increases the level of integration of AI technologies in defense activities, suggesting that policies aimed at strengthening NIS performance should have positive externalities on defense activities in terms of integrating AI technologies. Technological diversification, knowledge localization, and originality are key dimensions of NIS performance that significantly enhance the integration of AI technologies within defense activities. They exhibit similar average marginal effects, suggesting comparable impacts. The cycle time of technologies has an inverted-U shaped relationship with the level of integration.

Keywords: Integration of AI technologies; Defense activities; National innovation system
JEL codes: L64; O31; O34; O38

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1. Introduction

The concept of artificial intelligence, AI hereafter, first appeared in the mid-20th century, through the work of various mathematicians. These mathematicians wondered whether a machine could become "conscious," or it could carry out tasks requiring human intelligence. Since those first mentions, AI has become a common term and a widely exploited technology, fueling scientific discussions, and motivating numerous research programs. According to the European Commission, AI refers to "systems that display intelligent behaviour by analysing their environment and taking actions, with some degree of autonomy, to achieve specific goals."[4] Nevertheless, the boundaries of AI remain unclear, evolving in line with scientific progress. Indeed, the development of AI has brought about a profound change in the sphere of research, in some cases altering the development of entire sectors. The disruptive power of AI makes it one of the pillars of the fourth industrial revolution. As stressed by the European Patent Office (EPO), this fourth industrial revolution differs from previous ones in the nature of the change it brings about. Where the first three industrial revolutions replaced physical effort with machines, the fourth revolution fully automates increasingly complex processes.

Despite blurred boundaries, the World Intellectual Property Organization (WIPO, 2019) gives us an overview of the development of AI-related innovations. Scientific publications in this field began to expand rapidly in the early 1990s, ten years before the explosion in patenting. The 2010s witnessed the acceleration of AI innovations, with the number of annual patent applications filed in this field multiplying by around 6.5 between 2011 and 2017. The evolution of AI has influenced all sectors of the economy, with a notable impact on the defense sector in both developed and emerging countries, where the integration of AI technologies is steadily growing. Indeed, in recent years, the integration of AI technologies has emerged as a central element in the defense policies of many countries, as the disruptive nature of these technologies allows nations to gain a strategic edge in terms of defense capacity over competing countries.

This paper aims to analyze the integration of AI technologies in defense activities of countries with defense industries. This integration refers to the incorporation of AI technologies into various defense-related processes, such as surveillance, decision-making, or weapon systems. Specifically, the paper pursues a twofold objective. First, it aims to measure

[4] Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee, and the Committee of the Regions on Artificial Intelligence for Europe, Brussels, 25.4.2018 COM(2018) 237 final.

the level or extent of integration of AI technologies in defense activities of countries worldwide that have a defense industry. Second, the paper analyzes the effect of the national innovation system (NIS) performance on the level of integration of these technologies in defense activities.[5] Overall, there are at least two reasons why the present research is worthwhile.

First, the conception of groundbreaking armaments necessitates a technological advantage over the adversary (Dupuy, 2013). The disruptive innovations associated with AI can assist countries both in achieving and maintaining such an advantage. In this context, it is crucial for countries to conduct a thorough evaluation of the level of integration of AI technologies in their defense activities and to understand the factors influencing this integration. Second, as it enables countries to acquire the necessary technological and absorptive capacities for effective engagement in high-level AI technology development processes, the NIS performance could play a role in explaining differences in the level of AI technology integration in defense activities among countries worldwide that have a defense industry. This highlights the relevance of studying its potential impact on AI technology integration. Such an analysis would enable us to explore potential innovation policies that could be implemented to enhance the level of integration by improving NIS performance.

Using data from unbalanced panel data from 33 countries observed during the 1990-2020 period, we employ graph theory to measure the level of integration of AI technologies in defense activities. Results show that the United States is the top-performing country, followed by Germany and the United Kingdom. Very interestingly, the gap between the United States and the other countries is huge, underscoring the global leadership of the United States. Applying the fractional Probit regression with endogenous explanatory variable to our database, we find that the NIS performance significantly increases the level of integration of AI technologies in defense activities. This result is robust to additional controls, restricted samples, and an alternative estimation technique, suggesting that policies aiming to strengthen the NIS performance in countries with a defense industry should have positive externalities on their defense activities by inducing more integration of AI technologies in these activities. By disaggregating the NIS performance, we find that technological diversification, knowledge localization, and originality are the dimensions that most increase the level of AI integration. These dimensions are found to exhibit similar average marginal effects. The cycle time of

[5] The NIS is defined as "the elements and relationships which interact in the production, diffusion and use of new, and economically useful, knowledge [...] and are either located within or rooted inside the borders of a nation state" (Lundvall, 1992).

technologies (CTT) has an inverted-U shaped relationship with the level of integration of AI technologies in defense activities.

Ultimately, this paper contributes to the literature at three main levels. First, to the best of our knowledge, this is the first paper to measure the level of integration of AI technologies in defense activities of countries with a defense industry by relying on graph theory. Second, it demonstrates that NIS performance significantly increases the level of integration of AI technologies in defense activities. Third, the paper shows that technological diversification, knowledge localization, and originality are the dimensions of NIS performance that most increase the level of AI integration, and that the CTT has an inverted-U shaped relationship with the level of AI technology integration in defense activities. These contributions are crucial for advancing our understanding of how AI is integrated into defense activities, offering insights that can inform policy decisions and strategic investments in national defense capabilities. By identifying factors such as NIS performance, especially technological diversification, knowledge localization, and originality, that influence AI integration, this research offers actionable insights for governments and defense industries seeking to enhance their technological capabilities and competitive advantages.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the methodology applied to measure the level of AI technology integration in defense activities, and section 4 details the econometric methodology adopted to analyze the effect of NIS performance on this integration. Section 5 describes the data and variables, and discusses descriptive statistics. Section 6 presents and discusses the main estimation results. Results from estimations where NIS performance is disaggregated are presented in section 7. Section 8 discusses the results from some robustness check exercises. Section 9 concludes by discussing policy implications and highlighting avenues for future research.

2. Related literature

Technology adoption in defense activities has been an important workstream in defense economics. Mérindol (2015) studies the impact of information and communication technologies (ICTs) on innovation models in this field. Bellais (1998) analyzes the challenges and consequences of ICTs adoption in the defense sector. Haley (2014) works on determining the factors enabling a successful implementation of ICT. Over recent years, mastering AI technologies has become a key focus of armed forces around the globe. Indeed, AI technologies seem essential to keep a strategic superiority. Gautier (2019) highlights the importance of AI skills in keeping up in the technological race. Khan et al. (2021) analyze similarly the importance of investing in AI for states to maintain their strategic edge. Beyond national security, states need to anticipate technological advances for any competitive edge on the export market (Lemaire, 2018). In 2018, The United States Department of Defense has launched a multi-year investment program worth over 2 billion USD in more than 20 AI programs.[6] China nurtures a similar level of investment (Villani, 2019), while France plans to earmark 10 billion euros for AI research and development (R&D).[7]

Unsurprisingly, research on AI technology adoption in defense operations has flourished given the potential of these technologies to improve countries' defense capabilities. Two issues have received the most attention, namely the application of AI in defense and the ethical issues around it. In addressing ethical issues, The United States Defense Innovation Board has produced an analytical report (DIB, 2019), which establishes a list of ethical principles and recommendations. Taddeo et al. (2021) produce an ethical framework to help states supervise their use of AI in defense.

Regarding AI application or adoption in defense, Svenmarck et al. (2018) and Réal (2019) review the military fields in which AI could be integrated. Their results highlight that AI can improve the effectiveness of all areas of defense and at all levels of the army. In a more normative approach, Horowitz et al. (2018) work on the determinants of AI national power, providing recommendations on the data regulations and AI norms. More specifically, recent papers have studied the determinants of the process of AI adoption in various industries. Among others, Anh et al. (2024) find technology readiness to positively affect AI adoption of accountants and auditors. Lazo and Ebardo (2023) conduct a systematic review of the determinant of AI adoption in the banking industry. Chen et al. (2024) examine the use and implementation of chatbots in public organizations within the United States. These studies converge on the finding that factors such as ease of use, individual past technological experience, and institutional factors play a positive role in AI adoption.

Moreover, concerning NIS performance, the existing literature has often focused on its relationship with economic progress.[8] For instance, according to Schumpeterian theories and studies on the impact of NIS on economic growth, a high-performance NIS positively impacts

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[6] See Sayler (2020).

[7] This policy is incorporated in the famous "LOI n° 2023-703 du 1er août 2023 relative à la programmation militaire pour les années 2024 à 2030 et portant diverses dispositions intéressant la défense (1)."

[8] See Balzat and Pyka (2006), Castellacci (2011), Flippetti and Peyrache (2011), Lee and Lee (2020), and Lee et al. (2021), among others.

economic growth. Studies also have explored the impact of the technological regime on countries' growth of patenting green technologies, with some aspects of this regime being related to NIS. Among others, Corrocher et al. (2021) recently found a positive correlation between a country's growth in patenting within green technologies and factors such as technological opportunity, complexity, originality, and maturity of the technology.

Upon closer examination of the literature, it is notable that analyses of the impact of NIS performance on the integration of AI technologies in defense activities are lacking. This is the gap that the present study modestly seeks to fill. Furthermore, by aiming to elucidate the macroeconomic dimension of AI adoption in defense activities, our research contributes to two distinct areas of study: the field of AI, through an investigation into the macro-factors influencing the adoption of AI technologies, and the domain of defense innovation integration.

3. Measuring the level of integration of AI technologies in defense activities

To measure the level of integration of AI technologies in defense activities, we use a theoretical framework derived from knowledge economics. We analyze the evolution of the knowledge base of countries, that is, the collective knowledge that can be used by a country to achieve its production objectives (Henderson and Clark, 1990). The knowledge base has two components: knowledge bricks and knowledge architecture. Knowledge bricks represent the knowledge specifically associated with the technological bricks contained in a system, while the knowledge architecture corresponds to the functions enabling a wide variety of technologies to be combined and integrated when designing a complex system.

We represent technological knowledge bases in the form of a graph, a tool derived from network analysis (Krafft et al., 2011, 2014; Saviotti, 2009). Knowledge bricks are represented by the "nodes" of the network and the knowledge architecture is represented by the "links" between the nodes. The graphs produced from patent data are labeled by the technology codes contained in the patents (the Cooperative Patent Classification[9] codes), weighted by the intensities of the links between these technologies, undirected (relations between technologies are not oriented), and non-reflexive (a technology cannot, by construction, be related to itself) (Bollobás, 1998). From these graphs, we construct co-occurrence matrices. An occurrence occurs when technological classes are cited in the same patent (Fauconnet, 2021). To measure

[9] The Cooperative Patent Classification (CPC) is a bilateral system developed jointly by the EPO and the United States Patent and Trademark Office (USPTO).

the integration of AI technologies, we calculate from the co-occurrence matrices the strength of nodes. The strength of nodes corresponds to the number of times two technologies are cited in the same patent and reflects the importance of a node in a network. Figure 1 provides a simplified representation of the difference between degree and strength.

[Insert Figure 1 here]

Box (a) represents a sample of three patents (B1, B2 and B3) and the technologies included in these patents (T1, T2, T3 and T4). Box (b) is the representation of the knowledge base and relies on the previous sample of patents. Links are occurrences between technologies: there is a link when technologies are cited in the same patent. Box (c) is a table with the value of degree and strength for each technology. If we take the example of T1, its degree is equal to two. Indeed, the degree only considers the presence of a link between T1 and T3, without taking into account the quantity of such links. We decide to use the strength instead of the degree of nodes to measure the level of integration of AI technologies in defense activities because the strength better reflects the importance of a technology in a network and the frequency with which two technologies are associated in a country's knowledge base (Barrat et al., 2004).

The level of integration of a given AI technology in defense activities is measured as follows:

$$AItech = \sum_{q=1}^{N} b_{uq} \tag{1}$$

where B is the co-occurrence matrix in which the coefficient b_{uq} has a value greater than zero if the node u is connected to node q, equivalent to the number of co-occurrences between u and q. b_{uq} is the number of times technologies u and q are cited in the same patent.

The use of graph theory enables us to assess two aspects of the innovation process of defense activities. First, the appearance of new nodes, corresponding to genuine innovation. Second, the recombination of already existing knowledge via new links between different nodes already present in previous periods (Fleming and Sorenson, 2001; 2004). In this study, we take into account the cumulative nature of knowledge. Following the approach of Lebert and Meunier (2019), we consider that formal knowledge belonging to the defense sector's knowledge base, and which can be assembled at time t-n, remains controlled at time t.

This paper utilizes data on 36 major AI technologies integrated over time in defense activities.[10] We measure the level of integration for each of these technologies within defense activities using the formula described in (1). Subsequently, we apply Cámara and Tuesta's (2018) methodology, which utilizes a principal component analysis (PCA) procedure to construct a comprehensive composite index that combines the levels of integration of different AI technologies. PCA facilitates computing weights for the variables included in the calculation of the composite index, that is, variables that measure the levels of integration of the different AI technologies. Cámara and Tuesta's (2018) methodology was used recently by Gasmi et al. (2024) to compute composite indices of participation, provision, and protection in the MENA region.

Before performing the PCA to determine the weight of variables and then construct the composite index, it is important to standardize the data for two reasons (Jolliffe, 1990). First, standardizing variables ensures that each variable carries the same weight, even when the original variables have difference in their variances. In case of disparate variances, the principal components might be heavily influenced by those variables with high variance, leading them to dominate the initial components. Second, data standardization helps to correct for disparity in the units used to measure the variables. In such case, the magnitudes of variances and covariances are significantly influenced, often arbitrarily, by the choice of units used to measure variables.

To standardize the AI technology variables, we employ the "min-max scaling" method, following the approach of Gasmi et al. (2024). The rescaled version of $AItech_{it}$, a variable that measures the level of integration of a given AI technology in defense activities, observed for country i at year t, is defined as follows:

$$rs\_AItech_{it} = \frac{AItech_{it} - \min(AItech)}{\max(AItech) - \min(AItech)} \tag{2}$$

where $rs\_AItech_{it} \in [0,1]$, $\min(AItech)$ and $\max(AItech)$ are respectively the minimum and maximum realizations of the variable $AItech$ for all countries i and all year t in our dataset.

Once the AI technology variables are standardized, we can proceed to employ the methodology outlined by Cámara and Tuesta (2018) for calculating a composite index. This

[10] The list of these technologies is presented in Appendix A.

index quantifies the level of integration of AI technologies within defense activities and is defined as follows:

$$AI\_level_{it} = \sum_{j=1}^{m} \omega_j \left(rs\_AItech_{it}^{j} \right) \tag{3}$$

where $\forall j$, $rs\_AItech_{it}^{j} \in [0,1]$ and is the rescaled version of $AItech_{it}^{j}$, representing the integration of the j-th AI technology in the defense activities for country i in year t, with $j = 1, \ldots, m$. ω_j is the weight assigned to this specific variable and is defined as follows:

$$\omega_j = \frac{\sum_{k=1}^{m} \lambda_k \phi_{kj}}{\sum_{k=1}^{m} \lambda_k} \tag{4}$$

where λ_k represents the eigenvalue associated with the k-th principal component, and ϕ_k stands for its respective eigenvector. Consequently, ϕ_{kj} denotes the specific element of this eigenvector corresponding to $rs\_AItech_{it}^{j}$, $j = 1, \ldots, m$. This methodology accords greater weights to variables contributing more significantly to the variability of the data, and indeed, this should be the case. $\forall j$, $\omega_j \in [0,1]$ and $\sum_{j=1}^{m} \omega_j = 1$. Hence, AI_level_{it} emerges as a convex combination of the $rs\_AItech_{it}^{j}$, $j = 1, \ldots, m$. It falls within the unit interval, that is, its values range between 0 and 1.

4. Econometric methodology

We conduct an econometric analysis to determine the effect of NIS performance on the level of integration of AI technologies in defense activities. Our outcome variable, denoted as AI_level, represents the level of integration of AI technologies in defense activities and is "fractional," indicating that it can assume any value within the unit interval. Therefore, using linear regression is unsuitable for examining the effect of NIS performance on it, as it fails to guarantee that predicted values of AI_level remain within the unit interval (Papke and Wooldridge, 1996). Instead, it is appropriate to employ a fractional outcome model for estimation (Papke and Wooldridge, 1996, 2008; Wooldridge, 2019).

Considering the panel structure of our dataset, we implement the panel fractional Probit model proposed by Papke and Wooldridge (2008).[11] This model ensures that the predicted values of AI_level stay within the unit interval by integrating a link function, specifically a standard normal cumulative distribution function (CDF).[12] The model is outlined as follows:

$$E\left(AI\_level_{i,t} \middle| \boldsymbol{x}_{i,t}, c_i\right) = \Phi(\boldsymbol{x}_{it}\boldsymbol{\beta} + c_i) \tag{5}$$

where $AI\_level_{i,t} \in [0,1]$ and denotes the level of integration of AI technologies in defense activities of country i at year t. $\boldsymbol{x}$ represents a $1 \times K$ vector of explanatory variables including the NIS performance and a set of control variables. c_i represents the unobserved country effects, $\boldsymbol{\beta}$ is a $K \times 1$ vector of parameters to estimate, and $\Phi(.)$ is the standard normal CDF.

In this econometric framework, addressing the endogeneity of our independent variable of interest, namely the NIS performance, denoted as NIS_perf, is crucial to identify its effect on the level of integration of AI technologies in defense activities. The endogeneity arises from reverse causality and possibly omitted variable bias. To tackle this issue, we simultaneously undertake two key actions.

First, to handle the issue of reverse causality, we incorporate lagged values of NIS_perf into the regression instead of using the values observed at time t. This adjustment is grounded in the theoretical premise that $AI\_level_{i,t}$ should not causally explain $NIS\_perf_{i,t-1}$ due to the temporal separation introduced. Lagging NIS_perf also helps mitigate potential omitted variable bias by eliminating confounding factors observed at time t.

Second, we adopt the Instrumental Variable (IV) technique, following the approach suggested by Papke and Wooldridge (2008). More precisely, we estimate the fractional Probit model using the pooled quasi-maximum likelihood estimator (QMLE) and address the endogeneity of NIS performance through a control function (CF) approach (Papke and Wooldridge, 2008).[13] Subsequently, we acquire robust standard errors for parameter estimates through bootstrapping, conducting 500 bootstrap replications in line with Papke and Wooldridge (2008).

The coefficient of $\hat{v}_{i,t}$, the first stage reduced form residuals, helps perform a Hausman (1978) test to examine the endogeneity of NIS_perf. A rejection of the null hypothesis of

[11] For cross-sectional data, see Papke and Wooldridge (1996).
[12] For a discussion on the advantages of using a Probit link function instead of a Logit one, refer to Papke and Wooldridge (2008).
[13] For theoretical details on the CF methodology, see Wooldridge (2015).

exogeneity is expected, indicating that the NIS performance is endogenous. As will be seen later, this is indeed the case.

We instrument the NIS performance with two IVs. The first IV consists of lagged values of "general" R&D intensity. R&D intensity reflects the gross domestic spending on R&D, measured as a proportion of GDP. This measurement accounts for capital and current spending within the key sectors of business enterprise, government, higher education, and private non-profit. It encompasses expenditures on applied and basic research, and experimental development. Theoretical connections link R&D intensity to innovation capacity and performance. Over time, countries with heightened R&D intensity tend to demonstrate superior NIS performance, a factor pertinent to the integration of AI technologies in defense activities. Indeed, in general, countries that have substantially incorporated AI technologies into their defense activities, such as the United States, Germany, and the United Kingdom, achieved significant NIS performance earlier. This suggests that the influence of R&D intensity on the integration of AI technologies in the defense activities is likely indirect through NIS performance.

In the same light, it is crucial to emphasize that the IV in question is "general" R&D intensity, meaning the R&D under consideration is not specific to defense activities or AI technologies. For example, this may include R&D efforts aimed at developing new technologies in the agricultural sector to enhance farm productivity, or investments in research to discover new vaccines. While it may seem challenging to directly link these R&D investments with the integration of AI technologies in defense activities, such R&D is anticipated to bolster NIS performance. This, in turn, is expected to yield positive externalities for defense activities, notably through the enhanced integration of AI technologies, as discussed previously.

Moreover, general R&D intensity is less likely to be directly affected by the current state of NIS performance, as firms and governments typically allocate resources to R&D based on long-term strategies. Additionally, the introduction of temporal separation through lagged values of R&D intensity suggests that the integration of AI technologies in defense activities should not causally explain R&D intensity. All these points indicate that lagged general R&D intensity is an exogenous factor in the specific relationship under examination.

The second IV is tax revenue measured as a proportion of GDP. This is a major source of government financing to enhance the NIS. In fact, achieving higher NIS performance requires significant financing from both public and private sectors. The higher the tax revenue, the greater the financial support provided by the government for enhancing NIS performance, ceteris paribus. Countries with higher NIS performance should be more likely to engage in higher integration of AI technologies in defense activities. Those countries exhibiting lower NIS performance can reasonably be expected to focus more on standard defense technology development processes, either excluding AI technologies or incorporating them to a significantly lesser extent. As with general R&D intensity, all this suggests that tax revenue has an indirect effect on the level of integration of AI technologies in defense activities through NIS performance.

Furthermore, tax revenue is less likely to be directly influenced by the current state of NIS performance. Indeed, tax collection is driven by broader economic factors and government policies, making it independent of NIS performance. Additionally, as with general R&D intensity, due to temporal separation, lagged tax revenue should not be causally explained by the level of integration of AI technologies in defense activities observed at time t. All this suggests that tax revenue is exogenous to the relationship between the level of integration of AI technologies in defense activities and NIS performance.

As will be shown later, for all the estimations, statistical tests support the validity of general R&D intensity and tax revenue as IVs. Additionally, the null hypothesis that these IVs are weak is rejected.

5. Data, variables, and descriptive statistics

5.1 Patents data

This paper utilizes unbalanced panel data from 33 countries observed during the 1990-2020 period to measure the level of integration of AI technologies in defense activities and analyze the effect of NIS performance on this integration.[14] To identify patent that combine AI technologies and defense technologies over time, we make use of the *Orbit Intelligence* software to conduct patent queries. We perform three types of requests: entry by technology codes, entry by key words, and entry by associations between codes and expressions. The technology classification is based on work carried out in 2005 jointly by the Fraunhofer Institute for Systems and Innovation Research (ISI), the French *Observatoire des Sciences et Techniques* (OST) and *Institut National de la Propriété Industrielle* (INPI), which divides technological codes into thirty scientific fields. Queries are based on the WIPO's report titled

[14] The list of these countries is presented in Appendix A.

"Technology trends 2019: Artificial intelligence" (WIPO, 2019), which lists technological and key words linked to AI. Selected patents must have been filed for the first time between January 01, 1990 and December 31, 2020.[15] However, there are no restrictions on the legal status of patents and on the patent offices at the date of extraction from the *Orbit Intelligence* corpus.

We complete the patent data obtained on *Orbit Intelligence* with the PATSTAT[16] database (spring 2022 version), developed by the EPO, to retrieve the International Patent Documentation (INPADOC) family number,[17] the year of filing, and all CPC codes cited in a patent family. In order to have a specific selection of patents, the technological codes in queries are carried out with a high level of precision.

After creating the patent database, we aggregate the technological codes in a 4-digit format and we measure the strength of nodes based on these 4-digit technological codes. We decide to aggregate the technological codes to reduce the number of AI technologies studied and improve the readability of our study.

5.2 Data on NIS performance

Data on NIS performance are extracted from Lee et al. (2021). This article measures, classifies, and analyzes the NIS of 35 countries for the period 1975-2015 and their evolution. This measure of NIS performance is based on Lee and Lee's (2020) NIS index construction method. The authors use patent data to measure five different components of NIS performance, namely knowledge localization, technological diversification, cycle time of technologies (CTT), decentralization, and originality. We briefly present these components below. Technical details can be found in Appendix B.

Knowledge localization (KL) measures the proportion of knowledge created from domestic knowledge. Lee et al. (2021) follow the approach of Jaffe et al. (1993), who measure this variable by analyzing the patents created domestically by citing patents owned by inventors of the same nationality. A high level of knowledge localization means that the domestic diffusion of knowledge is high and the share of foreign patents in the citation is low.

[15] We select patents filed after 1990 because the number of patents filed before this date is extremely low (WIPO, 2019). We stopped at 2020 because of the time required by PATSTAT to obtain complete data on new patents.
[16] PATSTAT is a database developed by the EPO. It collects bibliographic and legal event data on patents filed in over 100 patent offices worldwide (the database covers 90% of the world's patents).
[17] INPADOC is a database offering insights into international patent documents and associated data. Managed by the WIPO, it encompasses bibliographic details and legal status information concerning patents originating from diverse countries. An "INPADOC family" includes all patents granted in different countries that are considered equivalent to the same original patent.

Technological diversification (TD) is the extent to which a country generates patents across a broad spectrum of technological domains. This variable measures the number of technological classes in which country i has registered patents. A large score of technological diversification signifies that a country has filed patents in a large number of classes.

CTT ($relativeCTT$) measures the "extent to which a patent relies on recent or old technologies for the invention of new knowledge" (Lee et al., 2021). A long CTT signifies the substantial importance of historical knowledge (Lee and Lee, 2020).[18]

The fourth indicator is the decentralization (versus concentration) variable ($1 - HHI$), which measures whether or not the producers of knowledge are led by a few big businesses or evenly distributed among a large number of innovators. Decentralization is measured based on the Herfindahl-Hirschman index (HHI) of concentration, and is calculated as $1 - HHI$. If the decentralization is large, then patents are filed by a large number of inventors.

The last component is originality (O) and assesses the extent to which a patent refers (backward) to patents across a broader spectrum of technological classes rather than being limited to a specific field of technologies. The more a patent cites technologies not belonging to its technology class, the higher the originality score.

For each country and each year of the study period, each component variable of the NIS (referred to as NIS_j, $j = 1, \ldots, 5$) is calculated and then standardized using the "min-max scaling" method (Lee and Lee, 2019). The NIS index is calculated from these standardized components and equals the sum of the five components, as follows:

$$NIS\_perf_{it} = rs\_O_{it} + rs\_relativeCTT_{it} + rs\_(1 - HHI)_{it} + rs\_TD_{it} + rs\_KL_{it} \quad (6)$$

where "$rs\_$" indicates the standardized variables. Note that Lee and Lee (2020) employed three different statistical techniques (PCA, data envelopment analysis, and the benefit of the doubt) to determine whether the components should have the same or different weights. The results of these three statistical methods of building a composite index validate the possibility of assigning equal weight to each variable. Whatever the weighting method chosen, an increase in the values of one of the NIS components increases the values of the NIS performance. The values of the NIS index range from 0 (lowest performance) to 5 (highest performance).

5.3 Control variables

[18] CTT is expressed in relative terms. For further details, refer to Appendix B.

The main control variables include financial development (proxied by domestic credit to the private sector), military spending, domestic investment (measured by gross capital formation), foreign direct investment (FDI) net inflows, imports, and population size. Financial development is crucial for boosting investment in areas such as innovation, infrastructure, and education, creating an environment conducive to AI adoption in defense. It also increases the probability of successful innovation (King and Levine, 1993), which is positive for the NIS performance. Military spending should foster AI integration through increased resources for specialized R&D. Additionally, military spending, through defense-related R&D, may promote innovation, and in turn improve the NIS, by crowding-in privately-funded R&D investments (Pallante et al., 2023).

Domestic investment is expected to enhance AI adoption in defense, while imports should provide access to cutting-edge AI technologies developed abroad, thus increasing their integration into defense mechanisms and strengthening military capabilities. Such investment through capital accumulation, could also increase the innovation capacity (Howitt and Aghion, 1998). FDI should contribute significantly to advancing AI capabilities in defense by bringing in funds, technology, and expertise, and fostering collaboration with global tech firms. Both imports and FDI could also enhance the NIS performance by improving the innovative capacity of domestic firms (Bertschek, 1995). A larger population could ensure a diverse talent pool for AI-related R&D, which is essential for innovation and practical AI application in defense.

For the purpose of robustness checks, we consider five additional controls, namely, inflation, unemployment, government spending, government debt, and private debt. Both inflation and unemployment capture economic conditions. Countries experiencing deteriorating economic conditions may focus their investment efforts on improving these conditions rather than supporting AI technology adoption in defense operations, leading to a lower propensity for integrating AI technologies in defense. Higher government spending could enhance the level of integration of AI technologies by increasing financing for AI-related research. Similarly, higher government and private debt could reduce AI integration by weakening countries' capacity to support AI-related research activities.

Table A3 in Appendix A summarizes the definitions of all the variables included in this research and their respective data sources. The key descriptive statistics are discussed in the next subsection.

5.4 Descriptive statistics

Descriptive statistics are presented in Tables A4 and A5 in Appendix A. We see from Table A4 that over the study period, the average level of AI integration in defense activities is 0.03. The minimum value of AI integration is 0, while the maximum is 0.96. The minimum value of NIS performance is 1.05, corresponding to the NIS performance in Russia in 1993. The highest value of is 3.77, which is the performance in the United States in 2009. The average level of NIS performance is 2.60. The index of decentralization is on average equal to 0.95, which is higher than the means of the other components of the NIS performance and close to the maximum level of decentralization (0.99). The average level of the knowledge localization index is lower than the average levels of the other components of NIS performance.

General R&D intensity ranges between 0.53% of GDP (South Africa in 1997) and 4.5% of GDP (Israel in 2016). On average, countries spend 2.14% of their GDP on general R&D. Furthermore, tax revenue averages 18.6% of GDP, with the highest and lowest levels being 30.3% of GDP (Sweden in 1999) and 3.33% of GDP (Saudi Arabia in 2015), respectively. The average levels of general government and private debts are very high, which is concerning for countries' self-financing capacity. Additionally, the average level of domestic credit to the private sector is high, suggesting a significant level of financial development in our sample, on average.

[Insert Table A4 here]

[Insert Table A5 here]

From Table A5, we observe a high correlation of 43% between the level of AI integration and NIS performance. The correlations between the level of AI integration and the dimensions or components of NIS performance are also relatively high. Similarly, the IVs and NIS performance exhibit important correlations, as expected. Most of the main controls have high correlations with the level of integration of AI technologies.

6. Estimation results

Table 1 presents the results of measuring the level of integration of AI technologies in defense activities.

[Insert Table 1 here]

The United States emerges as the top-performing country, followed by Germany and the United Kingdom. Notably, there is a significant gap between the United States and Germany, the second-highest performing country, underscoring the global leadership of the United States. Ceteris paribus, this difference may, in part, be attributed to the more recent commitments of many other countries to integrating AI technologies into defense activities, compared to the United States. The three countries with the lowest levels of integration of AI technologies are Malaysia, Saudi Arabia, and Greece, respectively.

China ranks among the top ten countries with the highest levels of integration of AI technologies in defense activities. The first Chinese patents containing defense and AI technologies were filed in 2013. Since then, China has strongly committed to integrating AI technologies into its defense operations, enabling it to leapfrog the other emerging countries and many developed nations.

Russia is ranked thirtieth in terms of the level of integration of AI technologies in defense activities. In fact, although Russian innovation activities combining AI and defense technologies have been ongoing for several decades (with the first patent filed in 1993), they include only a limited number of AI technologies, and these technologies are not diversified enough.

Table 2 presents the results of the QMLE parameter estimates of the fractional Probit with IV using the CF approach (Papke and Wooldridge, 2008).

[Insert Table 2 here]

As discussed previously, the coefficient of $\hat{v}$ helps perform a Hausman (1978) test to examine the endogeneity of NIS_perf. This coefficient is significant at the 1% level, indicating that the null hypothesis of exogeneity of NIS performance is rejected. This supports the choice of considering NIS performance as an endogenous variable and instrumenting it.

We see from Table 2 that NIS performance has a significant and positive effect on the level of integration of AI technologies in defense activities. A unit increase in the index of NIS performance increases the level of integration of AI technologies in defense activities by about 7%. Hence, policies aiming to strengthen the NIS performance in countries with a defense industry should contribute to enhancing these countries' level of integration of AI technologies in their defense activities. As previously explained, the NIS performance enables countries to acquire the necessary technological and absorptive capacities for effective engagement in high-level AI technology development processes. This increases their capacity for integrating AI technologies into various sectors of the economy, including the defense sector.

As to control variables, financial development, military expenditure, domestic investment, imports, and population size appear to exert significant and positive effects on the level of integration of AI technologies in defense activities. Indeed, as previously outlined, financial development is critical for increasing investment in areas such as innovation and infrastructure development, and for encouraging partnerships between governmental and private entities, as well as improving education and vocational training. These factors together create an optimal environment for the adoption and advancement of AI technologies in defense activities. Additionally, an upsurge in military spending plays a significant role in incorporating AI into military practices, primarily by providing additional resources for specialized R&D. Such investments are crucial for procuring advanced AI technologies and systems for military use. Moreover, enlarged military budgets support the enhancement of necessary infrastructure to facilitate AI deployment in defense strategies.

Higher domestic investment translates into greater resources allocated to the adoption and implementation of AI technologies within defense operations. The heightened integration of AI technologies is likely driven by increased funding for AI-related R&D, procurement of AI-enabled systems, and the establishment of infrastructure necessary for leveraging AI's capabilities in defense activities. Imports enable the armed forces to obtain the most current AI technologies and tools unavailable locally, which helps speed up the integration of AI in defense mechanisms and enhances military strength. Having a larger population offers a wider talent reservoir for AI-related R&D, providing the specialized workforce needed for both innovation and the practical application of AI in defense activities. Additionally, ceteris paribus, countries with larger populations may experience a higher demand for effective defense systems from their citizens, which could further encourage the use of sophisticated technologies, including AI, in defense operations.

Table 3 reports the results of the tests of validity and strength of the IVs used to instrument NIS performance. We fail to reject the null hypothesis of validity of the IVs. Cragg and Donald's (1993) minimum eigenvalue statistic is higher than all the crucial values suggested by Stock and Yogo (2005). Therefore, the null hypothesis of weakness of these IVs is rejected. Consequently, the IVs used are valid and strong, supporting their appropriateness for our analysis.

[Insert Table 3 here]

7. Disaggregating the NIS performance

Are all dimensions of NIS performance positively correlated with the level of integration of AI technologies in defense activities? Which specific dimension(s) of NIS performance most significantly affect(s) the level of integration? This subsection aims to provide answers to these questions. We ran separate econometric models for each of the dimensions/components of NIS performance, namely, knowledge localization, technological diversification, CTT, decentralization (versus concentration), and originality. Each variable was entered into the model individually to avoid multicollinearity issues. Additionally, to mitigate possible reverse causality, all variables are lagged by one year, consistent with our methodological approach in previous analyses.

The results of the estimations are presented in Table 4. For better interpretation, the average marginal effects are reported.

[Insert Table 4 here]

From Table 4, we note that knowledge localization, technological diversification, and originality significantly and positively affect the level of integration of AI technologies in defense activities. Specifically, a unit increase in the indices of knowledge localization, technological diversification, and originality leads to an increase in the AI technology integration level by approximately 23%, 22.4%, and 22.3%, respectively. These average marginal effects are closely aligned, indicating comparable impacts of knowledge localization, technological diversification, and originality on the integration of AI technologies in defense activities. Therefore, implementing policies that enhance knowledge localization, technological diversification, or the originality of patents should similarly benefit the extent of AI technology integration in defense activities. Conversely, we observe no significant impact from the decentralization versus concentration in knowledge creation across innovators on this integration level, although the average marginal effect is positive as expected.

The CTT exhibits an inverted-U shaped relationship with the level of integration of AI technologies in defense activities, aligning with our expectations. This variable indicates how quickly new innovations incorporate older ones. An inverted-U shaped effect suggests that initially, as the gap between old and new patents increases, there is a higher level of integration of AI technologies. This is because foundational knowledge and prior innovations provide a rich substrate for new advancements, encouraging deep integration of AI technologies and cross-fertilization of ideas. However, beyond a certain threshold, approximately 0.21 on a scale of 0 to 1, the CTT becomes too long, and this indicates that the field is relying excessively on old knowledge, which might not be as relevant to contemporary technological challenges. As a result, the level of AI technology integration in defense activities begins to decline because the newer developments are less connected to the foundational, yet now possibly obsolete, old knowledge, leading to a misalignment with current technological needs and standards.

Furthermore, across all estimations, the coefficient of $\hat{v}_{i,t}$ is significant, validating our approach to treating NIS performance as endogenous. Regardless of the specification, the null hypothesis asserting the validity of the IVs is not rejected, meaning the IVs are considered valid. Similarly, the null hypothesis suggesting that these IVs are weak is consistently rejected, indicating they are strong and appropriate for our analysis. For the sake of brevity, the results of the validity and strength tests of the IVs are not reported in this paper. However, they are available from us upon request.

8. Robustness checks

In this paper, we find that NIS performance increases the level of integration of AI technologies in defense activities. This section aims to check the robustness of this result. The robustness check exercise we undertake comprises three levels. First, we consider additional controls. This allows us to assess the influence of potential omitted variable bias on our findings. Second, we analyze the sensitivity of our results to a restricted sample. Third, we consider an alternative estimation technique, namely the entropy balancing impact evaluation method. As will be seen later, all these analyses show that NIS performance consistently increases the level of integration of AI technologies in defense activities, supporting the robustness of our findings.

8.1 Additional controls

We incorporate five additional controls to evaluate the sensitivity of our findings to potential omitted variable bias, as previously mentioned. These controls include inflation, unemployment, government spending, government debt, and private debt. To mitigate potential reverse causality, we lag these variables by one year. Additionally, to prevent multicollinearity issues, we introduce the additional controls into the model one at a time.

The results of the estimations are reported in Table 5. The average marginal effects are reported to allow for a finer interpretation. The results of the tests of validity and strength of the IVs indicate that the IVs are valid and not weak in all estimations. To maintain brevity, these results are not reported in this paper but are available from us upon request.

[Insert Table 5 here]

We see from Table 5 that, regardless of the specification, NIS performance significantly and positively affects AI technology integration in defense activities. The average marginal effects are significant at the 1% significance level, underscoring the strong impact of NIS. This also indicates that including additional controls does not change the significance of NIS's impact, supporting the robustness of our findings against potential omitted variable bias.

8.2 Restricted samples

We repeat the econometric analysis on restricted samples. This allows us to analyze the sensitivity of our findings to subgroups of countries. To be precise, we consider five cases. First, we exclude the United States from the sample. Indeed, as we found a significant gap between the United States and other countries in terms of the extent of integration of AI technologies in defense activities (see Table 1), it is important to know whether the results are influenced by the presence of the United States in the sample. Second, we exclude the BRICS. This exclusion is rationalized by the varied stages of economic development and innovation systems across the full sample, which mainly includes emerging and developed economies. The BRICS countries, being emerging economies, might have differing priorities and capacities for AI technology integration in defense. Excluding them can provide a clearer view of how NIS performance affects AI integration in more economically and technologically homogeneous groups.

Third, we exclude countries with nuclear weapons. This group's exclusion controls for the unique security dynamics and strategic priorities that nuclear capabilities introduce. Countries with nuclear weapons might have different approaches to defense technology integration, including AI, influenced more by their nuclear status than their national innovation systems. Removing them could lead to more accurate assessments of how NIS performance influences AI adoption in defense among non-nuclear states. Fourth, we focus on NATO countries. This subset allows for a focused analysis on a group of countries with shared defense policies and collaborative military initiatives, which can impact AI integration strategies. By examining NATO members, the study can reveal how NIS performance impacts AI technology adoption within a context of alliance-based defense strategies, offering insights into collective security dynamics and technological advancements.

Fifth, we focus on G7 countries. Limiting the sample to G7 countries, which are among the world's leading advanced economies, can shed light on how strong and established national innovation systems influence AI integration in defense activities within a context of economic similarity. This focus ensures the analysis is grounded in a context of similar economic scales, technological capabilities, and innovation policies, providing a clearer picture of the relationship between NIS performance and AI integration in defense activities among developed economies.

The results of the estimations are presented in Table 6, with the average marginal effects reported. The outcomes of the validity and strength tests for the IVs indicate that the IVs are valid and not weak. These results are not reported in the paper to maintain brevity. However, they are available upon request.

[Insert Table 6 here]

We observe from Table 6 that, irrespective of the sample considered, NIS performance exerts a significant and positive effect on the integration level of AI technologies in defense activities. This reinforces the robustness of our findings. The average marginal effect is higher when the sample is limited to G7 countries and smaller when countries with nuclear weapons are excluded. The higher average marginal effect observed when the sample is confined to G7 countries may indicate that these advanced economies, with their well-established NIS, are more adept at integrating AI technologies into their defense activities effectively. The G7, being technologically advanced and economically robust, likely invests more in R&D. This can lead to more efficient and impactful AI adoption in defense industries by enhancing NIS performance.

Conversely, the smaller average marginal effect when excluding countries with nuclear weapons could suggest that such countries, often possessing substantial military budgets and advanced technological infrastructure, play a crucial role in propelling the integration of AI in defense. These countries might be leveraging their AI capabilities for strategic defense purposes, including nuclear security, thereby demonstrating stronger marginal effect when included in the sample.

8.3 Alternative estimation technique

The last robustness check exercise we conduct consist of considering an alternative estimation technique. Specifically, we employ the entropy balancing method, which is a novel impact evaluation method introduced recently by Hainmueller (2012) for binary treatments and extended by Tübbicke (2022) and Vegetabile et al. (2021) to continuous treatments. In this paper, the treatment is NIS performance, which is continuous. The outcome variable is the level of integration of AI technologies in defense activities. The effect of NIS performance on AI integration is measured through the average treatment effect on the treated (ATT).

Estimating the ATT using the entropy balancing method involves two steps. In the first step, we compute weights to ensure that the balancing property is maintained in the re-weighted sample. These balancing weights are derived by addressing a globally convex optimization problem, specifically by minimizing the deviation from (uniform) base weights while adhering to normalization constraints and ensuring zero correlation between the treatment variable and the covariates. In the second step, these balancing weights are incorporated into a regression analysis to derive the ATT.

Entropy balancing has been widely used in the literature and offers several advantages over many traditional impact evaluation methods.[19] Among these advantages, entropy balancing allows for achieving a higher level of covariate balancing even with a small sample size. Tübbicke (2022) demonstrates through Monte Carlo simulations that the entropy balancing method for continuous treatment can outperform other re-weighting approaches, such as Generalized Boosted Modeling, Covariate Balancing Generalized Propensity Score, and Inverse Probability Weighting, in terms of bias and root mean squared error. Additionally, the entropy balancing method reduces model dependency, which is beneficial for the subsequent estimation of treatment effects.[20]

Figure 2 presents the Dose-Response Function (DRF), illustrating the response of the level of integration of AI technologies in defense activities to varying intensities or levels of NIS performance. The DRF is derived using a nonparametric approach employing local linear regression with an Epanechnikov kernel. Additionally, the 95% confidence interval is reported, with standard errors obtained through 500 bootstrap replications, following the approach of Tübbicke (2022) and Vegetabile et al. (2021).

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[19] For an overview of recent studies employing the entropy balancing method, refer to Kouakou and Yéo (2023).
[20] For a comprehensive discussion of the advantages of the entropy balancing method for continuous treatment, refer to Kouakou and Yéo (2023).

[Insert Figure 2 here]

We observe from Figure 2 that the DRF exhibits an upward trend, indicating that the higher the intensity or level of NIS performance, the greater the integration of AI technologies in defense activities. This finding aligns with previous results demonstrating a positive correlation between NIS performance and AI integration in defense.

Table 7 presents the ATTs. Columns (1) and (2) display the results without and with the inclusion of pre-treatment covariates or matching variables in the second step of entropy balancing, respectively. The inclusion of these covariates enhances estimation efficiency. It is worth noting that, as NIS performance, the treatment variable, is lagged by one year, the matching variables are lagged by two years to ensure they precede it.

[Insert Table 7 here]

Table 7 shows that, irrespective of the specification, NIS performance significantly and positively increases with the level of integration of AI technologies in defense activities. This supports the robustness of our previous findings. Summary statistics on balancing quality obtained from a (weighted) regression of the treatment variable on the pre-treatment covariates are reported in Appendix A. It appears that prior to weighting, the R-squared is equal to 0.31, suggesting that the covariates account for 31% of the variation in NIS performance. Additionally, the p-value of the F-test is equal to 0.000, indicating a rejection of the null hypothesis that NIS performance is not significantly impacted by the covariates overall. However, as expected, once the entropy balancing weighting is applied, the R-squared and the p-value of the F-test become equal to 0 and 1 respectively, implying that NIS performance is no longer affected by the covariates. Therefore, the balancing property is satisfied.

9. Conclusion

This paper aims to measure the level of integration of AI technologies in defense activities and explore how this integration is influenced by NIS performance. Based on data from 33 countries with a defense industry, empirical evidence shows that the United States leads globally, with a significant gap between the United States and other countries. Econometric evidence shows that NIS performance increases the level of integration of AI technologies in defense activities. Technological diversification, knowledge localization, and originality are the dimensions of NIS performance that significantly enhance the integration of AI technologies within defense activities, with similar average marginal effects. Meanwhile, the CTT has an inverted-U shaped relationship with the level of integration.

These results suggest that policies aiming to strengthen the NIS performance in countries with a defense industry should have positive externalities on their defense activities by inducing more integration of AI technologies in these activities. In particular, policies aimed at improving technological diversification, originality, and localization of knowledge creation and diffusion should lead to a greater integration of AI technologies in defense activities. In terms of policies, while various directions are possible, we believe that the key policies may encompass the following four.

First, public authorities could (further) incentivize interdisciplinary research grants. Encouraging interdisciplinary collaboration through research grants fosters originality by facilitating the integration of diverse technological perspectives, leading to patents that cite a broader spectrum of technologies and thus score higher in originality. This approach also promotes technological diversification by enabling researchers to explore novel areas and merge knowledge from multiple domains into innovative solutions. Moreover, by fostering collaboration among domestic researchers, this policy enhances knowledge localization by increasing the domestic diffusion of knowledge and reducing reliance on foreign patents for innovation.

Second, establishing technology transfer offices (TTOs) in academic institutions may be relevant to improve NIS performance. Indeed, TTOs could play a pivotal role in enhancing the NIS performance by bridging academia and industry, thereby facilitating the diffusion of academic research and promoting technological diversification. By translating research findings into practical applications across various domains, TTOs contribute to the creation of patents that span a broad spectrum of technologies, thus increasing originality within the NIS. Additionally, TTOs facilitate partnerships between domestic researchers and companies, promoting knowledge localization by encouraging the domestic diffusion of knowledge and reducing dependence on foreign patents for innovation.

Third, promoting public-private partnerships (PPPs) in research and innovation could be an effective policy to improve NIS performance. Indeed, PPPs may enhance technological diversification within the NIS by leveraging the expertise and resources of both public and private sectors to address complex technological challenges across various domains. Collaborative efforts between government agencies, research institutions, and private companies lead to a more diverse portfolio of patents and innovations. Additionally, PPPs foster originality by encouraging the integration of diverse perspectives and expertise into innovative solutions, resulting in patents that cite technologies from a broader spectrum of classes. Furthermore, PPPs support knowledge localization by fostering collaborations between domestic entities, promoting the domestic diffusion of knowledge, and strengthening the competitiveness of domestic industries.

Fourth, public authorities might need to accentuate tax incentives for R&D spending, especially in emerging and developing economies. As Kouakou and Yéo (2023) rightly noted, while such a policy is very often implemented in most advanced countries, such as France, the United Kingdom, and the United States, many other countries might need to make efforts to implement them. Tax incentives for R&D spending stimulate innovation across various technological domains, thereby fostering technological diversification within the NIS. By encouraging companies to invest in R&D across multiple fields, this policy leads to a broader range of patents and inventions. Moreover, tax incentives promote originality by incentivizing companies to explore unconventional approaches and technologies, resulting in patents that cite a wider array of technological classes. Furthermore, by incentivizing domestic R&D spending, this policy supports knowledge localization efforts by encouraging companies to conduct research domestically, thus strengthening the domestic knowledge base and reducing reliance on foreign patents for innovation.

The present research may be extended in various directions. Among others, first, future studies may examine cooperation in the field of defense-related AI, specifically how this cooperation influences the level of integration of AI technologies in defense operations. Second, and relatedly, future studies could identify divergences in AI applications between countries, explore the origins of these divergences, and investigate how they interrelate with the NIS. Third, investigating possible nonlinearities in the effect of NIS performance on AI integration in defense activities could be a fruitful avenue for future research. Such an analysis would allow to determine whether there is a threshold to be achieved by NIS performance before significantly impacting the level of integration of AI technologies. This analysis could be conducted within the framework of panel threshold regression modeling.

Fourth, future studies could consider different defense industries and categories of defense activities, analyzing potential heterogeneity in the effect of NIS performance on the level of integration of AI in defense. Fifth, in this paper, we do not conduct an econometric analysis of the transmission channels of the effect of NIS performance on AI integration in defense activities. Such an analysis could be undertaken by future research. Both macroeconomic and industry-level factors should be investigated.

Declaration of competing interests

The authors declare none.

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Appendix A

Table A1. List of the countries

Argentina	India	Saudi Arabia
Australia	Israel	Singapore
Austria	Italy	South Africa
Brazil	Japan	South Korea
Canada	Malaysia	Spain
Chine	Netherland	Sweden
Egypt	New Zealand	Switzerland
Finland	Norway	Türkiye
France	Poland	United Arab Emirates
Germany	Portugal	United Kingdom
Greece	Russia	United States

Table A2. List of the AI defense technologies

CPC	Titles
A61B	Measuring for diagnostic purposes (radiation diagnosis A61B 6/00; diagnosis by ultrasonic, sonic or infrasonic waves A61B 8/00); Identification of persons.
A63F	Video games, i.e., games using an electronically generated display having two or more dimensions.
B23K	Processes relevant to this subclass, specially adapted for particular articles or purposes, but not covered by only one of the preceding main groups.
B25J	Program-controlled manipulators.
B29C	Measuring, controlling or regulating using a neural network.
B60G	Indexing codes relating to particular elements, systems or processes used on suspension systems or suspension control systems.
B60W	Purposes of road vehicle drive control systems not related to the control of a particular sub-unit, e.g., of systems using conjoint control of vehicle sub-units.
B62D	Steering position indicators i.e., means for initiating a change of direction of the vehicle.
E21B	Equipment or details not covered by groups E21B 15/00-E21B 40/00.
F02D	Electrical control of supply of combustible mixture or its constituents (F02D 43/00 takes precedence).
F03D	Controlling wind motors (supplying or distributing electrical power H02J, e.g., arrangements for adjusting, eliminating or compensating reactive power in networks H02J 3/18; controlling electric generators H02P, e.g., arrangements for controlling electric generators for the purpose of obtaining a desired output H02P 9/00).

F05B	Indexing scheme relating to wind, spring, weight, inertia or like motors, to machines or engines for liquids covered by subclasses f03b, f03d and f03g: control algorithm fuzzy logic; with neural networks.
F05D	Indexing scheme for aspects relating to non-positive-displacement machines or engines, gas-turbines or jet-propulsion plants: control with neural networks.
F16H	Control functions within change-speed- or reversing-gearings for conveying rotary motion.
G01N	Investigating or analyzing materials by the use of ultrasonic, sonic or infrasonic waves; Visualization of the interior of objects by transmitting ultrasonic or sonic waves through the object (G01N 3/00-G01N 27/00 take precedence); Investigating or analyzing materials by specific methods not covered by groups G01N 1/00-G01N 31/00.
G01R	Arrangements for testing electric properties; Arrangements for locating electric faults; Arrangements for electrical testing characterized by what is being tested not provided for elsewhere (testing or measuring semiconductors or solid-state devices during manufacture H01L 21/66; testing line transmission systems H04B 3/46).
G01S	Details of systems according to groups G01S 13/00, G01S 15/00, G01S 17/00.
G05B	Adaptive control systems, i.e., systems automatically adjusting themselves to have a performance which is optimum according to some preassigned criterion (G05B 19/00 takes precedence).
G05D	Control of position, course or altitude of land, water, air, or space vehicles, e.g., automatic pilot.
G06F	Arrangements for program control, e.g., control units (program control for peripheral devices G06F 13/10).
G06K	Methods or arrangements for sensing record carriers, (e.g., for reading patterns) (methods or arrangements for marking the record carrier in digital fashion G06K 1/00; pattern recognition G06F 18/00; arrangements for image or video recognition or understanding G06V 10/00; character recognition, recognizing digital ink or document-oriented image-based pattern recognition G06V 30/00).
G06N	Computing arrangements based on biological models; Computing arrangements using knowledge-based models; Computing arrangements based on specific mathematical models, Subject matter not provided for in other groups of this subclass.
G06Q	Information and communication technology [ICT] specially adapted for commercial.
G06T	General purpose image data processing; Geometric image transformations in the plane of the image; Image analysis; mage coding (bandwidth or redundancy reduction for static pictures H04N 1/41; coding or decoding of static color picture signals H04N 1/64; methods or arrangements for coding, decoding, compressing or decompressing digital video signals H04N 19/00).
G08B	Checking or monitoring of signaling or alarm systems; Prevention or correction of operating errors, e.g., preventing unauthorized operation.
G10K	Details of active noise control [ANC] covered by G10K 11/178 but not provided for in any of its subgroups.
G10L	Speech synthesis; Text to speech systems; Speech recognition (G10L 17/00 takes precedence); Speaker identification or verification techniques; Speech or voice analysis techniques not restricted to a single one of groups G10L 15/00-G10L 21/00 (muting semiconductor-based amplifiers when some special characteristics of a signal are sensed by a speech detector, e.g., sensing when no signal is present, H03G 3/34); Subject matter not provided for in other groups of this subclass.

G11B	Signal processing not specific to the method of recording or reproducing; Circuits therefor.
H01J	Discharge tubes exposing object to beam, e.g., for analysis treatment, etching, imaging.
H01M	Fuel cells; Manufacture thereof.
H02P	Arrangements or methods for the control of electric machines by vector control, e.g., by control of field orientation; Arrangements or methods for the control of AC motors characterized by a control method other than vector control.
H04L	Data switching networks (interconnection of, or transfer of information or other signals between, memories, input/output devices or central processing units G06F 13/00); Baseband systems.
H04N	Selective content distribution, e.g., interactive television or video on demand [VOD] (real-time bi-directional transmission of motion video data H04N 7/14).
H04Q	Indexing scheme relating to selecting arrangements in general and for multiplex systems.
H04R	Deaf-aid sets.
Y10S	Data processing: artificial intelligence; Computer assisted medical diagnostics by comparison of patient data to other data using artificial intelligence; Neural network.

Table A3. Definitions of variables and data sources+

Variable	Definition	Source
AI integration level	Level of integration of AI technologies in defense activities. Ranges from 0 (lowest level) to 1 (highest level).	Authors based on Cámara and Tuesta's (2018) methodology.
NIS performance	NIS performance index. Ranges from 0 to 5.	Lee et al. (2021)
Knowledge localization	Index of localization of knowledge creation and diffusion. Ranges from 0 to 1.	Lee et al. (2021)
Relative CTT	Index of relative cycle time of technologies (CTT). Ranges from 0 to 1.	Lee et al. (2021)
Technological diversification	Index of technological diversification. Ranges from 0 to 1.	Lee et al. (2021)
Originality	Index of originality. Ranges from 0 to 1.	Lee et al. (2021)
1-HHI	Index of decentralization (versus concentration). Ranges from 0 to 1.	Lee et al. (2021)
R&D	Research and development expenditure (% of GDP). (in log)	WDI
Tax revenue	Tax revenue (% of GDP). (in log)	WDI
Financial development	Domestic credit to the private sector (% of GDP). (in log)	WDI
Military expenditure	Military expenditure (% of GDP). (in log)	SIPRI
Domestic investment	Gross capital formation (% of GDP). (in log)	WDI
Foreign direct investment	Foreign direct investment, net inflows (% of GDP). Rescaled to range from 0 to 1.	WDI
Imports	Imports of goods and services (% of GDP). (in log)	WDI
Population size	Total population. (in log)	WDI
Inflation	Inflation, consumer prices (annual %). Rescaled to range from 0 to 1.	WDI
Unemployment	Unemployment, total (% of total labor force). (in log)	WDI
Government spending	Expense (% of GDP). (in log)	WDI
Government debt	General government debt, total (% of GDP). (in log)	IMF
Private debt	Private debt, loans and debt securities (% of GDP). (in log)	IMF

+ IMF: International Monetary Fund; WDI: World Development Indicators (The World Bank); SIPRI: Stockholm International Peace Research Institute.

Table A4. Descriptive statistics+

Variable	Observations	Mean	Std. dev.	Min	Max
AI integration level	619	0.03	0.11	0	0.96
NIS performance	425	2.60	0.55	1.05	3.77
Knowledge localization	425	0.26	0.22	0	1
		[0.11]	[0.09]	[0]	[0.42]
Technological diversification	425	0.57	0.27	0	1
		[0.54]	[0.26]	[0.01]	[0.96]
Decentralization	425	0.87	0.17	0	1
		[0.95]	[0.06]	[0.64]	[0.99]
Relative CTT	425	0.44	0.17	0	1
		[1.08]	[0.12]	[0.77]	[1.46]
Originality	425	0.46	0.21	0	1
		[0.42]	[0.06]	[0.28]	[0.59]
R&D	322	0.66	0.47	- 0.64	1.50
		[2.14]	[0. 93]	[0.53]	[4.51]
Tax revenue	373	2.90	0.39	1.20	3.41
		[18.60]	[6.30]	[3.33]	[30.30]
Financial development	359	4.66	0.42	2.89	5.38
		[114.78]	[41.13]	[17.97]	[217.77]
Military expenditure	421	0.64	0.57	- 0.47	2.75
		[2.28]	[1.81]	[0.63]	[15.59]
Government spending	392	3.35	0.35	2.57	4.10
		[30.33]	[10.14]	[13.05]	[60.30]
Domestic investment	417	3.12	0.19	2.48	3.84
		[23.18]	[4.71]	[11.94]	[46.40]
FDI	417	0.09	0.08	0	1
		[3.47]	[6.90]	[-5.0]	[86.48]
Imports	417	3.31	0.44	1.94	4.32
		[30.01]	[12.45]	[6.94]	[75.16]
Inflation	409	0.025	0.0515	0	1
		[5.87]	[46.58]	[-16.91]	[887.84]
Population size	421	17.47	1.17	15.35	21.05
		[7.76e+07]	[1.46e+08]	[4660677]	[1.39e+09]
Unemployment	416	1.95	0.53	0.60	3.31
		[8.09]	[4.80]	[1.82]	[27.47]
Government debt	514	4.13	0.59	2.10	5.56
		[72.79]	[42.12]	[8.08]	[258.71]
Private debt	571	4.91	0.46	3.03	5.70
		[147.47]	[54.76]	[20.75]	[287.06]

+ For variables measured in natural logarithm or rescaled, the initial values are presented in brackets.

Table A5. Correlation coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) AI integ. level	1																			
(2) NIS performance	0.43	1																		
(3) Knowl. local.	0.38	0.63	1																	
(4) Relative CTT	-0.16	0.05	-0.46	1																
(5) Techno diversif.	0.37	0.73	0.70	-0.44	1															
(6) Originality	0.23	0.41	-0.12	0.23	-0.06	1														
(7) 1-HHI	0.16	0.69	0.26	0.18	0.38	0.09	1													
(8) R&D	0.22	0.29	0.46	-0.61	0.56	0.06	-0.05	1												
(9) Tax revenue	-0.29	-0.26	-0.45	0.24	-0.36	0.02	-0.06	-0.16	1											
(10) Fin. dev.	0.30	0.40	0.48	-0.17	0.39	0.02	0.11	0.19	-0.22	1										
(11) Mil. Exp.	0.27	-0.16	-0.18	-0.14	-0.13	0.1	-0.04	0.16	0.04	0.38	1									
(12) Domes. invest.	-0.09	-0.11	0.23	-0.53	0.15	-0.12	-0.20	0.39	-0.35	0.12	-0.07	1								
(13) FDI	-0.04	-0.04	-0.16	0.04	-0.06	0.17	-0.08	0.01	0.10	0.02	-0.12	-0.06	1							
(14) Imports	-0.27	-0.37	-0.60	0.19	-0.28	0.15	-0.28	0.05	0.09	0.20	-0.14	-0.05	0.40	1						
(15) Pop. size	0.39	0.34	0.44	-0.21	0.39	-0.09	0.18	-0.20	-0.33	0.16	0.07	-0.05	-0.22	-0.66	1					
(16) Inflation	-0.03	-0.22	-0.11	0.15	-0.20	-0.09	-0.27	-0.36	0.06	0.43	0.12	0.03	-0.04	0.0	0.09	1				
(17) Unemployment.	-0.09	0.19	-0.37	0.47	-0.39	-0.03	0.09	-0.48	0.36	0.24	0.14	-0.63	-0.14	-0.04	0.04	0.01	1			
(18) Gov. spending.	-0.14	-0.20	-0.42	0.27	-0.21	-0.02	0.0487	-0.17	0.69	0.34	0.28	-0.47	0.14	0.27	-0.22	-0.03	0.45	1		
(19) Gov. debt	0.15	0.31	0.34	0.05	0.13	-0.05	0.3904	-0.05	-0.01	0.07	-0.06	-0.41	-0.11	-0.23	0.27	-0.30	0.33	0.11	1	
(20) Private debt	0.08	0.19	0.17	-0.31	0.26	0.16	0.06	0.39	-0.13	0.44	-0.34	0.38	0.31	0.27	-0.22	-0.44	-0.55	-0.19	-0.10	1

Table A6. Entropy balancing method: Summary statistics on balancing quality[+]

	Before balancing	After balancing
R-squared	0.31	0
F-statistic	22.55	0
p-value	0.000	1

[+] Results from a (weighted) regression of the treatment variable on the pre-treatment covariates.

Appendix B

- Knowledge localization (KL)

$$KL_{it} = \frac{n_{ii}}{n_{it}} - \frac{n_{cit}}{n_{ct}} \quad \text{(B1)}$$

where $\frac{n_{ii}}{n_{it}}$ is the probability of country i's patent citing its own patents, n_{cxt} is the number of citations made to country i's patents by all patents, except for that country's patents, filed in year t and n_{ct} is the number of all citations made by all patents granted in year t, except for country i's patents.

- Technological diversification (TD)

$$TD_{it} = \left(\frac{N_j}{438}\right)_{it} \quad \text{(B2)}$$

where N_j is the number of technological classes that country i has filed patents in year t. N_j is divided by 438, the total number of three-digit patent classes in the US patent classification system in 2016.

- Cycle time of technologies (CTT)

$$CTT_x = APP\_YEAR_x - \ APP\_YEAR_y \quad \text{(B3)}$$

CTT_x represents the cycle time of technologies of patent x, APP_YEAR_x the application year of citing patent x, and APP_YEAR_y that of patent y cited by patent x. The average CTT of each patent is calculated and then transformed into a "relative" CTT, labeled as $relativeCTT$, by dividing it by the average CTT of all patents filed in the same year and belonging to the same class.

- Decentralization

$$1 - HHI_{it} = 1 - \ \sum_{p \in I_p} \left(\frac{N_{pt}}{N_{it}^*}\right)^2 \quad \text{(B4)}$$

where I_p is the set of assignees, N_{pt} is the number of patents granted by assignee p in year t, and N_{it}^* is the total number of patents granted by country i in year t, excluding the unassigned patents.

- Originality (O)

$$O_{it} = (1 - \ \sum_{k=1}^{N_x} \left(\frac{Ncited_{xk}}{Ncited_x}\right)^2)_{it} \quad \text{(B5)}$$

where k is the technological class, $Ncited_{xk}$ is the number of citations made by patent x to patents that belong to patent class k, and $Ncited_x$ is the total number of citations made by patent x. From this equation, the average for each country i at year t for each patent is calculated.

Tables

Table 1. AI integration-based country ranking

Country	Average level of integration of AI technologies in defense activities+
United States	0.4192787
Germany	0.0423728
United Kingdom	0.0364665
Japan	0.0354137
South Korea	0.0338278
France	0.0317705
Poland	0.0310844
Chine	0.0305679
Netherland	0.0174443
Finland	0.0160481
Israel	0.0122499
Türkiye	0.010323
United Arab Emirates	0.010323
Austria	0.0098163
India	0.0089185
New Zealand	0.0053854
Sweden	0.0037245
Singapore	0.0034646
Australia	0.0024373
Canada	0.0019729
Brazil	0.0018337
Norway	0.0017961
Egypt	0.0015449
Switzerland	0.0012325
Portugal	0.000767
Spain	0.0006078
Argentina	0.0005485
Italia	0.0004848
South Africa	0.0004005
Russia	0.0000914
Greece	0.0000727
Saudi Arabia	0.0000383
Malaysia	0.0000145

+ From 0 (lowest level) to 1 (highest level).

Table 2. QMLE parameter estimates of a fractional Probit with IV using the CF approach (average marginal effects reported)+

Lagged NIS performance	0.071***
	(0.007)
Lagged Financial development	0.048***
	(0.007)
Lagged Military expenditure	0.063***
	(0.005)
Lagged Domestic investment	0.043**
	(0.017)
Lagged FDI	0.026
	(0.023)
Lagged Imports	0.058***
	(0.011)
Lagged Population size	0.021***
	(0.004)
$\hat{v}$	-0.102***
	(0.024)
Observations	235

+ Robust standard errors in parentheses, obtained by setting 500 bootstrap replications. $*\ p < 0.1$; $**\ p < 0.05$; $***\ p < 0.01$.

Table 3. Tests of validity and weakness of IVs

H_0	Statistic	
Instruments are valid	Sargan	1.85
	p-value	0.17
Instruments are weak	Cragg and Donald's (1993) minimum eigenvalue	9.60
	Maximum critical value (Stock and Yogo, 2005)	8.68

Table 4. Disaggregating NIS performance: QMLE parameter estimates of a fractional Probit with IV using the CF approach (average marginal effects reported)+

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Knowledge localization	0.230***					
	(0.016)					
Lagged 1-HHI		0.126				
		(0.085)				
Lagged CTT			-0.588***	0.305**		
			(0.100)	(0.124)		
Lagged CTT squared				-0.718***		
				(0.170)		
Lagged Technological diversification					0.224***	
					(0.043)	
Lagged Originality						0.223***
						(0.039)
Main controls	Yes	Yes	Yes	Yes	Yes	Yes
$\hat{v}$	-0.316***	-0.179*	0.553***	0.191*	-0.230*	-0.209***
	(0.073)	(0.093)	(0.099)	(0.098)	(0.120)	(0.061)
Observations	235	235	235	235	235	235

+ Robust standard errors in parentheses, obtained by setting 500 bootstrap replications. $*\ p < 0.1$; $**\ p < 0.05$; $***\ p < 0.01$.

Table 5. Robustness checks: Additional controls, QMLE parameter estimates of a fractional Probit with IV using the CF approach (average marginal effects reported)+

	(1)	(2)	(3)	(4)	(5)
Lagged NIS performance	0.071***	0.071***	0.059***	0.050***	0.044***
	(0.009)	(0.008)	(0.006)	(0.008)	(0.007)
Main controls	Yes	Yes	Yes	Yes	Yes
$\hat{v}$	-0.104***	-0.106***	-0.096***	-0.123***	-0.113***
	(0.026)	(0.026)	(0.021)	(0.028)	(0.024)
Lagged Inflation	-0.200				
	(1.272)				
Lagged Unemployment		-0.011			
		(0.008)			
Lagged Government spending			-0.009		
			(0.009)		
Lagged Government debt				-0.004	
				(0.009)	
Lagged Private debt					0.031*
					(0.017)
Observations	233	235	232	205	219

+ Robust standard errors in parentheses, obtained by setting 500 bootstrap replications. In (3), we remove military expenditure from the set of main controls to avoid collinearity issue with government spending. $* \ p < 0.1$; $** \ p < 0.05$; $*** \ p < 0.01$.

Table 6. Robustness checks: Restricted samples, QMLE parameter estimates of a fractional Probit with IV using the CF approach (average marginal effects reported)+

	Exclusion of the United States	Exclusion of BRICS	Exclusion of countries with nuclear weapons	NATO	G7
Lagged NIS performance	0.016***	0.045***	0.007*	0.057***	0.295***
	(0.003)	(0.008)	(0.004)	(0.018)	(0.077)
Main controls	Yes	Yes	Yes	Yes	Yes
	(0.003)	(0.008)	(0.007)	(0.013)	(0.033)
$\hat{v}$	-0.020**	-0.119***	-0.019**	-0.090**	-0.264**
	(0.008)	(0.024)	(0.008)	(0.035)	(0.105)
Observations	215	203	144	149	98

+ Robust standard errors in parentheses, obtained by setting 500 bootstrap replications. $* \ p < 0.1$; $** \ p < 0.05$; $*** \ p < 0.01$. BRICS includes Brazil, Russia, India, China, and South Africa. NATO: North Atlantic Treaty Organization. G7 includes Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States.

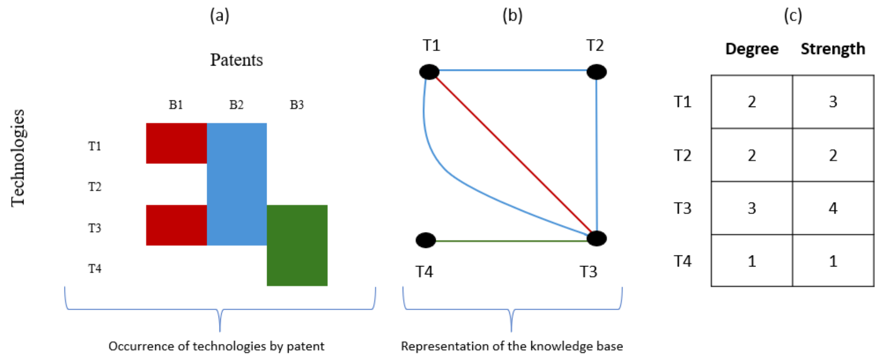
Table 7. Robustness checks: Entropy balancing method+

	(1)	(2)
Lagged NIS performance (ATT reported)	0.067***	0.049***
	(0.007)	(0.003)
Covariates in the second step	No	Yes
Observations	315	315

+ ATT: Average treatment effect on the treated. Robust standard errors in parentheses. Unreported constant term included. $* \ p < 0.1$; $** \ p < 0.05$; $*** \ p < 0.01$.

Figures

Figure 1. Simplified representation of the strength calculation method



Source: Meunier (2021).

Figure 2. Entropy balancing: Dose-response function