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Technical Innovations and Social Implications: Mapping Global Research Focus in AI, Blockchain, Cybersecurity, and Privacy

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Abstract: This study examines the balance between technical and social focus in artificial intelligence, blockchain, cybersecurity, and privacy publications in Web of Science across countries, exploring the social factors that influence these research priorities. We use regression analysis to identify predictors of research focus and cluster analysis to reveal patterns across countries, combining these methods to provide a broader view of global research priorities. Our findings reveal that liberal democracy index, life expectancy, and happiness are significant predictors of research focus, while traditional indicators like education and income show weaker relationships. This unexpected result challenges conventional assumptions about the drivers of research priorities in digital technologies. The study identifies distinct clusters of countries with similar patterns of research focus across the four technologies, revealing previously unrecognized global typologies. Notably, more democratic societies tend to emphasize social implications of technologies, while some rapidly developing countries focus more on technical aspects. These findings suggest that political and social factors may play a larger role in shaping research agendas than previously thought, necessitating a re-evaluation of how we understand and predict research focus in rapidly evolving technological fields. The study provides valuable information for policymakers and researchers, informing strategies for technological development and international collaboration in an increasingly digital world.

Keywords: research focus; artificial intelligence; blockchain; cybersecurity; data privacy; regression model; cluster analysis; AHDI

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1. Introduction

In today's digital age, the relationship between technical innovations and social implications in fields such as AI, cybersecurity, blockchain, and data privacy has become increasingly significant. Each of these technologies not only drives technical advancements but also introduces social, ethical, and governance challenges. For example, AI is not only about advancing computational capabilities but is closely linked to issues of bias and fairness, where algorithms can inadvertently perpetuate social inequities or inflict harm. By examining how AI affects decision-making processes, we can better understand its impact on social justice and equity. Similarly, data privacy is not merely a technical matter of securing personal information but also plays an important role in shaping power imbalances between individuals, corporations, and governments in a data-driven world. Blockchain's decentralized nature challenges traditional governance models and offers new frameworks for enhancing transparency and trust, particularly in systems where power is concentrated. Cybersecurity, too, extends beyond technical defenses to the realm of trust and social resilience, directly influencing how societies secure their digital infrastructures and protect civil liberties. These technologies are particularly well-suited for studying the balance between technical and social research because they inherently blend innovation with social impact.

This study is motivated by the need to better understand the balance between technical innovation and social considerations in these key technological fields. By examining how different countries prioritize technical versus social research in these areas, this study seeks to uncover patterns influenced by economic, political, and social factors. The findings aim to provide relevant information for policymakers and researchers in shaping future technological and research agendas.

In our previous study [1], we examined the factors influencing scientific productivity in the domains of blockchain, privacy, and cybersecurity across various countries. We focused on how economic, political, educational, and social factors drive research output in these fields. Our findings revealed that Gross National Income per capita and research spending as a percentage of GDP were significant predictors of publication rates. The current research extends this work by focusing on the balance between technical and social research within these fields, plus artificial intelligence. This shift from quantity to research focus is important for two main reasons. Firstly, as digital technologies become more prevalent, understanding the nature and focus of research, not just its volume, is crucial for informing technology development and regulation. Secondly, examining the technical-social balance provides information about national research priorities that productivity metrics alone cannot capture.

Building on this research, the present study shifts the focus from the quantity of scientific productivity to the qualitative balance between technical and social research within the realms of artificial intelligence, blockchain, cybersecurity, and privacy.

We thus aim to explore two key questions. First, we investigate how social factors influence a country's balance between technical and social research in selected digital technologies. This question is addressed through regression analysis, examining the relationship between various social, economic, and political indicators and the ratio of technical to social science publications across AI, blockchain, cybersecurity, and privacy. Second, we explore what patterns emerge when grouping countries based on their research focus across these multiple digital technologies. This question is approached through cluster analysis, identifying groups of countries with similar research prioritization profiles.

This study makes several contributions to the understanding of social factors in technological research. Firstly, it provides an analysis of the balance between technical and social research focus across multiple technologies simultaneously, offering a cross-domain perspective. Secondly, it identifies previously unexamined social predictors of research focus, highlighting the roles of democratic institutions, life expectancy, and overall social well-being. Thirdly, by employing both regression and cluster analysis, this study reveals not only the factors influencing research focus but also distinct global patterns in how countries approach these technologies. Finally, our findings challenge conventional assumptions about the primacy of economic and educational factors in shaping research agendas.

The remainder of this paper is structured as follows: Section 2 provides a literature review, examining existing research on factors influencing scientific output and bibliometric studies in AI, blockchain, cybersecurity, and privacy. Section 3 outlines our methodology, detailing data sources, variable selection, and analytical approaches, including regression analysis and cluster analysis. Section 4 presents the results of our study, first discussing the predictors of technical versus social research focus identified through regression analysis, followed by the findings from our cluster analysis of countries. Section 5 offers a discussion of these results, highlighting our original contributions and placing our findings in the context of the existing literature. Finally, Section 6 concludes the paper, summarizing key insights, acknowledging limitations, and suggesting directions for future research.

2. Literature Review

There is a rich strand of literature that discusses factors influencing scientific output at the country level, typically measured through the number of publications or scientific productivity (publications per population). Various studies have examined economic, social, and institutional factors that contribute to a country's scientific results.

2.1. Economic Factors

Economic wealth is consistently identified as a significant determinant of research output across multiple studies. Rodríguez-Navarro and Brito [2] highlight that while economic resources play a crucial role, they are not the sole determinant of a country's success in generating new knowledge. Lancho-Barrantes et al. [3] found that Gross Domestic Expenditure on R&D (GERD—a country's total expenditure on research and development performed within the country) as a percentage of Gross Domestic Product (GDP—the total economic output of a country) is a significant predictor of scientific production, explaining 98% of the variance among 19 countries studied over 17 years.

Several studies have found strong correlations between economic indicators and research output. Onyancha [4] reported significant correlations between research indicators (number of articles, citations, H-index) and economic indicators like GDP and GNI (Gross National Income, the total income earned by a country's residents and businesses, including income earned abroad) in sub-Saharan African countries. Similarly, Zhang et al. [5] observed a positive correlation between a country's GDP and its research output in the field of psychiatry. Rahman and Fukui [6] identified Gross National Product (GNP—the total value of all final goods and services produced by a country's residents and businesses in a given period, typically a year, regardless of where that production takes place) per capita and R&D expenditure as significant predictors of biomedical research productivity.

However, some studies suggest that the relationship between economic factors and scientific output is not straightforward and depends on the fields of study and the metrics used. Jamjoom and Jamjoom [7] found that GDP per capita and the percentage of GDP spent on R&D have only a moderate impact on productivity in clinical neurology research. Interestingly, Allik et al. [8] found that when controlling for social factors, economic wealth indicators such as Gross National Income (GNI) and research and development expenditure (GERD) did not significantly predict scientific excellence.

2.2. Social and Institutional Factors

Several studies highlight the importance of social and institutional factors in shaping scientific output. Szuflita-Żurawska and Basińska [9] emphasize the role of socio-economic factors such as research funding and university prestige in determining scientific productivity. They also highlight the importance of international collaboration in boosting global scientific output.

The presence and quality of academic and research institutions are also relevant factors. Lancho-Barrantes et al. [3] identified the presence of academic and research institutions as a significant predictor of scientific production. Jamjoom and Jamjoom [7] found that the number of universities in the world's top 500 strongly correlates with scientific productivity in clinical neurology research.

Wahid et al. [10] identified key drivers at individual, institutional, and national levels. Personal factors such as time management, academic rank, and qualifications significantly affect individual productivity. Situational factors, including funding and collaboration, impact both individuals and institutions. Environmental factors like library support and access to resources are important for institutional and national productivity.

Language and cultural factors also play a role. Gantman [11] found that linguistic factors positively influence productivity in the social sciences, medicine, and agricultural sciences. Tasli, Kacar, and Aydemir [12] highlighted the impact of language on citation rates, with English-language journals receiving more citations.

Political and historical contexts have been found to influence scientific output. Gantman [11] reported that political authoritarianism negatively impacts scientific output in some fields. Allik et al. [8] found that smaller countries with good governance and no communist past tend to produce high-quality scientific publications.

2.3. Other Factors

Some studies have explored more specialized factors. Dragos and Dragos [13] found that the Environmental Performance Index (EPI) significantly predicts research output in environmental sciences and ecology. Doi, Heeren, and Maurage [14] explored predictors of Nobel awards, finding that scientific activity, measured by the number of publications and research expenditure, is the most significant predictor.

Interestingly, some unconventional factors have been proposed to influence scientific excellence, illustrating the challenges of identifying determinants of research output and quality. Messerli [15] controversially suggested a link between dietary habits, particularly chocolate consumption, and Nobel Prize awards. However, subsequent research by Doi, Heeren, and Maurage [14] found that such dietary factors have only a minor predictive relevance for top-level scientific productivity when compared to more traditional indicators of scientific activity. Their analysis revealed that scientific activity measures, such as the number of publications and research expenditure, are the most significant predictors of scientific excellence as measured by Nobel awards. These studies highlight the importance of rigorous analysis in identifying true predictors of scientific output and the need to consider a wide range of potential factors in understanding the drivers of research productivity and focus.

2.4. Bibliometric Studies of Technical Fields

Unlike studies on general scientific production, the literature on scientific output and productivity in technical fields has been dominated by a bibliometric approach. Bibliometric studies in technical fields such as cybersecurity, blockchain, privacy protection, and AI typically employ similar methodologies to analyze research trends and productivity at the country level. These studies often use large bibliographic databases like Web of Science, Scopus, or specialized platforms to collect publication data over specific time periods, ranging from a few years to several decades. They then apply various quantitative analyses to identify leading countries in terms of publication output, examine collaboration patterns, and assess research impact through citation metrics, as discussed in Obreja [16]. For instance, studies by Loan, Bisma, and Nahida [17], Omote et al. [18], Dhawan, Gupta, and Elango [19], and Ravi and Palaniappan [20] consistently found the United States and China to be dominant contributors in their respective fields, with other countries like India, the UK, and various European nations also showing significant output. These analyses often reveal trends in research topics, such as the shift from Bitcoin to broader blockchain applications noted in several blockchain-related studies. While most of these studies primarily focus on absolute publication counts, some, like Cojocaru and Cojocaru [21], attempt to contextualize research output by comparing it with national cybersecurity rankings or other indicators. However, it is notable that few of these studies directly address scientific productivity relative to population or scientific focus, or explore other country-level factors that might influence research output, such as GDP, research investment, or political organization.

Building on the established bibliometric approach in cybersecurity research, studies have revealed interesting patterns in country-level contributions. Loan, Bisma, and Nahida [17] highlighted the importance of specialized terminology and institutional collaboration in cybersecurity research. Omote et al. [18] observed differences in research focus between countries, noting that the US tends to emphasize CPU security and theoretical research, while China focuses more on applied technologies, including IoT and cloud computing. Cojocaru and Cojocaru [21] found that factors such as political instability can negatively impact a country's performance in cybersecurity development and e-government rankings, despite relatively high research output. They also noted that the overall share of cybersecurity publications within the field of computer science is relatively low for all Eastern European countries, not exceeding 1% in most cases. Dhawan, Gupta, and Elango [19] suggested that factors like industrial/commercial computer use, digitization of the economy, cybercrime rates, and research funding may contribute to the United States' dominant position in the field. They also noted that countries like India need to focus on infrastructure development, manpower, and talent to boost their research capacity in cybersecurity. Ravi and Palaniappan [20], while focusing on cryptography, provided insights relevant to cybersecurity. They found India to be the top contributor in their study period (2011–2022), followed by China and the USA, highlighting the growing role of emerging economies in this closely related field.

Thus, these studies on scientific production on cybersecurity underscore the dominance of the United States and China, the growing contributions of emerging economies like India, and the importance of factors such as research funding, institutional collaboration, and national priorities in shaping a country's research output.

Bibliometric studies on blockchain research also reveal interesting patterns and trends in topics (such as Obreja [22]) and in country-level scientific output. Analyses by Khurana and Sharma [23], Guo et al. [24], Firdaus et al. [25], Dabbagh, Sookhak, and Safa [26], and Boakye, Zhao, and Ahia [27] consistently identify China and the United States as the leading contributors to blockchain research, with European countries also in the top of the distribution. Khurana and Sharma [23] noted the higher citation rates for open-access publications and varying collaboration patterns across countries. Guo et al. [24] and Firdaus et al. [25] observed that while some countries lead in publication volume, others demonstrate high impact through citations despite lower output. Dabbagh, Sookhak, and Safa [26] emphasized the role of funding, identifying China's National Natural Science Foundation as a major supporter of blockchain research. Boakye, Zhao, and Ahia [27], focusing on blockchain in finance, noted a disparity between China's high publication volume and lower citation impact compared to countries like the USA and Germany. Valencia-Arias et al. [28], while focusing on the intersection of machine learning and blockchain in security and privacy, corroborate these findings. They identified the United States, Australia, and India as top contributors in terms of both productivity and impact, with China showing high productivity but lower impact. These studies suggest that factors such as government support, research funding, expertise in related fields, and international collaboration significantly influence a country's contribution to blockchain research.

Bibliometric studies on privacy research reveal similar patterns and factors influencing country-level contributions. Dominic et al. [29], focusing on zero-knowledge proof applications for digital privacy from 2016 to 2021, found China and the United States leading in researcher affiliations, with European countries also actively involved. Their study highlighted the relevance of this technology to various applications, including IoT, cloud services, and blockchain. Yin et al. [30] conducted a comparative analysis of privacy protection research in China and internationally from 1976 to 2022. They found China produced the highest number of publications, followed by the United States and Australia. However, the United States showed the highest centrality in international collaboration networks. The study noted differences in research focus, with international research emphasizing user behavior and trust issues, while Chinese research focused more on technical aspects of privacy protection. Valencia-Arias et al. [28] examined research on machine learning and blockchain in security and privacy contexts from 2013 to 2023. They identified the United States, Australia, and India as top contributors in both productivity and impact, with China showing high productivity but lower impact. Their analysis revealed strong international collaborations and emerging research clusters in areas like IoT, federated learning, and smart contracts. Ali et al. [31] analyzed computer privacy research from 1976 to 2020, finding North America, particularly the United States, as the leading contributor, followed by European countries. They noted a correlation between research productivity and R&D investments, with the United States and European countries showing higher output due to greater funding. Shu and Liu [32] reviewed consumer privacy research from a marketing perspective, identifying the USA as the most prolific region, followed by China and the UK. Their study highlighted the evolution of research themes in consumer privacy, from privacy calculus to emerging topics like privacy-enhancing technologies and contemporary privacy contexts. The study by Dhawan, Gupta, and Elango [19], while primarily focused on cybersecurity, also touched on privacy aspects. They found the United States to be the dominant contributor, followed by the UK and China. Their analysis indicated that factors such as industrial/commercial computer use, digitization of the economy, and research funding influence a country's research output in this field. Thus, these publications show that the United States consistently leads in privacy research, both in terms of output and impact. China is a significant contributor, particularly in technical aspects of privacy protection. European countries, Australia, and India also show significant participation. Factors influencing country-level contributions include research funding, international collaboration, and alignment with national priorities in technology and data protection.

The bibliometric studies across cybersecurity, blockchain, and privacy research reveal interesting patterns in research focus, particularly regarding the balance between technical and social aspects. In cybersecurity, Omote et al. [18] observed that the US tends to emphasize CPU security and theoretical research, while China focuses more on applied technologies like IoT and cloud computing. Blockchain research has evolved from early Bitcoin-centric studies to broader applications in finance, security, and privacy, as noted by Guo et al. [24], Boakye, Zhao, and Ahia [27], and Stan, Barac, and Rosner [33]. In privacy research, Yin et al. [30] found that international studies often emphasize user behavior and trust issues, leaning towards social aspects, while Chinese research concentrates more on technical aspects of privacy protection. Valencia-Arias et al. [28] identified emerging research clusters blending technical and application-oriented focuses in areas like IoT, federated learning, and smart contracts. Shu and Liu [32] observed an evolution in consumer privacy research from privacy calculus, a more social science approach, to privacy-enhancing technologies and contemporary privacy contexts, indicating a shift towards more technical focuses. Similarly, Ali et al. [31] highlighted the growing importance of machine learning techniques in computer privacy research, further emphasizing the technical orientation in this field.

Thus, previous research indicates that while there is a strong emphasis on technical aspects across cybersecurity, blockchain, and privacy research, there is also a growing recognition of the importance of social, behavioral, and application-oriented research. The balance between technical and social focus varies by country, with some nations like China tending more towards technical aspects, while others like the US and some European countries show a more balanced approach or greater emphasis on social and behavioral aspects.

Interestingly, AI has been a substantial focus of bibliometric research across diverse fields. This allows us to compare studies of AI publications in technical areas with studies of AI publications in social areas, including AI ethics.

When examining AI research in general, Gao et al. [34] analyzed research from 2008 to 2018, finding China as the leading contributor with 39.46% of high-cited articles, followed by the United States with 19.27%. They attributed China's dominance to significant investments in AI and related technologies. The study also highlighted the importance of institutional collaboration, with 90.14% of publications being multi-authored. De la Vega Hernández et al. [35] conducted a comprehensive analysis of AI research from 1990 to 2019, revealing that the United States contributed 30.72% of global AI publications, followed by China with 17.33%. They noted that countries with the highest research output in AI were also among the largest economies globally, suggesting a correlation between economic strength and research productivity. The study emphasized the role of robust funding mechanisms, well-established research infrastructures, and collaboration networks in enhancing research productivity. Both studies identified key research areas in AI, including machine learning, deep learning, and robotics. They also observed an evolution in research focus, with emerging topics like big data and adversarial learning gaining prominence in recent years.

Research on AI in science and technology fields has also been analyzed through bibliometric studies. Guo et al. [36] conducted an analysis of AI in healthcare research from 1995 to 2019, revealing the dominance of high-income countries. They found that the United States contributed 45.42% of the research output, followed by China. The study highlighted a dramatic increase in publication output, particularly between 2014 and 2019, with a growth rate of 45.15%. Tran et al. [37] examined AI research in health and medicine from 1977 to 2018, confirming the leading roles of the United States, China, and major European nations. Their study documented the importance of global collaboration in enhancing research productivity, with the United States serving as a hub for international research networks. They also noted a shift in research focus from infectious diseases to non-communicable diseases. Boudry et al. [38] analyzed AI research in ophthalmology from 1966 to 2019. Their findings aligned with broader trends, showing the dominance of high-income countries like the USA, UK, and Germany. The study highlighted the importance of institutional resources and international collaborations in producing high-impact research.

Bibliometric studies on AI in social fields and ethics also identify a pattern of dominance by Western countries, particularly the United States and the United Kingdom, with China emerging as a significant contributor. Saheb, Saheb, and Carpenter [39], Zhang et al. [40], and Chuang et al. [41] all highlight the leading role of the USA and UK, with the latter authors providing a slightly different view by adjusting for GDP and population size, which elevated the UK and Switzerland in terms of relative productivity [41]. These studies again identify economic strength, institutional prestige, and research funding as key factors influencing a country's research output. Hinojo-Lucena et al. [42] and Calvo-Rubio, Mauricio, and Ufarte-Ruiz [43] emphasize the importance of institutional support and democratic traditions in fostering research productivity, particularly in fields like AI in higher education and journalism. International collaboration also emerges as a crucial factor across studies. Prieto-Gutierrez et al. [44] and Zhang et al. [40] note varying collaboration patterns, with some countries focusing on domestic partnerships while others, especially smaller European nations, prioritize international collaborations. Obreja, Rughiniș, and Rosner [45] and Bircan and Akdag Salah [46] offer insights into the evolving landscape of AI research in social sciences, noting China's growing influence in publication numbers but lower citation impact compared to Western counterparts. Bircan and Akdag Salah [46] also highlight the challenge of integrating AI and Big Data research into traditional social science disciplines. Shu and Liu [32], focusing on consumer privacy research from a marketing perspective, identified the USA as the most prolific region, followed by China and the UK.

Comparing bibliometric studies on AI in technical fields with those in social fields and ethics reveals interesting similarities and differences in country-level patterns and influencing factors. In both areas, the United States and China emerge as dominant contributors, with Western European countries also showing strong presence. However, the relative positions and strengths of these countries vary depending on the focus of AI research. In technical fields, such as healthcare and ophthalmology, studies by Guo et al. [36], Tran et al. [37], and Boudry et al. [38] consistently show the United States leading in both output and impact, with China following closely. These studies emphasize the importance of economic strength, research funding, and institutional infrastructure in driving productivity. In contrast, studies on AI in social fields and ethics, including those by Saheb, Saheb, and Carpenter [39], Zhang et al. [40], and Chuang et al. [41], reveal a more diverse picture. While the United States still leads, the United Kingdom and other European countries play a more prominent role, particularly when productivity is adjusted for factors like GDP or population size. These studies highlight the importance of democratic traditions, institutional prestige, and international collaborations in shaping research output. The focus of AI research also appears to influence the emergence of new contributors. In social fields and ethics, studies like Saheb, Saheb, and Carpenter [39] note the rising contributions from countries like Greece and Argentina, a trend less evident in technical AI research.

Another notable difference is in the nature of collaborations. In technical fields, studies show a trend towards large-scale, often domestic collaborations, especially in countries like the United States and China. In social fields and ethics, there is a greater emphasis on international collaborations, particularly among European countries. Lastly, while both areas show interdisciplinary tendencies, the integration challenges differ. In social fields and ethics, studies like Bircan and Akdag Salah [46] point to difficulties in integrating AI research into traditional social science frameworks. In technical fields, AI research more readily combines with existing disciplines, especially with discussions of AI ethics [47,48].

Our review of bibliometric studies on research across digital technology fields reveals a noticeable gap in the current literature. While numerous studies have examined country-level factors influencing overall research output and impact, there has been little to no inquiry into what determines the balance between technical and social research focus. This represents a novel area for investigation. Understanding the economic and social factors that influence a country's tendency to focus on technical aspects of technology versus its social implications could provide useful information for national research priorities and policy directions.

Thus, we aim to explore how factors like economic development and social features shape a country's research focus. Additionally, we investigate potential country clusters based on their research focus in these fields. This line of inquiry is particularly interesting given the observed differences in country-level patterns between technical and social research on technological fields, as highlighted in our review.

3. Methods and Data

This research utilizes existing statistical data from global sources to examine the relationship between social factors and research focus in four selected technologies. The study's dependent variables were derived from Web of Science (WoS) database queries, counting publications in both Science Citation Index Expanded (SCIE) and Social Sciences Citation Index (SSCI) for artificial intelligence, blockchain, cybersecurity, and privacy (see Table 1). The Science Citation Index Expanded (SCIE) and the Social Sciences Citation Index (SSCI) are databases within the Web of Science Core Collection, where the leading journals in their respective fields are indexed based on rigorous selection criteria, including high Impact Factors. SCIE covers scientific disciplines such as natural sciences, engineering, and medicine, indexing peer-reviewed journals that focus on technical research. SSCI focuses on the social sciences, including fields like sociology, psychology, and economics, and tracks research with a social and behavioral emphasis. Both indices are used by researchers to access publications, track citations, and analyze research output across scientific and social domains. Our queries used the following keywords: "Artificial Intelligence", "Privacy", "Blockchain", and "Cybersecurity" OR "Cyber-security" OR "Cyber Security".

Table 1. Total number of publications by topic in two Web of Science indexes.

Topic	SCIE	SSCI	SCIE/SSCI Ratio across All Countries
Artificial intelligence	95,468	17,111	5.58
Blockchain	17,177	4234	4.06
Cybersecurity	8404	2071	4.06
Privacy	47,348	16,466	2.88

We acknowledge that these fields are diverse, with numerous related terms and subfields. Our choice of keywords was deliberate, aiming to balance precision with scope and ensure consistency across countries and disciplines. These core terms are widely recognized and frequently used in both technical and social science literature, serving as reliable indicators of general research trends in these areas. While this approach may not capture every relevant publication, particularly in niche or emerging subfields, it provides a robust basis for comparing broad patterns of research focus across nations. More expansive queries including specific subfields (e.g., 'machine learning' for AI or 'data encryption' for cybersecurity) could potentially capture additional papers but might also introduce noise and reduce cross-country comparability. Furthermore, these specialized terms could be too closely tied to specific disciplines, such as engineering or social sciences, which may disproportionately affect the ratio of SCIE to SSCI publications captured by broader terms. We recognize this as a limitation of our study. Future research could employ more comprehensive search strategies, potentially using machine learning techniques to identify relevant publications across a wider range of keywords and related concepts. Such approaches could offer more granular insights into specific subfields or emerging research areas within these broader technological domains.

To estimate the relative technical to social focus in research approaches for the four selected topics in each country, we utilized the ratio of SCIE to SSCI publications. This analysis included all publications registered in each index as of 19–20 July 2024. We acknowledge that this ratio is an approximation and that SCIE journals often publish interdisciplinary research incorporating social and ethical considerations alongside technical aspects. Nevertheless, this measure provides a broad indicator of relative emphasis across a large corpus of publications. While this approach allows for the identification of general trends and patterns at a national level, we recognize its limitations. Future studies could enhance the precision of this measure through more granular content analysis of individual papers.

In our analysis, we excluded countries with fewer than seven SSCI-indexed publications to ensure statistical reliability and minimize the impact of outliers. This threshold was chosen based on several considerations. A minimum of seven publications provides a more representative sample of a country's research output, reducing the risk of individual papers disproportionately affecting the results. With very low publication numbers, small changes can lead to extreme ratio values. For example, a country with 1 SSCI and 10 SCIE publications would have a ratio of 10, while a country with 2 SSCI and 10 SCIE publications would have a ratio of 5. This volatility decreases as the number of publications increases. The threshold of seven strikes a balance between including as many countries as possible and maintaining reliable data. This approach allows us to include a wide range of countries in our analysis while mitigating the risk of skewed results due to very low publication numbers.

Our categorization of papers as "technical" or "social" is based on their indexing in SCIE or SSCI, respectively, rather than on specific content or keywords. SCIE journals predominantly focus on scientific and technical research, while SSCI journals emphasize social science perspectives. We acknowledge that AI, blockchain, privacy, and cybersecurity are interconnected fields, and papers may address multiple aspects simultaneously. Our approach provides a high-level view of research focus trends across countries, rather than a detailed classification of individual papers. Papers addressing multiple topics were included in counts for each relevant keyword. While this method has limitations, particularly for interdisciplinary work, it offers a useful proxy for distinguishing broader technical versus social research emphases. Future studies could employ more sophisticated categorization methods, such as content analysis or machine learning algorithms, to refine this approach. Additionally, a network analysis of keyword co-occurrences could provide further information into the interconnections between these technological domains and their social implications.

For independent variables, the study draws on the Augmented Human Development Index (AHDI), an enhanced version of the Human Development Index that incorporates civil and political freedoms alongside traditional measures of social progress. AHDI data was obtained from Our World in Data [49]. The Augmented Human Development Index (AHDI) is a measure of social progress that builds upon the traditional Human Development Index by incorporating an additional dimension of civil and political freedom. It encompasses four key aspects of human development: health, education, standard of living, and political freedom. Health is measured by life expectancy at birth, education by mean years of schooling, standard of living by GDP per capita (logarithmically adjusted to reflect diminishing returns as income increases), and political freedom by the Varieties of Democracy's liberal democracy index. To calculate the AHDI, each indicator is first normalized to a scale of 0 to 1 using predetermined minimum and maximum values. Life expectancy ranges from 20 to 85 years, mean years of schooling from 0 to 15 years, GDP per capita from 100 to 47,000 international dollars (at 1990 prices), while the liberal democracy index is already standardized between 0 and 1. The liberal democracy index, developed by the Varieties of Democracy (V-Dem) project and processed by Our World in Data, measures the extent to which countries achieve the ideals of liberal democracy. Ranging from 0 to 1, with higher values indicating greater democratic achievement, this index combines multiple aspects of democratic governance. It assesses voting rights, election integrity, freedoms of association and expression, civil liberties, and executive constraints. The index emphasizes the protection of individual and minority rights against state and majority overreach, evaluating factors such as constitutionally protected civil liberties, rule of law, judicial independence, and effective checks and balances. The AHDI is then computed as the geometric mean of these four normalized indices, resulting in a single value between 0 and 1, where higher values indicate greater overall human development [50]. This approach aims to capture a more comprehensive picture of human development beyond purely economic indicators.

The study also includes, as predictors, research funding as a proportion of GDP and a measure of national happiness, based on responses to the Cantril Ladder question in the Gallup World Poll, archived by Our World in Data [51]. This metric asks respondents to rate their life satisfaction on a scale from 0 to 10, with 10 representing the best possible life. Descriptive information for study variables is available in Table 2.

Table 2. Descriptive information for variables introduced in the analysis. The SCIE/SSCI ratio for each topic is calculated by dividing the number of SCIE-indexed publications by the number of SSCI-indexed publications within a given country. To ensure statistical reliability, countries with 6 or fewer SSCI-indexed publications on a specific topic were excluded from the analysis, resulting in varying sample sizes across topics. The differences in sample sizes (N) for other variables are due to missing data points in the original datasets.

Variable	N (Number of Countries)	Minimum	Maximum	Mean	Std. Deviation
Artificial intelligence publications per country: SCIE/SSCI Ratio	82	2.00	14.15	5.81	2.51
Blockchain publications per country: SCIE/SSCI Ratio	68	1.14	9.00	3.46	1.67
Cybersecurity publications per country: SCIE/SSCI Ratio	49	1.59	15.70	5.09	3.17
Privacy publications per country: SCIE/SSCI Ratio	85	0.80	10.28	3.10	1.98
AHDI	162	0.12	0.89	0.45	0.20
Life expectancy	195	52.53	85.95	71.28	7.75
Average years of schooling	191	2.11	14.09	8.99	3.17
GNI per capita	193	731.79	146,829.70	20,136.39	21,756.09
Liberal democracy index	176	0.01	0.89	0.39	0.26
Research spending/GDP	150	0.01	5.56	0.83	1.02
Happiness	165	1.86	7.80	5.43	1.17

For data visualization, we used Microsoft Excel (Office 365). Statistical analysis was conducted using IBM SPSS software version 29.0.2.0. We employed linear regression models, utilizing the Enter method for independent variables. This approach allows for the examination of relationships between social factors (as represented by AHDI components, research funding per GDP, and happiness) and the ratio of technical to social science publications in each technological domain. Detailed regression results are found in the Supplementary Material.

To complement the regression analysis, we also performed a K-means cluster analysis. This method groups countries based on similarities in their research focus across all four technological areas simultaneously. This dual approach of regression and cluster analysis [52] provides both a detailed examination of individual factor relationships and a larger view of country groupings based on overall research focus.

Exploratory Analysis and Identification of Outliers

Scatterplots in Figures 1–4 indicate that countries with lower AHDI often have surprisingly high ratios in these tech-related fields, indicating a stronger focus on technical relative to social research. The relationship between AHDI and these ratios is not very strong, suggesting that other factors (e.g., government policies, research priorities, or cultural factors) may play significant roles in determining these research focus areas. Each topic has its own outliers, though Japan consistently appears as an outlier across all categories, maintaining high ratios despite its high AHDI. Outliers that were excluded from regression and cluster analysis are indicated in Figures 1–4.

Developed nations, particularly in Western Europe and North America, generally show lower ratios across categories, indicating a greater focus on social implications of technology. Countries like the Netherlands, the United States, and many Scandinavian nations fall into this category. This trend might reflect these countries' advanced stages of technological integration, leading to increased attention to the social consequences and ethical considerations of tech adoption.

In contrast, many developing and emerging economies display higher ratios, suggesting a stronger focus on engineering and technical aspects of these technologies. This is particularly evident in countries like China, India, and several Middle Eastern nations. This pattern could be interpreted as these countries prioritizing technical skill development and technological advancement to boost their economic growth and global competitiveness.

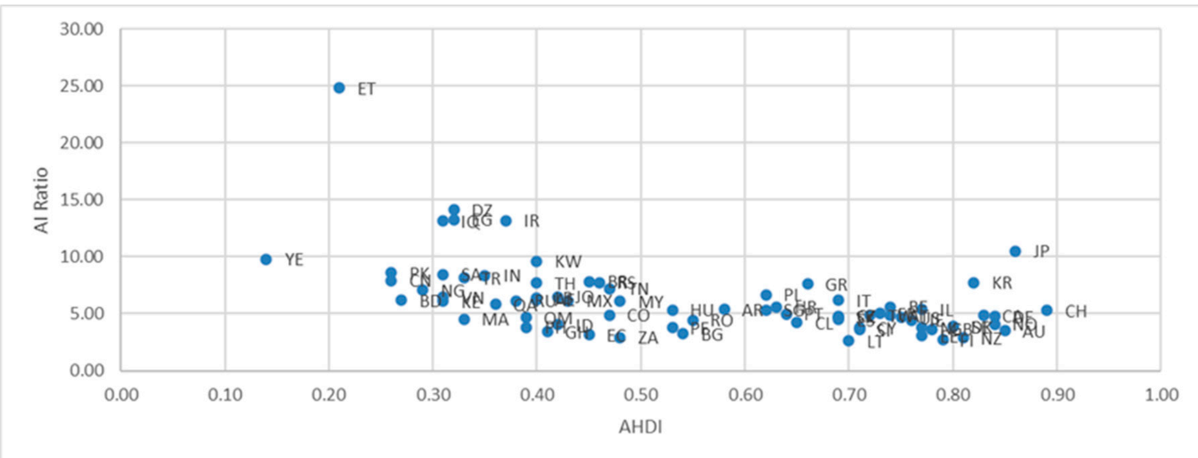

Figure 1. Scatterplot of AI publications' SCIE/SSCI ratio vs. AHDI. Outliers that will be excluded from analysis: Ethiopia. Source: Authors' analysis.

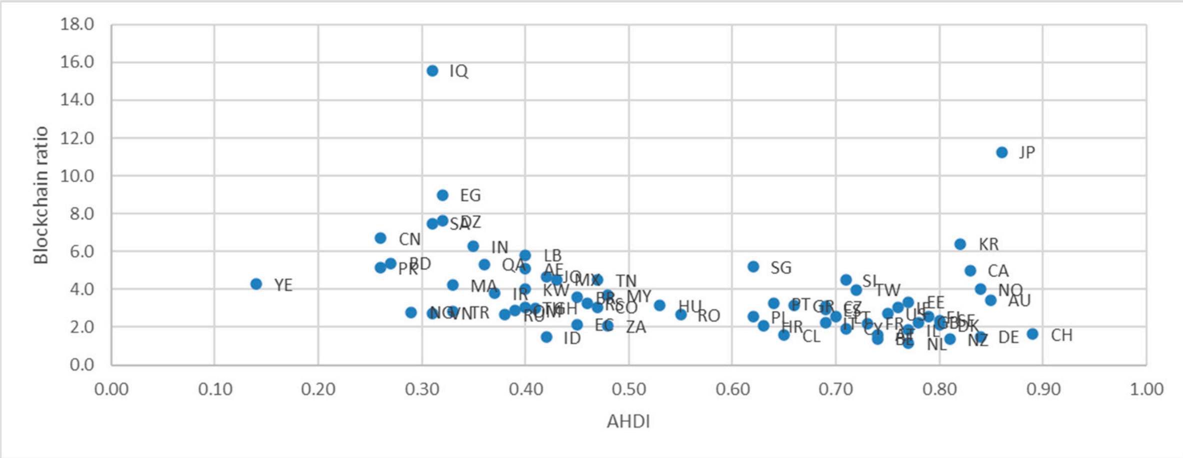

Figure 2. Scatterplot of blockchain SCIE/SSCI ratio vs. AHDI. Outliers that will be excluded from analysis: Iraq, Japan. Source: Authors' analysis.

Figure 3. Scatterplot of cybersecurity SCIE/SSCI ratio vs. AHDI. Outliers that will be excluded from analysis: Japan. Source: Authors' analysis.

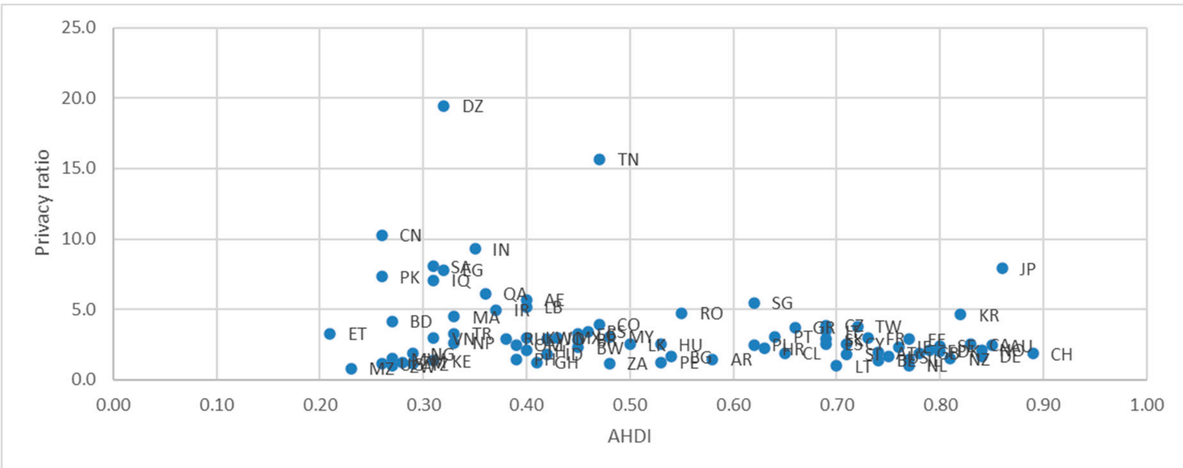

Figure 4. Scatterplot of privacy SCIE/SSCI ratio vs. AHDI. Outliers that will be excluded from analysis: Algeria, Tunisia. Source: Authors' analysis.

East Asian countries present an interesting case. Japan, despite its high AHDI, maintains relatively high ratios across all categories, indicating a continued strong focus on engineering aspects. This might reflect Japan's cultural emphasis on technological innovation and its position as a global leader in many tech industries. South Korea shows a similar trend, albeit to a lesser extent.

Middle Eastern and North African (MENA) countries, including Saudi Arabia, Iran, and Egypt, generally show high ratios across categories despite varying AHDI scores. This could indicate a strong push towards technical education and research in these fields, possibly as part of national strategies to diversify economies and reduce dependence on natural resources.

African nations present varied patterns. Ethiopia, for instance, shows an extremely high ratio in AI research despite a low AHDI, which could indicate targeted investment in technical AI capabilities. However, data for many African countries are limited, making broader regional conclusions difficult.

Latin American countries generally show moderate ratios, suggesting a balanced approach between technical and social aspects of technology research. This could reflect these nations' efforts to both develop technical capabilities and address the unique social implications of technology adoption in their cultural contexts.

Smaller, highly developed nations like Singapore and Luxembourg often show moderate to high ratios, indicating a continued focus on technical research despite high development levels. This might reflect strategic national priorities to maintain technological competitiveness.

Several Eastern European countries, such as Romania and Serbia, show higher ratios in some categories, suggesting a focus on technical aspects of selected technologies. This might be part of these nations' efforts to develop competitive advantages in the global tech market.

Romania presents an interesting case within the European context when examining its focus on engineering versus social implications in digital technologies. Romania, with an AHDI of 0.55, sits in a unique position among European countries, particularly when compared to Western European nations.

In the field of artificial intelligence, Romania shows a ratio of 4.43, which is relatively moderate in the European context. This figure is comparable to countries like France (5.04) and Germany (4.73), suggesting that Romania's relative focus on engineering aspects of AI research is on par with some of Western Europe's leading economies. Romania's blockchain ratio of 2.7 is notably higher than many Western European countries. For comparison, France has a ratio of 2.2, Germany 1.5, and the Netherlands just 1.1. This higher ratio suggests that Romania is placing a stronger emphasis on the technical aspects of blockchain technology compared to its social implications. The most striking aspect of Romania's technological focus is in the field of cybersecurity, where it shows a remarkably high ratio of 8.9. This figure is significantly higher than most Western European countries, such as France (4.1), Germany (2.9), and The Netherlands (1.6). Only Greece, with a ratio of 10.9, surpasses Romania in this domain among the countries in our dataset. This intense focus on the technical aspects of cybersecurity could be driven by several factors, including a response to increasing cyber threats globally and within the region, a strategic decision to develop a competitive advantage in cybersecurity within the European Union, and the presence of a strong IT sector in Romania, which may be leveraging its expertise to focus on this critical area. In terms of privacy research, Romania's ratio of 4.7 is again higher than many of its Western European counterparts. This suggests a stronger focus on the technical aspects of privacy technologies compared to countries like France (3.0), Germany (1.7), and the Netherlands (1.0). This emphasis could be related to Romania's efforts to align with EU data protection regulations while also developing technical expertise in this increasingly important field.

4. Results

4.1. Predictors of Technical vs. Social Focus

In analyzing the relative research focus, we can interpret life expectancy and happiness as proxy measurements for broader social structures [53]. These factors reflect the development of social infrastructures, trust, and overall quality of life, which in turn influence (and are influenced by) research priorities and technological development. In our interpretation, we take into account the absolute size of the coefficients rather than focusing on statistical significance, since we analyze the complete population of countries that have available data, rather than a random sample that would allow further generalization through inference.

Table 3 synthesizes Beta regression coefficients across the four models. Beta coefficients in multiple regression models are standardized measures that allow for direct comparison of the relative influence of different predictors on the dependent variable, regardless of their original scales. These coefficients represent the change in the dependent variable (in standard deviations) for every one standard deviation increase in the independent variable, while holding other variables constant. The absolute value of a Beta coefficient indicates the strength of the relationship, while its sign shows the direction.

Table 3. Standardized regression coefficients (Beta) and statistical significance for linear regression models. Coefficients larger than 0.2 in absolute size are marked in bold. Source: Authors' analysis.

Variable	AI Ratio		Blockchain Ratio		Cybersecurity Ratio		Privacy Ratio	
	Beta	Sig.	Beta	Sig.	Beta	Sig.	Beta	Sig.
Life expectancy	**0.329**	0.029	**0.258**	0.122	**0.545**	0.010	**0.522**	0.004
Average years of schooling	−0.065	0.640	−0.099	0.557	−0.094	0.630	−0.164	0.304
GNI per capita	−0.052	0.740	0.184	0.294	−0.099	0.622	**0.251**	0.150
Liberal democracy index	**−0.551**	0.000	**−0.524**	0.000	**−0.361**	0.044	**−0.524**	0.000
Research spending/GDP	**0.227**	0.069	0.132	0.352	−0.122	0.459	0.056	0.680
Happiness	**−0.410**	0.022	**−0.424**	0.039	**−0.443**	0.096	**−0.329**	0.084

We see that the liberal democracy index consistently emerges as a strong negative predictor across all technological domains (AI: −0.551, blockchain: −0.524, cybersecurity: −0.361, privacy: −0.524). This suggests that societies with more robust democratic institutions tend to prioritize research on the social implications of these technologies. Such societies may have developed structures that encourage critical examination of technological impacts, due to a culture of open debate and diverse stakeholder involvement in policy-making.

Life expectancy, as a proxy for social development and social services infrastructure, shows a positive relationship with technical research focus across all domains, most notably in cybersecurity (0.545) and privacy (0.522). This relationship might indicate that societies with well-developed infrastructures and higher overall well-being tend to invest relatively more in the technical aspects of these technologies. The strong positive correlation between cybersecurity and privacy could reflect the increased digital dependency and consequent security concerns in highly developed societies.

Happiness, which can be seen as a proxy for overall social well-being and trust, consistently shows a negative relationship with technical research focus (AI: −0.410, blockchain: −0.424, cybersecurity: −0.443, privacy: −0.329). This trend suggests that societies with higher levels of overall satisfaction and trust may prioritize understanding the social implications of these technologies. It is plausible that these societies have developed structures that encourage a deeper scrutiny of technological advancement, considering both technical progress and its social consequences.

In the AI ratio model, research spending as a percentage of GDP also shows a positive effect (0.227). This suggests that societies investing more in research infrastructure tend to produce more technical AI publications, possibly reflecting a focus on applied research and development in well-funded research ecosystems.

Interestingly, more traditional indicators of social development such as education (average years of schooling) and income (GNI per capita) show relatively weak relationships across all models. This suggests that the balance between technical and social science research in these domains may be more influenced by other social structures and values, rather than classical measures of education or wealth. Societies with well-developed democratic institutions, high life expectancy, and high levels of happiness appear to approach technological development with a balanced perspective, emphasizing both technical advancement and social implications. This dual focus likely stems from social structures that promote critical thinking and public engagement with technology.

The technical/social ratios of publications on the four topics—AI, blockchain, cybersecurity, and privacy—show distinct patterns in their relationships with predictive factors. AI ratio has the strongest negative relationship to the liberal democracy index (−0.551) and a notable positive relationship with research spending (0.227). This suggests that AI research tends to be more technically focused in less democratic societies and in countries that invest heavily in research. The social implications of AI might be more thoroughly explored in more democratic nations, possibly due to concerns about AI's potential impact on job markets, decision-making processes, and social structures.

The blockchain ratio shows a strong negative relationship with the liberal democracy index (−0.524) and happiness (−0.424), similar to AI. However, it has a weaker relationship with life expectancy (0.258) compared to other topics. This could indicate that blockchain research is less influenced by a country's overall development level and more by its governance structures and social satisfaction. The technical focus on blockchain in less democratic societies might reflect interest in its potential to bypass centralized authorities, enhance privacy, and establish trust in environments where traditional institutions may be weaker or less trusted. In these contexts, blockchain technology could be viewed as a tool for fostering transparency and accountability, circumventing government control, or enabling financial and social systems that operate independently of state mechanisms. However, in antidemocratic regimes, blockchain could also be co-opted to reinforce state control and surveillance. Instead of empowering individuals, the technology might be selectively applied to enhance government oversight, monitor citizens' activities, reduce financial anonymity, or control resource distribution in ways that bolster the regime's power. This dual potential could explain why blockchain research and development are prevalent in countries with lower liberal democracy indices, where the technology might be seen both as a tool to address governance gaps and as a means to strengthen authoritarian rule. The weaker relationship with life expectancy observed might be due to blockchain's use in these regimes not being primarily focused on improving social well-being, but rather on maintaining or enhancing the regime's stability and control.

Cybersecurity displays the strongest positive relationship with life expectancy (0.545) among all topics. It also has the weakest negative relationship with the liberal democracy index (−0.361). This may imply that cybersecurity research is more technically focused in highly developed countries, regardless of their democratic status. This could be due to the universal need for robust digital security in technologically advanced societies.

The privacy research ratio shows a strong positive relationship with life expectancy (0.522) and a strong negative relationship with the liberal democracy index (−0.524). Interestingly, it has the weakest negative relationship with happiness (−0.329) among all topics. This pattern might reflect a greater technical focus on privacy in developed countries, possibly due to higher digital literacy and data protection concerns. The strong negative relationship with democracy could indicate that less democratic societies focus more on technical privacy solutions, while more democratic ones might emphasize policy and social aspects of privacy.

4.2. Predictive Value of the Regression Models

Figure 5 compares the adjusted R-square values for the four linear regression models. Adjusted R-square is a statistical measure that evaluates the goodness of fit of a regression model while accounting for the number of predictors included. Unlike the regular R-square, which increases with the addition of more variables regardless of their significance, adjusted R-square provides a more reliable assessment by penalizing the inclusion of unnecessary predictors. The adjusted R-square is calculated using a formula that incorporates the sample size, the number of predictors, and the R-square value. Essentially, it reflects the proportion of the variance in the dependent variable that is explained by the model, while considering the complexity added by each predictor. The range of adjusted R-square typically falls between 0 and 1, although it can be negative in cases where the model fits the data worse than a simple horizontal line. A value closer to one indicates that the model explains a significant portion of the variance in the dependent variable, while lower values suggest that the model is not capturing much of the variance. A negative adjusted R-square implies that the predictors are not improving the model at all. Adjusted R-square is particularly useful in comparing multiple regression models. It helps to ensure that the model achieves a balance between accurately fitting the data and avoiding overfitting by adding unnecessary variables.

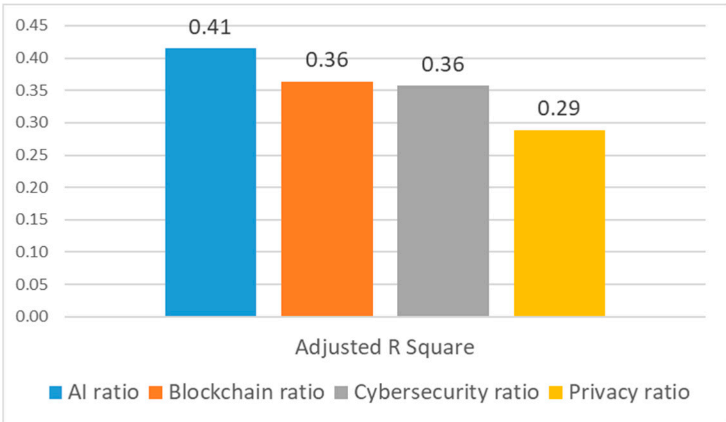

Figure 5. Adjusted R-square values for the four linear regression models. Source: Authors' analysis.

Adjusted R-square values of our models range from 0.288 to 0.415, indicating moderate explanatory power of the social factors for technical to social focus ratios across the selected research fields. The AI ratio model shows the highest adjusted R-square (0.415), suggesting that social factors explain a larger portion of the variance in AI research focus compared to other domains. Blockchain and cybersecurity models have similar values (0.363 and 0.357, respectively), while the privacy model has the lowest (0.288).

This variation in explanatory power across domains highlights differences in how these technologies interact with and are perceived by society. The moderate overall R-square values indicate that while the above-discussed factors play a significant role in shaping research priorities, other influential factors not captured in these models also exist. These could include specific national policies, industry trends, or global technological developments. The lower R-square for privacy suggests that the research focus in this domain may be influenced by a broader or different set of country attributes compared to the other technologies examined.

4.3. Cluster Analysis

To complement our regression analysis, we conducted a cluster analysis to identify groups of countries with similar patterns in their technical-to-social research ratios across the four technologies. K-means cluster analysis is a statistical method that groups similar data points into distinct clusters. The researcher specifies the number of clusters (K), and the algorithm iteratively assigns data points to the nearest cluster center, recalculating these centers until assignments stabilize. This approach minimizes within-cluster variation while maximizing between-cluster differences, revealing underlying patterns in large datasets. In SPSS, Euclidean distance is the default measure for calculating distances across multiple dimensions, which in our study are represented by the four ratio values in the domains we are examining. The final cluster centers represent the average characteristics of all data points within each cluster, essentially depicting the typical profile for that group. In our study, these centers indicate the average research focus ratios for AI, blockchain, cybersecurity, and privacy within each identified group of countries, providing a snapshot of distinct research prioritization patterns across nations.

We chose the 5-cluster classification as offering the highest degree of nuance while retaining enough members in all clusters. Thus, we identified five distinct profiles of countries based on their focus on technical versus social science publications across four technology domains: AI, blockchain, cybersecurity, and privacy. A total of 92 countries were included in the analysis, with a pairwise treatment of missing data. Final cluster centers are presented in Table 4 and Figure 6, and country membership is presented in Table 5.

Table 4. Final cluster centers in a K-means classification with 5 clusters. Source: Authors' analysis.

Ratio by Topic	1. Strong Social Focus	2. Balanced Focus	3. Technical Focus	4. Mixed: AI and Cybersecurity Technical/Blockchain and Privacy Social	5. Strong Technical Focus
Artificial Intelligence SCIE/SSCI Ratio	4.39	5.95	8.16	10.07	12.77
Blockchain SCIE/SSCI Ratio	2.54	3.82	6.40	3.80	8.31
Cybersecurity SCIE/SSCI Ratio	3.02	6.18	9.67	11.91	15.70
Privacy SCIE/SSCI Ratio	1.98	3.87	8.74	3.89	7.59
Number of countries in each cluster	**53**	**25**	**6**	**4**	**4**

Table 5. Country membership in the five identified clusters. Source: Authors' analysis.

Country	Type	Description	Country	Type	Description
Argentina	1	Strong social focus	Thailand	1	Strong social focus
Australia	1	Strong social focus	Uganda	1	Strong social focus
Austria	1	Strong social focus	Ukraine	1	Strong social focus
Belgium	1	Strong social focus	United Kingdom	1	Strong social focus
Bosnia and Herzegovina	1	Strong social focus	United States	1	Strong social focus
Botswana	1	Strong social focus	Zambia	1	Strong social focus
Bulgaria	1	Strong social focus	Zimbabwe	1	Strong social focus
Cameroon	1	Strong social focus	Bangladesh	2	Balanced focus
Canada	1	Strong social focus	Brazil	2	Balanced focus
Chile	1	Strong social focus	Colombia	2	Balanced focus
Croatia	1	Strong social focus	Ethiopia	2	Balanced focus
Cyprus	1	Strong social focus	Italy	2	Balanced focus

Table 5. *Cont.*

Country	Type	Description	Country	Type	Description
Czech Republic	1	Strong social focus	Jordan	2	Balanced focus
Denmark	1	Strong social focus	Lebanon	2	Balanced focus
Ecuador	1	Strong social focus	Luxembourg	2	Balanced focus
Estonia	1	Strong social focus	Malaysia	2	Balanced focus
Fiji	1	Strong social focus	Mexico	2	Balanced focus
Finland	1	Strong social focus	Morocco	2	Balanced focus
France	1	Strong social focus	Poland	2	Balanced focus
Germany	1	Strong social focus	Portugal	2	Balanced focus
Ghana	1	Strong social focus	Qatar	2	Balanced focus
Hungary	1	Strong social focus	Romania	2	Balanced focus
Indonesia	1	Strong social focus	Serbia	2	Balanced focus
Israel	1	Strong social focus	Singapore	2	Balanced focus
Kenya	1	Strong social focus	South Korea	2	Balanced focus
Lithuania	1	Strong social focus	Spain	2	Balanced focus
Malawi	1	Strong social focus	Sweden	2	Balanced focus
Malta	1	Strong social focus	Taiwan	2	Balanced focus
Mozambique	1	Strong social focus	Tunisia	2	Balanced focus
Nepal	1	Strong social focus	Turkey	2	Balanced focus
Netherlands	1	Strong social focus	United Arab Emirates	2	Balanced focus
New Zealand	1	Strong social focus	Vietnam	2	Balanced focus
Nigeria	1	Strong social focus	China	3	Technical focus
Norway	1	Strong social focus	Georgia	3	Technical focus
Oman	1	Strong social focus	India	3	Technical focus
Palestinian Authority	1	Strong social focus	Kazakhstan	3	Technical focus
Peru	1	Strong social focus	Pakistan	3	Technical focus
Philippines	1	Strong social focus	Saudi Arabia	3	Technical focus
Republic of Ireland	1	Strong social focus	Greece	4	Mixed
Russia	1	Strong social focus	Iran	4	Mixed
Slovakia	1	Strong social focus	Kuwait	4	Mixed
Slovenia	1	Strong social focus	Yemen	4	Mixed
South Africa	1	Strong social focus	Algeria	5	Strong technical focus
Sri Lanka	1	Strong social focus	Egypt	5	Strong technical focus
Switzerland	1	Strong social focus	Iraq	5	Strong technical focus
Tanzania	1	Strong social focus	Japan	5	Strong technical focus

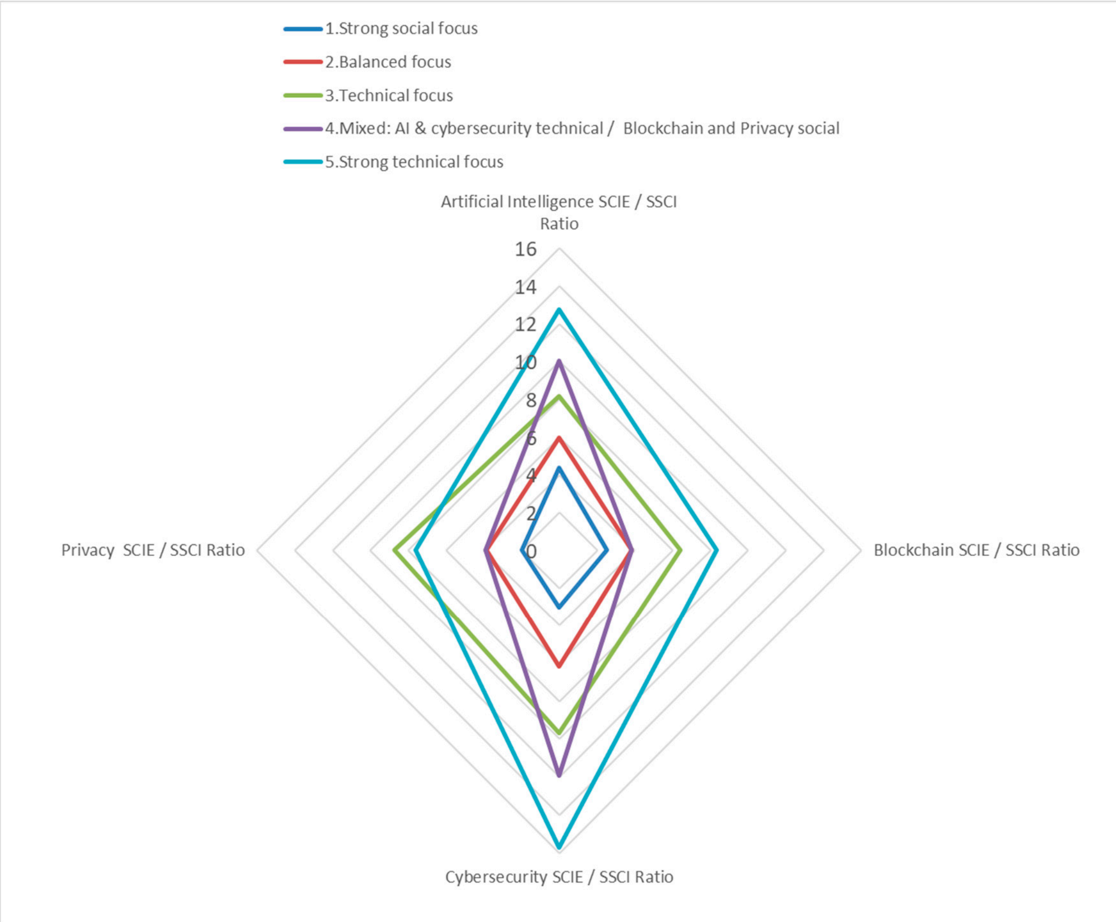

Figure 6. Radar visualization of cluster profiles. Source: Authors' analysis.

The "Strong social focus" cluster shows the lowest SCIE/SSCI ratios across all technologies, and it is also the largest type, with 53 members. These countries prioritize the most the understanding of the social implications of these technologies.

The "Balanced focus" cluster exhibits slightly higher ratios but maintains a relatively balanced approach. This group shows a particular interest in the social aspects of blockchain and privacy and it is the second largest, with 25 members.

The "Technical focus" cluster demonstrates higher ratios across all domains, indicating a stronger emphasis on technical research. This group shows a specifically strong technical focus in privacy and AI, including only six members.

The "Mixed: AI and cybersecurity technical/blockchain and privacy social" cluster presents an interesting mixed profile, as can be seen in the visualization in Figure 6. These countries show a strong technical focus in AI and cybersecurity, with ratios even higher than the "Technical focus" cluster. However, they maintain a more balanced approach to blockchain and privacy, with ratios like the "Social focus" cluster. This could indicate a strategic prioritization of technical development in AI and cybersecurity while maintaining a more socially oriented approach to blockchain and privacy.

Finally, the "Strong technical focus" cluster exhibits the highest ratios across all domains, indicating a clear emphasis on technical research. This group shows particularly high ratios in cybersecurity and AI, suggesting a strong prioritization of technological development in these areas.

These cluster profiles reveal diverse approaches to balancing technical and social science research across different technologies. Some countries maintain a consistent approach across all domains, while others show varying focuses depending on the specific technology.

The cluster analysis reveals interesting regional patterns and some notable cases in how countries approach the balance between technical and social science research in digital technologies, as illustrated in Figure 7.

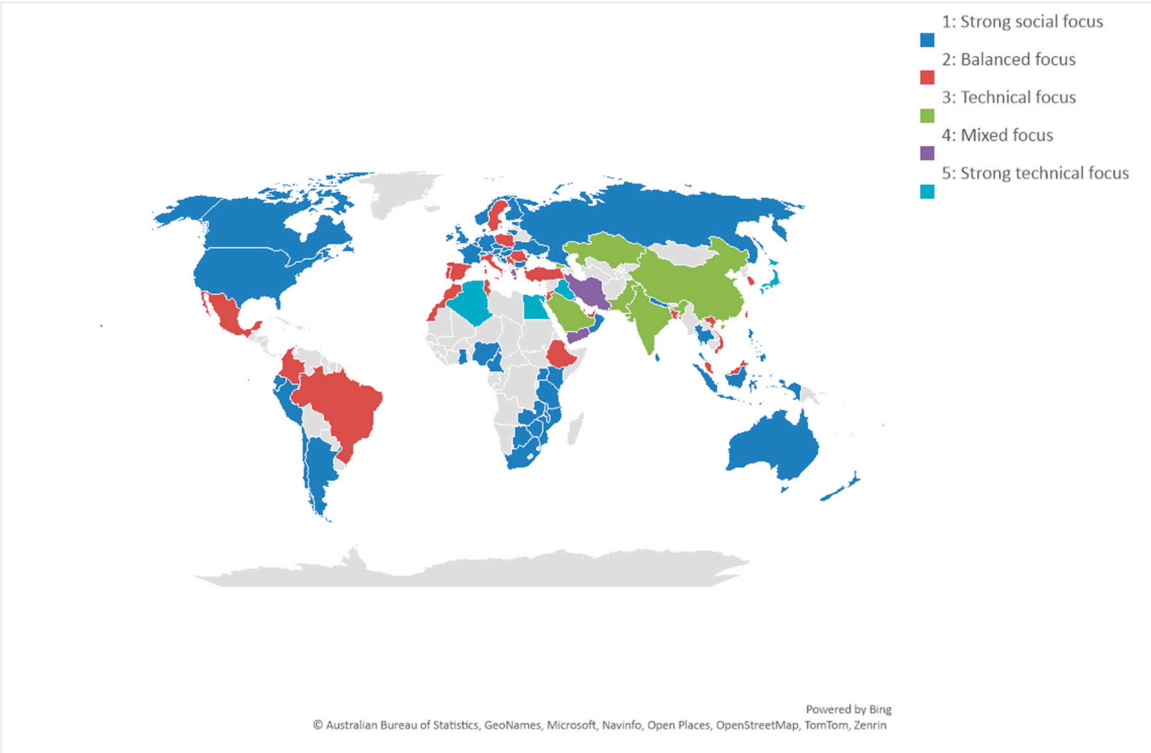

Figure 7. Country distribution across the five identified clusters. Source: Authors' analysis.

Western countries, including the United States, Canada, the United Kingdom, Germany, and France, are predominantly classified in the "Strong social focus" cluster. This suggests that these nations tend to emphasize research on the social implications of AI, blockchain, cybersecurity, and privacy. This trend might reflect the mature democratic institutions and developed civil societies in these countries, which often prioritize understanding the social impacts of new technologies.

Several large emerging economies, such as Brazil, Mexico, and Turkey, fall into the "Balanced focus" cluster. This indicates a more even distribution between technical and social science research in these technologies. These countries might be striving to develop technical capabilities while simultaneously addressing social concerns related to these technologies.

China and India, two of the world's most populous countries and rapidly growing technological powers, are categorized in the "Technical focus" cluster. This classification suggests a stronger emphasis on the technical aspects of these technologies, possibly reflecting national strategies to become global leaders in these fields.

Japan is an interesting case, being the only highly developed economy in the "Strong technical focus" cluster. This could indicate Japan's continued prioritization of technological development and innovation, particularly in fields like AI and robotics where it has historically been a leader.

Russia's placement in the "Strong social focus" cluster is noteworthy, as it differs from other BRICS nations like China and India. This could suggest a more balanced approach to technology research in Russia, with significant attention paid to social implications.

The "Mixed: AI and cybersecurity technical/blockchain and privacy social" cluster includes countries like Iran and Greece. This profile might reflect specific national priorities or strengths in certain technological domains.

Among African nations, there is a split between those in the "Strong social focus" cluster (such as South Africa, Nigeria, and Kenya) and those in the "Balanced focus" cluster (like Ethiopia and Morocco). This division might reflect differences in research capacity, national priorities, or the influence of international collaborations.

In Southeast Asia, Indonesia is in the "Strong social focus" cluster, while Malaysia and Vietnam are in the "Balanced focus" cluster. This variation could indicate different national strategies or stages of technological development within the region.

The cluster analysis complements the multiple regression analysis by providing a broader view of countries' research focus simultaneously across AI, blockchain, cybersecurity, and privacy. This grouping reveals patterns that were not apparent in the regression results. For instance, it identifies countries like Japan that have a strong technical focus across all domains, contrasting with Western countries that generally emphasize social implications. The cluster analysis also highlights unique cases like the mixed group focusing on technical aspects of AI and cybersecurity but social aspects of blockchain and privacy, a nuance not captured by the regression models. This multidimensional perspective helps explain some variations and the moderate predictive power in the regression results, such as why certain countries might deviate from expected relationships between social factors and research focus.

The analysis of demographic and social profiles (see Table 6) reveals distinct characteristics among the country clusters based on their research focus on digital technologies. The "Strong social focus" cluster, which includes major Western countries like the United States, Germany, and the United Kingdom, shows the highest average Augmented Human Development Index (AHDI) at 0.57. These countries also lead in the liberal democracy index (0.55) and research spending as a percentage of GDP (1.35%). They have a relatively high average life expectancy of 73.72 years and the highest mean years of schooling at 10.73. This cluster also ranks highest in happiness, with a score of 5.90. These factors suggest a well-developed socio-economic environment that may contribute to their emphasis on the social implications of technology.

Table 6. Demographic and social profiles of country clusters. Source: Authors' analysis.

Cluster	AHDI—Total	Life Exp.	Avg. Years of Schooling	GNI/Capita	Liberal Democracy Index	Research Spending/GDP	Happiness
	Mean	Mean	Mean	Mean	Mean	Mean	Mean
1. Strong social focus	0.57	73.72	10.73	28,364	0.55	1.35	5.90
2. Balanced focus	0.50	76.52	9.85	32,410	0.42	1.28	5.73
3. Technical focus	0.36	71.59	9.21	18,906	0.22	0.68	5.35
4. Mixed: AI and cybersecurity technical/blockchain and privacy social	0.39	74.10	8.15	24,059	0.27	0.81	5.28
5. Strong technical focus	0.45	75.44	9.73	18,696	0.30	1.20	5.14

The "Balanced focus" cluster, which includes countries like Brazil, South Korea, and Spain, shows the second-highest AHDI (0.50) and the highest life expectancy (76.52 years) and GNI per capita (USD 32,410). These countries maintain a moderate liberal democracy index (0.42) and research spending (1.28% of GDP).

The "Technical focus" cluster, featuring large emerging economies like China and India, has the lowest AHDI (0.36) and liberal democracy index (0.22). This cluster also shows the lowest life expectancy (71.59 years) among the five types and research spending

(0.68% of GDP). Countries in this cluster prioritize technical research possibly as a strategy for rapid technological and economic development.

The "Mixed: AI and cybersecurity technical/blockchain and privacy social" cluster, which includes countries like Iran and Greece, shows moderate figures across most indicators.

The "Strong technical focus" cluster, which notably includes Japan, shows mid-range values for most indicators. Given its overall membership, it has the second-highest life expectancy (75.44 years) and research spending (1.20% of GDP), but the lowest happiness score (5.14). Japan's strong emphasis on technical research across all domains, despite its high development level, sets it apart from other developed nations and reflects its longstanding focus on technological innovation.

5. Discussion

Regression analysis provides novel information about the factors influencing the balance between technical and social research focus in digital technologies, complementing existing literature on scientific output in these fields.

5.1. Original Contributions of Regression Analysis

One of the most striking findings is the consistent negative relationship between the liberal democracy index and the technical-to-social research ratio across all examined technologies (AI, blockchain, cybersecurity, and privacy). This shows that more democratic societies tend to place greater emphasis on the social implications of these technologies rather than purely technical aspects. This finding aligns with and extends the observations of Gantman [11], who reported that political authoritarianism negatively impacts scientific output in some fields. Our results indicate that the nature of the political system not only affects overall scientific productivity but also shapes the focus of research within specific technological domains.

The positive relationship between life expectancy and technical research focus, particularly strong in cybersecurity (β = 0.545) and privacy (β = 0.522), offers a new perspective on the role of social development in shaping research priorities. While previous studies such as Onyancha [4] and Zhang et al. [5] have consistently found correlations between economic indicators and research output, our findings show that broader measures of social well-being also play a role in determining the nature of research focus. This relationship might reflect the increased digital dependency and consequent security concerns in highly developed societies, as evidenced by studies like Dhawan, Gupta, and Elango [19] in the context of cybersecurity research.

The negative association between happiness and technical research focus across all domains presents a different perspective from traditional economic indicators. This finding indicates that societies with higher levels of overall satisfaction and trust may prioritize understanding the social implications of these technologies. This relationship between social well-being and research focus adds a new dimension to the literature, which has primarily focused on economic factors (e.g., Rodríguez-Navarro and Brito [2]; Lancho-Barrantes et al. [3]).

Interestingly, our analysis reveals that traditional indicators of social development such as education (average years of schooling) and income (GNI per capita) show relatively weak relationships across all models for research focus. This diverges from previous findings by researchers like Rahman and Fukui [6], who identified gross national product (GNP) per capita as a significant predictor of research productivity. Our results suggest that the balance between technical and social science research in these domains may be more influenced by political social structures and values, rather than measures of national education or wealth.

The varying strength of relationships across different technological fields is also informative. For instance, the AI ratio model shows the strongest negative relationship to the liberal democracy index ($\beta = -0.551$) and a notable positive relationship with research spending (β = 0.227). This aligns with observations by Gao et al. [34] and De la Vega

Hernández et al. [35] about the dominance of countries like China in AI research output, potentially reflecting the influence of political systems and research investments on the nature of AI research.

In the cybersecurity domain, the strong positive relationship with life expectancy ($\beta = 0.545$) and weaker negative relationship with the liberal democracy index ($\beta = -0.361$) compared to other technologies complements the observations of studies like Loan, Bashir, and Nasreen [17] and Omote et al. [18], suggesting that the technical focus in cybersecurity research might be more influenced by overall social development than by political structures.

The blockchain ratio's strong negative relationship with both the liberal democracy index ($\beta = -0.524$) and happiness ($\beta = -0.424$) provides a new lens through which to view the findings of studies like Khurana and Sharma [23] and Guo et al. [24]. While these previous studies focused on overall research output and impact, our results suggest that the nature of blockchain research—whether technically or socially focused—may be significantly influenced by a country's governance structures and social satisfaction.

In the privacy domain, the strong positive relationship with life expectancy ($\beta = 0.522$) and strong negative relationship with the liberal democracy index ($\beta = -0.524$) adds to the findings of studies like Yin et al. [30] and Valencia-Arias et al. [28], indicating that while developed countries may lead in privacy research output, the balance between technical and social focus in this research is differently shaped by social features.

The moderate explanatory power of our models (adjusted R-square values ranging from 0.288 to 0.415) indicates that while social factors play a significant role in shaping research priorities, other influential factors not captured in these models also exist. This aligns with the multifaceted nature of influences on scientific output identified in the literature review, including factors such as international collaboration (Szuflita-Żurawska and Basińska [9]), institutional prestige (Wahid et al. [10]), and evolving research themes (Shu and Liu [32]).

5.2. Original Contributions of Cluster Analysis

The cluster analysis of countries based on their technical-to-social research ratios in AI, blockchain, cybersecurity, and privacy also complements and extends the existing literature on research output in these fields.

Our cluster analysis identifies groups of countries with similar research focus patterns across multiple technologies. This multi-dimensional view of research priorities offers a new understanding compared to previous studies that typically examined each technology in isolation. For instance, while studies like Gao et al. [34] and De la Vega Hernández et al. [35] identified leading countries in AI research output, our analysis reveals how countries' AI research focus relates to their approach in other technological domains.

The identification of a cluster characterized by a high technical focus across all four technologies, including countries like China, India, and several Middle Eastern nations, is informative for the research strategies of emerging economies. This finding extends the observations of studies such as Guo et al. [36] and Tran et al. [37], which noted the rising contributions of these countries in specific fields like AI in healthcare. Our results suggest that this technical emphasis is not limited to a single domain but represents a broader strategy across multiple cutting-edge technologies.

Conversely, the cluster of primarily Western European and North American countries showing lower technical-to-social ratios across categories sheds additional light on the research priorities of developed nations. While previous studies like Saheb, Saheb, and Carpenter [39] and Zhang et al. [40] highlighted the dominance of these countries in AI ethics research, our analysis indicates that this emphasis on social implications extends across multiple technological domains. These countries' specific focus possibly reflects their advanced stage of technological integration and heightened awareness of the social impacts of these technologies.

The identification of countries with divergent focuses across different technologies is particularly novel and interesting. For example, our analysis reveals that some countries prioritize technical aspects in certain technologies while maintaining a more balanced or socially focused approach in others. This mixed view of national research priorities was not captured in previous bibliometric studies that tended to focus on overall output or impact in individual technological domains.

Our findings regarding East Asian countries, particularly Japan and South Korea, provide an interesting contrast to the previous literature. While studies like Boudry et al. [38] noted the high research output of these countries in fields like AI in ophthalmology, our cluster analysis reveals their tendency to maintain a strong technical focus across multiple technologies despite high development levels. This persistent technical emphasis may clarify the national strategies of these technologically advanced nations.

The positioning of countries from regions like Latin America and Eastern Europe in our clusters provides novel perspectives on their research priorities. While previous studies such as Hinojo-Lucena et al. [42] and Calvo-Rubio, Mauricio, and Ufarte-Ruiz [43] noted the growing contributions of these regions in specific technological domains, our analysis reveals how their research focus compares across multiple technologies and in relation to other global regions.

The case of smaller, highly developed nations like Singapore and Luxembourg, which our analysis shows maintain a relatively high technical focus despite their high development levels, offers an interesting counterpoint to the general trend observed in Western developed nations. This finding shows that factors beyond social development influence their research priorities.

Our cluster analysis also brings new information about the research focus of Middle Eastern and North African (MENA) countries. While studies like Prieto-Gutierrez et al. [44] noted the increasing research output from this region, our findings reveal a strong emphasis on technical aspects across multiple technologies. This suggests a concerted effort to develop technical expertise, possibly as part of broader economic diversification strategies.

The varying patterns observed for African nations in our clusters, such as Ethiopia's high technical focus in AI research despite lower overall development, provide new insights into the diverse research landscapes within the continent. This granular view extends beyond the broad regional trends noted in previous bibliometric studies, highlighting the importance of considering country-specific factors in understanding research priorities.

5.3. Theoretical and Practical Implications

This study offers several theoretical and practical implications. From a theoretical perspective, our findings challenge the notion that economic development is the primary determinant of research focus in digital technologies. Instead, we found that political and social factors, especially the strength of democratic institutions, significantly shape research priorities. The observed relationship between life expectancy and technical research focus, particularly in cybersecurity and privacy, suggests a connection between social development and digital security concerns. This adds a new dimension to our understanding of technological development and social progress. Our analysis also revealed that social factors influence research focus differently across technology domains, indicating that each field may have specific interactions with social structures and priorities. The identification of distinct country clusters based on research focus provides a novel framework for understanding global patterns in technology research, complementing traditional categorizations based on economic development or geographic region.

The relationship between democratic societies and research focus justifies a deeper exploration to understand the underlying mechanisms. Democratic societies might prioritize social over technical research in these technological domains for several reasons. The robust systems for public debate and government accountability in democracies likely encourage researchers to consider the social implications of new technologies, as there is more public scrutiny and demand for understanding these impacts. Democratic systems involve a wider range of stakeholders in decision-making processes, which may lead to a broader consideration of technological impacts, including social, ethical, and policy implications.

In more democratic societies, researchers often enjoy greater academic freedom to pursue diverse research agendas, including those that question or critically examine the social impacts of technologies. Additionally, democratic governments may be more likely to allocate research funding towards understanding the social implications of technologies, responding to public concerns and the need for informed policy-making. The emphasis on individual rights and freedoms in democratic societies may also translate into increased research on how new technologies affect these rights. Stable democratic systems might also be more inclined to consider the long-term social impacts of technologies, beyond immediate technical capabilities or economic benefits. Last but not least, the free press in democratic societies may play a role in highlighting social concerns about new technologies.

Life expectancy, likely a proxy for social development, and happiness, possibly indicating social cohesion, show stronger correlations with research focus than traditional economic indicators like GDP or education levels. This shows that broader measures of social progress might better predict research priorities in digital technologies. As societies develop and achieve higher levels of well-being, they may shift their research focus to consider wider implications of technologies beyond technical advancements. Countries with higher life expectancy might prioritize research on how technologies can improve the quality of life, while more cohesive societies might focus on maintaining social harmony through technology.

In practical terms, our findings have several implications for policymakers and researchers. The role of democratic institutions in fostering research on social implications of technologies suggests that strengthening democratic processes and public engagement in technology discourse could help countries develop more balanced research portfolios. The varying research focus profiles we identified across countries highlight the potential for more effective international collaborations. Partnerships between countries with complementary strengths, such as those with a strong technical focus and those emphasizing social implications, could lead to more comprehensive technological development. Furthermore, the study underscores the importance of assessing research priorities for different technologies individually, as focus can vary significantly between technological domains even within the same country. Finally, our findings suggest that the development of technology policies and research funding strategies should consider a broader range of social factors beyond traditional economic and educational indicators, including measures of democracy, overall well-being, and social development.

6. Conclusions

To conclude, our study makes several original contributions to the current state of knowledge regarding research focus in digital technologies across different countries. Firstly, it introduces a novel approach by examining the balance between technical and social research focus across multiple technologies simultaneously, providing a wider view of national research priorities than previous studies that typically focused on single technologies or overall research output. Secondly, the study combines regression analysis of social factors with cluster analysis of research ratios, offering a better understanding of both the drivers and patterns of research focus globally. This dual approach reveals how deeper social structures, such as democratic institutions and overall well-being, influence research priorities beyond traditional economic and educational factors.

Our study finds interesting patterns in how countries balance technical and social research across AI, blockchain, cybersecurity, and privacy technologies. We observe that democratic institutions play a key role in shaping research priorities. Countries with higher liberal democracy indices tend to focus more on the social implications of these technologies rather than purely technical aspects. This suggests that democratic societies may encourage a more critical examination of technological impacts.

Life expectancy, which we used as an indicator of social development, showed a positive relationship with technical research focus, especially in cybersecurity and privacy. This could reflect the increased digital dependency and security concerns in highly developed societies. Interestingly, traditional development indicators like education levels and income showed weaker relationships with research focus compared to factors like democracy and overall social well-being.

The regression models explained a moderate amount of variance in research focus, with R-squared values ranging from 0.288 to 0.415 across the four technologies. This indicates that while social factors play a significant role in shaping research priorities, other influential factors not captured in our models also exist. AI research focus showed the strongest relationship with our selected social factors, while privacy research showed the weakest.

The cluster analysis identified five distinct profiles of countries based on their balance of technical and social science research across AI, blockchain, cybersecurity, and privacy technologies. The largest group, "Strong social focus," included 53 countries, mainly Western nations, consistently showing the lowest ratios of technical to social science publications. The "Balanced focus" group of 25 countries, including several emerging economies, demonstrated a more even distribution between technical and social research. A smaller "Technical focus" cluster of six countries, including China and India, showed higher ratios across all domains, indicating a stronger emphasis on technical research.

Interestingly, a "Mixed" cluster of four countries showed a strong technical focus in AI and cybersecurity but a more balanced approach to blockchain and privacy. The smallest "Strong technical focus" cluster, notably including Japan, exhibited the highest technical-to-social ratios across all domains.

Regional patterns emerged, with most Western countries in the "Strong social focus" cluster, while many Middle Eastern and North African countries showed a stronger technical focus. East Asian countries like Japan and South Korea maintained a relatively high technical focus despite their high development levels. These findings reveal that countries' approaches to balancing technical and social aspects of technology research are not uniformly determined by development level or region, but likely reflect national strategies, cultural factors, and development trajectories.

6.1. Study Limitations

This study has several limitations to consider when interpreting its results. Our analysis is based solely on publications indexed in Web of Science, which does not represent the full scope of research output in these fields. Furthermore, we only included English-language publications, thus under-representing research from non-English speaking countries and introducing a bias towards countries where English is commonly used in academic writing. Our analysis is also limited to countries with a sufficient number of publications in both technical and social science indexes, potentially excluding smaller or less developed nations from the analysis.

The study relies on broad keyword searches for each technology domain, which may miss relevant publications that use different terminology or focus on specific subfields. Our use of publication ratios as a proxy for research focus, while informative, does not fully capture national research priorities. The classification of publications into technical or social categories based on their indexing in SCIE or SSCI databases is a simplification that may not always accurately reflect the content of individual papers, particularly in interdisciplinary research.

The analysis is based on a snapshot of publications at a single point in time, not accounting for potential temporal changes in research focus or social factors. Another limitation is the use of country-level aggregate data, which may obscure important variations in research focus within individual countries, such as regional or institutional differences.

Lastly, while our regression models explain a moderate amount of variance in research focus, they do not account for all factors that might influence a country's research priorities, such as technological infrastructure, specific government policies, industry influence, or historical research traditions.

6.2. Directions for Future Study

Future research could explore several directions to deepen our understanding of global research priorities in digital technologies. Related studies might explore why happiness or life expectancy are correlated with research focus, or further investigate the role of political structures. A more detailed analysis of interdisciplinary publications could clarify how technical and social aspects interact within studies. Expanding the analysis to other databases like Scopus or regional repositories could offer a broader view, especially of under-represented regions. Investigating the impact of specific policy frameworks or government initiatives on research focus, particularly in rapidly developing countries, could also provide valuable insights. Additionally, studying the role of industry-led research and its influence on academic priorities could highlight how private sector dynamics shape the balance between technical and social considerations. Longitudinal studies could track shifts in research focus over time, revealing trends influenced by economic or political changes. Finally, examining international collaboration through co-authorship patterns could shed light on how cross-border knowledge exchange affects research priorities.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/computers13100254/s1, Supplementary material with complete information on regression models and analyzed dataset.

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