

Signals and Metrics Identifying Partnerships for Innovation

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Abstract: The global science and technology landscape is rapidly changing. In an environment where collaboration is necessary for scientific and technological innovation, it is nonetheless challenging to identify and establish relationships between international partners, especially in emerging technological fields where no country has yet demonstrated a clear advantage. This paper describes a model to facilitate a quantitative assessment and ranking of national innovation potential based on the integration of established (e.g., patents and peer-reviewed publication counts) as well as non-obvious or subjective (e.g., national attitudes towards particular veins of research) measures to predict future performance. Such an assessment can provide a helpful step towards improving projections of scientific performance, particularly for those countries with a relatively limited footprint in the scientific landscape, and help identify and engage newcomers early in the innovation process to maximize benefits from a potential bilateral or multilateral relationship.

Keywords: Innovation, International Partnerships, Metrics, Decision Modeling

1. Introduction

Innovation in science and technology is a fundamental determinant of national competitiveness, industrial productivity, and social well-being. Advancements in emerging fields such as artificial intelligence, quantum technologies, biomedical science, and sustainable energy have the power to radically improve the quality of life of individuals, enhance national defense and security, strengthen the economy, and solve critical global challenges [1]. However, the financial, labor, and innovative cost of such scientific development can be prohibitive for any single country to pursue on its own.

As science becomes more collaborative, and the convergence of interdisciplinary teams is needed to address global issues, it is more important than ever to forge new partnerships in the international science arena. Seeking opportunities to partner with other countries that have complementary innovation capabilities can facilitate the transfer of knowledge and technology. However, a critical question remains regarding which countries with whom to prioritize co-development of scientific research, particularly at the earliest stages of scientific inquiry.

While one course of action is to only collaborate with known and well-established partners, there is a risk of missing out on the next “up and coming” player and losing the beneficial products that might have been realized if collaboration had been established earlier. Newcomers are nations that are developing competencies and breakthroughs in specific disciplines but have not yet attained global recognition for such expertise and capacity. These field-specific capabilities commonly remain unnoticed by the global community for several years or even decades. The ability to identify these lesser-known countries would provide an advantage to both newcomer nations and more established partners through the co-production of shared scientific knowledge.

However, it is not clear how to identify which countries will emerge as leaders in various technology sectors, especially countries that may not typically be thought of as leaders in innovation. This paper proposes a proof-of-concept model for identifying potential newcomers, and highlights challenges in the areas of metrics, modeling, and policy.

2. Identifying Scientific Newcomers: A Proof-of-Concept

Scientific newcomers are difficult to preemptively identify. Signals denoting their arrival can be opaque, indirect, leading/lagging, or misleading. Further, many potential newcomers may include nations with a more hostile political attitude to one's own, making any effort at cost-sharing, institutional collaboration, and co-development of scientific knowledge difficult. As such, navigating a mixture of quantitative and qualitative variables would offer a more realistic portrayal not only of scientific development within a given discipline or technology, but also how open that country is to collaborate with others through formal or informal mechanisms.

To structure and evaluate disparate sources of signals and metrics for scientific newcomers, we utilized a multi-objective decision model [2], which allows for a comparative analysis of disparate criteria and datasets for a given objective (i.e., comparatively ranking potential for future scientific growth) against a set list of alternatives (for this case, different countries). Such approaches are inspired by similar models that generated statistically relevant predictions for the allocation of Olympic medals considering only 3-4 metrics of national size, wealth, and other pertinent resources [3]. Though this exercise is intended to be demonstrative using well-established methods and practices rather than a causal or exhaustive approach, it does serve as a helpful reference point to show how various qualitative and quantitative inputs can assess future scientific

capabilities of multiple actors, with special consideration given to those who do not have an extensive record of leading international scientific research within a given field.

2.1. Identifying Metrics

Drawing from several data sources described below, we explored differing institutional, political, sociological, and scientific drivers of scientific research and development [4]. Pertinent variables include:

- (a) Human Capital (metrics that measure the human assets of a country)
- (b) Physical Capital (resource and infrastructural investments and capabilities)
- (c) Social Capital (cultural willingness and desire to pursue a specific vein of science)
- (d) Openness (participation within bilateral or multilateral agreements for scientific collaboration)

Human capital includes the buildup of a workforce capable not only of executing scientific discovery and technological commodification, but also the ability to think creatively and non-intuitively to solve new problems with various scientific fields. Perhaps the most notable consideration includes investment in education (or national education investment). A well-funded and structured education system will produce a more educated workforce that will have the ability to innovate [5, 6]. An investment in education will also help to create long term economic growth [7], which is described as accompanying innovation [5].

For physical capital, emphasis is placed upon the resources, infrastructure, and non-human systems that can be garnered to further scientific research. Possible considerations include the percentage of public and private funding on an annualized basis for scientific purposes [5, 8-10]. Other likely drivers include the quality and capability of existing institutions, which serve as a

nexus for subject-matter experts to collaborate as well as to facilitate cutting-edge research with expensive machinery and other equipment.

Social capital is a more indirect driver for scientific innovation, but is one that likely has considerable influence on the nature of scientific research as well as what is permissible within various industries and government laboratories. Sociopolitical drivers can foster a fertile environment that enables considerable support and resources to further complex or risky science (i.e., early research on space travel in the 1960s). These drivers, however, can dampen political or economic support for products deemed unnecessary or antithetical to the public good (i.e., genetically modified foods and agricultural products in the European Union).

The final category of metrics used is Openness. To measure a country's economic openness, the willingness of a country to trade goods relates with their willingness to also exchange ideas [5, 6, 11]. Also, a country that is open will benefit from a "technology spillover" from other nations [12]. Another criterion for determining a quality research partner is a country's level of intellectual property protection. A relationship has been shown between strong intellectual protections and innovation [5, 6, 11].

2.2. Building a Model

The data were assembled, and then cleaned and prepared by performing linear interpolation for missing years within each country. Data were smoothed to three year averages. Additionally, data were normalized to 0-1 scales by identifying the *best* and *worst* values for that raw metric across countries and years and calculating $|score - worst| / |best - worst|$. The normalized score for the i^{th} metric is denoted in general as x_i , and for country j as x_{ij} .

Next, Research Partnership Potential (RPP) Scoring Model indicators for each country were calculated as weighted sums of the metrics, where the weights (obtained as described below) sum to 1. To obtain weights for each metric, we used a bootstrapping technique that benchmarked relative performance against various databases such as the World Economic Forum [13], the World Bank [14], and the Nature Index [15], creating a strawman representation of purposeful comparative analysis of each country's possible performance. This provided a relative performance ranking of a subset of the countries in two ways. First, a numerical rank from best to worst was identified for around 60 countries at several different time points. A country's estimated rank j is denoted $\langle r_j \rangle$. Second, a larger set of around 200 countries was classified more coarsely (and thus easily) as 4 (known innovators), 3 (recognized as having the potential to innovate), 2 (having an active research community), 1 (having a functional higher education community), or 0 (having no functional research capacity). The strawman classification for country j is denoted $\langle c_j \rangle$.

For a given set of weights, $w_1, \dots, w_6$, for each country j for which the expert gave a classification above 0, an RPP score is calculated as $y_j = w_1 x_{1j} + \dots + w_6 x_{6j}$. Where data are missing, the score is normalized to account only for scores which are present, e.g., if x_{1j} is missing, $y_j = (w_2 x_{2j} + \dots + w_6 x_{6j}) / (w_2 + \dots + w_6)$.

The calculated rank of country j in terms of the calculated score is r_j^* . Calculated classifications are simply the quartiles of the ranks classified by quartile, with $c_j^* = 1$ (lowest quartile), 2, 3 or 4 (top quartile). An evolutionary algorithm [16] identified coefficient weights $w_1, \dots, w_6$ for the metrics that minimized the sum over all countries of $(\langle c_j \rangle - c_j^*)^2$, i.e., the least squares best fit. The results did not vary substantially when different fitness functions were substituted for least squares.

2.3. Comparative Analysis

Exploratory results indicate that while prior research potential is unsurprisingly the most significant indicator of future scientific performance across all scientific domains, other variables (i.e., within physical capital, social capital, and human capital) can play a small role in shaping research trajectories (Table 1). Such variables can be particularly helpful in breaking ties within countries of limited data (i.e., peer-reviewed publication data or patents). More importantly, such weights would likely be shifted for specific technologies – sociopolitical variables become more important as a given technological sector is more uncertain or controversial.

Table 1. Calibrated weights derived from an evolutionary algorithm

	Edu	IP	Trade	EconFree	Res	UncertAvoid
Normalized Weights	0.006	0.025	0.076	0.000	0.889	0.003

The countries identified as having the most rapid percent increases in RPP may be the most ideal partners to pursue – they are less likely to have been receiving attention in the past when their scores were lower, and their increased scores suggest that they are more likely to produce benefits in the future (Figure 1). An important caveat is that due to the relative ranking of such scores, certain countries may have periodic increases or decreases in their RPP due to exogenous shocks that may be temporary and/or easily rectified.



Figure 1. Greatest swings in percentage change in overall score for years 2011 and 2015 for the 174 countries with available data for non-zero weighted criteria

A critical caveat of Figure 1 is that it assesses *relative* performance of a country, not necessarily absolute performance. Nations like Estonia with longstanding track records of scientific growth can appear to relatively decline despite continued prominence in many sectors such as cybersecurity and digital information systems, while other nations may appear to rise or grow due to their emergence from civil conflict or a sudden and substantial investment into their science sector that had previously been limited or nonexistent. Figure 1 is a helpful first step towards understanding relative performance and shifts in national scientific development as it does not place insurmountable weight upon the accomplishments and capabilities of top scientific

performers, although more inter-year comparative analysis would be needed to arrive at a more deterministic outcome indicating a strong trajectory of the continued growth of a newcomer.

This effort serves as a proof of concept. The approach proved practical – data are not in short supply, and modeling requirements are modest. We believe, more sophisticated extensions of such an approach would still require efforts that are miniscule compared to the nation's expenditures on research partnerships – let alone the potential benefits from pursuing fruitful ones. The approach also demonstrates a potential contribution in that the results appear both reasonable and to some extent non-obvious. Most importantly, the type of results produced have practical relevance: a scoring model developed from historical data and expert judgment may consider recent changes in the performance of specific countries to allow identification of the relative newcomers in science, technology and education, as well as emerging disciplines.

3. Assessing International Scientific Potential – A Path Forward

Newcomer identification has significant potential benefits in an era where scientific research and technology development is increasingly globalized. However, the mathematical process of rank-ordering newcomers for potential partnership remains a challenging task. We view such challenges as threefold, including (i) the difficulty of selecting and maintaining robust data sources, (ii) the construction and maintenance of proper models to utilize such data, and (iii) accounting for the multitude of governance and sociopolitical concerns that add further layers of complexity into any bilateral or multilateral arrangement of science collaboration between countries.

3.1 Metrics

Despite the many metrics proposed, it remains unclear which metrics have the best predictive value, especially in the long-term. The need to narrow the set of metrics to a manageable quantity is a major challenge, as it is inefficient to collect hundreds of metrics for each country when perhaps a dozen would have roughly the same predictive power. The value of information gained by each additional indicator will likely diminish, especially when balanced against the costs of data collection.

Other challenges identified included the issue of scale. On the geographic scale, country-level variation matters. Regarding time scales, quantitative metrics tend to be lagging. Metrics might be 1 to 3 years old by the time the trends show up in statistics. Another consideration is the data sources themselves. Scholarly databases such as SCOPUS and Web of Science may only cover certain disciplines, excluding other disciplines where interesting advances may be taking place (e.g., computer science or cybersecurity).

3.2 Modeling

A major challenge is that the problem can be conceptualized at various scales. Depending on where one draws the boundaries, different methods may be appropriate for the task. Specifically, questions of scale present themselves with respect to partner (nation, institution, individual researcher), specificity of the scientific problem (from general, e.g., chemistry, to specific, e.g., carbon nanotubes), and time horizon (20 years, 6 months). Another related consideration is that of collaboration objectives. There might be many strategic objectives, some perhaps competing with others, to pursue collaboration with a particular partner. Before choosing an appropriate methodology, one must fully understand the assumptions around collaborations with whom, on what topic, over what time frame, and why.

There exists a vast array of modeling approaches that can be utilized, individually and in combination, to identify collaboration opportunities. These methods range from qualitative, expert-driven exercises to computationally sophisticated and complex analytics. Among others, such approaches include qualitative expert elicitation-based methods, cross-impact analysis, bibliometric tracking techniques, decision analysis (including game theory and portfolio decision modeling), data science and machine learning techniques, and complex systems-based models.

Clearly, there is no single “best” modeling approach. Instead, there are many methodologies, which can be used together to provide a picture of the overall scientific landscape. Since the decision of what method to select was too contextual to advocate for or against a single method, maintaining a computational “toolbox” is preferred to reliance upon a single methodological approach.

3.3 Governance and Sociopolitical Drivers of International Scientific Collaboration

Governance and policy challenges relative to international scientific engagement center upon two core tasks: (a) fostering standards and protocols to execute surveys and data gathering/analysis of the international scientific landscape, and (b) developing processes for engagement of potential scientific partners in a manner that accounts for their unique economic, political, and social characteristics.

For the former, one common program with demonstrated success is the Embassy Science Fellows Program¹, where scientific experts are stationed at US embassies of potential trade and research partners to facilitate the process of scientific investment and bilateral cooperation [17]. Senior government leadership, such as a chief technology advisor, can also help steer a nation’s

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scientific engagement opportunities. Such institutional mechanisms enable horizon scanning of potential collaboration opportunities abroad, and a means of enabling direct collaboration through knowledgeable stakeholders and clear bilateral agreements. Regular data gathering and analysis of science and technology opportunities should involve future projections of scientific growth rates and political and economic drivers that influence the growth or decline of a given scientific discipline. Such an exercise clarifies what metrics are used to inform such insights and what decision support tools are acceptable to process such metrics.

For the latter, once potential newcomers have been identified, concerns remain regarding how best to engage them in a shared and mutually beneficial platform. Social, governance, and cultural differences and challenges can frame or determine whether newcomer engagement is practical or sustainable over time. Science does not exist in a vacuum, but instead is framed by the value and importance that societies place upon it. One factor is the institutional composition of the target country's government and science sector. Engagement with a relatively open and democratic society may differ in strategy and goals than with a more authoritarian regime – particularly when the decision makers in more autocratic countries are unpredictable or untrustworthy in their adherence to bilateral and multilateral scientific agreements.

If there is a degree of trust in a potential partnership, direct investment into a given country in the form of financial aid or technology transfer can kick-start bilateral science arrangements. If trust is limited or political differences are strong, temporary or permanent immigration of select scientists from a target country may be a more sustainable and politically/economically acceptable alternative. A second factor is the social influence of its culture, including the cultural willingness of a country to innovate in a certain field. Regardless of funding and infrastructure, innovation cannot occur if the people in a country disapprove of the direction or motivation of a given

scientific endeavor – either from a lack of economic incentive, or a belief that such technologies are against the best interest of broader society.

Ultimately, engagement is defined by multiple strategies: (a) political incentives/bilateral trade agreements, (b) investment into the country and its scientific sector, or (c) incentivizing select individuals within the foreign country to relocate for purposes of research and development. Strategies chosen in this regard are defined on a case-by-case basis relative to the target nation's general stance (are they friendly or unfriendly), their relative scientific capacity, and the institutional, social, and cultural values.

4. Conclusion

Scientific and technological innovation holds the potential to enhance a nation's economy and provide benefits to populations around the world. The following practical takeaways can help inform policymakers and practitioners working at the intersection of science and policy charged with identifying potential international partners:

- Relatively simple models can be built to identify potential partners, however simple models may not account for dependencies within and across scientific communities, trends at various geographic scales, and patterns in scientific engagement.
- More computationally advanced techniques can be leveraged to gain information about the global scientific landscape, including tools from machine learning.
- When developing data-driven models to identify collaboration opportunities, utilize an ensemble of quantitative and qualitative data sources.

- By establishing research relationships with high-innovation potential in certain fields early, innovative technologies can be more rapidly developed and fielded, accelerating the benefits of these technologies to be enjoyed by society.

This paper has attempted to frame the problem of identifying high-value innovation partnerships with newcomers on the international stage. In light of this initial analysis, further analysis is warranted across three complementary areas of inquiry, which are addressed by the following papers in this issue:

- Metrics and indicators [18]
- Modeling approaches [19]
- Policy and governance challenges [20].

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References

1. G7 Academies of Science (2017) “New economic growth: the role of science, technology, innovation and infrastructure”.
2. Linkov, I., Moberg, E. (2011). *Multi-Criteria Decision Analysis*. Boca Raton: CRC Press.

3. Bernard, A. B., Busse, M. R. (2004). Who wins the Olympic Games: Economic resources and medal totals. *Review of Economics and Statistics*, 86(1), 413-417.
4. Porter, M.E. (1998) *The Competitive Advantage of Nations*. The Free Press.
5. Furman, J. L., Porter, M. E., Stern, S. (2002). The determinants of national innovative capacity. *Research Policy*, 31(6), 899-933.
6. Krammer, S. M. (2009). Drivers of national innovation in transition: Evidence from a panel of Eastern European countries. *Research Policy*, 38(5), 845-860.
7. Barro, R. J. (2001). Education and economic growth. The contribution of human and social capital to sustained economic growth and well-being, 14-41.
8. Chen, Y., Puttitanun, T. (2005). Intellectual property rights and innovation in developing countries. *Journal of Development Economics*, 78(2), 474-493.
9. Lane, D., Pumain, D., van der Leeuw, S. E., West, G. (Eds.). (2009). *Complexity Perspectives in Innovation and Social Change* (Vol. 7). Springer Science & Business Media.
10. Leydesdorff, L., Wagner, C. (2009). Macro-level indicators of the relations between research funding and research output. *Journal of Informetrics*, 3(4), 353-362.
11. Padilla-Pérez, R., Gaudin, Y. (2014). Science, technology and innovation policies in small and developing economies: The case of Central America. *Research Policy*, 43(4), 749-759.
12. Carvalho, N., Carvalho, L., Nunes, S. (2015). A methodology to measure innovation in European Union through the national innovation system. *International Journal of Innovation and Regional Development*, 6(2), 159-180.
13. World Economic Forum. <https://www.weforum.org/reports/how-to-end-a-decade-of-lost-productivity-growth>
14. World Bank Science & Technology. <https://data.worldbank.org/topic/science-and-technology>

15. Nature Index. <https://www.natureindex.com/annual-tables/2019/country/all>
16. Frontline Systems. "Genetic and Evolutionary Algorithms – Introduction." <https://www.solver.com/genetic-evolutionary-introduction>
17. Linkov, I., Basu, S., Fisher, C., Jackson, N., Jones, A.C., Kuklja, M.M., Trump, B.D. (2016). Diplomacy for science: strategies to promote international collaboration. *Environment Systems and Decisions*, 36(4), 331-334.
18. Hollenback, K., Collier, Z.A., Lambert, J.H., Linkov, I. (2020). "Indicators and Metrics of Emerging Country-Level STEM Innovation." *IEEE Engineering Management Review*, this issue.
19. Keisler, J.M., Collier, Z.A., Ayyub, B.M., Dempwolf, C.S., MacDonald Gibson, J., Porter, A.L., Schweizer, V.J., Thorisson, H., Wang, L., Ye, M., Lambert, J.H., Linkov, I. (2020). "Modeling and Analytics to Support Emerging International Innovation Partnerships." *IEEE Engineering Management Review*, this issue.
20. Klasa, K.A., Trump, B.D., Linkov, I., Lambert, J.H. (2020). "Identifying New Partnerships for Innovation: Governance and Policy Challenges." *IEEE Engineering Management Review*, this issue.