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Decoding National Innovation Capacities: A Comparative Analysis of Publication Patterns in Cybersecurity, Privacy, and Blockchain

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Featured Application: This analysis can guide national science policy for enhancing research in blockchain, privacy, and cybersecurity. Policymakers can use the findings to allocate resources effectively. For blockchain and cybersecurity research, countries might focus on economic development and research funding. To boost privacy research, nations could strengthen democratic institutions alongside economic factors. International organizations could use this analysis to identify high-potential countries for targeted support.

Abstract: This study examines the factors influencing scientific productivity in blockchain, privacy, and cybersecurity research across countries. While previous research has explored the determinants of general scientific output, less is known about the patterns of influence in these technological fields, which have been dominantly studied with a bibliometric focus. Using regression models, we analyze the impact of economic, political, educational, and social factors on the publication rates in these domains. Data from international databases on country-level indicators and scientific publications form the basis of our analysis. The results show that Gross National Income per capita is the strongest predictor of research output across all the fields studied. Research spending as a percentage of GDP also demonstrates a consistent positive relationship with publication rates. However, the impact of the factors varies across fields. This research provides insights for policymakers and institutions aiming to enhance research capabilities in these critical areas of technology.

Keywords: research productivity; cybersecurity; privacy; blockchain; Augmented Human Development Index; Web of Science; regression analysis

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1. Introduction

Scientific research in emerging technologies such as cybersecurity, privacy, and blockchain has become increasingly important in shaping the future of global innovation, economic competitiveness, and national security. As these fields rapidly evolve, understanding the factors that drive scientific productivity at the country level is essential for policymakers, researchers, and industry leaders alike.

By examining the country-level determinants of scientific productivity in cybersecurity, privacy, and blockchain, this study aims to provide a comprehensive analysis of the factors shaping the global landscape of cutting-edge technological research. The information

gained from this analysis can contribute to more effective policymaking, strategic investment decisions, and international cooperation in these critical areas of scientific endeavor.

The importance of studying the country-level determinants of scientific productivity in these domains derives from several considerations. Firstly, these technologies are at the forefront of the Fourth Industrial Revolution, with the potential to dramatically transform industries, economies, and societies. The nations that excel in these areas are likely to gain significant economic and strategic advantages in the coming decades. Secondly, the development of these technologies raises ethical, legal, and societal questions that vary across different cultural and political contexts. Understanding how different national environments foster research in these fields can provide insights into the diverse approaches to addressing these challenges globally. Thirdly, the rapid pace of advancement in these technologies has led to intense global competition, often referred to as a "tech race" among nations. Analyzing the factors that contribute to a country's research output can help identify the key ingredients for fostering innovation ecosystems and inform national strategies for technological development. Lastly, as these technologies become increasingly central to national security and economic policies, there is a growing need to understand the global distribution of expertise and research capabilities. This knowledge can inform international collaboration efforts, identify potential gaps in global research coverage, and highlight opportunities for knowledge transfer and capacity building.

In recent years, there has been a marked increase in both the public interest and scientific focus on cybersecurity, privacy, and blockchain technologies. This surge of attention is evident across various spheres, from media coverage and public discourse to academic research and industry investments. The rapid advancement and widespread application of these technologies have sparked intense debates about their societal implications, ethical considerations, and potential risks. Concurrently, the scientific community has responded with a proliferation of research, as evidenced by the growing number of publications, conferences, and dedicated journals in these fields. This heightened interest is driven by the transformative potential of these technologies to reshape industries, economies, and daily life, as well as by increasing concerns about data protection, digital security, and the ethical use of AI. The convergence of public awareness and scientific inquiry has created a dynamic environment where technological progress is closely linked with societal needs and concerns, further fueling the imperative to understand the factors driving research productivity in these domains at a national level.

For example, the chart in Figure 1 illustrates publication trends for the selected technology topics from 2015 to 2024 based on Web of Science data. The total publication count, divided by 100 for scale, is also represented.

The chart in Figure 2 from Google Trends illustrates the public interest, approximated through the Google Search interest over time for the three technology-related topics: data privacy, blockchain, and cybersecurity, spanning from 2004 to 2024. The data reveals distinct patterns of public interest in these subjects, reflecting the broader societal trends and technological developments.

Cybersecurity shows a gradual increase in interest over time, with a more pronounced upward trend starting around 2013. This steady growth likely reflects the increasing digitization of society and the consequent rise in cyber threats, prompting greater awareness and concern about digital security measures.

Data privacy maintains a relatively low but consistent level of interest throughout the period. This stability suggests an ongoing, baseline level of concern about personal data protection among internet users. The lack of significant spikes may indicate that data privacy has become a persistent rather than episodic concern in the public consciousness, probably consolidated by the implementation of the GDPR in 2018.

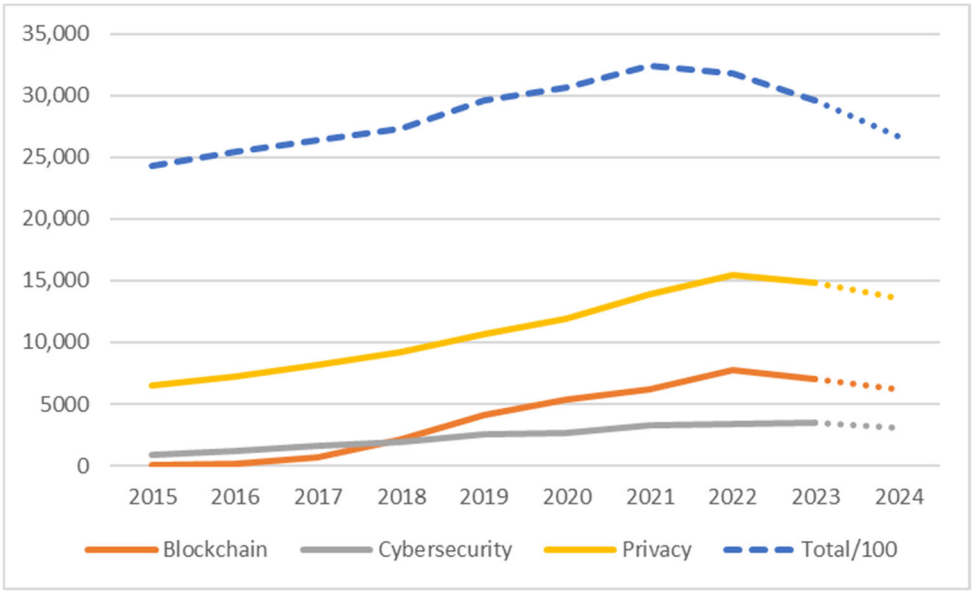


Figure 1. Number of published articles for each year since 2015, on different topics and in total, extracted from the Web of Science database on 13 July 2024 (the values for 2024 were predicted through approximation by doubling the number of existing articles until 13 July; the total number of published articles (derived from searching "the" as a keyword) is divided by 100 in order to fit the graph.

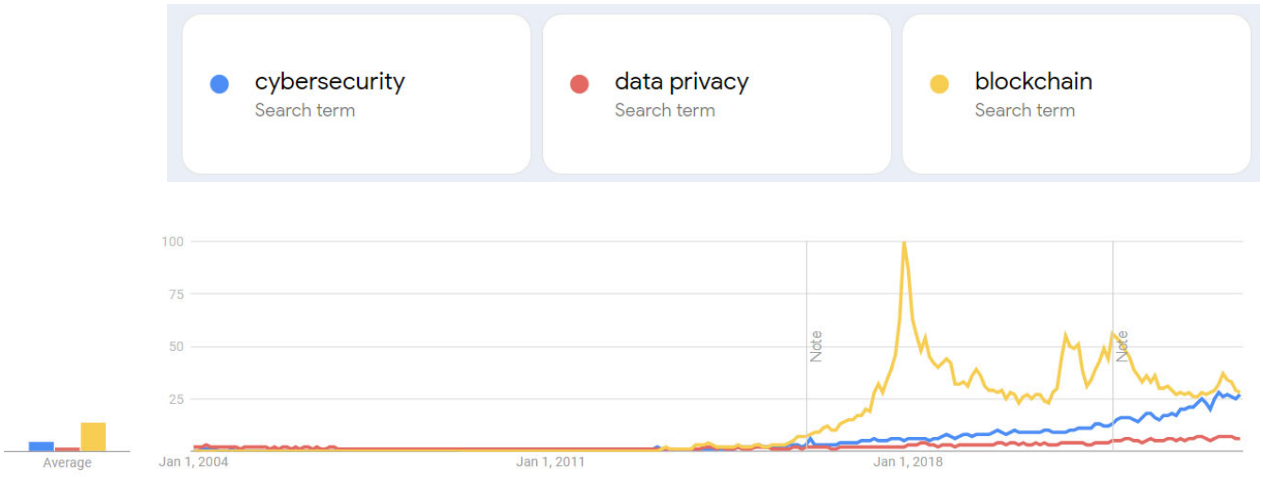


Figure 2. Interest over time in the four selected topics, measured through Google Search. Source: Google Trends, 13 July 2024.

Blockchain exhibits the most dramatic fluctuations. It remains relatively unknown until around 2017, when it experiences a meteoric rise in interest, peaking sharply in late 2017 to early 2018. This spike coincides with the cryptocurrency boom (Obreja in [1]), particularly the Bitcoin frenzy. Following this peak, the interest in blockchain has been volatile but generally higher than the pre-2017 levels, suggesting its enduring relevance in technological discourse (Stan, Barac, and Rosner in [2]).

The chart in Figure 3 from Google Trends illustrates the evolution of search interest concerning privacy in five privacy-related terms from 2004 to 2024: "internet privacy", "data privacy", "digital privacy", "information privacy", and "online privacy". The visualization reveals shifting public concerns and awareness about privacy in the digital age.

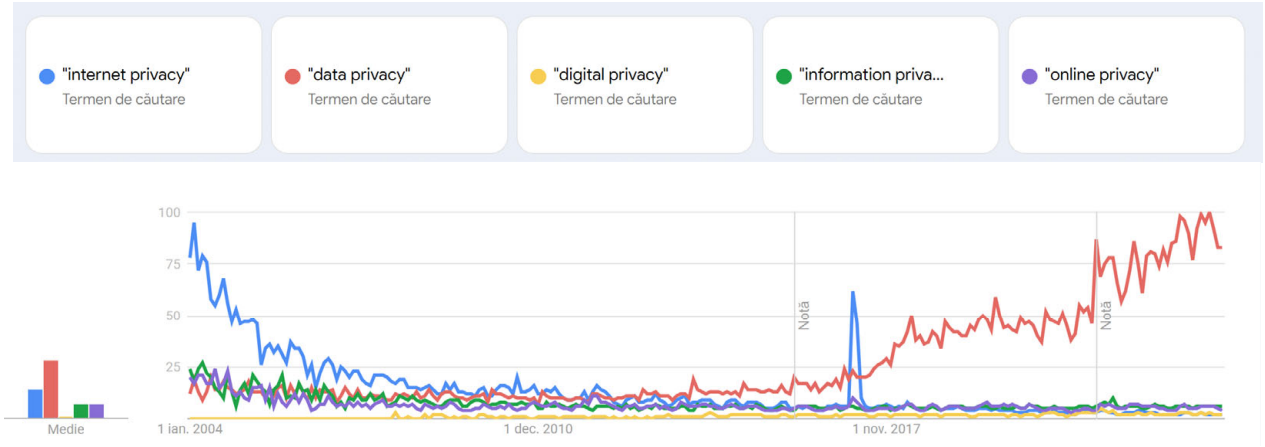


Figure 3. Interest over time in five queries related to privacy, measured through Google Search. Source: Google Trends, 13 July 2024.

"Internet privacy" shows the highest initial interest in 2004, likely reflecting the early concerns about online safety as internet usage became widespread. However, this term experiences a steady decline over time, suggesting a shift in how people conceptualize privacy issues. A notable spike in "internet privacy" searches occurs in early 2017, possibly linked to the US Congress voting to allow internet service providers to sell users' browsing data. This event may have momentarily rekindled interest in the broader concept of internet privacy.

"Data privacy" emerges as the dominant term by the end of the period, showing a marked increase in interest from around 2017 onwards. This surge likely corresponds to high-profile data breaches, the implementation of GDPR in 2018, and the growing awareness of how companies collect and use personal data. The terms "digital privacy", "information privacy", and "online privacy" maintain relatively consistent, lower levels of interest throughout the period. Their stability suggests these concepts have become part of the broader privacy discourse without dominating public attention.

The overall trend indicates a shift from general concerns about "internet privacy" to more specific worries about "data privacy". This change reflects the evolving digital landscape, where data have become a valuable commodity and their protection a significant societal issue. The rising prominence of "data privacy" searches also suggests increased public awareness of the implications of personal information management in the digital era.

Scholarly research on scientific output and productivity at the country level has gained significant attention in recent years, reflecting the growing recognition of science and innovation as the key drivers of national development and global competitiveness. Scholars have consistently explored the factors that influence a nation's capacity to produce and disseminate scientific knowledge, employing various methodologies and focusing on different scientific domains. This body of research seeks to understand the interrelationships of the economic, institutional, political, and social factors that shape scientific results across countries. By examining recent findings in this field, we can gain valuable insights into the determinants of national scientific productivity and the potential strategies for enhancing research performance in diverse global contexts.

The relationship between economic factors and country-level scientific productivity has been the subject of extensive research. Multiple studies across various scientific disciplines have demonstrated a strong correlation between economic indicators and research output. Rodríguez-Navarro and Brito [3] identified economic wealth as a significant determinant of research output, while Zhang et al. [4] found a positive correlation between GDP and research productivity in psychiatry. Similarly, Jamjoom and Jamjoom [5] observed a moderate impact of GDP per capita on scientific productivity in clinical neurology research, and Tasli, Kacar, and Aydemir [6] reported a significant correlation between GDP and publication numbers in dermatology across OECD countries. Gantman's [7] cross-disciplinary

study found that the size of the economy consistently predicted scientific productivity across all the fields examined. In the realm of biomedical research, Rahman and Fukui [8] identified gross national product (GNP) per capita as a significant predictor of output.

However, some research suggests a more nuanced relationship. For example, Allik et al. [9] found that when controlling for societal factors, economic wealth indicators did not significantly predict scientific excellence as measured by their High-Quality Science Index.

Research and development (R&D) expenditure has been consistently identified as a crucial factor in determining country-level scientific productivity. Lancho-Barrantes et al. [10] found that Gross Domestic Expenditure on R&D (GERD) as a percentage of GDP was a significant predictor of scientific production, explaining a large portion of the variance in output among countries. This finding is supported by Jamjoom and Jamjoom [5], who observed a moderate impact of R&D spending on productivity in clinical neurology research. In the field of biomedical research, Rahman and Fukui [8] identified R&D expenditure as a significant predictor of output. Similarly, Dragos and Dragos [11] found that countries allocating more funds to education exhibited higher scientific productivity in environmental sciences and ecology. Doi, Heeren, and Maurage [12] extended this concept to elite scientific achievement, identifying research expenditure as a key predictor of Nobel awards.

However, the relationship between R&D spending and scientific output may not be straightforward in all contexts. Allik et al. [9] found that when controlling for societal factors, research and development expenditure did not significantly predict scientific excellence as measured by their High-Quality Science Index.

While economic factors are crucial, the literature indicates that institutional factors significantly contribute to the variations in scientific productivity across countries. Lancho-Barrantes et al. [10] identified the presence of academic and research institutions as a key predictor of scientific output, complementing economic indicators. This finding is corroborated by Jamjoom and Jamjoom [5], who observed a strong correlation between the number of world-ranked universities in a country and its scientific productivity in clinical neurology research across multiple metrics. The importance of institutional factors extends beyond mere presence to include quality and prestige. Szuflita-Żurawska and Basińska [13] highlighted the role of university prestige in determining scientific productivity among Visegrád Group countries. Wahid et al. [14] further emphasized the significance of institutional characteristics, such as funding opportunities and collaborative environments, in driving both individual and institutional productivity.

Interestingly, Allik et al. [9] found that the factors related to institutional quality, such as governance, played a more substantial role in predicting scientific excellence than economic wealth indicators when controlling for societal factors. This suggests that the quality of institutions and their governance may be as important as, if not more important, in some contexts, than raw economic power in fostering high-quality scientific output.

The literature also reveals that political and societal factors play a significant role in shaping scientific productivity at the country level. Gantman [7] observed that political authoritarianism negatively impacts scientific output in certain fields, suggesting that democratic governance may foster a more conducive environment for research. This finding aligns with the work of Allik et al. [9], who identified good governance as a significant predictor of scientific excellence. Historical and societal contexts also emerge as important factors. Allik et al. [9] also found that a country's communist past negatively influenced its current scientific performance, with the nations lacking such historical baggage tending to produce higher-quality scientific publications. This underscores the long-term impact of political systems on scientific development. The relationship between political priorities and research productivity is further illustrated by Dragos and Dragos [11], who noted that the developed countries with strong environmental policies led in scientific output in environmental sciences and ecology. This suggests that political commitment to specific areas can drive research productivity in related fields.

Broader societal conditions also play a role, as highlighted by Onyancha [15] in the context of sub-Saharan African countries. Socio-economic factors were found to significantly influence research output, indicating that scientific productivity is embedded within wider societal structures and development.

The relationship between population size and scientific productivity presents a nuanced picture in the literature. While some researchers, such as Zhang et al. [4], found a positive correlation between population size and the total research output in specific fields like psychiatry, this relationship does not hold when productivity is adjusted for population. In fact, the same authorsobserved that smaller countries like Australia, the Netherlands, and Norway demonstrated higher per capita productivity in psychiatry research. This pattern is further supported by Jamjoom and Jamjoom [5], who found no significant correlation between population size and the various indicators of productivity in clinical neurology research. Similarly, Allik et al. [9] noted that smaller countries with good governance tended to produce high-quality scientific publications, suggesting that factors other than population size play a crucial role in determining scientific productivity.

The ability of smaller countries to achieve high levels of scientific output is also evident in specific fields. Tasli, Kacar, and Aydemir [6] observed that while large countries dominated in total publications in dermatology, smaller nations like Turkey and South Korea ranked among the top 10, outperforming several Northern European countries with smaller populations but higher per capita income. Gantman's [7] cross-disciplinary study further supports this view, finding that the size of the economy, rather than population size, consistently predicted scientific productivity across various fields. This suggests that a country's ability to invest in research and maintain strong institutions may be more important than its population size in determining scientific output.

Research excellence, often measured by indicators such as Nobel Prizes or highly cited papers, exhibits patterns that diverge somewhat from those of overall scientific productivity. While economic factors play a role, excellence in research appears to be more strongly associated with other variables. Doi, Heeren, and Maurage [12] identified scientific activity, measured by publication output and research expenditure, as the primary predictor of Nobel awards. This indicates that sustained investment in scientific infrastructure and consistent research output are crucial for achieving the highest levels of scientific recognition.

However, Allik et al. [9] found that when controlling for societal factors, the traditional economic indicators like Gross National Income and research and development expenditure did not significantly predict scientific excellence as measured by their High-Quality Science Index. Instead, factors such as governance quality and historical context emerged as more substantial predictors. This aligns with Rodríguez-Navarro and Brito's [3] assertion that the efficiency of a country's research system is particularly important for producing high-impact research. Institutional prestige also appears to play a significant role in fostering research excellence. Szuflita-Żurawska and Basińska [13] emphasized the importance of university prestige in scientific productivity, while Jamjoom and Jamjoom [5] found a strong correlation between the number of top-ranked universities in a country and the various metrics of scientific impact, including the h-index.

The literature reveals significant disciplinary variations in scientific productivity and its sensitivity to economic, political, and societal factors. These variations suggest that the drivers of scientific output and excellence may differ across research areas, necessitating tailored approaches to enhance productivity in specific fields. Gantman's [7] cross-disciplinary study found that while economic factors consistently influenced productivity across all the fields, other factors showed discipline-specific effects. For instance, linguistic factors positively influenced productivity particularly in social sciences, medicine, and agricultural sciences, highlighting the varying importance of language and communication across different research areas. In the field of psychiatry, Zhang et al. [4] observed a dominance of high-income countries, suggesting a strong economic influence in this discipline. Similarly, Jamjoom and Jamjoom [5] found that in clinical neurology research, factors such as the number of top-ranked universities and field-specific journals were strong predictors of

productivity, emphasizing the importance of specialized infrastructure and publishing opportunities in this area.

Environmental sciences and ecology showed sensitivity to different factors, as reported by Dragos and Dragos [11]. The countries with higher Environmental Performance Index scores and education expenditure demonstrated increased scientific productivity in these fields, showing that policy priorities and educational investment play a crucial role in environmentally focused research.

In dermatology, Tasli, Kacar, and Aydemir [6] found that factors such as GDP, population, and language influenced both productivity and impact. This indicates that in some medical specialties, a combination of economic resources, demographic factors, and linguistic considerations may shape research output.

The relationship between research output and economic strength is reciprocal. Research output, measured by the number of publications, has been found to have a significant relationship with economic growth across countries. Several studies have identified a positive impact of research output on GDP growth, particularly in developed nations and STEM fields (such as by Jin and Jin in [16]; Moyo and Phiri in [17]). However, the direction of causality varies among countries, with some exhibiting bidirectional relationships (Zaman et al. in [18]; Ntuli et al. in [19]). The alignment of research output with national development goals also plays a role in economic productivity (Ogot and Onyango in [20]). Factors such as internet usage, R&D expenditure, and international collaboration influence publication productivity and its economic impact (Gholizadeh et al. in [21]). Network analysis reveals similarities in research productivity profiles among high-income countries, while lower-income nations show more diverse patterns (Jaffe et al. in [22]). Overall, these studies suggest that promoting research output, especially in key areas, can contribute to economic growth (Dębski et al. in [23]). Still, in our study, we model research output as a dependent variable on economic and social development. Disentangling the bidirectional relationship falls outside the scope of this article.

Research concerning scientific production on the specific topics of cybersecurity, blockchain, and privacy has mostly employed bibliometric methods. The most frequent topics of analysis, at the country level, are the absolute number of publications and identifying the top countries in terms of total output rather than discussing productivity and the factors that account for its variability. The studies also include other topics that are specific to this methodology (Obreja in [24] and Obreja, Rughiniș, and Rosner in [25]), such as publication trends over time, citation patterns and impact, collaboration networks among authors and institutions, keyword analysis to identify research themes, and journal analysis to determine influential publication venues. Many studies also examine the distribution of publications across different research areas or subject categories, identify top authors and institutions, and analyze funding patterns. Some more detailed analyses include thematic evolution over time, emerging research trends, and the use of visualization tools to map intellectual structures within the field. While these studies provide valuable insights into research output and collaboration patterns, they often lack an in-depth analysis of the country-level factors influencing scientific productivity beyond basic metrics.

As regards cybersecurity research, the United States and China consistently appear as the top two producers globally. According to Loan, Bisma, and Nahida [26], these two countries are the leading contributors, followed by South Korea, the UK, and India. Omote et al. [27] confirm this finding, noting that the US and China are the leading producers across all the major research clusters in cybersecurity. There is a significant concentration of research output among a few countries. Dhawan, Gupta, and Elango [28] found that the top 10 countries accounted for 76.52% of the global publications, with the United States alone contributing 43.75% of the global publications, followed by the United Kingdom (7.73%) and China (5.33%). Regionally, in Eastern Europe, Cojocaru and Cojocaru [29] identified the Russian Federation, Poland, Romania, Czech Republic, and Ukraine as the top five most productive countries in cybersecurity research, accounting for approximately 90% of the region's cybersecurity publications. Omote et al. [27] observed a shift in leadership over time,

noting that while the US initially led in the number of top 10% of the publications, China later overtook it in all four major research clusters they identified. While not directly related to productivity, citation impact varied among countries. Dhawan, Gupta, and Elango [28] found that Canada, the United States, and China had the highest relative citation indices among the top productive countries. International collaboration appears to be a significant factor in research productivity. Loan, Bisma, and Nahida [26] noted that 90.14% of the publications were multi-authored, suggesting high levels of institutional collaboration. Different countries showed varying emphases in their research. Omote et al. [27] noted that the US tends to emphasize CPU security and theoretical research, while China focuses more on applied technologies, including IoT and cloud computing. Several studies suggested various factors influencing country-level productivity, including economic factors, national priorities, the existing technological infrastructure, international collaborations (Loan, Bisma, and Nahida [26]), and government strategies (Omote et al. [27]). Dhawan, Gupta, and Elango [28] also mentioned factors like industrial/commercial computer use, the digitization of the economy, cybercrime rates, and research funding as potential contributors to the United States' dominant position.

As regards blockchain research, China and the United States again emerge as the top two producers globally. Khurana and Sharma (2024) [30] found that China was the most productive country, contributing 18.2% of the global publications, followed by the USA (13%). This is corroborated by Guo et al. (2021) [31], who reported that China contributed 25.38% and the USA 20.65% of the global publications. There is a significant concentration of research output among a few countries. Guo et al. (2021) found that the top 10 countries accounted for 84.93% of the total publications. The UK consistently appears as the third most productive country after China and the USA (Khurana and Sharma [30]; Guo et al. [31]). Citation impact varied among countries. Guo et al. [31] found that the USA had the highest total citations (6082) and citations per paper (7.61) among the top countries. Firdaus et al. [32] noted that smaller countries like Switzerland and Singapore published fewer articles but received high numbers of citations, indicating high-quality research output. International collaboration patterns also varied by country. Khurana and Sharma [30] found that countries like Singapore published a high proportion of internationally collaborative papers (83.6% of its total), while others like Russia focused more on national collaborations (79.3% of its total). Different countries focused on specific sub-topics. Firdaus et al. [32] noted that the US focused more on security aspects, while Asian countries emphasized IoT applications. Several factors influencing country-level productivity were identified, including government policies and national strategies promoting blockchain development, strength in related fields like computer science and cryptography, international collaborations, and institutional research capacity (Guo et al. [31]).

As regards research on the topic of privacy, it is also the United States and China that consistently emerge as the primary contributors. Yin et al. [33] reported that China produced the highest number of publications (3106), closely followed by the United States (2640). This leadership is also reflected in other studies focusing on the specific aspects of privacy research. Valencia-Arias et al. [34] identified the United States, Australia, and India as the top contributors in terms of both the productivity and impact of research on machine learning and blockchain for privacy applications. Ali et al. [35] observed that North America leads in the number of publications, with Europe following closely behind. Significant contributions were noted from European countries such as the United Kingdom, Germany, Italy, and France. The study also mentioned that Asia, Oceania, Africa, and South America contribute to a lesser extent. As expected, citation impact varied among countries. Yin et al. [33] noted that while China had high productivity, its impact was lower compared to the other leading countries. The United States, on the other hand, demonstrated high centrality (0.34) in international collaboration networks, indicating its influential role in the field. International collaboration patterns also varied by country and region. Yin et al. [33] also highlighted that Chinese institutions showed limited collaboration compared to the dense international collaboration networks observed globally. Research focus also varied

by country. The same authors noted that international research tends to focus more on user behavior and trust issues, while Chinese research emphasizes the technical aspects of privacy protection. Several factors were identified as influencing country-level productivity, including research funding, R&D investments, and the quality of research institutions. Ali et al. [35] specifically mentioned that higher R&D investments in the United States and European countries correlate with their higher output in privacy research.

Thus, the current scientific literature on cybersecurity, blockchain, and privacy research heavily relies on bibliometric methods, mainly highlighting publication counts and top contributors without deeply exploring the underlying factors that drive cross-country productivity variations. This oversight underscores a critical gap: the need for research focusing on identifying the specific country-level factors that influence scientific productivity, addressing a neglected area in these rapidly evolving fields.

In light of the state-of-the-art, we aim to address the following research questions concerning scientific productivity on the topics of blockchain, privacy, and cybersecurity:

1. To what extent do economic factors, particularly GNI per capita and research spending as a percentage of GDP, influence scientific productivity across different fields?
2. How does the impact of these economic factors vary between general scientific output and specific technological domains like blockchain, privacy, and cybersecurity?
3. What role does political structure, as measured by the liberal democracy index, play in shaping scientific productivity across various fields?
4. How does educational attainment, represented by the average years of schooling, affect scientific output in emerging technological fields compared to overall scientific productivity?
5. Is there a relationship between overall societal development, as indicated by life expectancy, and scientific productivity in different research areas?
6. How do the determinants of scientific productivity differ between the established scientific domains and emerging technological fields?
7. To what extent can a combination of economic, political, educational, and social factors explain the variation in scientific output across countries?

2. Materials and Methods

This study employs a secondary analysis of publicly available statistical data, including countries across the globe. The number of countries available for each model is presented in Table 1.

Table 1. Number of countries in multiple regression models for the four research publication topics. Source: authors' analysis.

Topics	Model Cases (Countries)
Total publications per population	137
Blockchain publications per population	124
Privacy publications per population	132
Cybersecurity publications per population	126

As regards the dependent variables, we queried Web of Science (WoS) for the total number of publications as a benchmark, and the three specific research subjects, as listed in Table 2 These subjects are presented in ascending order based on the total worldwide publications, with the total EU publications and the exact WoS query also provided. For each country, we extracted the total number of publications since 2015. To account for population differences, we standardized the data by dividing the total number of publications for each country by its population. This approach allows for a more meaningful comparison across countries of varying sizes.

Table 2. Research topics and publications included in analysis. Source: authors' analysis.

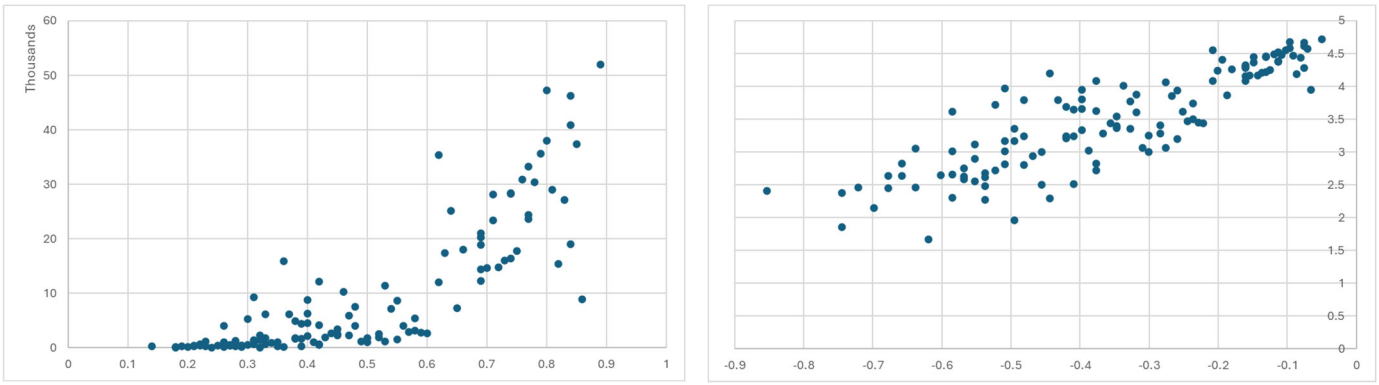
No.	Subject	Query (Keywords)	World Count	EU Count
1	Total	"the" (capturing all the publications with a generic keyword)	27,105,149	8,330,370
2	Privacy	"Privacy"	104,802	30,896
3	Blockchain	"Blockchain"	36,460	10,888
4	Cyber Security	"Cybersecurity" OR "Cyber-security" OR "Cyber Security"	22,376	7545

As regards the independent variables, the Augmented Human Development Index (AHDI) data were extracted from Our World in Data. The Augmented Human Development Index (AHDI) is a comprehensive measure of societal progress that expands upon the traditional Human Development Index (HDI) by incorporating an additional dimension of civil and political freedom (de la Escosura in [36]). This multidimensional approach reflects the understanding that human well-being and development cannot be captured by economic indicators alone. HDI and AHDI are widely used as predictors for country-level performance in various fields (Rughinis et al. [37], C. Rughinis et al. [38]). The AHDI is composed of four key dimensions: health, education, the standard of living, and civil and political freedom. Health is measured by life expectancy at birth, education by average years of schooling, the standard of living by GDP per capita (logarithmically adjusted to account for diminishing returns), and freedom by the Varieties of Democracy's liberal democracy index (Herre in [39]). Human development can be understood as a process of expanding people's choices and opportunities. This concept goes beyond mere economic growth, emphasizing the importance of health, knowledge, and political freedom in enabling individuals to reach their full potential. To create a standardized scale, each AHDI indicator is normalized to a range between 0 and 1 based on predetermined minimum and maximum values. This process allows for meaningful comparisons across different dimensions and countries. The AHDI is then calculated as the geometric mean of these four normalized indices, giving equal weight to each dimension. By using a geometric mean rather than a simple average, the AHDI reduces the substitutability between dimensions. This approach recognizes that high achievement in one area cannot fully compensate for deficiencies in another, providing a more nuanced picture of overall human development.

We chose to use a logarithmic scale for both the dependent and independent variables given the visualization of the relationships between the dependent variables and the Augmented Human Development Index (AHDI). The raw data exhibited a positive but highly variable relationship, making it difficult to discern a clear pattern. By applying a logarithmic transformation using the Lg10 function in the IBM SPSS version 29.0.2.0 statistical analysis software, we reduced the impact of outliers and achieved linear relationships. This transformation is crucial for satisfying the assumptions of linear regression models, leading to more reliable and interpretable results. The log–log scale helps in depicting a consistent, multiplicative relationship between the AHDI and total publications, thereby improving the robustness and accuracy of our analysis. The visualizations for the total publications per capita are presented in Figures 4–7 below.

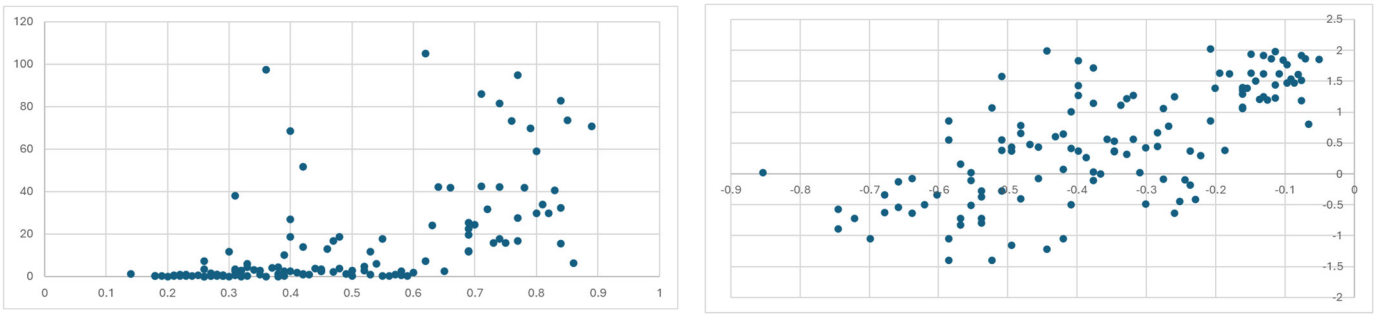
While we tried to introduce measures of country-level digitalization in the regression analysis, specifically the Network Readiness Index (NRI), which has values across a wide range of countries, this variable was highly correlated with GNI/capita and created collinearity issues.

Statistical analyses were performed using the IBM SPSS version 29.0.2.0 software, employing linear regression with the Enter method for the independent variables. The visualizations were generated using Microsoft Excel (Office 365).



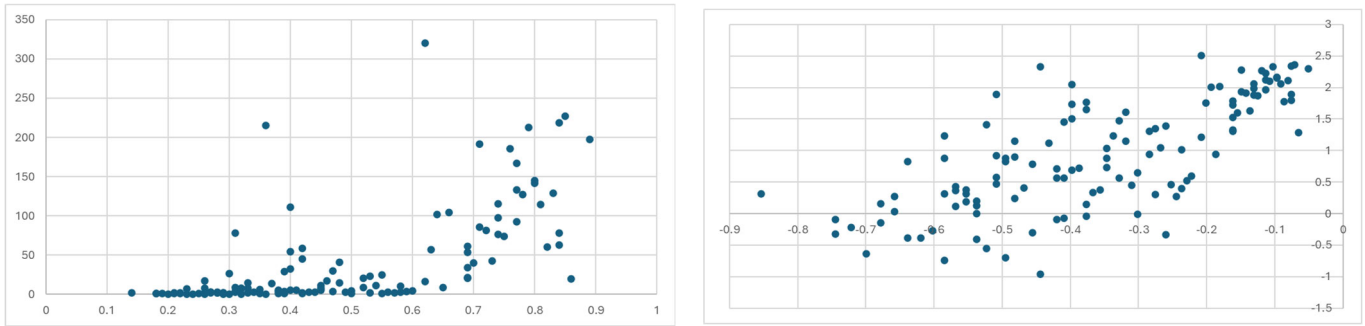
(**a**) (**b**)

Figure 4. Scatterplots of the total publications as a function of AHDI in raw numbers and logarithmic form. The logarithmic transformation permits linear regression modeling. Source: authors' analysis. (**a**) The total publications per million (*y*-axis) as a function of AHDI (*x*-axis). (**b**) The lg10 of the total publications per million (*y*-axis) as a function of lg10 AHDI (*x*-axis).



(**a**) (**b**)

Figure 5. Scatterplots of blockchain publications as a function of AHDI in raw numbers and logarithmic form. The logarithmic transformation permits linear regression modeling. Source: authors' analysis. (**a**) The total blockchain publications per million (*y*-axis) as a function of AHDI (*x*-axis). (**b**) The lg10 of the total blockchain publications per million (*y*-axis) as a function of lg10 AHDI (*x*-axis).

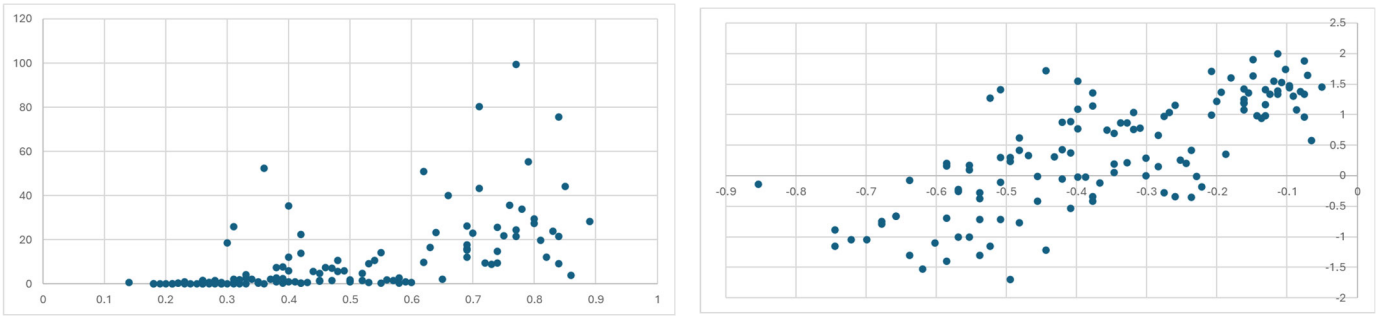


(**a**) (**b**)

Figure 6. Scatterplots of privacy publications as a function of AHDI in raw numbers and logarithmic form. The logarithmic transformation permits linear regression modeling. Source: authors' analysis. (**a**) The total privacy publications per million (*y*-axis) as a function of AHDI (*x*-axis). (**b**) The lg10 of the total privacy publications per million (*y*-axis) as a function of lg10 AHDI (*x*-axis).

The study encompasses 16 regression models, with 4 primary models reported in the main text and the remaining 12 presented only in the Supplementary Materials. The preliminary analysis revealed multicollinearity issues with an additional digitalization indicator, which was subsequently excluded. The Supplementary Materials contain models using both raw numbers and log transformations, as well as models solely utilizing AHDI

indicators and those incorporating research spending as a percentage of GDP. The inclusion of research spending enhanced the predictive value without introducing collinearity concerns. Consequently, the article reports only log-transformed models incorporating all five predictors. This approach provides a comprehensive statistical foundation for the research findings.



(**a**) (**b**)

Figure 7. Scatterplots of cybersecurity publications as a function of AHDI in raw numbers and logarithmic form. The logarithmic form indicates a linear relationship. Source: authors' analysis. (**a**) The total cybersecurity publications per million (*y*-axis) as a function of AHDI (*x*-axis). (**b**) The lg10 of the total cybersecurity publications per million (*y*-axis) as a function of lg10 AHDI (*x*-axis).

3. Results

This analysis explores the factors influencing scientific publications in blockchain, privacy, and cybersecurity across different countries. We examine how economic resources, research spending, education, life expectancy, and political systems affect research productivity in these fields. By comparing these areas to overall publication trends, we aim to understand what drives innovation in these important technological domains. The findings offer insights into how countries can support research and development in these rapidly evolving fields. This study provides a foundation for discussing the relationship between societal factors and scientific productivity in the digital age.

In what follows, we discuss, comparatively, the relevance of each AHDI component for predicting scientific productivity at the country level. The results are synthesized in Figure 8 and detailed in Table 3.

Table 3. Beta coefficients for the AHDI components in the multiple regression models for the selected research publication topics. Both the dependent and independent variables are transformed with a lg10 function. Source: authors' analysis. Coefficients marked with * are statistically significant for $p = 0.05$; coefficients marked with ** are statistically significant for $p = 0.01$; coefficients marked with *** are statistically significant for $p = 0.001$.

Dependent Variable (Publications)	Beta Coefficients				
	Life Expectancy at Birth	*Average Years of Schooling*	*Gross National Income per Capita*	*Liberal Democracy*	*Research Spending % of GDP*
Total per population	**0.125** **	0.027	**0.535** ***	**0.149** ***	**0.281** ***
Blockchain per population	0.132	**−0.165** *	**0.736** ***	0.031	**0.200** ***
Privacy per population	0.081	**−0.165** *	**0.651** ***	**0.133** **	**0.298** ***
Cybersecurity per population	0.001	0.063	**0.651** ***	0.092	**0.184** **

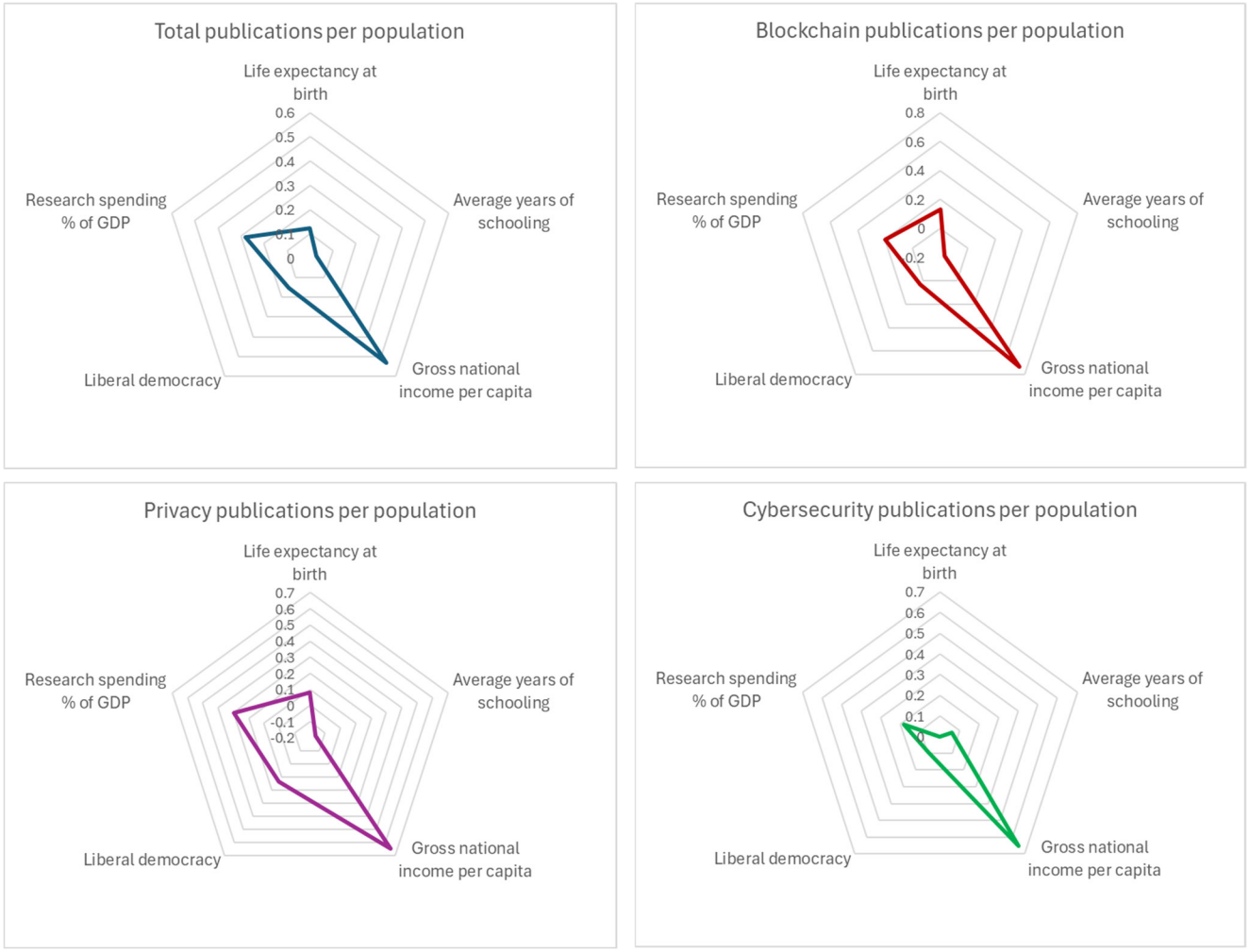


Figure 8. Radar visualizations of the beta coefficients in the four regression models. Source: authors' analysis.

The regression models provide insights into the factors influencing scientific publications in total and on the selected topics, per capita, across countries. Their explanatory power is synthesized in Figure 9.

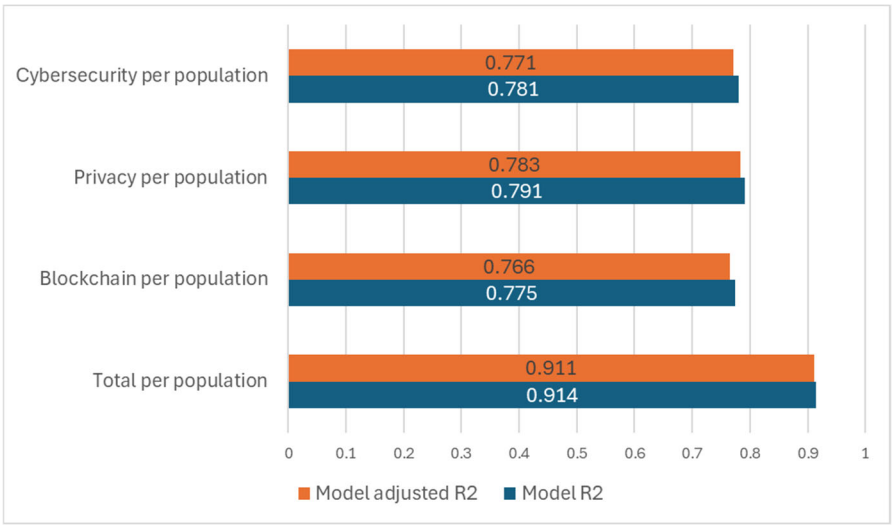


Figure 9. Explanatory power (R2 and adjusted R2 values) of multiple regression models. Source: authors' analysis.

The regression models for scientific publications in various fields demonstrate substantial explanatory power, as indicated by their R-squared values. The model for total publications per population shows the highest explanatory power, with an R-squared value of 0.914. This suggests that the selected independent variables account for 91.4% of the variation in the total scientific output across countries, indicating a very strong fit between the model and the data.

The models for specific technological fields—blockchain, privacy, and cybersecurity—show somewhat lower but still considerable explanatory power. Their R-squared values range from 0.775 to 0.791. The slightly lower R-squared values for the specific fields compared to the total publications suggest that while the chosen variables are still highly relevant, there may be additional factors influencing research output in these areas that are not captured by the model. This could include field-specific elements such as technological infrastructure, industry partnerships, or national priorities in digital innovation.

The similarity in the R-squared values among blockchain, privacy, and cybersecurity models (all around 0.78) indicates that the selected variables have comparable explanatory power across these emerging technological fields. This suggests a certain consistency in the factors driving research productivity in these areas despite their distinct focuses.

3.1. Total Publications per Capita

As regards the total publications per capita, the strongest predictor appears to be GNI per capita with a substantial positive effect (beta = 0.535). This suggests, in line with previous findings, that wealthier nations tend to produce more scientific publications, likely due to greater resources for research infrastructure, funding, and educational opportunities.

Research spending as a percentage of GDP also shows a notable positive relationship (beta = 0.281), indicating that countries allocating more resources specifically to research see higher publication outputs. This direct investment in scientific endeavors appears to translate into measurable increases in published work.

Life expectancy demonstrates a positive association with the publication rates (beta = 0.125). This could reflect the broader societal development (Rughiniș et al. in [25]), including health systems, which may create conditions conducive to scientific productivity. Alternatively, it might indicate that societies with higher scientific output benefit from advances that improve longevity.

The liberal democracy index shows a positive relationship (beta = 0.149), suggesting that more democratic societies tend to produce more scientific publications. This could be due to greater academic freedom, the open exchange of ideas, or institutional support for research in democratic systems.

Interestingly, average years of schooling has a very small positive effect (beta = 0.027). While education is undoubtedly important for scientific capability, this model suggests that at a national level, other factors like economic resources and research investment may play a more significant role in determining publication output.

3.2. Blockchain Publications per Capita

The second regression model examines the factors influencing blockchain publications per capita across countries, revealing some notable differences compared to both total scientific publications. The most striking feature of the blockchain model is the even stronger positive effect of GNI per capita (beta = 0.736), the largest among all the studied dependent variables. This suggests that blockchain research is highly concentrated in economically advanced countries, possibly due to the field's novelty, its ties to financial technology, and the need for sophisticated technological infrastructure.

Research spending as a percentage of GDP maintains a positive relationship (beta = 0.200) with blockchain publications, though slightly weaker than for the total publications. This might indicate that while general research investment benefits blockchain research, the field may also draw support from sources outside the traditional academic funding structures, such as private sector investments or cryptocurrency-related ventures.

Interestingly, life expectancy shows a stronger positive association with blockchain publication rates (beta = 0.132) compared to the total publications. This could suggest that blockchain research is more prevalent in countries with higher overall development levels, possibly due to its interdisciplinary nature spanning technology, economics, and law.

The most surprising finding is the negative relationship between average years of schooling and blockchain publications (beta = −0.165) when controlling for the other variables in the model. This contrasts with the negligible associations seen in the total publications. It might indicate that blockchain research is driven more by specialized expertise or entrepreneurial activity rather than broad educational attainment. Alternatively, it could suggest that countries with less established traditional education systems might be more open to emerging technologies like blockchain.

The liberal democracy index shows a very weak positive relationship (beta = 0.031) with blockchain publications, much smaller than for the total publications. This could imply that blockchain research is less sensitive to political systems, possibly reflecting its origins in decentralized and alternative economic thinking.

The specificities of blockchain publications compared to the total scientific output suggest that blockchain research is even more strongly tied to economic factors and less influenced by the traditional indicators of societal and educational development. This could reflect the field's close ties to financial innovation, its appeal in countries looking to leapfrog the traditional financial systems, and its potential attraction for countries seeking technological niches for economic development.

3.3. Privacy Publications per Capita

The third regression model examines the factors influencing privacy-related publications per capita across countries, revealing interesting patterns when compared to the total scientific publications and blockchain publications.

The strongest predictor for privacy publications remains GNI per capita, with a substantial positive effect (beta = 0.651). This is higher than for the total publications but lower than for blockchain, suggesting that while economic resources are crucial for privacy research, it may be slightly less dependent on economic factors than cutting-edge tech fields like blockchain.

Research spending as a percentage of GDP shows a stronger positive relationship (beta = 0.298) with privacy publications compared to the total and blockchain publications. This indicates that general research investment particularly benefits privacy research, possibly due to its interdisciplinary nature spanning technology, law, and social sciences.

The liberal democracy index demonstrates a more pronounced positive relationship (beta = 0.133) with privacy publications compared to the total publications and is notably stronger than for blockchain. This suggests that democratic societies tend to produce more privacy-related research, potentially reflecting greater concerns for individual rights and data protection in these political systems.

Life expectancy maintains a positive but weaker association with privacy publication rates (beta = 0.081) compared to the total and blockchain publications. This might indicate that while overall societal development contributes to privacy research, it is not as influential as for some other fields.

Interestingly, average years of schooling shows a negative relationship (beta = −0.165) with privacy publications, similar to blockchain and in contrast to the negligible association seen in the total publications. This unexpected finding might suggest that privacy research, like blockchain, is driven more by specialized expertise or emerging concerns rather than broad educational attainment.

The specificities of privacy publications compared to the other fields suggest that this research area occupies a unique position. It shares the strong economic dependency seen in blockchain research, but shows a stronger connection to democratic political systems. This could reflect the importance of privacy issues in liberal democracies and the relationships between technological advancement and individual rights. The negative association with

educational attainment, similar to blockchain, might indicate that privacy research is responding to rapidly evolving technological and societal challenges, potentially outpacing the traditional educational curricula. Alternatively, it could suggest that countries with less established educational systems might be more attuned to the emerging privacy concerns in the digital age. The strong influence of research spending on privacy publications highlights the field's academic nature and its reliance on dedicated research funding. This contrasts with blockchain, which showed a weaker relationship with research spending, possibly due to more diverse funding sources.

3.4. Cybersecurity Publications per Capita

The fourth regression model examines the factors influencing cybersecurity publications per capita across countries, revealing distinct patterns when compared to the total scientific publications, blockchain, and privacy publications.

The strongest predictor for cybersecurity publications is GNI per capita, with a substantial positive effect (beta = 0.651). This coefficient is similar to that for privacy publications and lower than for blockchain, but higher than for the total publications. This suggests that economic resources play a crucial role in cybersecurity research, reflecting the field's technological demands and its strategic importance to developed economies.

Research spending as a percentage of GDP shows a positive relationship (beta = 0.184) with cybersecurity publications. This effect is weaker than that for privacy publications but stronger than for blockchain, indicating that while general research investment benefits cybersecurity research, it may rely on diverse funding sources beyond the traditional academic channels.

The liberal democracy index demonstrates a positive relationship (beta = 0.092) with cybersecurity publications, stronger than that for blockchain but weaker than for privacy publications. This suggests that democratic societies tend to produce slightly more cybersecurity research, possibly due to greater concerns for digital rights and national security in open societies.

Interestingly, average years of schooling shows a slight positive relationship (beta = 0.063) with cybersecurity publications, contrasting with the negative associations seen in blockchain and privacy publications. This could indicate that cybersecurity research benefits, at least to some extent, from broader educational attainment, perhaps due to its integration into various academic disciplines.

Life expectancy shows a negligible association (beta = 0.001) with cybersecurity publication rates, the weakest among all the fields examined. This suggests that overall societal development, as measured by life expectancy, has little direct influence on cybersecurity research output.

The specificities of cybersecurity publications compared to other fields suggest a unique position for this research area. Like other tech-focused fields, it shows a strong dependence on economic factors. However, it differs in its positive association with educational attainment and its moderate relationship with democratic systems. The positive relationship with education, unlike blockchain and privacy, might reflect the integration of cybersecurity into the broader curricula and its relevance across multiple sectors. This could indicate that countries with well-developed educational systems are more likely to produce cybersecurity research.

The moderate influence of democracy on cybersecurity publications, stronger than that for blockchain but weaker than for privacy, might reflect the field's dual nature—balancing national security concerns (which can be prioritized in various political systems) with individual digital rights (more emphasized in democracies).

These findings highlight the diversified nature of cybersecurity research, shaped by economic resources, educational systems, and political structures. For countries aiming to boost their cybersecurity research output, these results suggest a multi-directional approach: substantial economic investment, support for broad educational attainment, fostering a democratic environment that values digital security, and ensuring robust research funding.

4. Discussion

The analysis of the regression models for scientific publications in blockchain, privacy, and cybersecurity reveals patterns of influence from various societal factors.

4.1. Patterns of Influence

Across all the fields, economic resources emerge as a dominant predictor of publication output, with GNI per capita consistently showing the strongest positive effect. This underscores the critical role of economic development in fostering scientific research, particularly in technology-intensive domains.

Research spending as a percentage of GDP also demonstrates a consistent positive relationship with publication rates across all the fields, though its influence varies. Privacy research appears to benefit most from general research investment, while blockchain shows a weaker relationship, possibly due to alternative funding sources in the private sector.

The impact of political systems, as measured by the liberal democracy index, varies across the fields. Privacy research shows the strongest positive association with democratic governance, suggesting that open societies may place greater emphasis on individual data protection. Cybersecurity research also benefits from democratic environments, albeit to a lesser extent, while blockchain research appears relatively insensitive to political systems.

Educational attainment, represented by average years of schooling, shows an intriguing pattern. While it has a negligible effect on total publications, it unexpectedly shows a negative relationship with blockchain and privacy research, contrasting with a slight positive association for cybersecurity. This suggests that emerging fields like blockchain and privacy may be driven more by specialized expertise or entrepreneurial activity than by broad educational foundations.

Life expectancy, often used as a proxy for overall societal development, shows varying degrees of positive association across the fields, with the strongest effect on blockchain publications and a negligible impact on cybersecurity research.

4.2. Field Specificities

The specificities of each field provide insights into their unique positions within the scientific landscape. Blockchain research emerges as highly dependent on economic factors, potentially reflecting its close ties to financial innovation and its appeal in countries seeking technological niches for economic development. It appears less influenced by the traditional indicators of societal and educational development, suggesting a field driven by specialized knowledge and alternative economic thinking.

Privacy research, while sharing a strong economic dependency with blockchain, shows a more pronounced connection to democratic political systems. This likely reflects the importance of privacy issues in liberal democracies and the relationship between technological advancement and individual rights. The field's strong reliance on research spending highlights its academic nature and dependence on dedicated funding.

Cybersecurity research occupies a middle ground, showing strong economic dependence like other tech-focused fields, but differing in its positive association with educational attainment and moderate relationship with democratic systems. This suggests a more integrated field, relevant across multiple sectors and benefiting from broader educational foundations.

4.3. Relationship with the State-of-the-Art on General Research Productivity

Our analysis of the societal factors that shape research output on topics such as blockchain, privacy, and cybersecurity largely converges with the broader state-of-the-art in research on country-level scientific productivity, while also offering some nuanced insights.

Consistent with the literature, the models confirm the strong positive influence of economic factors on scientific output. The finding that GNI per capita is the strongest predictor across all the examined fields (total publications, blockchain, privacy, and cyber-

security) aligns with numerous studies highlighting the crucial role of a country's economic resources in fostering scientific productivity.

The positive relationship between research spending as a percentage of GDP and publication rates in the models also corroborates the established understanding that targeted investment in R&D significantly impacts scientific output. This reinforces the widely accepted view that both overall economic health and specific research funding are key drivers of scientific productivity.

However, the models reveal some interesting variations across different research fields, which adds nuance to the existing literature. For instance, the stronger effect of GNI per capita on blockchain publications compared to other fields suggests that emerging, technology-intensive areas may be particularly dependent on economic resources. This aligns with the studies indicating that different scientific disciplines may have varying sensitivities to economic factors.

The models' findings on the role of education, measured by average years of schooling, present an intriguing divergence from some previous research. While the literature generally suggests a positive relationship between educational attainment and scientific productivity, the models show a negligible or even negative effect for some fields. This unexpected result may indicate that in rapidly evolving technological domains, factors other than general educational levels, such as specialized expertise or entrepreneurial activity, play a more significant role.

The positive association between the liberal democracy index and publication rates, particularly strong for privacy research, aligns with the studies suggesting that political openness and democratic governance can enhance scientific output. This adds to the growing body of evidence on the importance of political and institutional factors in shaping research productivity.

4.4. Relationship with the State-of-the-Art on Specialized Fields

Bibliometric research on factors influencing research productivity in cybersecurity, blockchain, and privacy has traditionally focused on publication counts, top contributors, and collaboration patterns. Previous studies have identified the United States and China as leading producers across these fields, noting a significant concentration of output among a few countries. Various factors influencing productivity have been suggested, including economic conditions, national priorities, technological infrastructure, government strategies, and research funding.

Our study presents several original contributions to this field of research. By employing regression models to analyze the factors influencing research productivity, it provides quantitative measures of their influence, allowing for more precise comparisons. This approach enables a direct comparison of how different factors affect productivity across blockchain, privacy, and cybersecurity, revealing field-specific patterns.

The study's distinction between the impact of general research spending and other economic factors offers more detailed insights into the role of dedicated research funding. This specificity allows for a clearer understanding of how different types of investment affect research output.

Our study also sheds new light on the influence of political systems on research output. The varying impact of the liberal democracy index across the fields, particularly its strong influence on privacy research, provides novel insights into the relationship between political structures and research focus.

One of the most striking findings is the unexpected negative relationship between average years of schooling and research output in blockchain and privacy. This challenges assumptions about the role of general education in these fields and suggests that specialized knowledge or entrepreneurial activity may be more crucial drivers of productivity.

By including multiple factors in a single regression model, the research offers a more comprehensive view of how various societal elements interact to influence research produc-

tivity. Unlike many previous studies that examined absolute numbers, this analysis focuses on per capita output, providing a deeper understanding of country-level productivity.

4.5. Research Limitations

The research presented in this study has several limitations that should be acknowledged. First, the reliance on data from the Web of Science may not capture the full scope of scientific publications, particularly those in non-English languages or from emerging research communities that are less represented in this database. This could lead to an incomplete picture of global research productivity.

Another limitation is the potential overemphasis on economic factors such as GNI per capita and research spending. While these are significant predictors of scientific output, other important factors like cultural influences, specific national innovation policies, and the structure of research institutions may also play crucial roles but were outside the scope of this study.

Potential biases in the publication data, such as self-citation practices or the varying impact of conferences versus journals in different fields, could affect the results. Additionally, while the study uses the Augmented Human Development Index (AHDI), this measure may miss other influential factors such as the quality of education, research infrastructure, and specific government policies on technology and innovation.

The correlations identified in the study do not establish causal relationships, leaving room for further investigation into the causality between the variables and scientific productivity. Moreover, the rapidly evolving nature of the fields of blockchain, privacy, and cybersecurity means that the study may not fully capture the latest developments and trends.

4.6. Future Research Directions

Building on the current study, future research could extend our understanding of scientific productivity at the country level in several ways. A longitudinal analysis would be valuable to track how the relationships between socio-economic factors and scientific output evolve over time, potentially revealing the impact of policy interventions or global trends. Exploring field-specific factors, such as national cybersecurity policies or cryptocurrency regulations, could provide deeper insights into the unique drivers of productivity in blockchain, privacy, and cybersecurity research.

Further investigation into institutional factors, like university rankings or industry-academia collaboration rates, would complement the current macro-level analysis. This could be enriched by the qualitative case studies of countries showing exceptional performance or unexpected patterns. Examining the international collaboration networks and their relation to national productivity levels would add another dimension to our understanding.

Future studies could also explore the link between publication quantity and the various measures of research impact or innovation outcomes. Extending the analysis to other rapidly evolving technological fields would help identify common patterns or divergences in the factors influencing scientific productivity across different domains. Evaluating the effectiveness of specific national policies aimed at boosting research in these areas would provide practical insights for policymakers.

Additionally, analyzing the effect of human capital flow, such as brain drain or gain, on national scientific productivity in these specialized fields could reveal important dynamics. Finally, exploring how the interdisciplinary nature of blockchain, privacy, and cybersecurity research might influence productivity factors would contribute to a more nuanced understanding of these technological fields.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app14167086/s1, Supplementary Materials with additional charts and regression models.

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