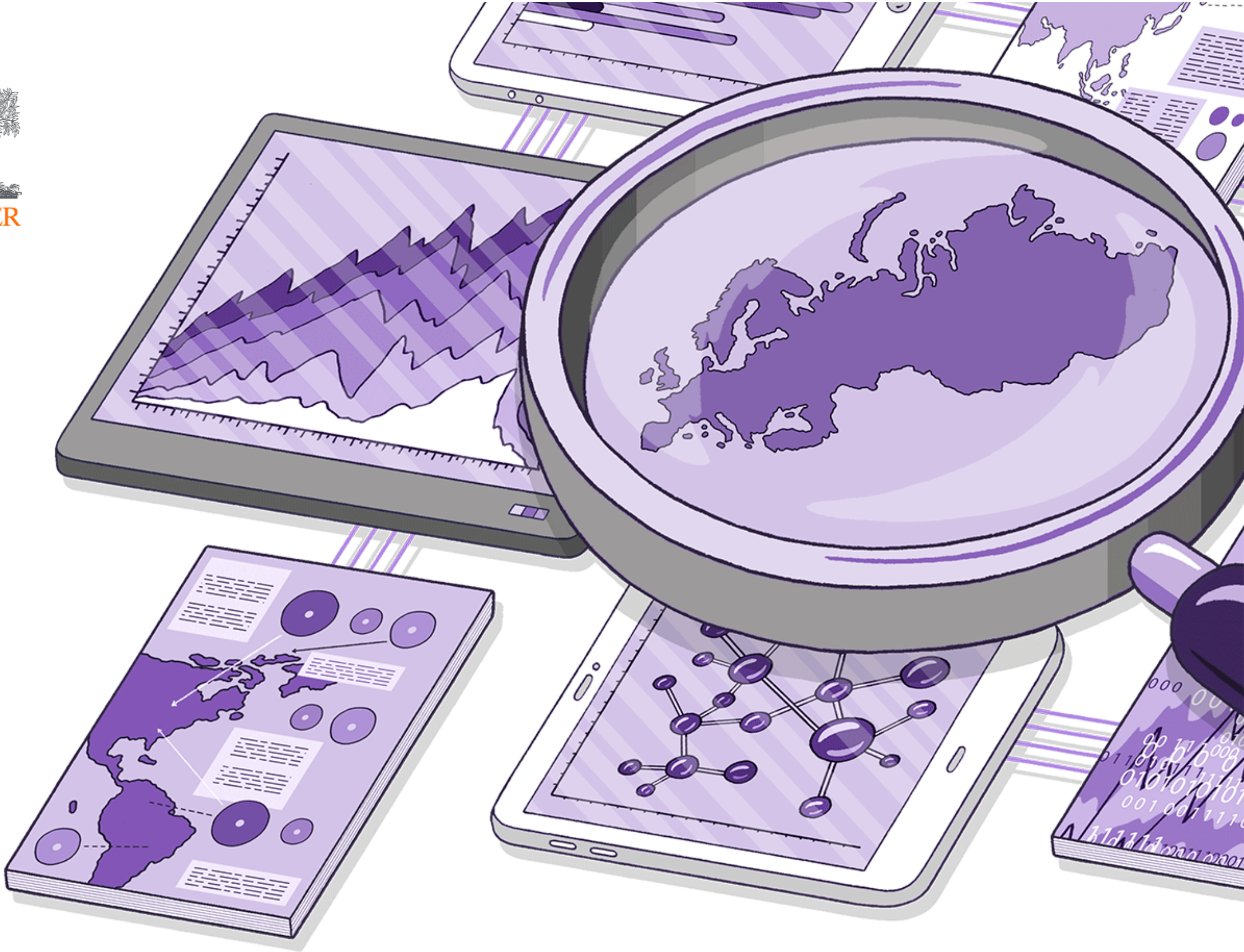


Quantitative analysis of Dutch research and innovation on key technologies

A report for the

Ministry of Economic Affairs and Climate, 2023

Analytical Services

Executive summary

The Dutch Ministry of Economic Affairs and Climate (MinEZK) is actively shaping a National Technology Strategy (NTS) to optimize resource allocation and enhance the Netherlands' global technological competitiveness. This report, commissioned by the MinEZK offers insights into the Netherlands' research capabilities across 44 key technologies and comparative data showcasing the country's standing in the global research landscape.

The Dutch Ministry of Economic Affairs and Climate (MinEZK) is actively engaged in the development of a National Technology Strategy (NTS), a crucial initiative aimed at optimizing resource allocation and enhancing the Netherlands' technological competitiveness on a global scale. The central objective of the NTS is to provide a structured vision that guides the allocation of resources to key technologies, thus enabling the Netherlands to make informed, effective, and strategic investment decisions in the complex technological landscape. This strategic approach necessitates a comprehensive review and refinement of the list of 50 key technologies initially identified in 2017 through collaborative research conducted by the Netherlands Organisation for Scientific Research (NWO), the Netherlands Organisation for Applied Scientific Research (TNO), and Elsevier.

This extensive report, commissioned by MinEZK, serves as an impartial and evidence-based assessment of the Netherlands' research capabilities across 44 key technologies. Notably, the compilation of these key technologies was significantly enriched by the valuable input of NWO and TNO, who provided insights and guidance during the formulation of the keyword sets used to define these technologies. Throughout this analysis, we employ fundamental bibliometric indicators to provide a comprehensive and nuanced overview of the Netherlands' scientific standing, complete with comparative insights into the research landscapes of 15 EU countries, China, the United States, and the broader global research community.

Impressive research output and citation impact

The Netherlands, despite representing a mere 0.22% of the global population, boasts a research community that has consistently demonstrated remarkable productivity and impact. Dutch researchers have collectively authored and published over 575,000 research papers spanning the period from 2013 to 2022, an impressive contribution that accounts for nearly 2% of the world's research output. What is particularly noteworthy is that Dutch research consistently exceeds the global average in terms of citation impact, as evidenced by a field-weighted citation impact (FWCI) of 1.75, signifying a citation rate that is 75% higher than the global average.

In a global context, while Dutch research ranks sixth in terms of output within the EU-15, it firmly secures the third-highest position in terms of FWCI, trailing only Luxembourg and Denmark.

Furthermore, within the domain of key technology research, comprising 28% of Dutch research output, the Netherlands continues to exhibit impressive citation impact, reinforcing its prominent position on the global research stage. It should be noted, however, that the comparators—especially China—display a higher share of research dedicated to the key technologies.

Focus area of key technologies

Within the spectrum of key technologies, Dutch researchers demonstrate a discernible focus on BIOTECHNOLOGY AND LIFE SCIENCES, DIGITAL TECHNOLOGIES, and QUANTUM TECHNOLOGIES. It is worth noting that these areas at least partly surpass the global average in relative activity, underscoring their strategic importance in the Netherlands' research landscape. However, what sets Dutch research apart is its diverse and multifaceted research portfolio, which, in comparison to other nations, exhibits a somewhat lower overall concentration on key technologies. This diversity is a testament to the adaptability and dynamism of Dutch research.

An in-depth exploration of technological complexity and relatedness reveals the economic potential inherent in BIOTECHNOLOGY AND LIFE SCIENCES, as well as select DIGITAL TECHNOLOGIES. These domains enjoy the advantage of a favorable supply of related technologies and exhibit medium complexity, making them prime candidates for future development and innovation.

Innovative power signaled through patent analysis

Dutch research's profound impact on the global technological landscape is further evident in its substantial recognition through patent citations. On a global scale, the Netherlands ranks second only to the United States in this regard. Notably, BIOTECHNOLOGY AND LIFE SCIENCES and CHEMICAL TECHNOLOGIES emerge as the frontrunners in patent citation averages, firmly establishing the Netherlands as a commendable player among EU-15 countries.

Dynamic clusters with key technologies

A closer examination of research topics reveals dynamic clusters within various domains and key technologies. These clusters reflect the evolving and adaptive nature of Dutch research. In the BIOTECHNOLOGY AND LIFE SCIENCES domain, there is a discernible emphasis on biological aspects, showcasing the multifaceted nature of this critical field. Conversely, the EnMat domain brings to light emerging topics within the sphere of car battery technologies, exemplifying Dutch researchers' commitment to exploring cutting-edge developments.

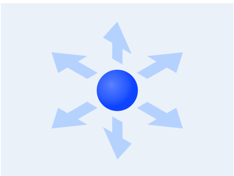
The Netherlands as signficant player on the global research landscape

In conclusion, Dutch research holds a significant and enduring influence on the global scientific landscape, a remarkable achievement considering the country's modest size. To sustain and enhance this competitive edge, it is imperative for the Netherlands to foster collaborative partnerships with other European nations. Such strategic alliances will be instrumental in balancing the research prowess of larger global players, such as China and the United States. The Netherlands is undeniably well-positioned to make substantial and lasting contributions to the advancement of key technologies in the years ahead. This comprehensive report provides an objective, data-driven foundation upon which strategic decisions can be made to further strengthen the country's technological capabilities and global influence, positioning it as a leader in the ever-evolving world of research and innovation.

Key findings

Total Dutch publications account for 2% of global publications

- Dutch researchers produced more than half a million publications between 2013 and 2022, accounting for 2% of global scholarly output.
- Almost 30% of Dutch publications are dedicated to key technologies, which is lower than any competitors share.



Dutch research is highly impactful

- Dutch research achieved an FWCI of 1.75 (75% more citations than global average), making it one of the leading reseach nations by impact.
- The Netherland's publication share of the top 1% most highly cited publications is three times that of the global average.

Few focus areas with the key technologies, but overall high quality research

- Relative activity index for Dutch research across all key technologies is below the level of comparators, but several key technologies and domains stand out for high activity.
- Citation impact of key technology research is one of the highest of European (and global) comparators.

Biotechnology and Life Sciences

- The Biotechnology and Life Sciences domain shows the highest relative activity for all of its key technologies.
- It also showed a citation impact above world level, both for FWCI and for share of publications in top citation percentiles.

Patent portfolio is valuable and well balanced with a global outreach

- Market coverage for the Netherlands is on average 1.75, indicating the global outreach of the patent portfolio.
- The technological impact of these patent families is 1.43, well above world levels.
- The overall value of the Netherlands' patent portfolio is fourth of all European competitors, assessed by the Patent Asset Index.

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Introduction

This report assesses the research performance of Dutch research in 44 key technologies defined by the Ministry of Economic Affairs and Climate in the context of global and European research. Publication and patent indicators provide insights into particular strengths and potential weaknesses.

The Dutch Ministry of Economic Affairs and Climate (Ministerie van Economische Zaken en Klimaat, MinEZK) is developing a National Technology Strategy (NTS). Its aim is to form a vision as a basis for the allocation of resources to key technologies, thereby contributing to more efficient and targeted investment choices. The NTS is therefore guiding the shaping of the development of key technologies and the priorities set within and between them.

The starting point of the NTS consists of a reevaluation of the list of key technologies, which was established in 2017 after a preliminary study by the Netherlands Organisation for Scientific Research (NWO) and the Netherlands Organisation for Applied Scientific Research (TNO) and a more in-depth bibliometric analysis by Elsevier in 2018 (see references). That list of 50 key technologies, divided into eight domains, was subsequently incorporated into the "Kennis- en Innovatieagenda Sleuteltechnologieen (KIA-ST)" (Knowledge and Innovation Agenda Key Technologies) in 2019.

Apart from the knowledge and innovation questions within the KIA Key Technologies itself, the list of key technologies plays a role in the broad deployment of key technology development within Top Sectors (through KIA programs), the National Growth Fund, NWO calls, and as a basis for the allocation of regional resources and EU co-financing.

The list of key technologies for the NTS has been refined recently in a joint process by NWO and TNO and as a result 44 key technologies within 8 clusters have been used. A full list of these key technologies can be found in Appendix A.

This report was commissioned by the Dutch Ministry of Economic Affairs and Climate to conduct an objective, bibliometrics-based assessment of the Netherlands research base across 44 key technologies as an update of the 2018 report. NWO and TNO provided significant insight and advice on the keyword sets used to define the key technologies during, and prior to, the analysis.

Methodology used in this report

The quantitative analyses of the key technologies provided in this report are based on publication and patent data. For this purpose, publication (and patent) sets needed to be created. A publication set for a key technology aims to cover all relevant publications related to this particular key technology ("recall" or sensitivity) while at the same time excluding all publications not relevant to the topic ("precision" or specificity). Creation of these sets is a highly complex and time-consuming task—in the previous report, it entailed several workshops with NWO and TNO and domain experts to define keywords, create sets and verify and refine these sets for each key technology.

This report adjusted the previously used approach. While the 2018 report used only keywords to define the publication sets, the current approach combined (the updated) keywords and citation links (i.e., identifying publications which relate to the topic without using specific vocabulary or keywords). Samples of the resulting final publication sets have been reviewed by domain experts to assess the precision of the final set. The definition of the key technologies and the expert review process used to validate the resulting publication sets had some important limitations to consider, for details see Appendix A with a full description of the methodology.

For visual reasons the key technologies are abbreviated throughout the report. The eight technology domains and their respective key technologies and abbreviations are presented in TABLE 0-1.

Technology domain	Abbreviation	Key technology
Advanced materials	EnMat	Energy materials
	OptMat	Optical, electronic, magnetic and nanomechanical materials
	MetaMat	Meta materials
	SoftMat	Soft/bio materials
	ThinFilms	Thin films and coatings
	ConStruct	Construction and Structural materials
	SmaMat	Smart materials
Photonics and optical technologies	PhoVolt	Photovoltaics
	OptSystems	Optical systems and integrated photonics
	PhoDetect	Photonic/Optical detection and processing
	PhoGen	Photon generation technologies
Quantum Technology	QuaComp	Quantum computing
	QuaComm	Quantum communication
	QuaSens	Quantum sensing
Digital and information technologies	AI	Artificial intelligence
	DataScience	Data science, data analytics and data spaces
	CyberSec	Cyber security technologies
	SoftTech	Software technologies and computing
	DigiConnect	Digital connectivity technologies
	DigiTwins	Digital Twinning and Immersive technologies
	NeurMorph	Neuromorphic technologies
Chemical technologies	ProcessTech	(Bio)Process technology, including process intensification
	ReactEngi	(Advanced) Reactor engineering
	SepTech	Separation technology
	Catalysis	Catalysis
	AnalyticsTech	Analytical technologies
	ElectReact	Electricity-driven chemical reactor technologies
Nanotechnology	NanoManufac	Nanomanufacturing
	Nanomat	Nanomaterials
	FuncDevice	Functional devices and structures (on nanoscale)
	NanoFluid	Micro- and nanofluidics
	NanoBioTech	Nanobiotechnology / Bionanotechnology
Life science and biotechnologies	BioCellTech	Biomolecular and cell technologies
	BioSystems	Biosystems and organoids
	BioManufact	Biomanufacturing and bioprocessing
	BioInformatics	Bioinformatics
Engineering and fabrication technologies	SensActuat	Sensor and actuator technologies
	ImagingTech	Imaging technologies
	OptoMecha	Mechatronics and Opto-mechatronics
	AddiManufact	Additive manufacturing
	Robotics	Robotics
	DigiManufactTech	Digital manufacturing technologies
	MicroElectro	Micro electronics
	SystEngi	Systems engineering

TABLE 0-1
Technology domains, key technologies and abbreviations used in this report.

Structure of the report

Basic bibliometric indicators are used throughout this report to assess the scientific strength of the Netherlands, benchmarked against 15 EU countries[1], the group of EU-15, China, the US, and the World.

Chapter 1 gives an overview of the Netherlands' research performance across all subjects to give some context. Indicators used are the number of Dutch publications, the field-weighted citation impact, and the number and share of top 10% and top 1% most cited publications. Together, these indicators provide a first impression of the quantity and quality of Dutch research overall.

Chapter 2 focuses on analysis of key technologies, first across the combined research output on all key technologies, and the second part on the individual key technologies. Besides the bibliometric indicators already used in the first chapter, this analysis utilizes some new and additional assessments such as research levels and a composite indicator of citation impact and research activity. The degree of maturity of each key technology is examined on the basis of compound technology lifecycle curves, based on the principle that developments in a broad field of research are in essence a composite of breakthroughs in various aspects of that field. An assessment of complexity and relatedness (first employed by Balland (Balland & Boschma, 2020)) follows, as well as an evaluation of the technology monopoly risk (developed by the Australian Science Policy Institute). The chapter concludes with citation links between research publications and patents to lead into the patent analysis in Chapter 3.

The final chapter assesses topics of prominence, a new method to evaluate clusters of publications relating to the same subject. This chapter reveals some emerging clusters within each key technology to give some insights into possible future (or at least emerging) areas within the broader technology concepts.

1 A list of the comparator countries is provided in Appendix B.

Chapter 1

Dutch research in a global context

1.1 Output and impact of Dutch research

Dutch research is highly productive and impactful. Almost 2% of the global research output was published by Dutch researchers—growing by 3% annually—and the citation impact of Dutch research is around twice the global average.

The analysis of journal articles, reviews, and conference papers provides useful insights into the comparative performance of the research base of a country, although journal article and citation-based indicators capture the research performance better in some fields than in others. This chapter examines the scholarly output, growth, impact, and excellence of the Dutch research base across all subject areas, to provide a baseline for the following analyses of Dutch research in key technologies.

The Netherlands accounts for 0.22% of the world's total population[2], but its research is regarded as highly productive and impactful.

A basic bibliometric indicator is the number of scholarly outputs a country (or its researchers) produces. Dutch researchers published more than 575,000 publications in the period 2013–2022, which accounted for almost 2% of the global publication output (FIGURE 1-1). This share was relatively stable across the period, although the number of published grew by almost 3% annually until 2022, with a small decline in the most recent year. World research output grew within a similar range, therefore the share of research output of Dutch researchers remained stable.

[2] According to data from the World Bank: https://data.worldbank.org/indicator/SP.POP.TOTL?name_desc=true

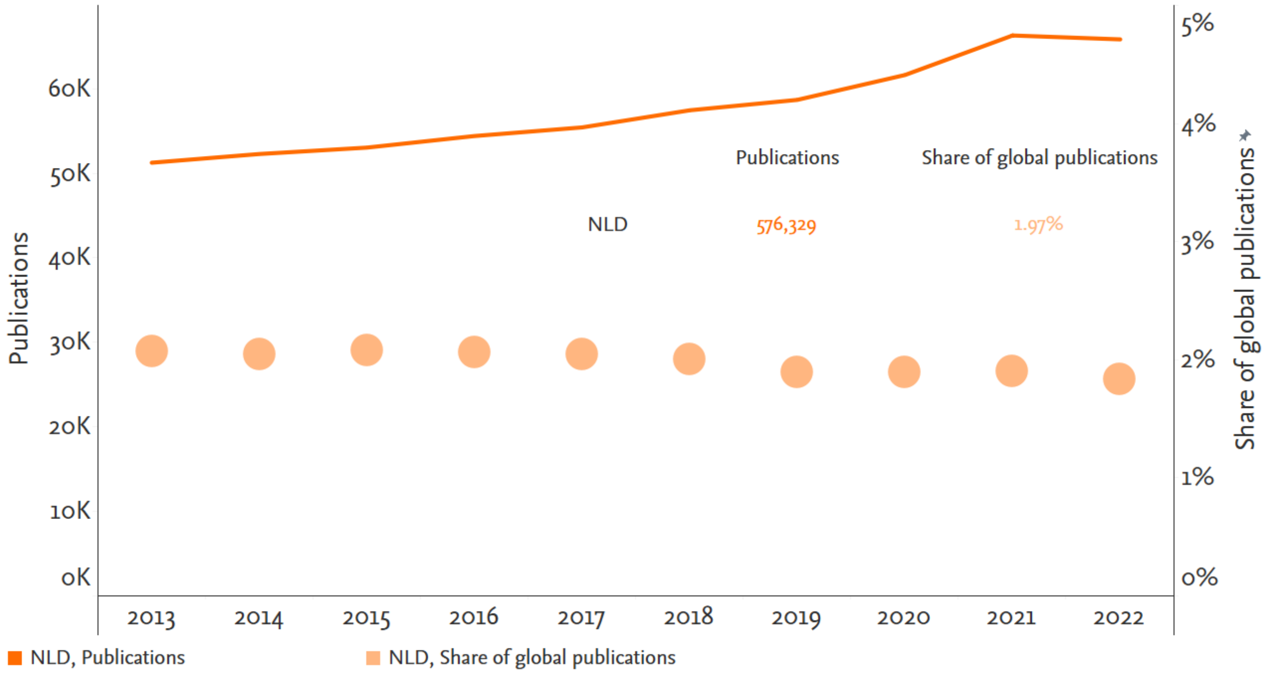


FIGURE 1-1
Annual Dutch research output (solid line) and share of global research output (dots) across all subjects, 2013–2022.
Source: Scopus

While the output accounts for 2% of the world production, the impact of Dutch research is assessed to be very high. One indicator used to assess the breadth of excellent research is the share of research outputs in the world's most highly cited publications (usually the top 1% and the top 10% most highly cited publications are used for this). If around 1% of a country's publications are within the global top 1% most highly cited, that is on par with the global average.

Dutch research had a share of 3% within the top 1% and of 22% within the top 10% most highly cited. In other words, Dutch researchers contributed three times the global average to the most highly cited publications and more than twice the global average to the top 10% percentile. FFIGURE 1-2 shows the annual numbers and FIGURE 1-3 displays the share for the period.

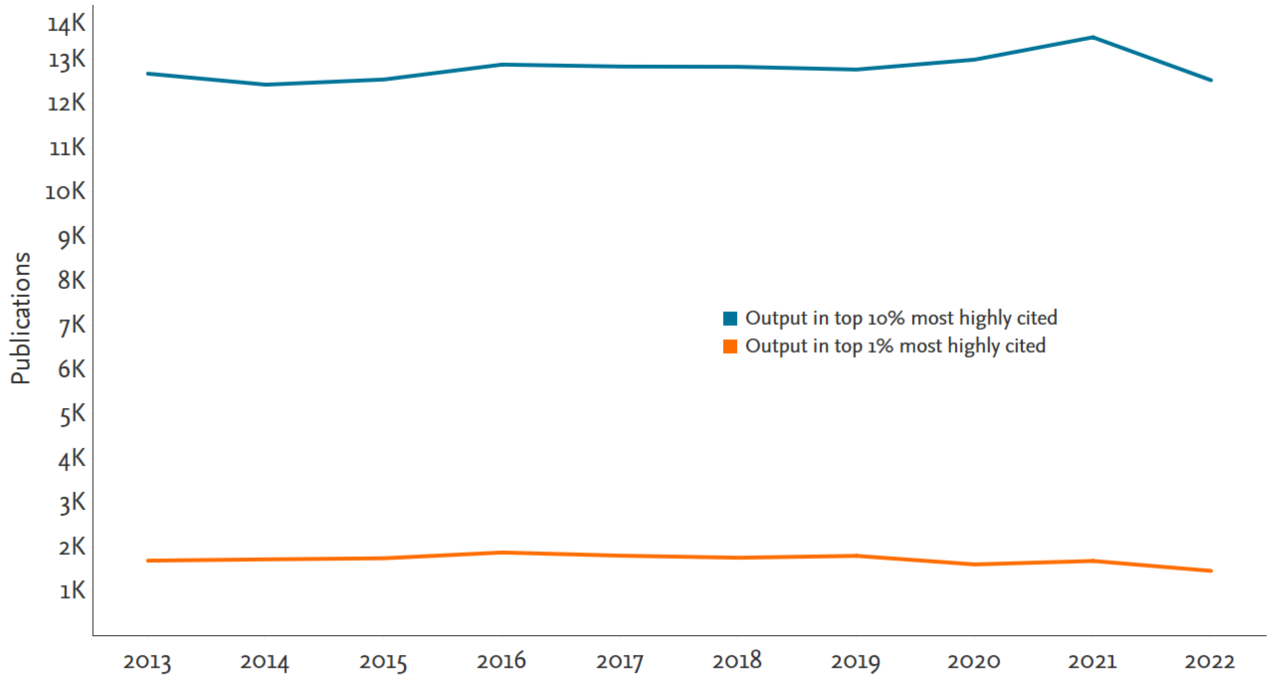


FIGURE 1-2
Annual Dutch research output in top 1% (orange line) and top 10% (blue line) most highly cited global publications across all subjects, 2013–2022.
Source: Scopus

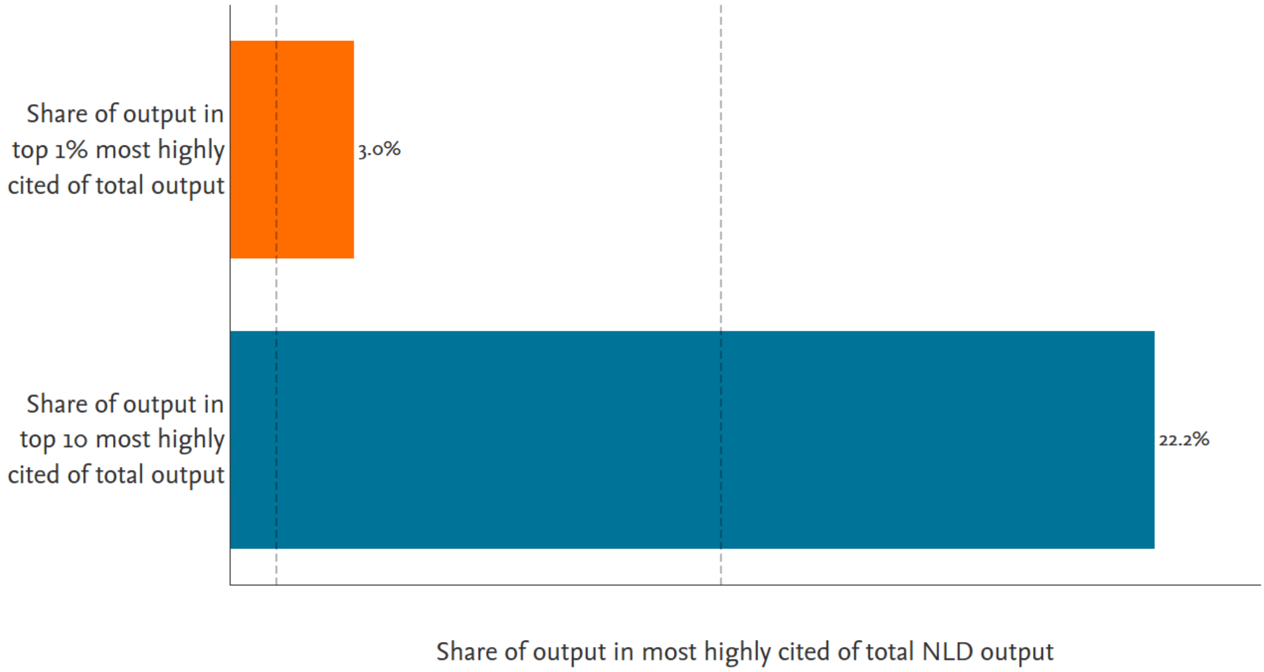


FIGURE 1-3
Dutch research output in top 1% (orange bar) and top 10% (blue bar) most highly cited global publications as a share of total Dutch research output, for the period 2013–2022.
Source: Scopus

It can be noted, however, that the share of publications in these most highly cited is slightly decreasing over time (FIGURE 1-4).

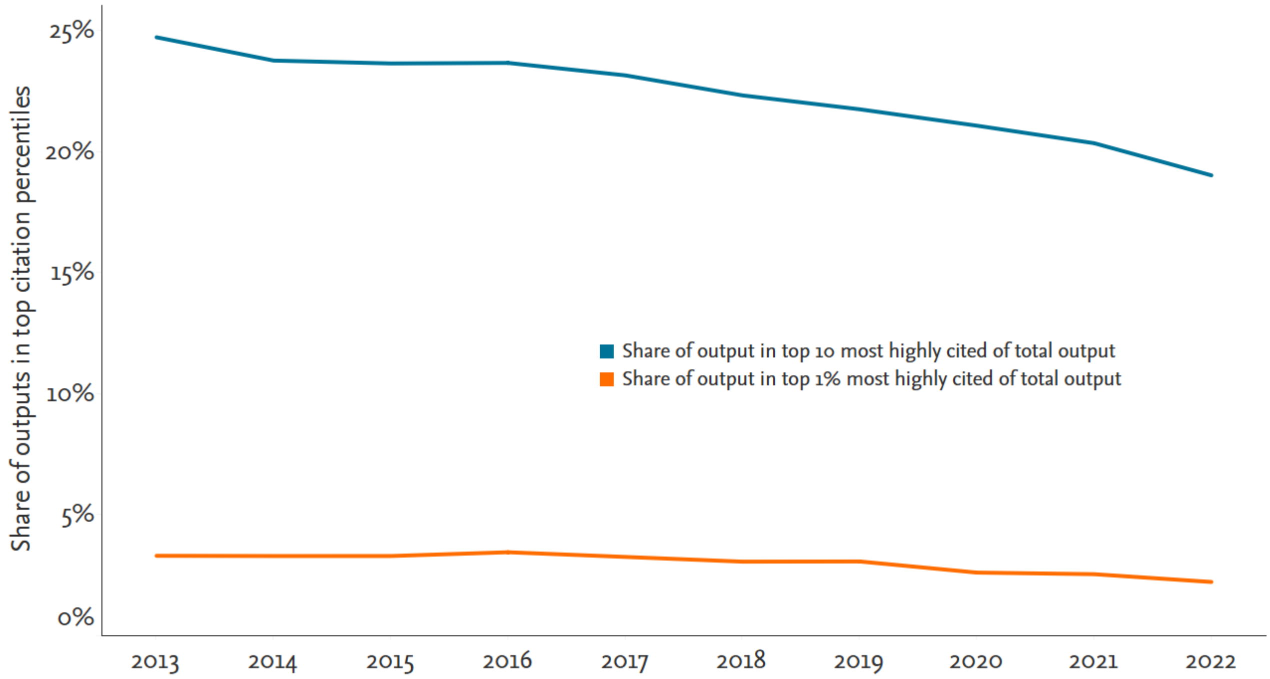


FIGURE 1-4
Annual share of Dutch research output in the top 1% (orange line) and top 10% most highly cited global publications of total Dutch research output, for the period 2013–2022.
Source: Scopus

While the share in most highly cited publications indicates the breadth of research excellence (by calculating the share of publications), the field-weighted citation impact (FWCI) looks at the citation impact of individual publications. It normalizes the citation counts of publications by the year of publication, the subject area, and the document type. This is required as these factors can influence the citation counts heavily. FWCI is always calculated with the global average being 1, so a value above 1 indicates that the research is more frequently cited than a global average output of the same year, subject area, and document type.

Looking at the FWCI of Dutch research outputs again highlights the excellent research of Dutch research. Across the period, Dutch research resulted in an FWCI of 1.75—meaning that on average, Dutch research output received 75% more citations that average global research outputs (FIGURE 1-5).

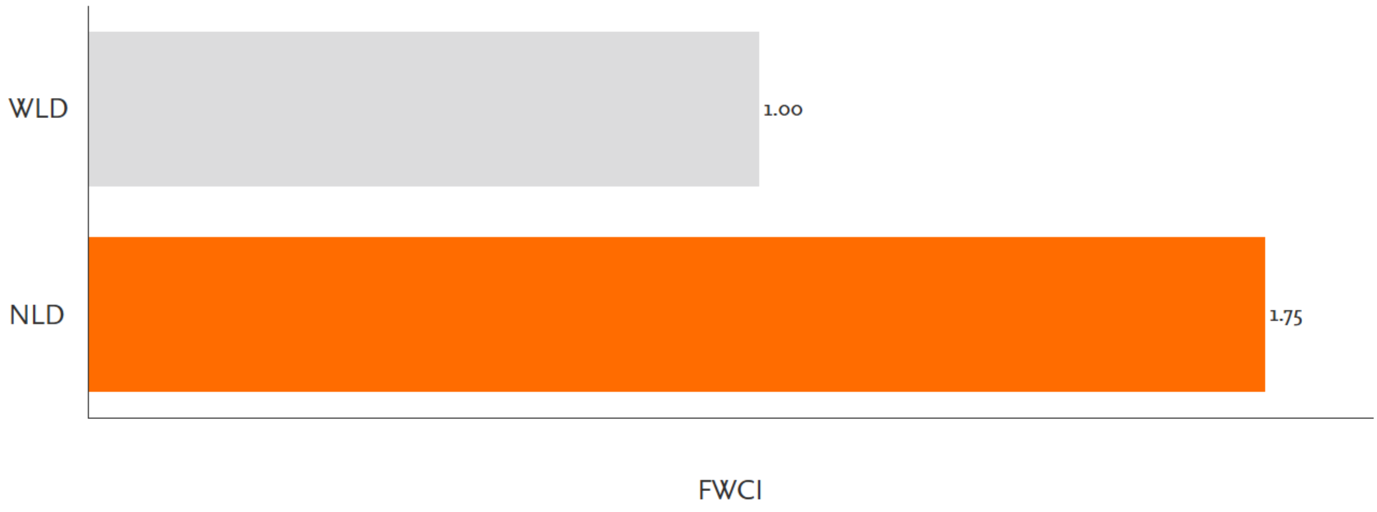


FIGURE 1-5
Field-weighted citation impact (FWCI) of Dutch (orange bar) and global (grey bar) research output across all subjects, for the period 2013–2022.
Source: Scopus

Annually, the FWCI seems to be declining, with a peak in 2015 and 2016 (FIGURE 1-6). This finding would be consistent with the share of top cited publications going down in the past few years. This effect, however, can at least partly be attributed to India and China's steep increase in publication output and impact, since these countries are so active that their output has effects on a global scale as well.

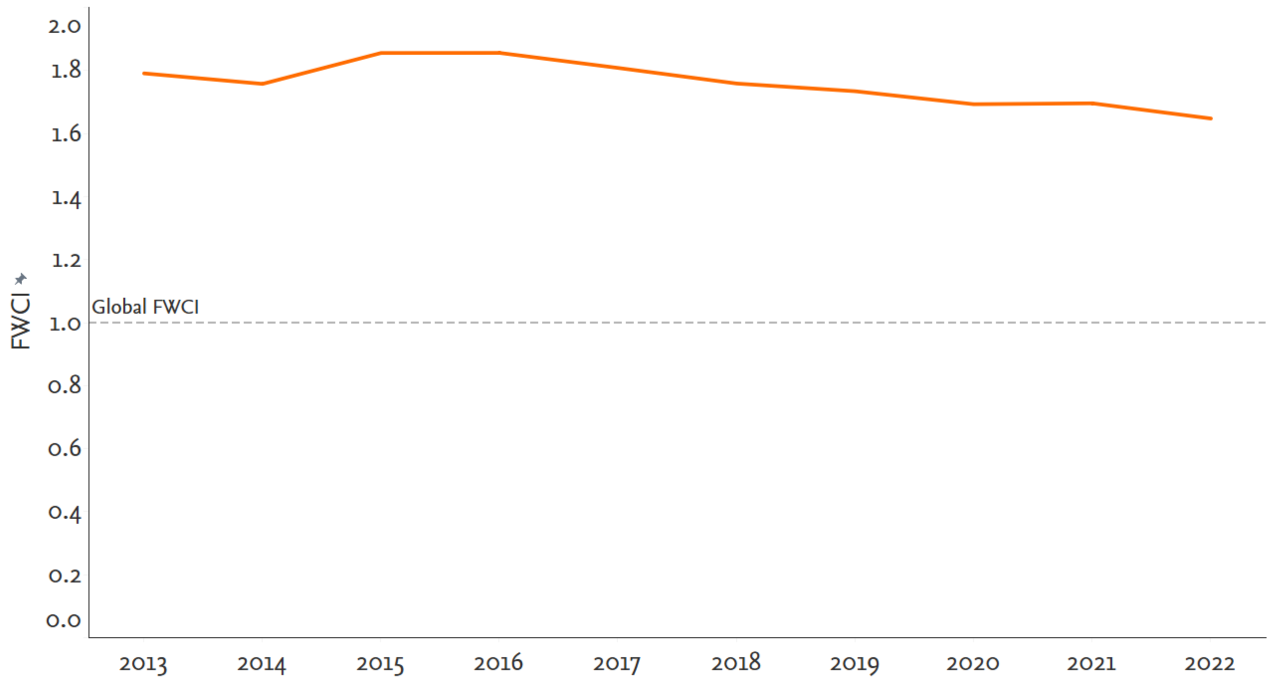


FIGURE 1-6
Annual field-weighted citation impact (FWCI) of Dutch (orange line) research output across all subjects, 2013–2022.
Source: Scopus

1.2 Dutch research in a European context

Dutch research is a strong contributor to the European research landscape and the Netherlands' breadth of excellent research tops any comparator country within the EU-15.

As seen in the previous chapter, the Netherlands is a strong contributor to the global research landscape with relative output and impact well above the global averages. Because Europe, along with China and the United States, is considered to be a global research powerhouse, it is interesting to assess the position of the Netherlands within the European research landscape. For that purpose, we created a benchmark group consisting of the initial EU-15 countries.

TABLE 1-1 indicates the total output and the share of global and EU-15 publications for each of the countries. Not surprisingly, the UK, Germany, and Italy are the biggest contributors to the global and EU-15 research output, with the UK sharing almost a quarter of EU-15 output.

As mentioned already in the previous chapter, research by Dutch researchers accounted for 2% of the global output and 7.6% of EU-15 output—making it the sixth largest contributor on the EU-15 level. The Netherlands is only topped by much larger countries such as the UK, Germany, Italy, France, and Spain—again a signal of the strong research landscape of the country.

Country or group	Publications	Share of publications from EU-15	Share of global publications
WLD	29,232,309		100.00%
EU-15	7,561,977	100.00%	25.90%
GBR	1,821,696	24.10%	6.20%
DEU	1,692,945	22.40%	5.80%
ITA	1,130,870	15.00%	3.90%
FRA	1,120,896	14.80%	3.80%
ESP	929,559	12.30%	3.20%
NLD	576,329	7.60%	2.00%
SWE	397,928	5.30%	1.40%
BEL	325,041	4.30%	1.10%
DNK	270,330	3.60%	0.90%
PRT	257,215	3.40%	0.90%
AUT	252,371	3.30%	0.90%
FIN	202,752	2.70%	0.70%
GRC	191,893	2.50%	0.70%
IRL	142,721	1.90%	0.50%
LUX	20,924	0.30%	0.10%

TABLE 1-1
Total research output, share of EU-15 and share of global output for NLD and comparators, 2013–2022.
Source: Scopus

The strong contribution of the Netherlands is even more obvious when looking at the citation impact (FIGURE 1-7). While Dutch research is ranked sixth by share of EU-15 output, it is ranked third by FWCI, only topped by Luxembourg and Denmark. Luxembourg, however, makes up only 0.3% (or 20,924 publications) of EU-15 outputs, so its high FWCI may be an effect of some exceptional publications (like the Global Burden of Disease Study[3] or other so-called hypercollaborative papers[4]). Denmark holds around 3.6% of the EU-15 production and its FWCI is slightly above that of the Netherlands.

3 The Global Burden of Disease is collected and analyzed by a consortium of more than 9,000 researchers in 162 countries and territories (https://www.healthdata.org/gbd/about).

4 Although no consensus definition exists on the number of co-authors required to constitute "hypercollaborative" co-authorship, numbers in the hundreds or thousands seem worthy of the term. As an indication of the frequency of such hypercollaborative publications, it is noteworthy that while the number of publications with more than 3,000 authors was 76 in 2012 and 52 in 2011, these were outlier years. In all other years from 2008 to 2017, the number of publications with more than 3,000 authors never exceeded five.

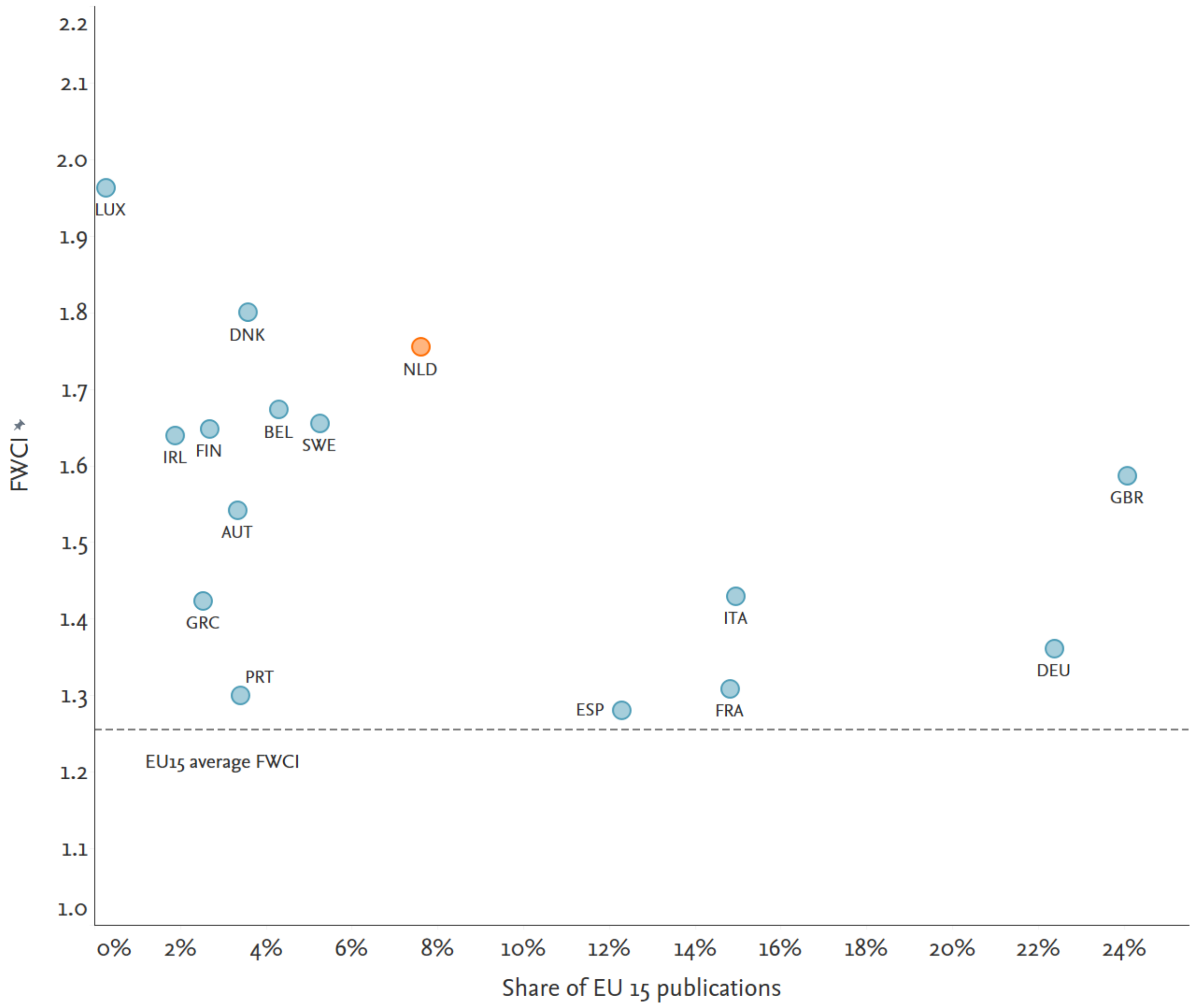


FIGURE 1-7
FWCI (y-axis) and share of EU-15 total publications for NLD and comparators, for the period 2013–2022. The dashed line indicates the average FWCI value for all EU15 publications, not the average value of all EU 15 countries. Therefore it can have the lowest value and does not need to reflect an average FWCI.
Source: Scopus

The assumption that the very high FWCI of Luxembourg may be the result of some exceptional publications is supported by the share of publications in the most highly cited outputs (FIGURE 1-8).[5] Research from the Netherlands holds the top position in share of top 10% and top 1% most highly cited publications. With its 3% in the top 1% most highly cited global publications, and more than 20% of publications in the top 10%, Dutch research is well above any other country in this analysis, although closely followed by Denmark. Luxembourg has a strong position with 2.6% and 18.0%, but overall, this signals that the Netherlands has more breadth of excellent research than the comparator countries.

5 The share of most highly cited articles is calculated from of the number of articles published by dutch researchers which belong to the global top 10% (or top 1%) most highly cited publications across all subjects as a share of all dutch publications. Being at global average, one would expect 10% of a country's publications being in that group. A higher share indicates a high number of top articles and therefore research excellence.

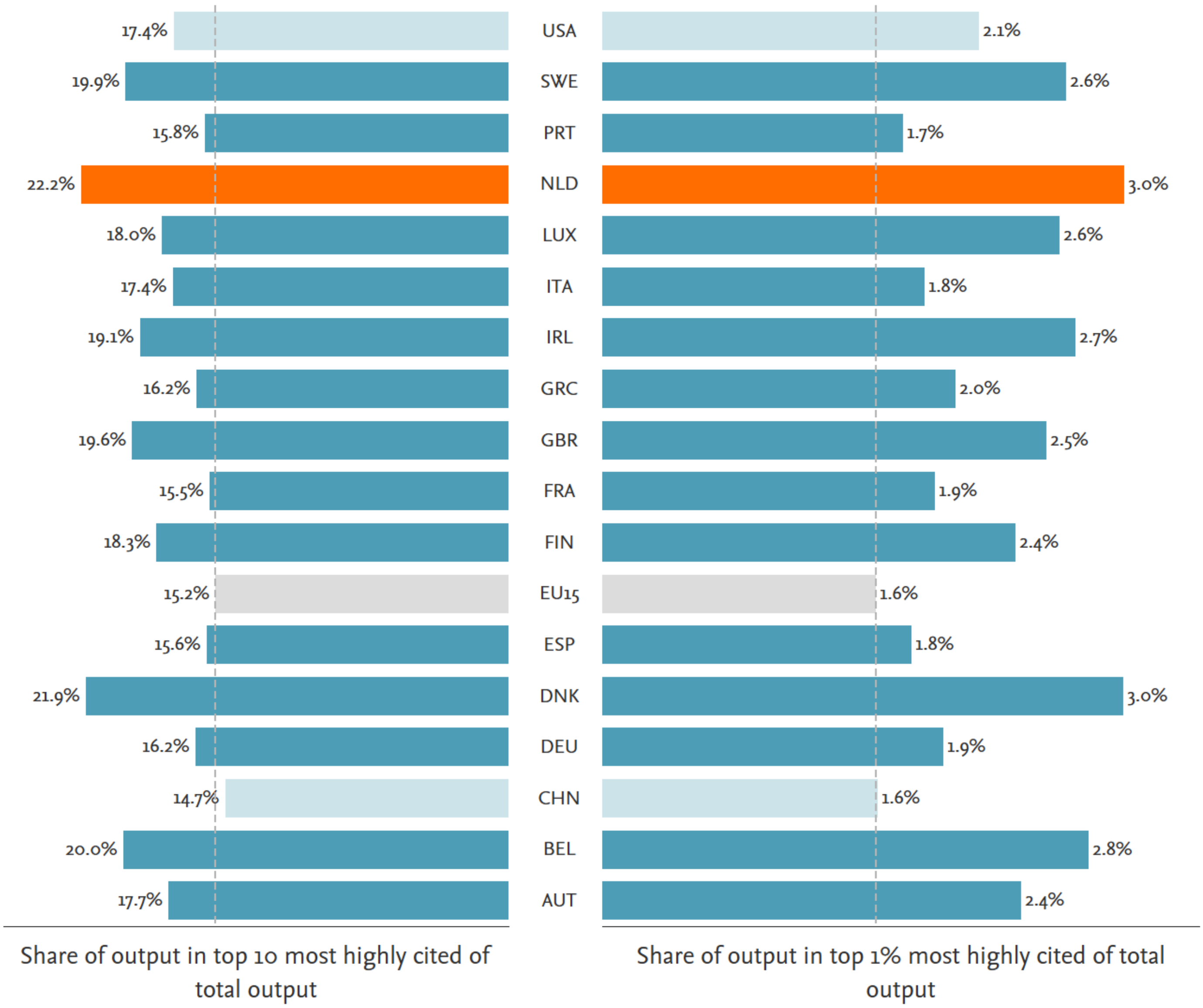
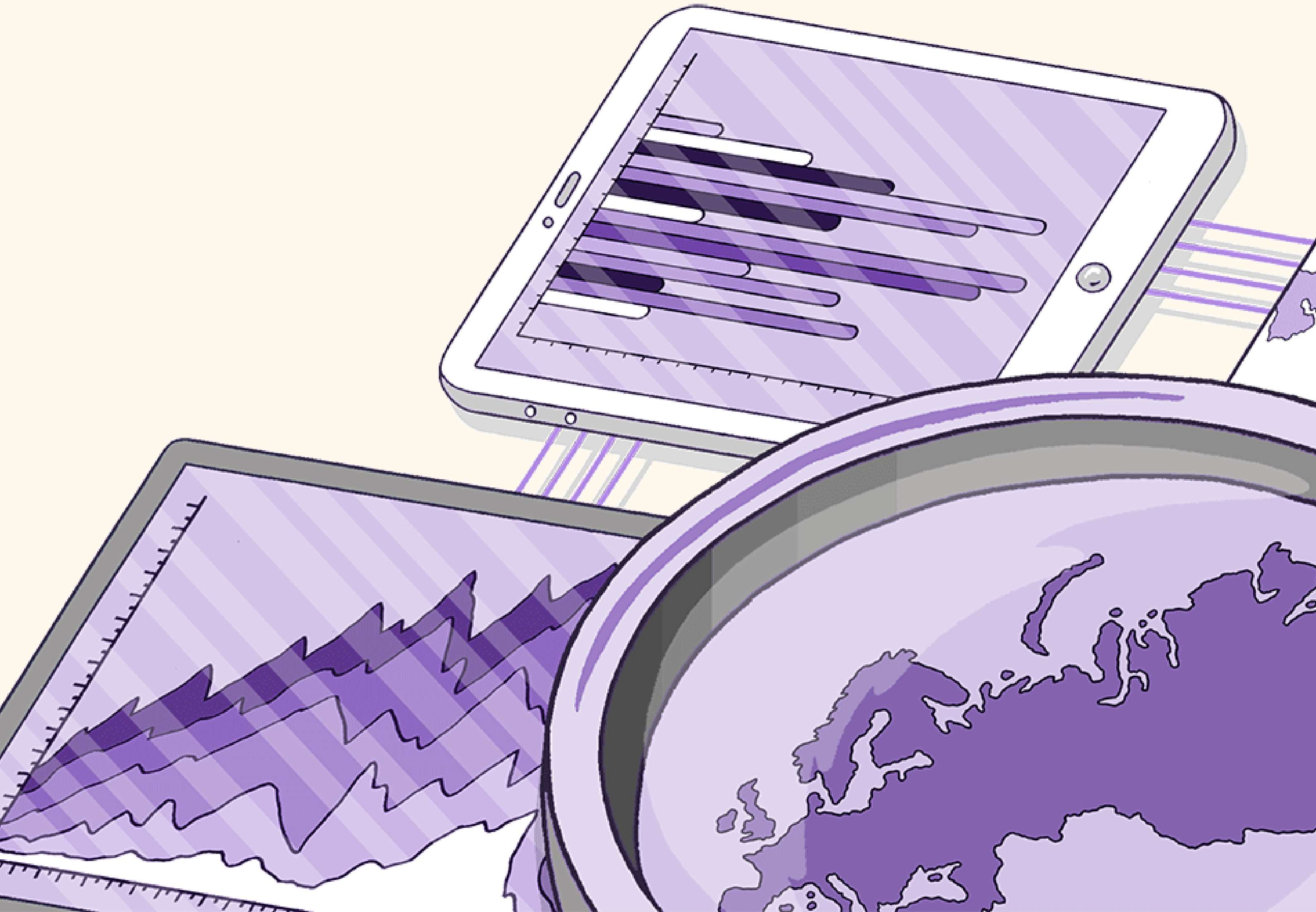


FIGURE 1-8
Share of country publications in top 1% (right panel) and top 10% (left panel) most highly cited global publications for NLD and comparators, for the period 2013–2022. Dashed lines indicates the EU15 averages as benchchmark.
Source: Scopus

Chapter 2

Publication analysis of key technologies



2.1 Dutch research across all key technologies

Research on key technologies comprised around 28% of overall Dutch research output. Although this is lower than the average share for the world and the EU-15, the citation impact of this Dutch research is topped only by that of Luxembourg and Denmark. China, the main driver of global research output within these fields, published more than half of its research related to key technologies.

While the previous chapter assessed the Netherlands' general position in the global research landscape, this chapter and the following will take a deep look into research mapped to the 44 key technologies that the Ministry of Economic Affairs and Climate defined.

Across all key technologies, Dutch researchers published 163,634 publications between 2013 and 2022 (global output was 11.5 million publications). This calculates to 28.4% of the total output of the Netherlands (FIGURE 2-1). The global share of research that was on key technologies was almost 40%, mainly driven by China as the single biggest contributor (see FIGURE 2-3).

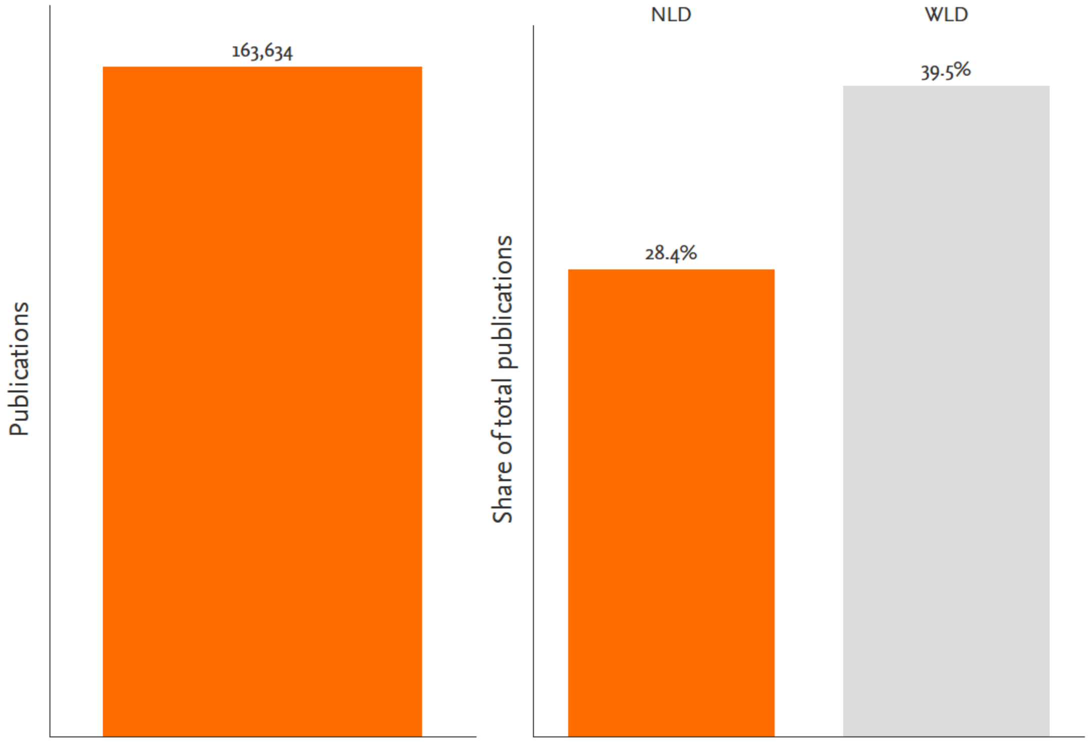


FIGURE 2-1
Key technology related research output for NLD (left panel) and share of overall output (across all subjects) for NLD and World, for the period 2013–2022.
Source: Scopus

The overall Dutch research output rose from 15,000 publications in 2013 to a peak in 2021 of 18,250 (solid line, FIGURE 2-2). The share of Dutch total output on key technologies (light orange dots), however, declined in the same period, which is in line with different growth rates. While research on key technologies grew by 1.2% annually (CAGR), overall research grew more than twice as fast (CAGR = 2.8%). So, although key technology research grew in the Netherlands, it lost ground against overall research.

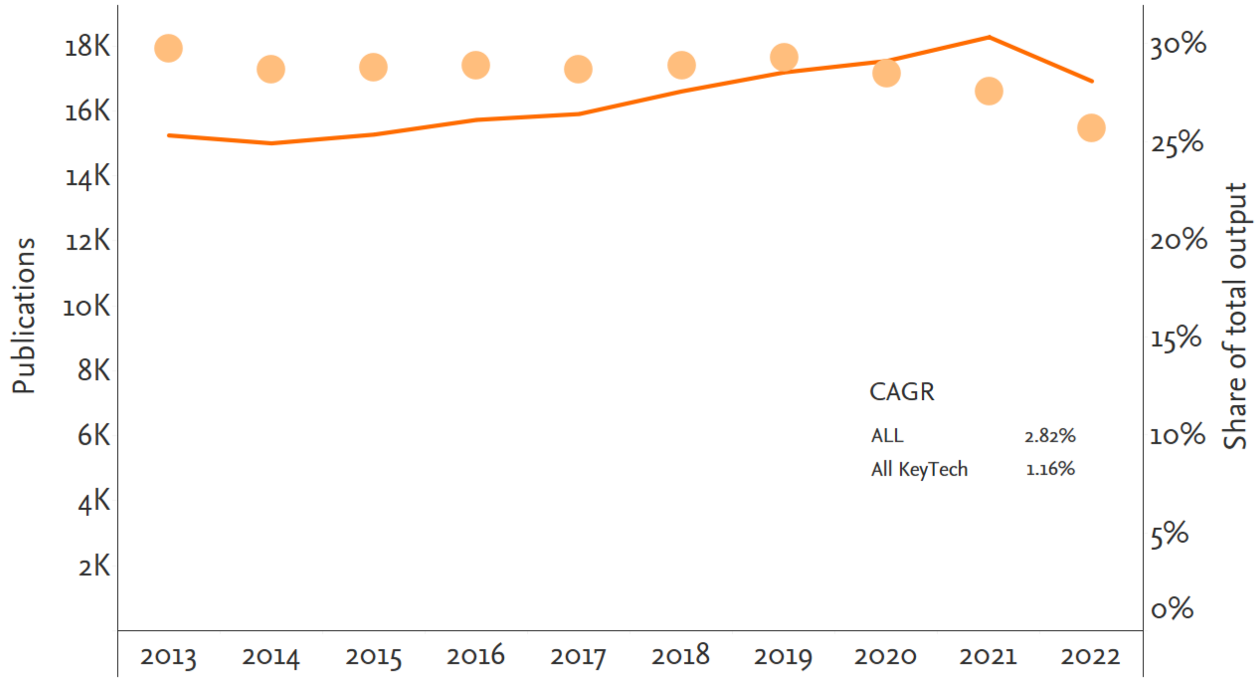


FIGURE 2-2
Annual Dutch research output (solid line, left axis) in key technologies and share of total NLD research output (dots, right axis), 2013–2022.
Source: Scopus

As mentioned above, research on key technologies holds a share of around 28% of Dutch total research, which is below any comparator country (FIGURE 2-3)[6]. China is the single biggest contributor with more than half of its research dedicated to key technologies—and with more than 3.5 million publications, it is driving global research in these areas.

EU-15 countries are all above a share of 30% for key technology research, with Luxembourg and France leading by share and Germany and the UK leading by total output.

[6] The Netherlands seems to have a comparatively large portion of its research dedicated to Social Sciences and Medicine related fields, which may be a reason for the lower share of key technology research.

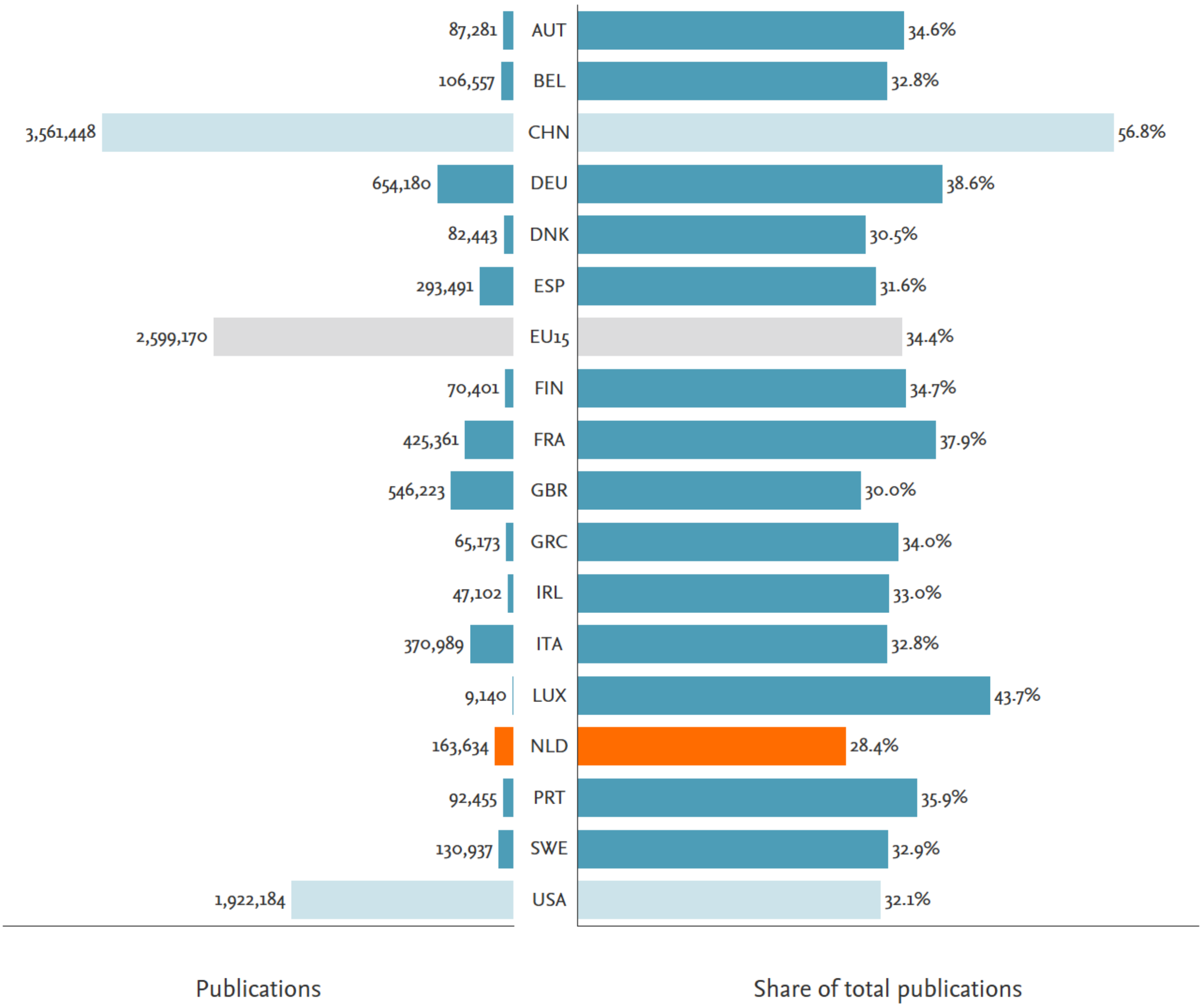


FIGURE 2-3
Research output for key technology research (left panel) and share of total output (right panel) for NLD and comparators, for the period 2013–2022.
Source: Scopus

While the share of research on a specific topic is an indicator of research focus, it may be difficult sometimes to assess or compare with other countries. Therefore, we calculated the relative activity index (RAI), which normalizes the share of publications on a specific topic (or key technology) of total output with the global share of publications on the same topic (or key technology). An RAI above 1 indicates a stronger focus in a specific topic that the global average, while an RAI below 1 indicates a lower focus.

As indicated already with the shares, the Netherlands displayed a lower focus on research on key technologies than any other comparator (FIGURE 2-4). The main driver of research is clearly China, with an RAI of 1.44, while Dutch research is exactly at half that activity with 0.72. But again, of the EU-15 countries, only Luxembourg shows an activity level above the global average and Germany and France are almost at that level. Overall, the EU-15 group is well below global average, but still above the US. Given that China holds almost 30% of the global output in key technology research, it clearly pulled the average, so that all comparators (except Luxembourg) were below the average line.

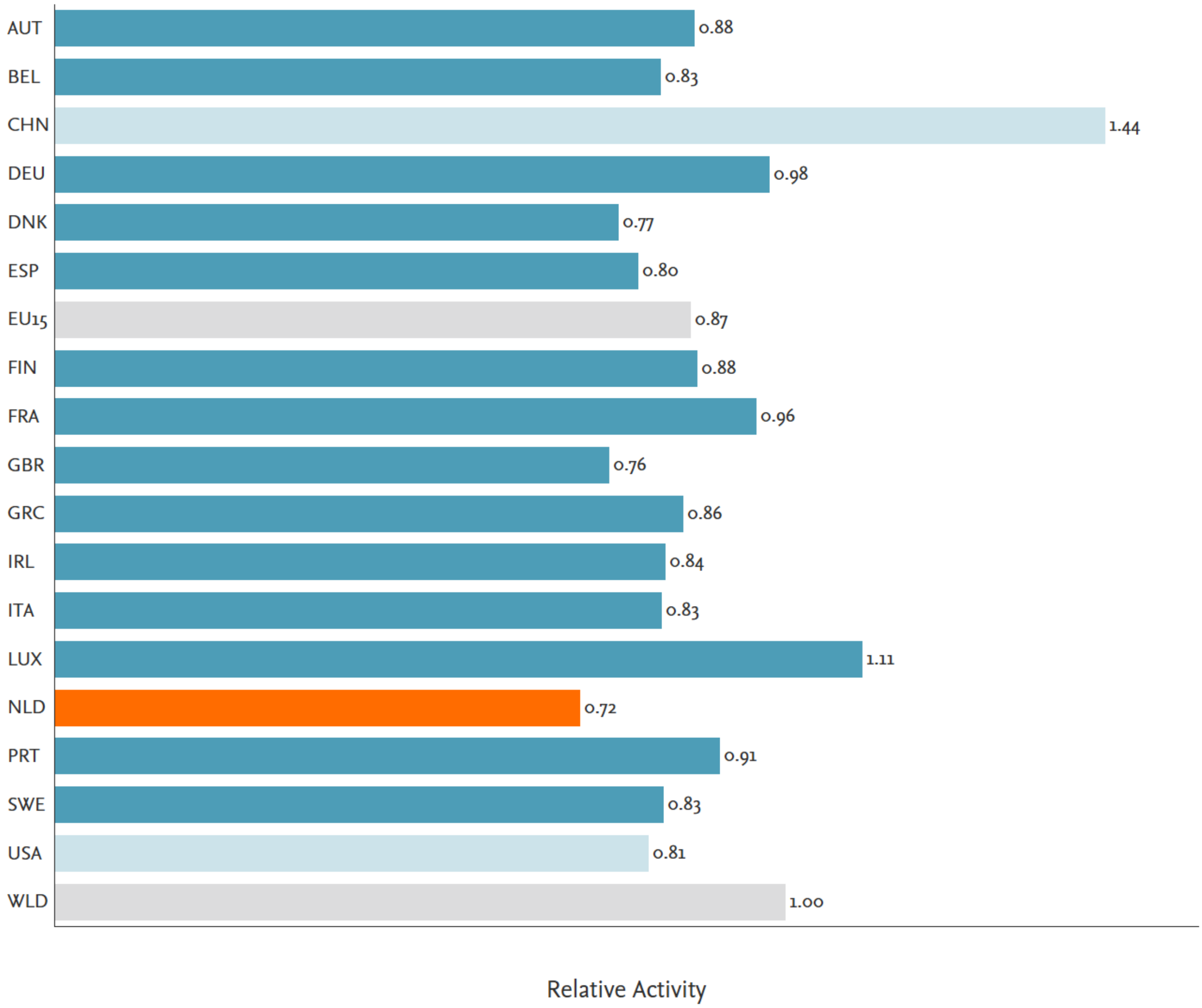


FIGURE 2-4
Relative activity index (RAI) for key technology research for NLD and comparators, for the period 2013–2022.
Source: Scopus

If an entity focuses its research activities on a particular subject, it is expected (or at least hoped) that this results in highly impactful outcomes. For these topics, this would mean a “correlation” of focus and impact, i.e., a higher RAI is connected with a higher FWCI. In the case of key technologies, however, this does not hold true. China’s FWCI in key technology research is still below the global average although its RAI outperforms any comparator (FIGURE 2-5). This may be a signal that for China, despite publishing a high number of publications, the quality (or more precise the citation impact) of this output lagged behind.

Luxembourg, with relatively high RAI and FWCI, could be a quite exceptional case, as due to its small output (9,140 publications) its FWCI and its share could still be affected by relatively few (highly cited) publications.

Although Dutch research is not focusing on key technologies as the comparators do, its citation impact in these areas is still a testament to the strong research environment. The FWCI of Dutch key technology research (1.56) was topped only by Luxembourg and Denmark—similar to the overall citation impact assessed in the previous chapter. Overall, all EU-15 countries showed a citation impact well above the global average—as the United States did as well.

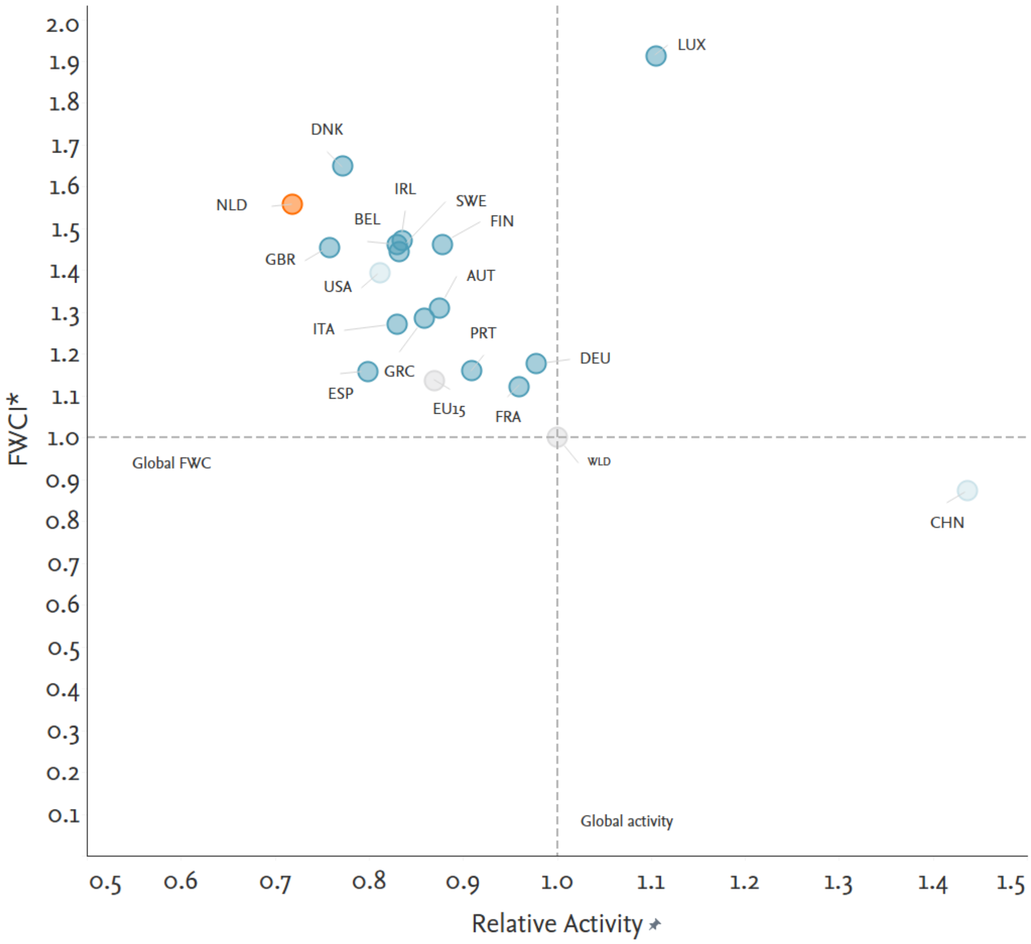


FIGURE 2-5
Relative activity index (x-axis) and FWCI (y-axis) of key technology research for NLD and comparators, for the period 2013–2022.
Source: Scopus

Taking relative activity index and citation impact into account, this report employs a composite indicator[7] to enable an easier comparison of country performance. As the OECD states, "it often seems easier for the general public to interpret composite indicators than to identify common trends across many separate indicators, and they have also proven useful in benchmarking country performance. However, composite indicators can send misleading policy messages if they are poorly constructed or misinterpreted. Their 'big picture' results may invite users (especially policy-makers) to draw simplistic analytical or policy conclusions (OECD et al., 2008)." Nevertheless, composite indicators which compare country performance are increasingly recognized as a useful tool in policy analysis and public communication.

The composite indicator used in this report was created from RAI and FWCI, thus combining the notion of focused research areas and return on investment (through citation impact). It enables a relatively quick assessment of a country's performance in these dimensions without comparing both separate indicators across different dimensions and/or charts. Therefore, it can support other analyses used in this report (or in external analyses) by giving an aggregated view on fcous ond impact. It should not be used, however, as a sole source for decisions.[8] Basically, the values provided in FIGURE 2-6 draw a similar picture than the previous scatter plot, but inherently the scatter plot gives both indicators the same weight since it used the raw data. Simplified, it tells the story that China is focusing a lot on key technology research but lags behind in quality. A well-designed composite indicator could level that out and could tell a more balanced story (although losing some of the background nuances). Thus, the composite indicator may indicate possible "compensation" effects.

Luxembourg is taking the lead by this composite indicator (FIGURE 2-6), likely driven by its high FWCI, while China (most likely with its high RAI), Finland, and Denmark are second. The Netherlands is well above the global average, and well above the EU-15 average. Its strong citation impact may keep Dutch research in this position although—as seen above—its RAI is relatively low.

For China, the composite indicator pronounces the compensation of the lagging impact by the huge focus on key technology research.

7 For the creation of this composite indicator, please see Appendix E.

8 Which is anyway a requirement for most bibliometric and other assessments. Indicators should be used in combination and preferably coming from various different angles and sources.

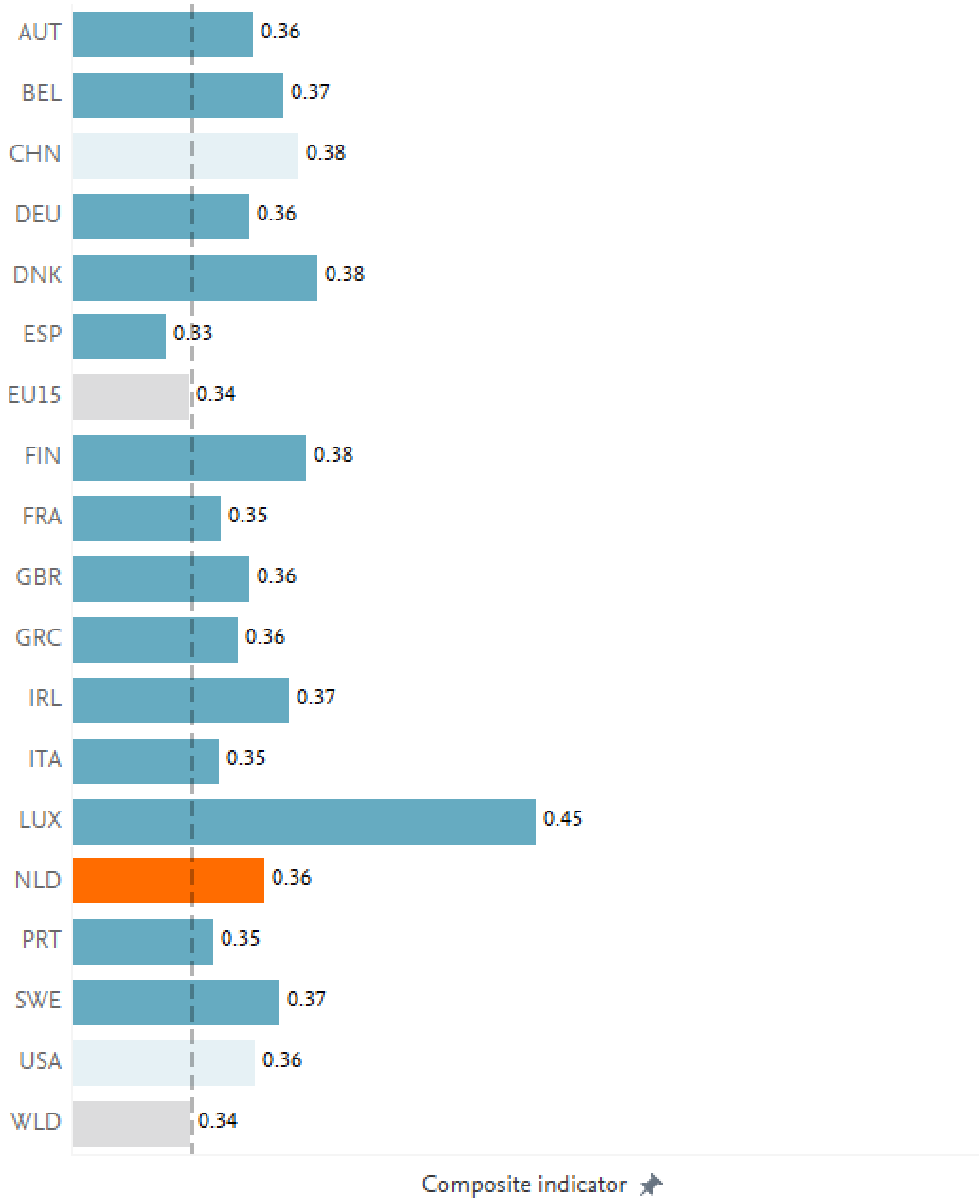


FIGURE 2-6
Composite indicator for NLD and comparators for all key technology research, for the period 2013–2022. The dashed line shows the global average.
Source: Scopus

2.2 Dutch research in individual key technologies

Key technology research by Dutch researchers displays high citation impact and excellent research across all technologies, but research efforts seem to focus on BIOTECHNOLOGY AND LIFE SCIENCES, DIGITAL TECHNOLOGIES, and QUANTUM TECHNOLOGIES with a relative activity index above global average.

Section 2.1 assessed research across all key technologies, and now this chapter will focus on individual key technologies. Throughout this report, acronyms for the key technologies have been used to align between figures and text. A glossary of used acronyms can be found in Appendix A. The 44 key technologies display a wide variety in publication output, globally as well as on a national level. Scholarly output in the Netherlands ranges from only 40 publications in Quantum Sensing (QuaSens) to more than 42,000 publications in BioCellTech (FIGURE 2-7). This wide range reflects the global pattern, which ranges from 2,720 publications for QuaSens to 1.4 million for BioCellTech to almost 2.4 million for NanoMat.

Partly this may be due to the definition of the publication sets (see Appendix for a detailed description). But partly this may be due simply to differences between the fields. While key technologies such as NanoMat or BioCellTech are well explored and cover a wide range of aspects, other fields like QuaSens are either narrow/emerging or have only a few keywords to describe them.

Therefore, it needs to be noted that all of the following analyses are reflective of the methodology and will provide insights into research on key technologies but will still be “subjective” as any definition of a topic or key technology is based on the input for the definition of the field.

FIGURE 2-7 displays the total output of Dutch research in the period and the compound annual growth rate as CAGR.[9] Some fields have a negative trend, such as SepTech (-5.1%), Analytics (-2.7%), or NanoManuFact (-4.1%) while others are growing, such as NeuroMorph (+16.1%) and AI (+10.6%). It seems, however, that these growth rates correlate with expectations. Key technologies that are perceived as relatively new (such as QuaSens, QuaComp, QuaComm, NeuroMorph, DigiTwins, etc.) display positive growth, while more established ones (such as SepTech, MetaMat, OptDetect) are declining.[10]

9 The compound annual growth rate, or CAGR for short, is the average rate at which some value (investment) grows over a certain period of time assuming the value has been compounding over that time period.

10 The growth rates shown in the figure are reflective of the full period—some of the declining key technologies over that period still had positive growth in the first half of the period (like OptoMecha, ThinFilm, SmartMat, OptMat, and others).

Advanced materials	ConStruct	1.90%	9,765
	EnMat	1.37%	10,795
	MetaMat	-2.07%	1,424
	OptMat	-0.75%	20,018
	SmartMat	-0.79%	8,307
	SoftMat	1.01%	8,145
	ThinFilm	-1.21%	11,216
Biotechnology and Life Sciences	BioCellTech	1.65%	42,402
	Bioinformatics	4.60%	11,073
	BioManufact	-1.88%	8,131
	BioSystems	1.17%	2,886
Chemical technologies	Analytics	-2.70%	19,332
	Catalysis	-1.65%	12,517
	ChemReact	-2.62%	7,344
	ElectReact	3.20%	5,512
	ProcessTech	-3.54%	9,730
	SepTech	-5.12%	4,306
Digital technologies	AI	10.64%	13,405
	CyberSec	8.34%	2,651
	DataScience	3.08%	1,022
	DigiConnect	0.95%	16,142
	DigiTwins	7.54%	4,043
	NeuroMorph	16.08%	541
	SoftTech	1.33%	5,162
Engineering technologies	AddiManufac	15.51%	1,946
	DigiManufact	9.16%	1,837
	ImagingTech	2.02%	12,783
	Microelectronics	-0.74%	11,809
	OptoMecha	-0.38%	3,665
	Robotics	7.82%	4,721
	SensActuat	2.32%	2,126
	SystEngi	1.07%	18,245
Nanotechnologies	FuncDev	1.44%	5,073
	NanoBioTech	1.42%	8,544
	NanoFluid	-3.69%	1,924
	NanoManufact	-4.06%	4,858
	NanoMat	-0.08%	23,811
Photonics and light technologies	OptDetect	-4.12%	2,696
	OptGen	-5.17%	636
	OptSyst	-3.79%	2,238
	PhoVolt	4.46%	3,285
Quantum technologies	QuaComm	6.26%	2,068
	QuaComp	6.15%	757
	QuaSens	8.01%	40

FIGURE 2-7
Scholarly output and CAGR per key technology for NLD, for the period 2013–2022. Orange bars and right-hand numbers indicate full publication output and percentages the CAGR for the period.
Source: Scopus

More insightful than the total numbers for publication output is a look at the relative activity index (RAI) (FIGURE 2-8). This analysis indicates the areas in which Dutch research has a larger share of its total output than expected from the global averages—therefore it may signal the areas in which the Netherlands are focusing. Overall, as seen in the previous chapter, Dutch research seemed to be less focused on key technologies (given that China is "distorting" the averages), but within individual key technologies, the

Netherlands is showing a high relative activity, especially in BIOTECHNOLOGY AND LIFE SCIENCES (all key technologies within this group have an RAI above 1), QUANTUM TECHNOLOGIES (two out of three), and DIGITAL TECHNOLOGIES (two out of seven). These are as well the key technologies for which the Dutch relative activity is higher than that of the EU-15 as a benchmark (right hand column).

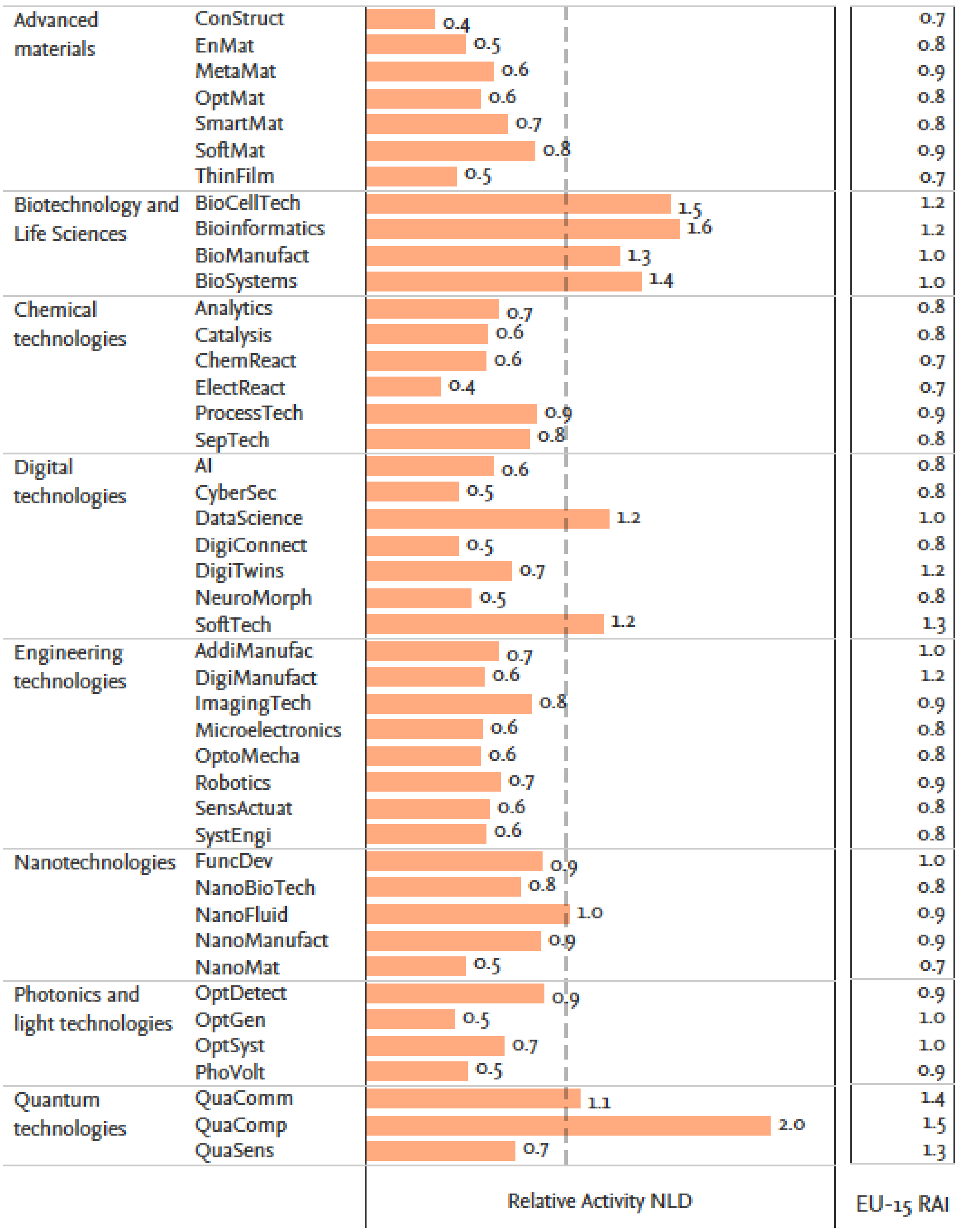


FIGURE 2-8
Relative activity index for NLD per key technology, for the period 2013–2022. Separate column on the right inidcates RAI for EU-15. Dashed line indicates the global RAI per key technology of 1.
Source: Scopus

This is interesting as it does not reflect the overall output or the share of the Netherland's total research but sets it in context with global patterns. BioCellTech for example, as the largest key technology by output in the Netherlands, comprises more than 7% of total Dutch output, which is correlated with its high relative activity (1.5), while NanoMat, as the second largest area (23,811 publications or 4.1% share) displays only an RAI of 0.5. Both results should be taken into account when analyzing key technologies as the RAI is heavily influenced by China as the biggest contributor. Below, FIGURE 2-9 displays the share of Dutch total output against the FWCI. All key technologies have an FWCI above world average, with QuaSens and OptGen leading. The exceptionally high FWCI of QuaSens may be the result of only a few publications, because with only 40 publications in total the FWCI is susceptible to outliers.

Key technologies within the BIOTECHNOLOGY AND LIFE SCIENCES group (blue shaded dots) are quite diverse in their share of Dutch total output, ranging from 0.5% for BioSystems to 7.4% for BioCellTech. Their FWCI is relatively high, between 1.5 and 1.8.

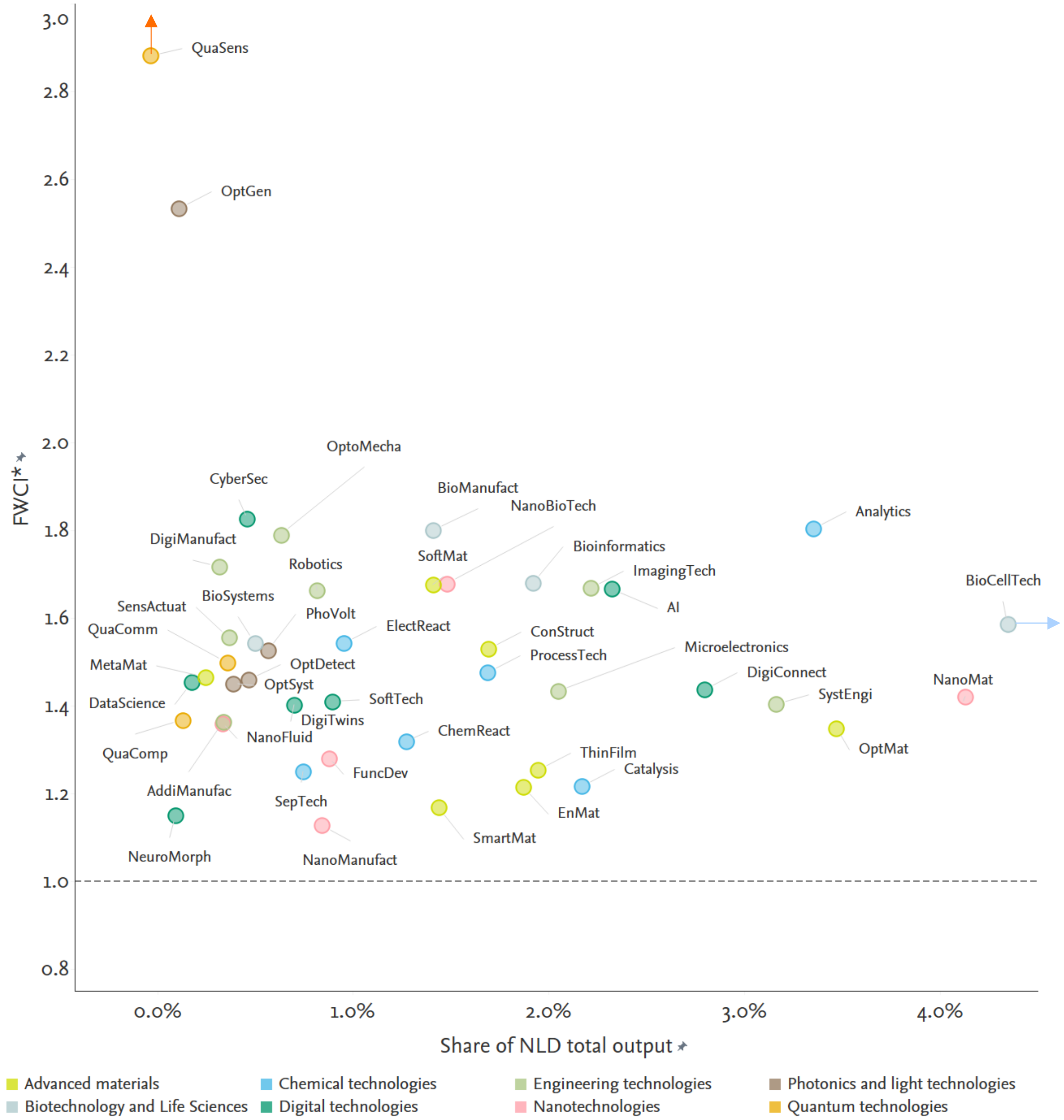


FIGURE 2-9
FWCI and share of total NLD (across all subjects) research output per key technology, for the period 2013–2022. QuaSens and BioCellTech are outside the figure area with BioCellTech having a share of 7.4% and QuaSens an FWCI of 4.97 (both indicated by arrows). FWCI* indicates rebased FWCI (based against global FWCI per respective KT).
Source: Scopus

The strong role of biotechnology becomes even more obvious when looking at RAI and FWCI. As mentioned, all Biotechnology and Life Sciences key technologies showed both an RAI and an FWCI above the global average.

The upper right corner within the matrix view of FIGURE 2-10 indicates key technologies with high focus and high impact, which can be regarded as having a high return on investment. All other key technologies are below global activity levels, but still have high impact. The red shaped box is an exploded view of the “crowded” area in the red dashed box.

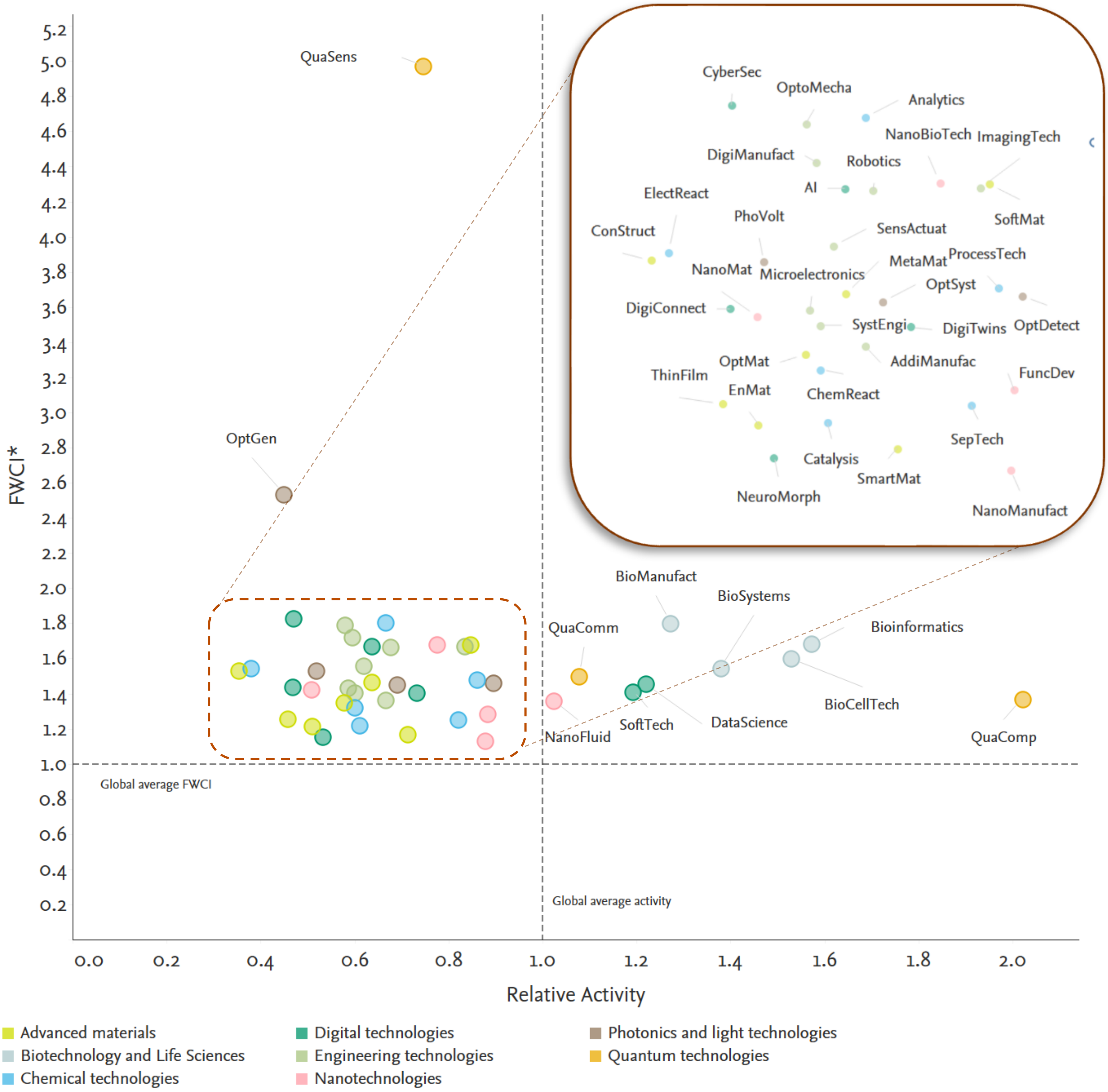


FIGURE 2-10

RAI and FWCI for NLD research output per key technology, for the period 2013–2022. FWCI* indicates rebased FWCI (based against global FWCI per respective KT). Inset box provides view of red shaped box.

Source: Scopus

A separate view for the EU-15 paints a somewhat different picture (FIGURE 2-11). Maybe due to the higher number of publications, outliers have been leveled out. Activity levels or some of the key technologies have moved towards a higher activity level, while the general picture on impact remains similar.

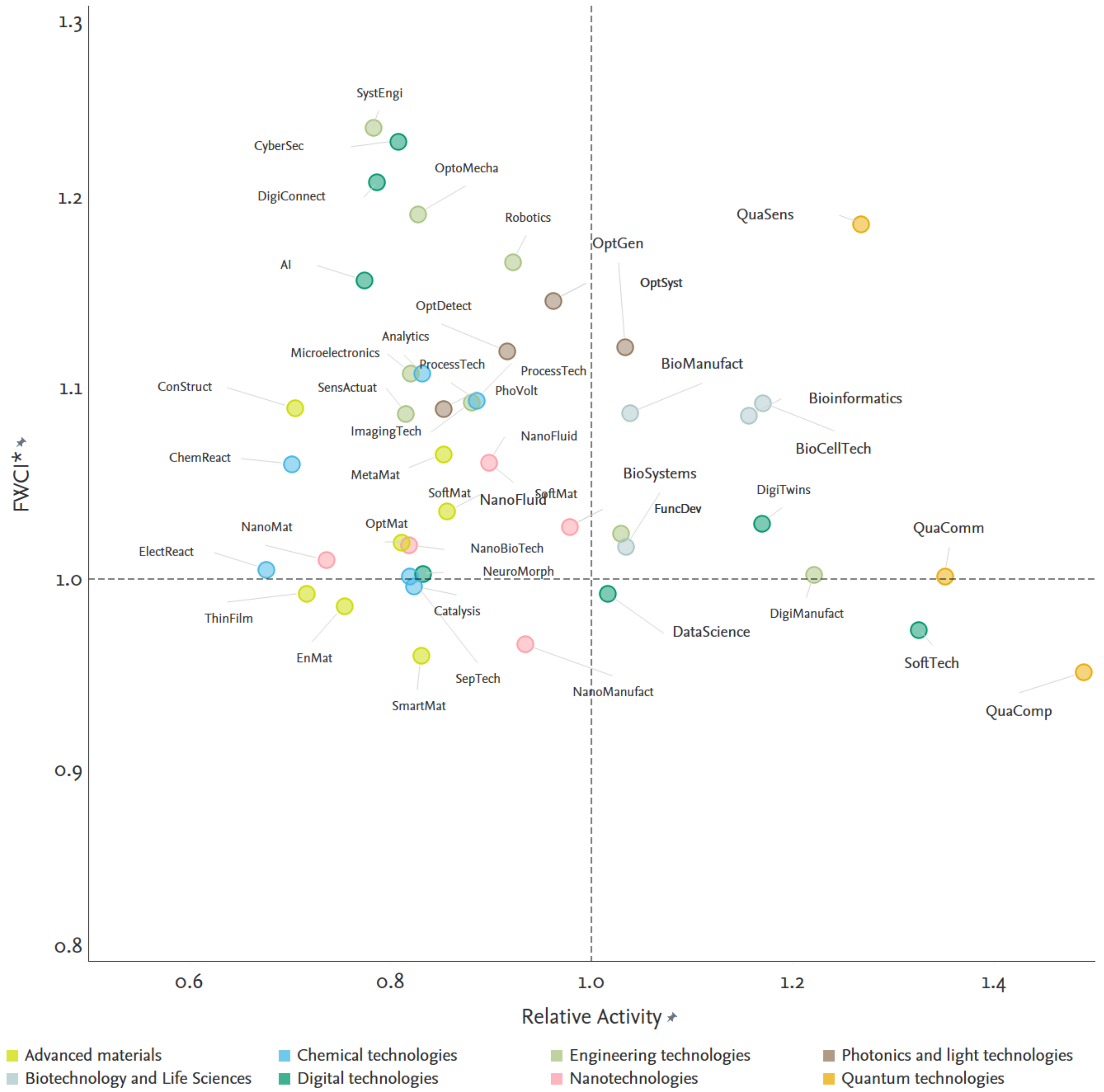


FIGURE 2-11
RAI and FWCI for EU-15 research output per key technology, for the period 2013–2022. FWCI* indicates rebased FWCI (based against global FWCI per respective KT). Inset box provides view of red shaped box.
Source: Scopus

The composite indicator introduced in the previous chapter reveals some interesting insights (FIGURE 2-12) and confirms the impressions of the prevous scatter plot. The BIOTECHNOLOGY AND LIFE SCIENCES technologies score highest for this indicator, but especially the QUANTUM TECHNOLOGIES and some of the PHOTONICS AND LIGHT TECHNOLOGIES and NANOTECHNOLOGIES show particular strength as well. Within BIOTECHNOLOGY AND LIFE SCIENCES, Bioinformatics has the highest value, as it displays both high RFAI and FWCI. For QuaSens within QUANTUM TECHNOLOGIES this may be the result of an outlier (given the low number of publications), but the other key technologies appear to score very high as well. QuaComp and QuaComm have a rather high activity while displaying a relatively low FWCI which drove their composite score. For the other domains, the picture is a bit more mixed with some technologies above and some below the average score.

The column on the right indicates the composite score for EU15 as a benchmark, green highlights Dutch values above EU15 level and orange below EU15 level. The relative performance to EU15 level correlates with the overall picture – key technologies with a relative high composite score are mostly above EU level as well.

Overall, the composite indicator used in combination with the previous analyses provides some insights into particular areas of strength and focus or whether these key technologies have an overweight of one of these indicators.

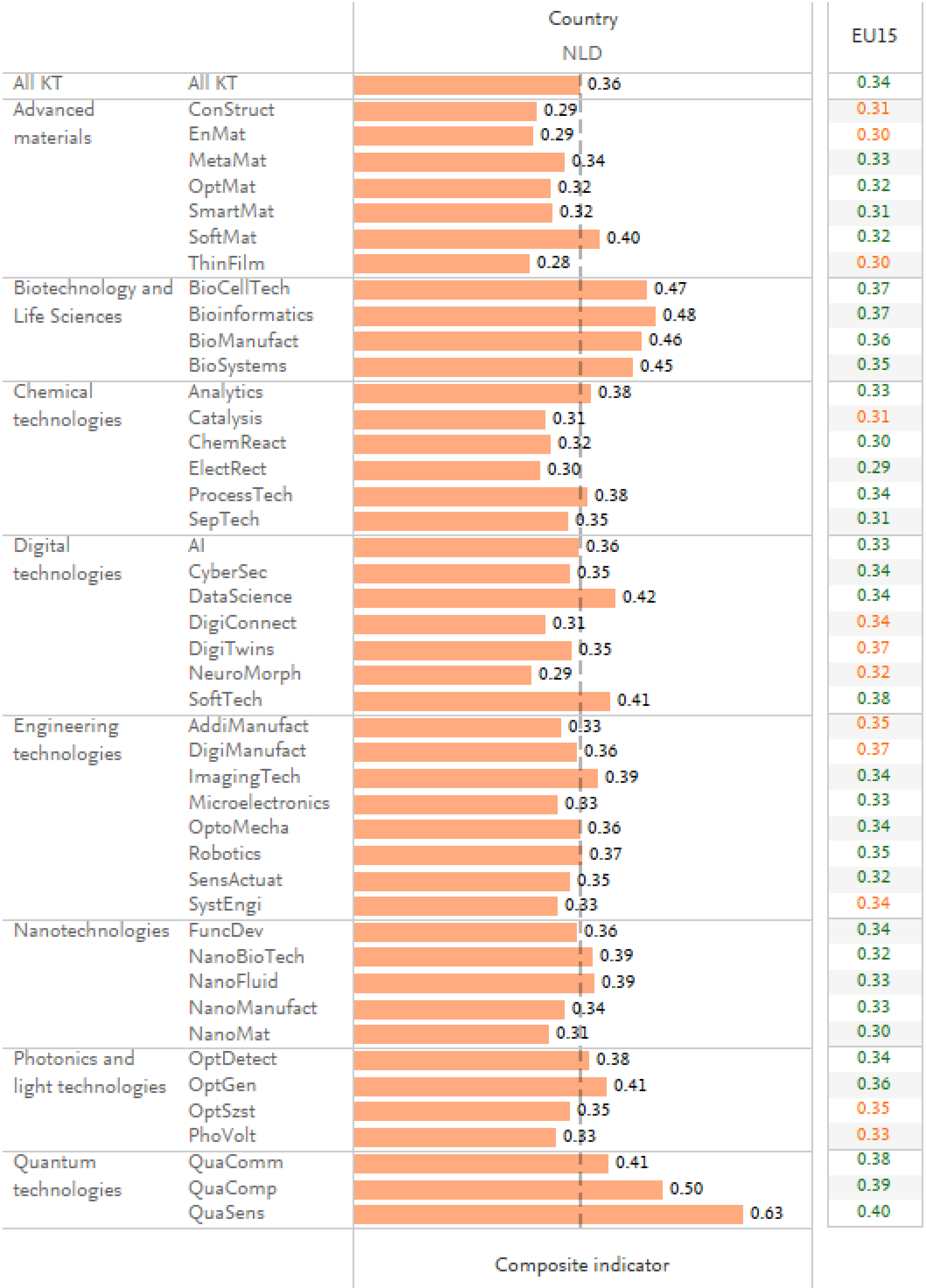


FIGURE 2-12
Composite indicator per key technology for NLD research output, for the period 2013–2022. Dashed line indicates composite indicator value for all key technologies.
Source: Scopus

Citation impact, as measured through FWCI, can be influenced by outliers, especially in areas of key technology research with relatively low output numbers. The share of publications in highly cited global publications, based on global publication output in both key technology areas and other fields, is therefore a complementary indicator. Across most key technologies, the share of publications within the most highly cited publications of all dutch publications (orange) in that key technology exceeds the world shares (grey) by far, underlining the excellence of Dutch research (FIGURE 2-13).

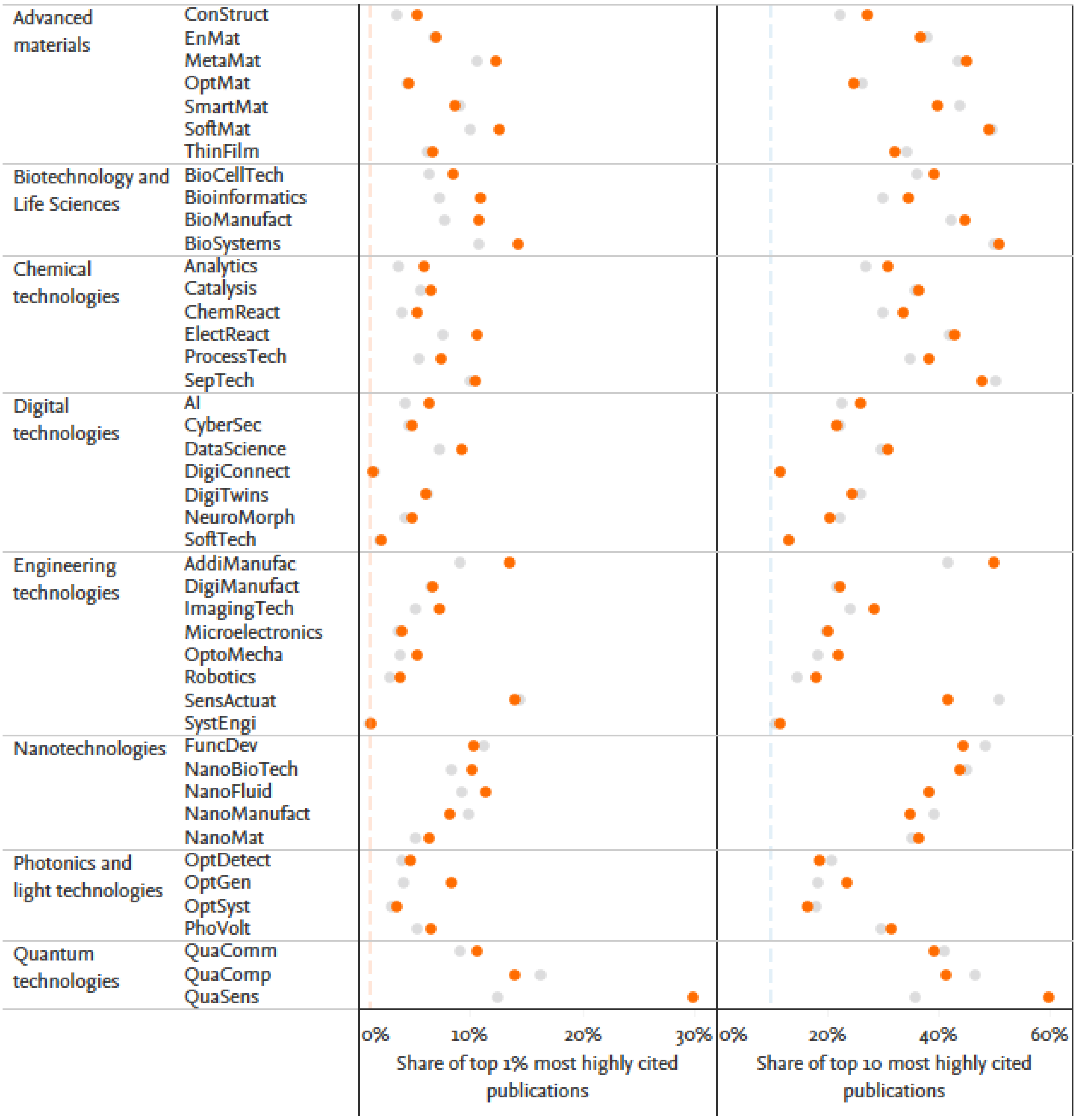


FIGURE 2-13
Share of top 1% (left panel) and top 10% (right panel) most highly cited publications for NLD (orange dots) and global (grey dots) research output per key technology, for the period 2013–2022.
Source: Scopus

Research Levels

While citation impact and research excellence indicators give an idea of the contribution of Dutch research to the global landscape, there are other indicators painting a complementary picture of the research landscape of key technology research in the Netherlands. Research levels describe the spectrum from basic research to applied research and further on to experimental development.

The OECD defines these levels of research as follows (OECD, 2015):

- Basic research is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundations of phenomena and observable facts, without any particular application or use in view.
- Applied research is an original investigation undertaken in order to acquire new knowledge. It is, however, directed primarily towards a specific, practical aim or objective.
- Experimental development is systematic work, drawing on knowledge gained from research and practical experience and producing additional knowledge, which is directed to producing new products or processes or to improving existing products or processes.

The relationship between basic research, applied research, and experimental development has to be seen within a dynamic perspective. Applied research and experimental development could adapt fundamental knowledge arising from basic research directly for general application. However, the linearity of such a process is affected by the feedback that takes place when knowledge is used to solve a problem. This dynamic interaction between knowledge generation and the solution of problems links basic and applied research and experimental development.

Not directly aligned with the OECD definitions, but pointing in the same direction, Klavans and Boyack (Boyack et al., 2014) assessed research levels (which translates into types of R&D)[11]. They used a keyword-based approach, combined with citation vectors[12]. This worked best in life sciences and biomedical sciences, though it can be applied for other subject areas as well. There is some debate in literature about a potential mapping of research levels to technology readiness levels (TRL)[13], but it may be possible to correlate research levels with the four rather basic technology readiness levels (TRL). Higher TRLs seem to correspond more to commercial environments and the patenting landscape.

[11] The initial four levels have been defined by Narin (Pinski & Narin, 1976) as basic research, applied research, engineering-technological mix, applied technology.

[12] Further details on the methodology can be found in the Appendix.

[13] For a basic introduction to TRL, see https://en.wikipedia.org/wiki/Technology_readiness_level and literature cited there.

Research level	Technology Readiness Level
RL 1 – basic research	TRL 1 - Basic principles observed
RL 2 – applied research	TRL 2 - Technology concept formulated
RL 3 – engineering-technological mix	TRL 3 - Experimental proof of concept
RL 4 – applied technology	TRL 4 - Technology validated in lab

TABLE 2-1
Possibly mapping of Technology Readiness Levels with Research Levels

An analysis of research levels against relative activity index may give additional insights into a potential trade-off between focus areas and research stage (FIGURE 2-14). While basic research builds the fundament of knowledge generation, the (economic) gains of applied research close to deployment may be higher. It should be noted, though, that the shown research levels of key technologies are calculated as averages of the underlying publications (with a spectrum of values). So, any given key technologies will most likely include publications of all research levels. Therefore, the analysis is mainly useful in provinding a general overview of key technologies. Additionally, it may be expected that a key technology with a higher number of publications in the more applied spectrum may be closer to a rather mature status.

Key technologies, however, varied dramatically between the four levels, revealing no clear pattern. Some of the relatively new key technologies such as QuaComm, QuaComp and SmaMat are more within the basic research level, but there are also “established” key technologies such as Catalysis.

Key technologies within DIGITAL TECHNOLOGIES are more geared towards applied technology, which may indicate that these technologies are closer to deployment and practical application.[14]

[14] Generally speaking, the fields of physics, chemistry, biology, and parts of medicine are found to be more associated with basic research, while the fields of engineering, computer science, social sciences, and the more clinical areas of medicine are more associated with applied research (Boyack et al., 2014).

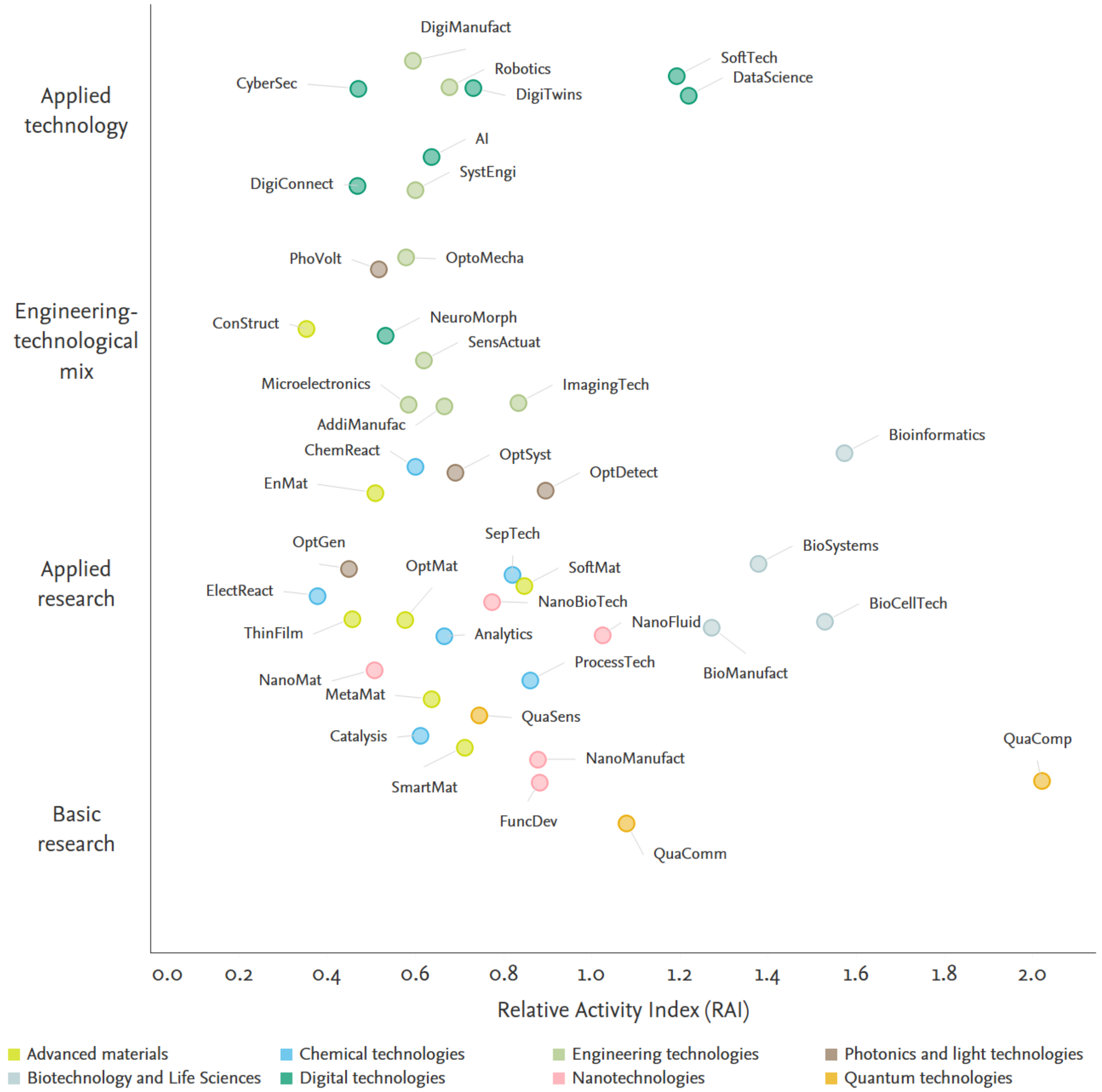


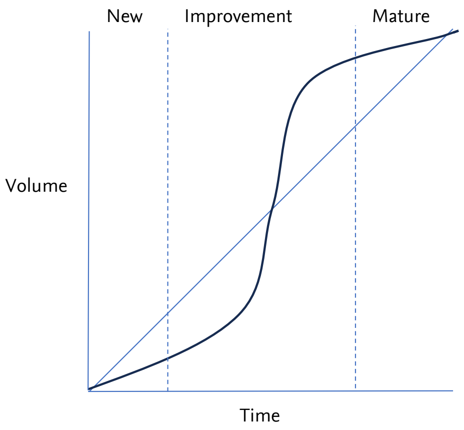
FIGURE 2-14
Research levels (y-axis) and RAI (x-axis) per key technology for NLD research output, for the period 2013–2022.
Source: Scopus

Technology maturity

Another indicator giving insight into research levels is the maturity of a research field.

Patterns of cumulative growth in output of scientific publications are very good indicators of maturity levels and show where radical developments in science, technology and innovation occur. As the world produces more research, leading to more scientific publications, there will always be competition for resources, be it funding for basic or applied research or competition for people who are able to undertake this research. Science, technology and innovation reinforce and stimulate each other.

Researching in little-explored areas can be time-consuming, but the rewards for first movers can be high. As an area gains more attention, the cost of entry is lowered as more and more of the fundamentals are uncovered, and potential applications are found, and the number of researchers and thus output increases. As an area reaches maturity, interest stabilizes or even wanes and the cumulative count of publications in an area stabilizes.



The cumulative growth is not linear as might be expected but exponential, often in the form of an S-curve. Within science and technology analytics this cycle is commonly referred to a technology life-cycle curve, which is modelled in FIGURE 2-15. The cycle is split into 3 phases, the new/novel first phase, followed by the improvement and uptake phase, and lastly the mature phase.

FIGURE 2-15
Model of a technology life-cycle curve.

Extracting the cumulative growth output per key technology, a logistic curve can be fitted to the values and predicted growth rates (slope of the curve = alpha) and expected maximum publication level (cumulative maximum count of publications as the “end’ of the mature phase) can be estimated.

The classification of a technology into new/novel, improvement/uptake and mature phases is based on the current (2022) percentage share of the estimated maximum of publications and the growth rate. The growth rate can be considered a proxy for the interest in the field (the steeper the slope, the more publications are published annually), and the share of estimated maximum indicates the staying power of the technology (the higher the value, the closer to the expected maximum publications). Based on these two factors, the chart in FIGURE 2-16 displays the world output growth rates (alpha) and share of estimated maximum, using 2022 publication counts, for each key technology. Whilst no fixed borders can be described to separate the phases, a general approach is to assign technologies in the lower right of the chart (higher growth rates and lower share of estimated maximum publications) to the novel/new technologies in promising fields, and the top left (lower growth rates and higher share of estimated maximum) to mature, well-researched fields.

Highest growth rates are exhibited by key technologies such as QuaComm, DataScience, and SensActuat, while BioCellTech and Bioinformatics seems to be rather stable with lower growth rates. As mentioned above, a high growth rate might be associated with topics of high interest (high number of annual publications adding to the field). Therefore, the mentioned QuaComm, SensActuat, and DataScience are creating still many new publications per years and may be considered as growing. On the other hand, they display already an high share of the expected peak—indicative of being at least in the improvement phase.

The lowest share of expected peak is shown for AI, which is still vastly growing on a global scale, but with a rather continous, steady growth instead of more unstable peak years.

It should be noted that interpretation of the results of this analysis must be done with care. In general, the context of the subject area in the global research landscape needs to be meaningful, i.e., a very broad field of research or technology could capture multiple smaller technologies or fields of research whereby large growth rates may be offset by other, lesser, growth rates.

FIGURE 2-16
Technology maturity as share (percentage) of predicted peak publications (y-axis) and growth rate alpha (x-axis) per key technology for NLD research output, for the period 2013–2022. The size of the dots indicates publication output.
Source: Scopus

2.3 Complexity and relatedness

An analysis of technological complexity and relatedness indicates key technologies with economic potential for future development, building on existing strength and capabilities. BIOTECHNOLOGY AND LIFE SCIENCES and some DIGITAL TECHNOLOGIES appear to be some of these areas.

The previous chapters gave some insights into the Netherlands' performance in the 44 key technologies and how these key technologies relate to maturity and research levels, i.e., whether the key technologies are already advanced or still emerging. This is relevant from a technological and/or entrepreneurial point of view. If technologies are still emerging, or at a very early stage of the technology life cycle, research in that area may be time-consuming, but the return on investment can be quite high if successful. Funding decisions and investments into particular key technologies can be based on these considerations.

From a political point of view, there may be additional questions to be asked. The pandemic and other rising environmental and geopolitical instabilities fostered discussions on technological and data sovereignty. Significant supply chain disruptions and their effects have intensified these discussions (European Commission, Directorate-General for Research and Innovation, 2022). Whether the EU or a particular country can reach this sovereignty depends on various factors. One of these factors is the complexity of a key technology and the likelihood (or capacity) that a country can develop and/or master this technology. A complex technology is not easy to replicate and therefore provides a competitive advantage, whereas less complex technologies are relatively easy to copy, therefore providing a lower value. If a country or region is not able to develop a complex technology, it may become dependent on other countries that are able to do so, thereby posing a risk to the country.

Closely connected to the concept of complexity is the concept of relatedness. Basically, relatedness can be visualized as a network indicator. It indicates if technologies rely on the same knowledge and competencies. The closer the required competencies and knowledge of two technologies are, the higher is their relatedness and the closer they would appear in a network map. A good overview of these considerations and background can be found in a recent R&I paper series from the European Commission (Di Girolamo et al., 2023).

With this background, the following chapter assesses the complexity and relatedness of the key technologies. Literature on this topic often relies on patent data and related indicators, with some known weaknesses around data availability, coverage, and scope. This chapter utilizes publication data, and therefore the methodology needed to be adjusted and adapted. The granularity of the analysis requires special consideration. Most of the analyses so far have used regional levels (NUTS2 or NUTS3)[15], and only a few of them have used national levels (EC 2023). Therefore, further analyses are required to refine the

[15] Nomenclature of territorial units for statistics, further information see: https://ec.europa.eu/eurostat/web/nuts/background

methodological approach, but the initial findings are already interesting and are presented in this chapter. Still, this may be considered as an exploratory analysis which warrants further testings and checks.

For the following analyses, two different concepts are relevant:

Knowledge Complexity

Relative complexity indices can be derived through relative comparative advantages which in turn can be calculated via relative activity.[16] If a country has a relative comparative advantage above 1 in a given key technology, it can be considered as having a competitive advantage in this particular technology with respect to other countries.

Relatedness

Relatedness can be seen and visualized as a network indicator, clustering related technologies together. Relatedness density indicates the number of similar activities in a region or country. Therefore, it describes the extent to which a key technology is close to the existing set of technologies in this region of country.

The complexity of the 44 key technologies has been calculated and normalized between 0 and 100, visualized in FIGURE 2-17 and sorted by complexity.

OptDetect, followed by NanoManufact and QuaComp, ranks the highest in terms of complexity. Not surprisingly, key technologies within QUANTUM TECHNOLOGIES and some within ADVANCED MATERIALS are attached with relatively high values for complexity. On the lower end of complexity are technologies such as ChemReact, SystEngi, and ConStruct that are related to more mature and sometimes rather process-oriented technologies.

The general trends match the results found by Balland et al. (Balland et al., 2019; Balland & Boschma, 2020; Di Girolamo et al., 2023). DIGITAL TECHNOLOGIES rank as of a moderate level of complexity than in other analyses, but this may be a result of the different data source (publications versus patents). These findings could require further investigation.

[16] Mathematically this is calculated as eigenvector reformulations of specialization indices. For a detailed description of the methodology, see Appendix F.

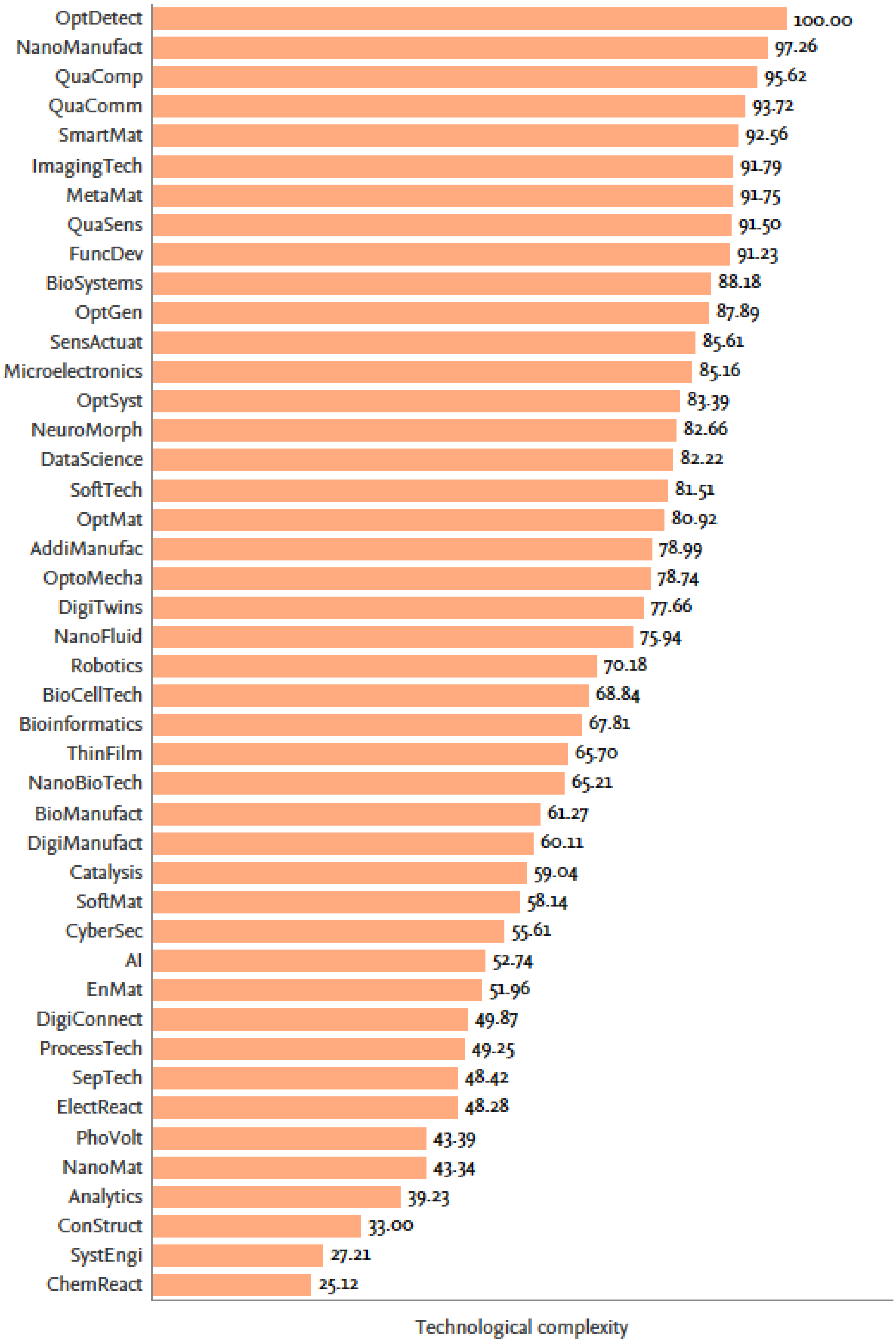


FIGURE 2-17
Technological complexity index of key technologies, based on global publications 2013–2022. Values have been normalized between 0 (lowest complexity) and 100 (highest complexity).
Source: Scopus

As mentioned above, the “connectedness” or relatedness of key technologies can be visualized as a network map with clusters of connected technologies emerging (FIGURE 2-18), e.g., DigiConnect, AI, and CyberSec. As expected, key technologies within the same technology domain appear in the same clusters, but there are quite a lot of technologies that rely on other technologies outside their domain, such as DigiTwins, SoftTech, and DataScience which are connected to other domains as well. Overall, there is high relatedness of key technologies. A bit surprisingly, PhoVolt is completely disconnected, as well as SystEngi and ConStruct.

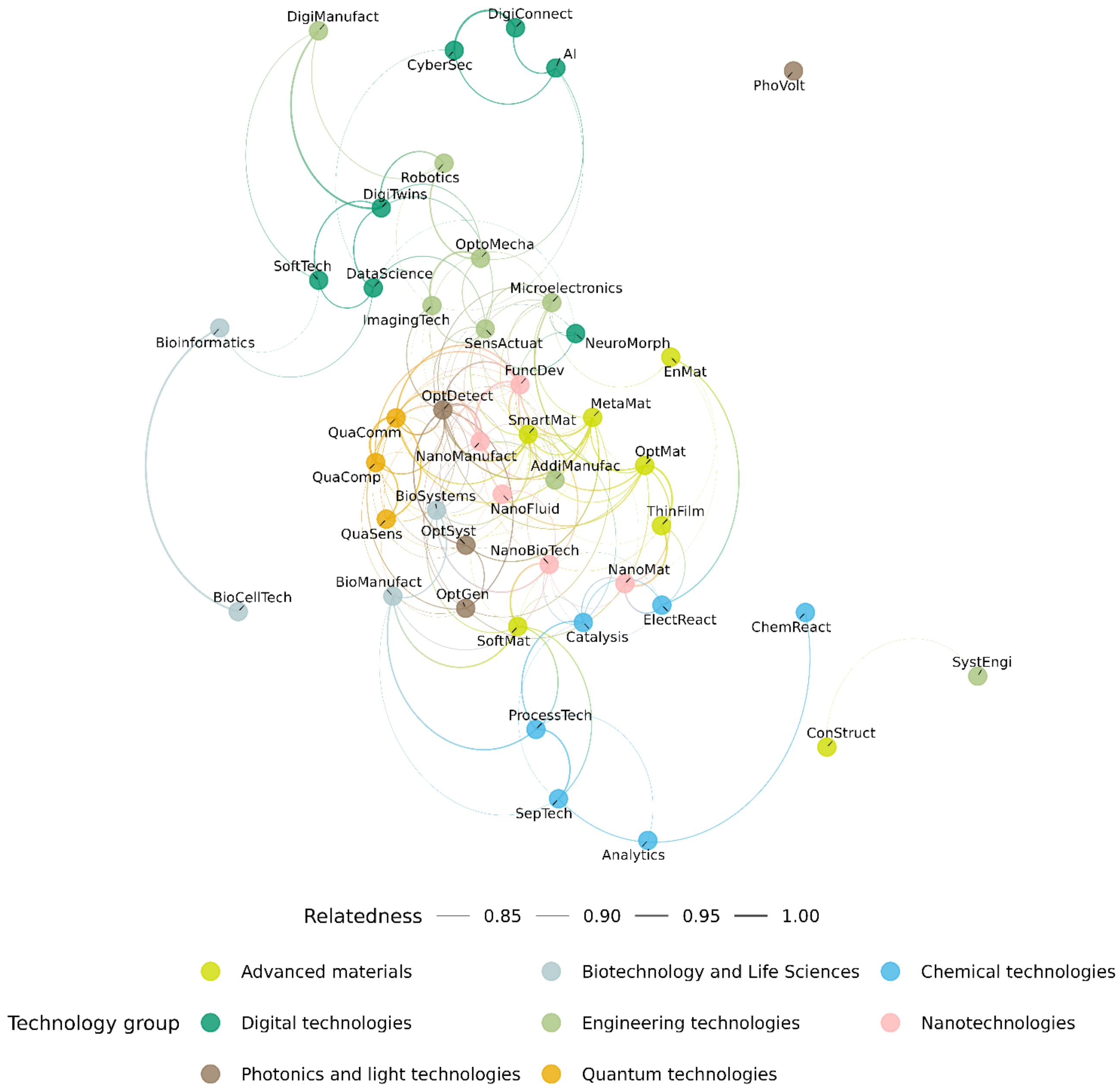


FIGURE 2-18
Network map of the relatedness of key technologies, based on global publications 2013–2022. The thickness of the lines indicates relatedness; the color coding of the dots indicates technology domain.
Source: Scopus

While the relatedness in the above figure indicates the general relatedness of key technologies across global publications, the relatedness density[17] for a region or country gives insights into the regional availability of knowledge and capabilities. The higher the value of relatedness density, the higher the number of other technologies related to a particular technology in which a given country shows revealed technological advantage.

The economic prospects of regions or countries, however, are determined not only by the relatedness of the existing technologies but also by their complexity. The more complex a new activity is, the more difficult it is for other regions to replicate it, and the higher its potential economic returns.

Therefore, assessing relatedness density and technological complexity for a region may reveal areas of strength or opportunities for future developments. If a country or region focuses on key technologies with a relatively high relatedness to existing technologies, it may have an advantage as it can build on existing knowledge. The more technologically complex these technologies, the more difficult it is for other regions to replicate it.

In FIGURE 2-19 below, the relatedness density for the Netherlands (x-axis) and the technological complexity (y-axis) of key technologies is depicted. The size of the dots indicates the specialization index. The specialization index is similar to the relative activity index (showing the relative specialization in a key technology), but it is based in this case on all key technologies and not on the global output across all subjects.

The analysis points in a similar direction as the results from the previous chapters. BIOTECHNOLOGY AND LIFE SCIENCES is a domain with a relatively high relatedness density and specialization index. This seems logical, as there is a greater regional supply of related technologies and capabilities to build upon. These technologies appear to be medium-complex.

Other potential focus areas, as revealed in the previous chapter, are some technologies within the DIGITAL TECHNOLOGIES domain. SoftTech, DigiTwins, NeuroMorph, and DataScience are highly complex, with a relatively high relatedness density—which indicates some potential for future opportunities.

[17] The relatedness around a key technology in a region is measured by dividing the sum of the relatedness of the key technology with all other technologies in which the region specializes by the sum of the relatedness of the key technology with all technologies in the world as a whole.

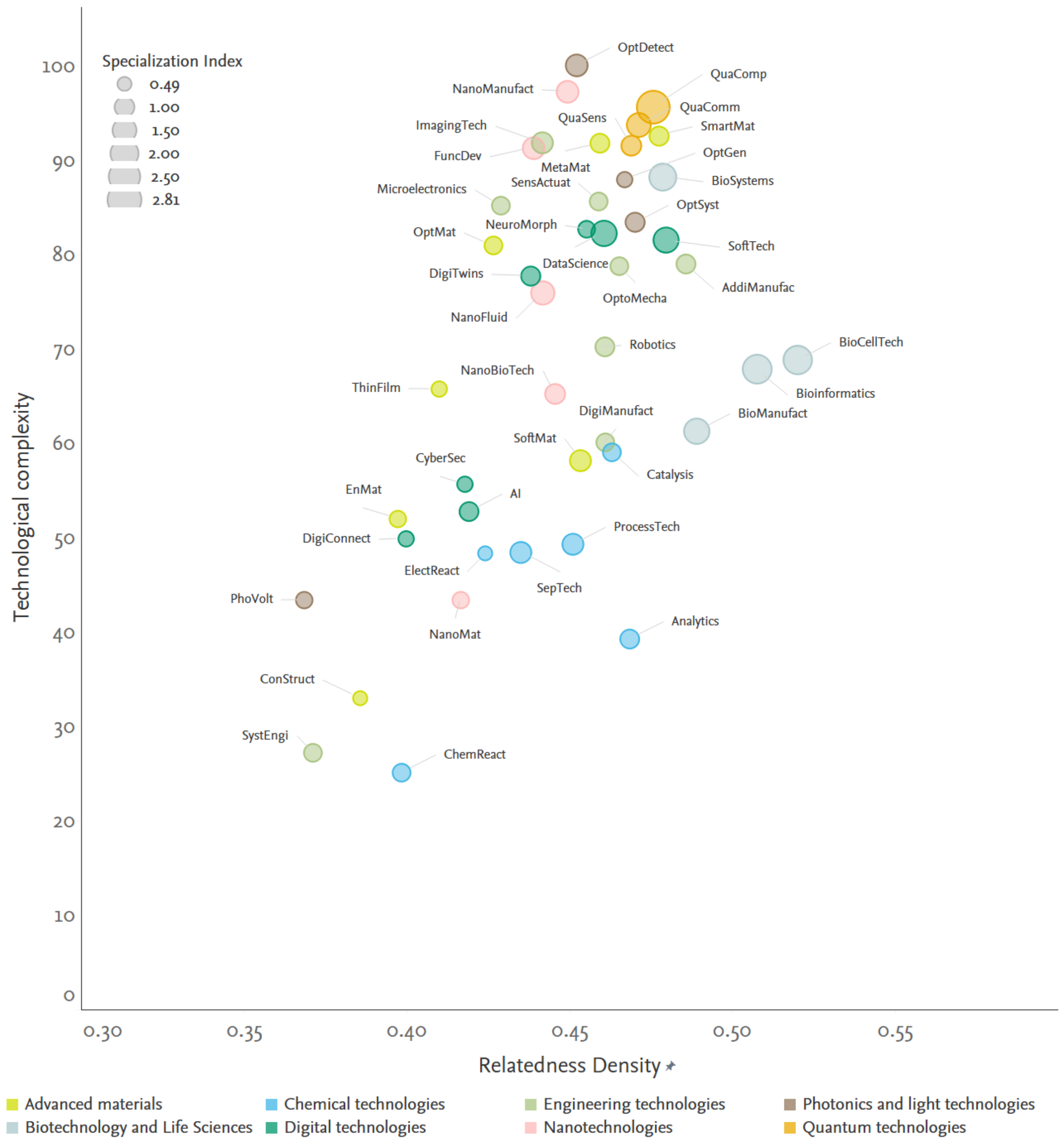


FIGURE 2-19
Technological complexity (y-axis) and relatedness density (x-axis) per technology for Dutch publications, 2013–2022. Size of the dots indicates specialization index (based on all key technologies); color coding indicates technology domain.
Source: Scopus

An assessment of the relatedness density per key technology for all countries in scope of this report is shown in FIGURE 2-20. For almost all key technologies, the Netherlands are in a medium range compared with other countries. The United States, China, and Germany stand out as they seem to have a high relatedness density for almost (if not) all key technologies—which may not be surprising given the research power of these countries. However, further analysis of these results would be required to draw final conclusions on this. Especially, a regional assessment may be interesting to indicate clusters of prospects.[18]

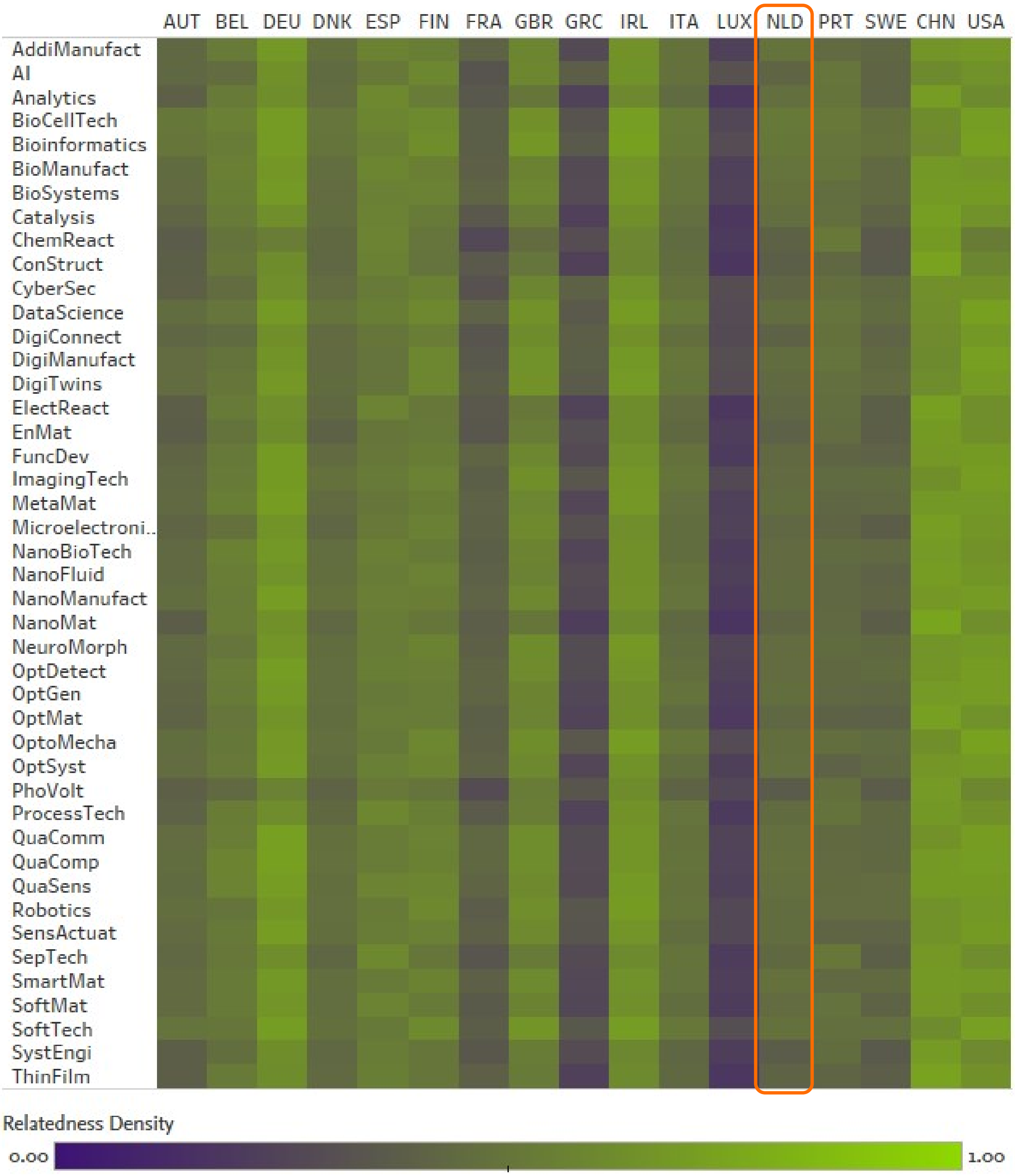


FIGURE 2-20
Relatedness density per key technology for NLD and comparators, 2013–2022.
Source: Scopus

[18] For a regional outlook based on patent data, see the analysis on "Inter-Regional Linkages and Smart Specialization" (Balland & Boschma, 2020)

2.4 Technology monopoly risk

EU-15 institutions do not have a dominant position in any of the key technologies, although a number of the key technologies see a large share of most highly cited publications for the region. China and the US lead in research on most key technologies, but the monopoly risk is still only moderate.

One question relevant to the decision-making progress from a more political perspective (in contrast to research-based interests) could be a strategic assessment of leadership in a technology area and the potential for monopoly.

The Australian Strategic Policy Institute (ASPI) recently published a report entitled "Policy Brief: ASPI's Critical Technology Tracker: the global race for future power."[19] This report (Gaida et al., 2023) and the accompanying webpage assessed critical key technologies with the aim of providing "decision-makers with a new evidence base to make more informed policy and investment decisions."

One of the metrics used in the report is a Technology Monopoly Risk traffic light. "The technology monopoly risk traffic light seeks to highlight concentrations of technological expertise in a single country. It incorporates two factors: how far ahead the leading country is relative to the next closest competitor (research lead), and how many of the world's top 10 research institutions are located in the leading country."[20] We have used ASPI's Technology Monopoly Risk Metric to display our own findings. However, we note that our approach does not use the same search strings as ASPI, nor undertake the same data clean and repair practices, so the results will be different.

This traffic light combines the number of institutions from the leading (by publications in the top 10% most highly cited) country in the key technology and the leading power (calculated by the share of publications in top 10% most highly cited of that leading country divided by the share of the following country). The default position of the traffic light is green (or low). To move up a level, BOTH criteria must be met.

- High risk = 8+/10 top institutions in no. 1 country and at least 3x research lead, i.e., the share of publications in most highly cited of the leading country divided by the second country's share
- Medium risk = 5+/10 top institutions in no. 1 country and at least 2x research lead
- Low risk = medium criteria not met

The metric is intended to give an estimation of a potential future dominance in key technologies which can pose a threat to other countries.

[19] https://www.aspi.org.au/report/critical-technology-tracker
[20] https://techtracker.aspi.org.au/methodology/

The previous chapters already revealed that China holds a dominant position in research output and publications across most, if not all key technologies. Citation impact did not step up with this advantage as the FWCI of China in these key technologies is still below global averages. The analysis of this potential future (or current) dominance may reveal complementary insights into more strategic dimensions of key technology research.

Because individual countries, except China and the US, likely do not have an exceptional share of most highly cited publications, TABLE 2-2 assesses the technology monopoly risk for the EU-15, China, and the US (with the Netherlands included in the table for reference). "Lead country" indicates the country with the highest number of institutions in the top 10 of most highly cited publication shares and research lead indicates the share of the top country divided by the following country/region.

Interestingly, according to the definition used by ASPI, none of the key technologies has a high monopoly risk, although it should be mentioned that China and the US hold dominant positions in almost all of them. Only a few key technologies display a rather even distribution of shares and institutions; these include BioManuFact, Robotics, NanoFluid, and all Quantum technologies. None of the key technologies is dominated by the EU-15—at least not for the number of leading institutions, although quite a number of key technologies have the largest share of most highly cited publications in the EU-15. Particularly these are key technologies in the Quantum technologies, Biotechnology and Life Sciences group and one in the areas of the Digital technologies, with DigiTwins.

The results provided in this analysis are different from some of the results retrieved by ASPI, which may be based on the different definition and scope of the key technologies. Overall, the ASPI report indicates a few technologies with a high monopoly risk, while this assessment indicates only a few medium risk technologies. It should be noted that—although the ASPI evaluated the same number (44) of key technologies as well—these are different from the ones assessed in this report. So, any comparisons between both reports would be like comparing apples with peas. For example, one key technology with a high risk from the ASPI report was "advanced radiofrequency communications (incl. 5G and 6G)" which might be included as a subset within AI or DigiConnect.

Key Tech Group	Key Technology	CHN	EU15	USA	NLD	Lead country	Count of Institutions	Research Lead CHN/EU15/USA	Monopoly Risk
Advanced Materials	EnMat	51%	20%	18%	1%	CHN	9	2.51	Medium
	OptMat	46%	22%	22%	1%	CHN	8	2.14	Medium
	MetaMat	43%	26%	32%	2%	CHN	8	1.35	Low
	SoftMat	38%	24%	23%	2%	CHN	8	1.60	Low
	ThinFilm	51%	19%	19%	1%	CHN	9	2.67	Medium
	ConStruct	47%	21%	17%	1%	CHN	10	2.23	Medium
	SmartMat	51%	21%	22%	2%	CHN	9	2.33	Medium
Photonics and optical technologies	PhoVolt	35%	26%	17%	1%	CHN	8	1.33	Low
	OptSyst	37%	31%	26%	2%	CHN	6	1.22	Low
	OptDetect	35%	30%	33%	2%	CHN	6	1.06	Low
	OptGen	37%	35%	26%	2%	CHN	6	1.08	Low
Quantum technologies	QuaComp	31%	37%	39%	3%	USA	5	1.03	Low
	QuaComm	30%	40%	37%	3%	CHN	5	1.08	Low
	QuaSens	31%	43%	31%	2%	CHN	6	1.39	Low
Digital and information technologies	AI	34%	25%	27%	2%	CHN	7	1.33	Low
	DataScience	19%	31%	49%	3%	USA	8	1.60	Low
	CyberSec	31%	28%	29%	1%	CHN	7	1.08	Low
	SoftTech	18%	37%	40%	3%	USA	7	1.06	Low
	DigiConnect	35%	26%	25%	1%	CHN	9	1.32	Low
	DigiTwins	32%	34%	26%	2%	CHN	9	1.06	Low
	NeuroMorph	38%	24%	31%	1%	CHN	7	0.63	Low
Chemical technologies	ProcessTech	37%	27%	19%	2%	CHN	8	1.35	Low
	ChemReact	43%	21%	13%	2%	CHN	9	2.10	Medium
	SepTech	44%	22%	16%	2%	CHN	9	1.97	Low
	Catalysis	46%	22%	17%	2%	CHN	9	2.07	Medium
	Analytics	37%	25%	20%	2%	CHN	8	1.49	Low
	ElectReact	53%	18%	17%	1%	CHN	10	2.95	Medium
Nanotechnology	NanoManufact	47%	24%	28%	2%	CHN	7	1.71	Low
	NanoMat	47%	20%	18%	1%	CHN	9	2.33	Medium
	FuncDev	41%	27%	30%	2%	CHN	6	1.37	Low
	NanoFluid	37%	24%	27%	3%	CHN	7	1.35	Low
	NanoBioTech	41%	22%	23%	2%	CHN	8	1.82	Low
Life science and biotechnologies	BioCellTech	22%	37%	40%	5%	USA	8	1.08	Low
	BioSystems	27%	29%	33%	4%	USA	5	1.14	Low
	BioManufact	26%	32%	28%	3%	USA	4	1.12	Low
	Bioinformatics	19%	37%	47%	5%	USA	10	1.27	Low
Engineering and fabrication technologies	SensActuat	48%	22%	26%	1%	CHN	8	1.80	Low
	ImagingTech	33%	29%	32%	3%	CHN	5	1.04	Low
	OptoMecha	35%	28%	28%	2%	CHN	6	1.28	Low
	AddiManufac	36%	29%	26%	2%	CHN	8	1.24	Low
	Robotics	39%	28%	26%	2%	CHN	8	1.39	Low
	DigiManufact	31%	33%	26%	2%	CHN	9	1.06	Low
	Microelectronics	40%	24%	27%	2%	CHN	7	1.51	Low
	SystEngi	37%	27%	19%	2%	CHN	9	1.35	Low

TABLE 2-2
Technology monopoly risk for key technologies by share of 10% most highly cited publications (percentages) and number of country institutions within the top 10% most highly cited publications (count of institutions). Research lead calculates the share of leading country/region divided by following country/region. NLD share of most highly cited publications shown only as reference. *Source: Scopus (methodology adapted from ASPI Critical Technology Tracker)*

2.5 Dutch research cited in patents

Dutch research in key technologies is often cited by patents. With the exception of the US, the Netherlands is the only country cited above the world average in all key technologies. Biotechnology and Life Sciences, Nanotechnologies, and Chemical technologies stand out as the technology domains with the highest patent citation averages.

Dutch research overall is utilized heavily by technology-oriented entities around the world. This section provides insights into the technological areas of application in which Dutch research in key technologies is cited by patent applications around the world. Citations from patents to scholarly outputs indicate a link between academia and industry, in other words knowledge flows. It is not possible from patents to see whether the results of the research are eventually commercially exploited, but research cited by patents is a strong indicator of the relevance that research could have to industry.

To aid understanding of the terminology used in this chapter, description and definitions of the indicators are included below.

Patent documents citing scientific literature

Indicators of patent citations of scientific literature are considered proxies of the economic value of research output. The resources required to patent a technology are significant, and just the act of applying for a patent indicates that the technology has some economic value to the applicant. These lists of cited documents, especially scientific literature, provide a unique window into the knowledge that the technology relies on and provide confirmation that the expected economic gains are partially derived from the underlying research.

Counting patent families versus counting patent applications

A patent family represents the collective patent applications and granted patents of a specific technology. Counts of patent families, rather than counts of patent applications (or granted patents), are increasingly used in evaluation studies as they more accurately capture the collective knowledge that is relevant to a specific technology.

Patent lifecycle

All patent information is publicly available and can be found in patent databases. It takes around 18 months, however, for a patent application to be published after the initial application date. Therefore, there is a time-lag in the availability of patent information—everything we see today is at least 18 months old. It takes a further 3 to 5 years for a patent application to be granted or rejected by a patent office.

Research outputs from Dutch researchers have been cited by patents extensively (FIGURE 2-21), especially in the BIOTECHNOLOGY AND LIFE SCIENCES, but as well in CHEMICAL TECHNOLOGIES and NANOTECHNOLOGIES. It needs to be noted, however, that these technology areas are also the most prolific, and the more output, the higher the chances of getting cited. Therefore, the total citations may be misleading, so the figure displays the patent citations per output (i.e., the average number of citations per publication) as well. These numbers are usually much lower than citations in research output and the numbers in FIGURE 2-21 are proof of that. But amongst the key technologies, similar to the counts of total patent citations, BIOTECHNOLOGY AND LIFE SCIENCES, CHEMICAL TECHNOLOGIES, and NANOTECHNOLOGIES display the highest average patent citations.

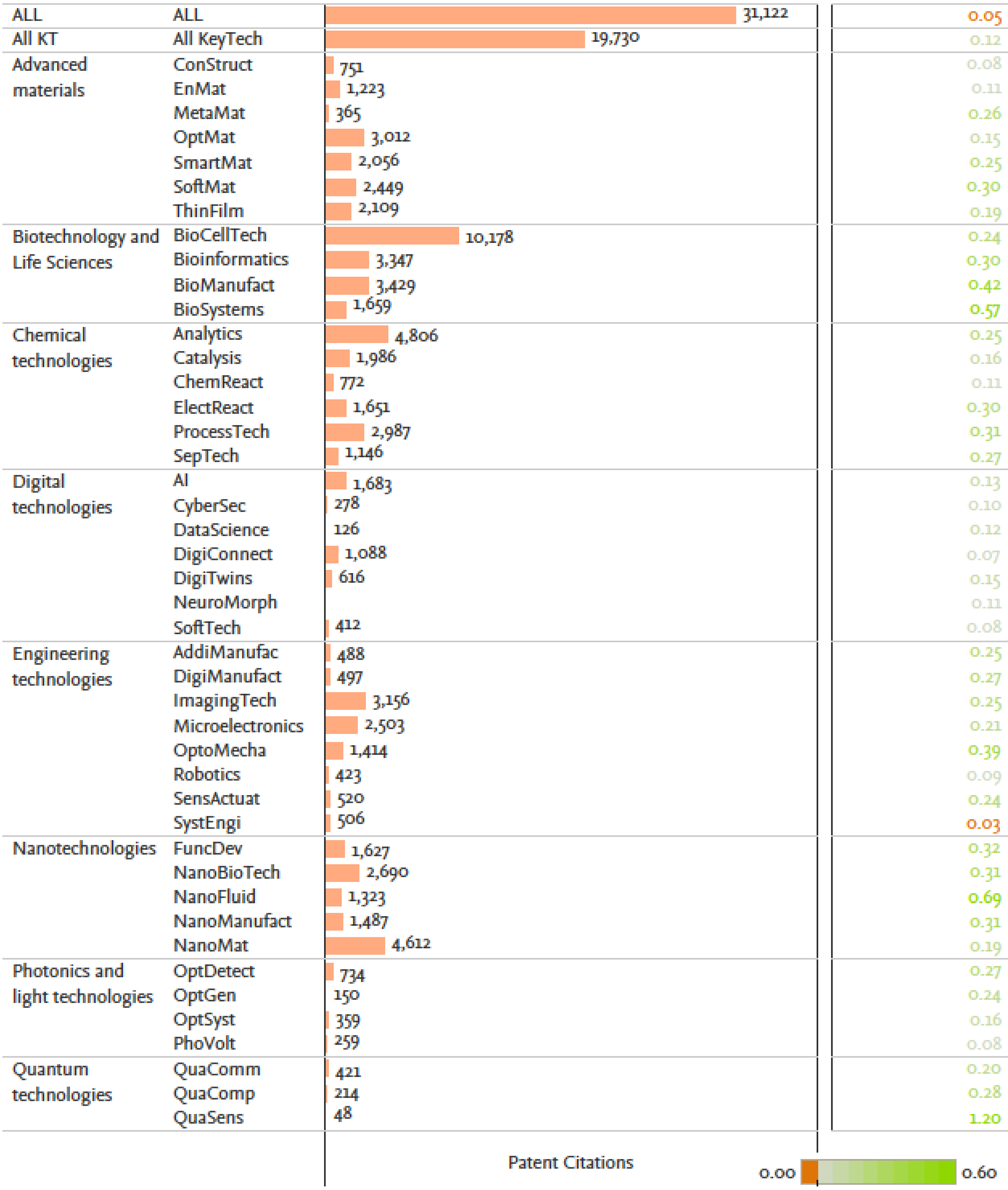


FIGURE 2-21
Total patent citations (left panel) and patent citations per output (right panel) for NLD key technology publications, for the period 2013–2022.
Source: Scopus, LexisNexis IP

As a general observation, research in key technologies attracted more patent citations than overall research—for the Netherlands (0.12 patent citations per output for key technologies vs. 0.05 for all research, FIGURE 2-21) as well as on a global scale (0.06 vs. 0.03, not shown in figures).

This is not surprising as key technologies are, more or less by definition, technologies which may be more attractive for corporates, whereas overall research includes fields like the social sciences, which are less patentable and relevant for this sector.

A comparison with comparator countries and benchmarks reveals that Dutch research seems to hold a leading position in patent citations per output, together with the US (FIGURE 2-22). Research across all key technologies has been cited twice as much (0.12) as the world average (0.06), only topped by the US, which has 0.13 patent citations per research output.

The color-coding of the figure indicates all key technologies with an average patent citation count above or exactly at World average (per key technology) in green and all below that average in orange. The Netherlands is, besides the US, the country with the most key technologies above world.[21] It is interesting to see that China received only few citations, but that could be an artefact as China has a very local patent filing strategy (the majority of Chinese patents are filed only in China) which may hinder global visibility.

The high values for QuaSens are most likely the result of outliers. This is a very small field and a few exceptional publications which are cited heavily may distort the picture. Just 40 publications from Dutch researchers attracted 46 patent citations, which is likely due to an "outlier."

Across all countries, key technologies in the BIOTECHNOLOGY AND LIFE SCIENCES domain have the highest average patent citation count, followed by NANOTECHNOLOGIES.

It seems that in these domains current research is rather heavily influencing corporate innovation, whereas in other domains possibly there is a disconnect between academic research and patenting activities.

It should be noted again, though, that as a general pattern, patents rely more on other patents and citations to scholarly output are less frequent. Therefore, this analysis leads to the following chapter, which looks in more detail at the patenting landscape.

[21] It seems that the values being below or at world average are likely to be based on rounding errors. World average is 0.015 for SysEngi and several countries are above that, but being round down while world average is rounded up.

	AUT	BEL	CHN	DEU	DNK	ESP	FIN	FRA	GBR	GRC	IRL	ITA	LUX	NLD	PRT	SWE	USA	EU15	WLD
All KeyTech	0.08	0.09	0.02	0.07	0.09	0.05	0.07	0.06	0.08	0.03	0.08	0.05	0.07	0.12	0.04	0.09	0.13	0.06	0.06
ConStruct	0.04	0.05	0.01	0.04	0.04	0.05	0.04	0.04	0.05	0.01	0.07	0.03	0.03	0.08	0.02	0.04	0.09	0.04	0.03
EnMat	0.11	0.09	0.03	0.08	0.04	0.06	0.06	0.06	0.09	0.04	0.09	0.05	0.06	0.11	0.04	0.06	0.16	0.07	0.07
MetaMat	0.48	0.31	0.06	0.24	0.21	0.16	0.09	0.16	0.25	0.10	0.27	0.17	0.01	0.26	0.07	0.18	0.35	0.20	0.21
OptMat	0.08	0.11	0.03	0.07	0.08	0.06	0.08	0.07	0.10	0.04	0.10	0.06	0.05	0.15	0.05	0.09	0.16	0.08	0.08
SmartMat	0.24	0.15	0.05	0.15	0.19	0.10	0.11	0.14	0.21	0.06	0.20	0.11	0.10	0.25	0.09	0.18	0.34	0.15	0.15
SoftMat	0.33	0.21	0.06	0.20	0.24	0.16	0.16	0.22	0.23	0.09	0.17	0.14	0.31	0.30	0.11	0.25	0.43	0.18	0.19
ThinFilm	0.10	0.11	0.04	0.08	0.08	0.07	0.12	0.09	0.11	0.04	0.11	0.07	0.07	0.19	0.06	0.08	0.18	0.09	0.08
BioCellTech	0.21	0.20	0.06	0.19	0.21	0.12	0.17	0.17	0.19	0.08	0.18	0.12	0.21	0.24	0.11	0.24	0.30	0.16	0.19
Bioinformatics	0.33	0.28	0.08	0.27	0.30	0.15	0.18	0.20	0.21	0.07	0.15	0.11	0.20	0.30	0.10	0.37	0.34	0.18	0.23
BioManufact	0.44	0.30	0.10	0.33	0.37	0.21	0.23	0.33	0.32	0.12	0.19	0.15	0.91	0.42	0.14	0.47	0.67	0.26	0.31
BioSystems	0.56	0.44	0.13	0.36	0.47	0.18	0.36	0.42	0.33	0.11	0.16	0.18	1.64	0.57	0.21	0.64	0.78	0.29	0.42
Analytics	0.13	0.13	0.03	0.14	0.17	0.07	0.14	0.11	0.17	0.06	0.11	0.07	0.16	0.25	0.06	0.21	0.26	0.11	0.10
Catalysis	0.14	0.11	0.03	0.10	0.13	0.06	0.10	0.09	0.13	0.05	0.10	0.06	0.09	0.16	0.06	0.14	0.21	0.09	0.08
ChemReact	0.07	0.08	0.02	0.07	0.06	0.05	0.05	0.05	0.08	0.03	0.06	0.04	0.06	0.11	0.04	0.11	0.12	0.06	0.04
ElectReact	0.13	0.13	0.04	0.12	0.11	0.09	0.08	0.11	0.13	0.06	0.11	0.08	0.12	0.30	0.09	0.11	0.23	0.10	0.09
ProcessTech	0.25	0.16	0.05	0.18	0.25	0.09	0.16	0.16	0.19	0.06	0.16	0.10	0.23	0.31	0.10	0.25	0.44	0.15	0.15
SepTech	0.22	0.18	0.04	0.16	0.16	0.09	0.17	0.16	0.18	0.06	0.12	0.10	0.18	0.27	0.09	0.17	0.26	0.14	0.11
AI	0.11	0.11	0.02	0.09	0.10	0.06	0.08	0.09	0.10	0.03	0.04	0.05	0.17	0.13	0.06	0.08	0.12	0.07	0.06
CyberSec	0.06	0.09	0.03	0.08	0.05	0.11	0.11	0.06	0.10	0.10	0.06	0.07	0.06	0.10	0.05	0.13	0.15	0.08	0.08
DataScience	0.08	0.10	0.06	0.18	0.01	0.22	0.17	0.14	0.25	0.03	0.09	0.05	0.10	0.12	0.08	0.09	0.24	0.15	0.17
DigiConnect	0.06	0.06	0.02	0.06	0.05	0.05	0.07	0.04	0.06	0.04	0.07	0.04	0.07	0.07	0.04	0.08	0.09	0.05	0.04
DigiTwins	0.08	0.09	0.04	0.10	0.03	0.09	0.11	0.11	0.12	0.08	0.06	0.05	0.09	0.15	0.04	0.12	0.22	0.08	0.10
NeuroMorph	0.14	0.22	0.05	0.14	0.06	0.06	0.11	0.17	0.27	0.03	0.10	0.06	0.11	0.11	0.14	0.05	0.29	0.15	0.15
SoftTech	0.06	0.03	0.05	0.06	0.03	0.07	0.07	0.07	0.11	0.04	0.03	0.04	0.03	0.08	0.03	0.04	0.14	0.06	0.08
AddiManufac	0.22	0.16	0.05	0.11	0.16	0.11	0.12	0.15	0.16	0.10	0.16	0.11	0.13	0.25	0.09	0.11	0.31	0.13	0.16
DigiManufact	0.10	0.07	0.06	0.10	0.05	0.12	0.14	0.12	0.21	0.13	0.05	0.08	0.10	0.27	0.04	0.12	0.29	0.11	0.12
ImagingTech	0.22	0.15	0.04	0.14	0.14	0.12	0.11	0.12	0.16	0.06	0.14	0.09	0.11	0.25	0.10	0.15	0.23	0.13	0.12
Microelectronics	0.10	0.13	0.04	0.09	0.07	0.08	0.10	0.09	0.14	0.04	0.13	0.07	0.07	0.21	0.06	0.11	0.19	0.10	0.10
OptoMecha	0.25	0.11	0.04	0.13	0.15	0.12	0.13	0.12	0.18	0.05	0.15	0.09	0.03	0.39	0.08	0.09	0.26	0.14	0.11
Robotics	0.10	0.05	0.02	0.08	0.03	0.07	0.03	0.05	0.11	0.03	0.05	0.05	0.05	0.09	0.04	0.06	0.13	0.07	0.06
SensActuat	0.29	0.41	0.07	0.21	0.23	0.19	0.17	0.15	0.30	0.26	0.25	0.13	0.11	0.24	0.11	0.14	0.39	0.20	0.20
SystEngi	0.02	0.02	0.01	0.02	0.02	0.03	0.02	0.01	0.03	0.01	0.03	0.02	0.01	0.03	0.02	0.02	0.04	0.02	0.02
FuncDev	0.18	0.18	0.07	0.16	0.18	0.10	0.20	0.15	0.23	0.07	0.16	0.13	0.07	0.32	0.14	0.16	0.40	0.17	0.22
NanoBioTech	0.30	0.25	0.06	0.20	0.25	0.17	0.13	0.23	0.23	0.09	0.17	0.14	0.35	0.31	0.13	0.28	0.40	0.18	0.18
NanoFluid	0.62	0.53	0.11	0.38	0.28	0.19	0.27	0.31	0.38	0.16	0.22	0.25	0.38	0.69	0.18	0.40	0.67	0.31	0.35
NanoManufact	0.26	0.15	0.07	0.15	0.23	0.13	0.20	0.16	0.24	0.07	0.21	0.15	0.07	0.31	0.09	0.16	0.36	0.18	0.20
NanoMat	0.12	0.13	0.03	0.09	0.11	0.07	0.09	0.09	0.12	0.04	0.11	0.07	0.08	0.19	0.06	0.11	0.21	0.09	0.09
OptDetect	0.30	0.23	0.05	0.17	0.18	0.13	0.13	0.15	0.24	0.07	0.17	0.13	0.07	0.27	0.11	0.15	0.34	0.18	0.18
OptGen	0.13	0.15	0.03	0.12	0.15	0.09	0.07	0.09	0.18	0.07	0.42	0.15		0.24	0.11	0.13	0.29	0.13	0.13
OptSyst	0.23	0.19	0.03	0.13	0.14	0.12	0.07	0.11	0.22	0.07	0.15	0.10		0.16	0.08	0.07	0.28	0.14	0.13
PhoVolt	0.07	0.10	0.03	0.08	0.07	0.06	0.03	0.05	0.13	0.03	0.10	0.05	0.03	0.08	0.02	0.05	0.18	0.07	0.07
QuaComm	0.13	0.19	0.05	0.13	0.14	0.10	0.10	0.13	0.20	0.07	0.18	0.11	0.22	0.20	0.14	0.16	0.31	0.15	0.20
QuaComp	0.24	0.39	0.12	0.20	0.30	0.24	0.16	0.21	0.38	0.18	0.87	0.21		0.28	0.35	0.18	0.44	0.26	0.39
QuaSens	0.26	0.12	0.07	0.66	0.39	0.35	0.07	0.37	0.49		5.00	0.09		1.20	0.17	0.70	0.69	0.46	0.51

FIGURE 2-22

Patent citations per output by key technology for NLD and comparators, for the period 2013–2022.

Source: Scopus

Chapter 3

Patent analysis of key technologies

3.1 Introduction to patent analyses

Patent analyses can be used to assess the economic and technological value of patents, providing insights into the innovation potential of a country within a key technology.

This chapter assesses innovation activities through patent metrics for the key technologies across the countries in this analysis. As mentioned in the previous section, patent analysis has some similarities, but also some key differences, with publication-based analyses.

Because the same inventions can be patented at multiple offices, and to avoid counting duplicates of the same inventions across different markets, all analyses in this chapter are based on counts of INPADOC patent families. These families are defined by linking together patents that share one priority or more with at least one other patent in the family.

The concepts of inventorship and ownership are also important to address here as they refer to two distinct but related notions. Inventorship is linked to the individuals who invented the novel content of the new intellectual property (IP) to be protected. These individual inventors are recognized as such on the patents. However, they do not necessarily own the IP associated with the patent, and thus there is a disconnect between patent inventorship and ownership. Often, companies act as owners of the IP, appearing as assignees on patents, while the employees responsible for the invention will appear as inventors. Therefore, preparing data based on either inventorship or ownership data will return slightly different results at the country level, especially in the case of large companies whose main headquarters determine the country of ownership but whose IP production occurs elsewhere. For this project, most analyses are based on inventorship data[22] because they are more aligned with the location where the innovation took place.

The are various indicators available which support the assessment of the value of patents or a patent portfolio (i.e., all patents either owned or invented by an entity) beyond the number of patents.

The number of patent families an entity owns (or has filed) is regarded as **portfolio size**. Utilizing indicators developed by PatentSight, this report also employs **market coverage**, **technology relevance**, **competitive impact**, and **patent asset index** (Ernst & Omland, 2011).

Market coverage assesses the commercial value of a patent family by the total size of the worldwide markets in which patent protection[23] exists. The more markets (e.g., the US, China, Japan or the EU) a patent family covers, the more valuable the patents are estimated to be. This is because innovators spend more effort and resources on protection in multiple (global) markets via patents if they believe an invention is more valuable. Technology relevance, in contrast, indicates the technological impact of a patent through citations

[22] Inventor country refers in this context to the country that is given in the address of the inventor. Since many patents (especially patent families) will have multiple inventors, full counting is used in this regard, similar to publication analysis.

[23] A patent provides, from a legal standpoint, the right to exclude others from making, using, selling, offering for sale, or importing the patented invention for the term of the patent, which is usually 20 years from the filing date subject to the payment of maintenance fees.

from subsequent patents. The more citations a patent accumulates from later patents, the higher the estimated technological impact.

Finally, competitive impact and patent asset index indicates the overall perceived value of individual patents or the entire portfolio. Competitive Impact is the product of market coverage and technology relevance and as such combines economic value and technological impact, while the patent asset index aggregates all individual competitive impacts across the full portfolio of an entity.

Definition of key technologies

Patent language is very complex and keyword search can be misleading for several reasons: Keywords may be context-sensitive and often synonyms, especially for some subjects such as chemistry, are used. Additionally, patents use a language of their own. For reasons of legal certainty and sometimes perhaps to hide patents from being found, drafters resort to specialized and deliberately obscure terminology, vocabulary, nomenclature and grammar. Therefore, it is advised to use patent classifications instead of keyword search.

Patent classifications are hierarchical. Patent classification is a fast track to finding relevant documents very quickly, leveraging the intellectual effort of the examiners who classified patent documents in the first place. There are a number of classification schemes in place, the International Patent Classification System (IPC), administered by the World Intellectual Property Organization, the F-term scheme at the Japan Patent Office and the Cooperative Patent Classification (CPC) scheme implemented by the European Patent Office and the United States Patent and Trademark Office.

For the definition of the key technologies, this report utilizes PatentSight's Technology Clusters. PatentSight's Technology Clusters are sets of similar patent families based on full-text patent data under consideration of IPC classifications by an automated machine learning technique. Built from all documents from all patent families and other IP rights in the PatentSight database, irrespective of their legal status, Technology Clusters comprise four levels of hierarchy.[24] Each patent can only be in one Technology Cluster.

Patent sets for each key technology were created by selecting relevant technology clusters. For this purpose, the technology clusters of citing patents (see Section 2.5) have been identified as they likely have a common interest and relate to the research question or key technology. These relevant clusters were selected to comprise the underlying patents for each key technology. Similar to the publication set, there is an overlap between the patent clusters, because patents from a particular technology cluster may relate to different key technologies. Therefore, the number of patents for the key technologies will not add up to the overall patent count across all key technologies.

[24] https://knowledge.lexisnexisip.com/patentsight/technology-clusters

3.2 Key technology patent indicators

The Netherlands holds a strong position amongst the EU-15 countries with its patenting activities in the key technologies. NANOTECHNOLOGIES and BIOTECHNOLOGY AND LIFE SCIENCES seem to be focus areas with large portfolios and highly valuable patents.

Across all key technologies, Germany is the leading country in patent filings within the EU-15 (FIGURE 3-1). Inventors from Germany hold more than a third of all EU-15 patent families, followed by France and the UK. The Netherlands is fourth by portfolio size with more than 22,000 patent families. Globally, more than 3 million patent families have been filed (and published) between 2013 and 2022 across all key technologies (not shown in FIGURE 3-1).

The size of a patent portfolio, however, is similar to publication output and dependent on the size (i.e., the number of researchers/innovators) in the country. Therefore the "normalized" indicators such as market coverage and technology relevance may be more insightful than assessing comparators of different sizes. On both indicators, the Netherlands is in a good position. By market coverage, it is only topped by Denmark and Sweden. This indicates that patent families with at least one Dutch inventor cover multiple markets, meaning that these are filed in several countries like the US, EU, or others. The dashed line in FIGURE 3-1 indicates the global average (0.91 for market coverage)[25] and the Netherlands is well above that—and well above the EU-15 average.

For technology relevance, i.e., the technological impact, the Netherlands is not in a leading role, but well above global (1.11, dashed line) and EU-15 (1.23) averages. Here, again Denmark, followed by Belgium, takes the leading role.

Overall, patent families with at least one Dutch inventor seems to be highly valuable from an economic as well as from a technological point of view.

[25] Per definition, a market coverage of 1 indicates a protected market of the size of the US market as benchmark. Globally, the average protected market size is therefore slightly below the US market.

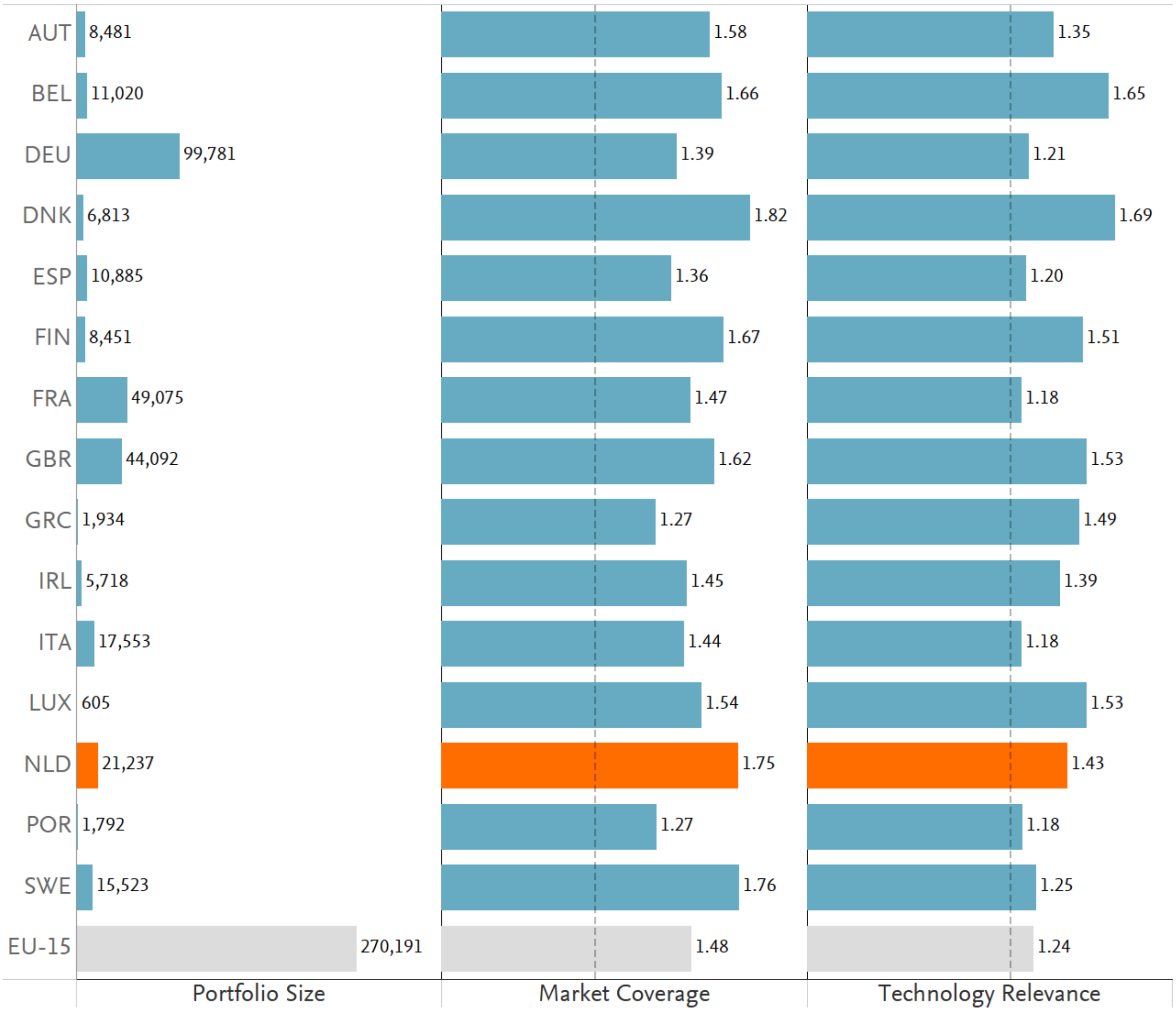


FIGURE 3-1
Portfolio size (left panel), market coverage (middle panel) and technology relevance (right panel) for all key technologies for NLD and comparators, for the period 2013–2022.
Source: PatentSight

As mentioned above, the overall value of inventions can be assessed by the competitive impact, the product of economic and technological impact and value. The Netherlands is in a strong position with a competitive impact of 2.72, although topped by Denmark, Greece, Belgium, and the UK (FIGURE 3-2).

The patent asset index aggregates the individual values across the whole portfolio and given that the Netherlands has the fourth biggest portfolio, its overall portfolio value ends on the same position, topped only by Germany, the UK, and France.

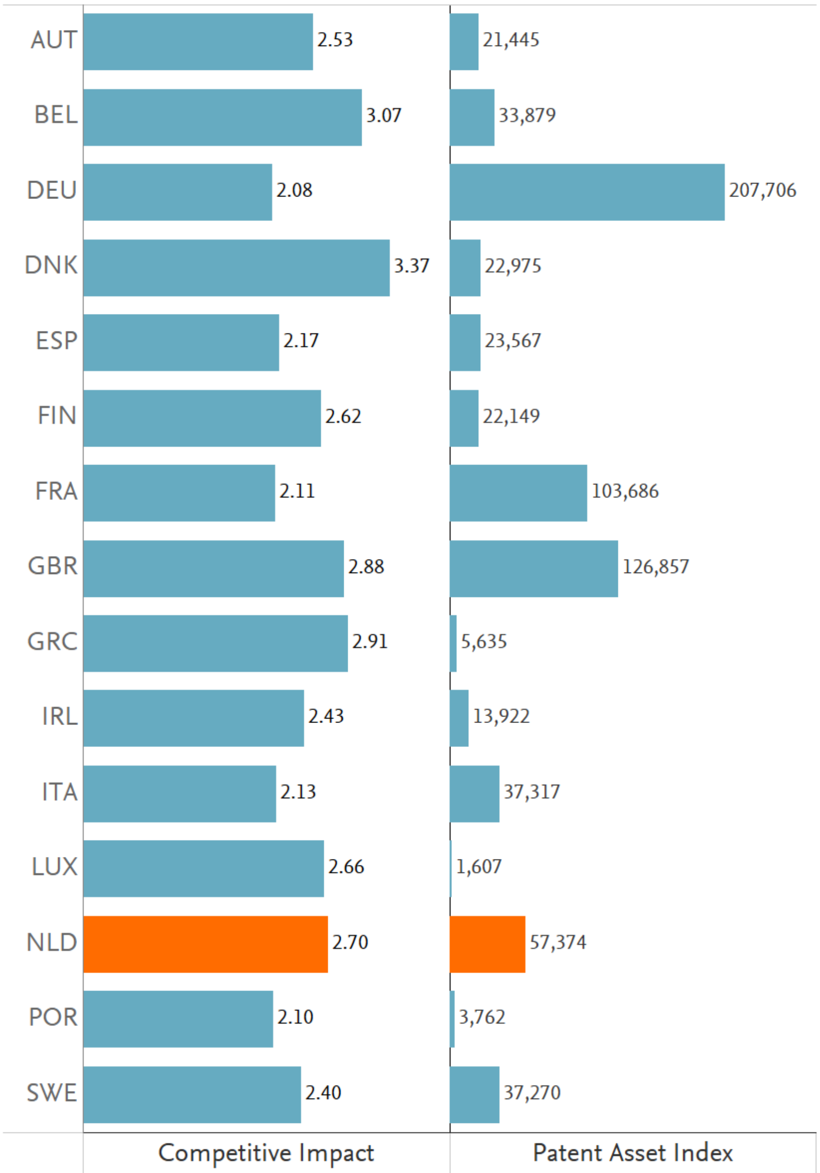


FIGURE 3-2
Average competitive impact and patent asset index for all key technologies for NLD and comparators, for the period 2013–2022.
Source: PatentSight

The distribution of patent families across the key technologies is shown in FIGURE 3-3, with NanoMat, ImagingTech, and Analytics as the key technologies with the highest number of patent families. Looking at the share of patents per key technology of all 22,005 key technology patents (see FIGURE 3-1), it paints a similar picture to the previous chapters. BIOTECHNOLOGY AND LIFE SCIENCES and NANOTECHNOLOGIES seem to be focused technology domains with all their underlying key technologies having a share above 10%. ENGINEERING TECHNOLOGIES and CHEMICAL TECHNOLOGIES follow with a big group of relatively large key technologies by share of overall patent portfolio.

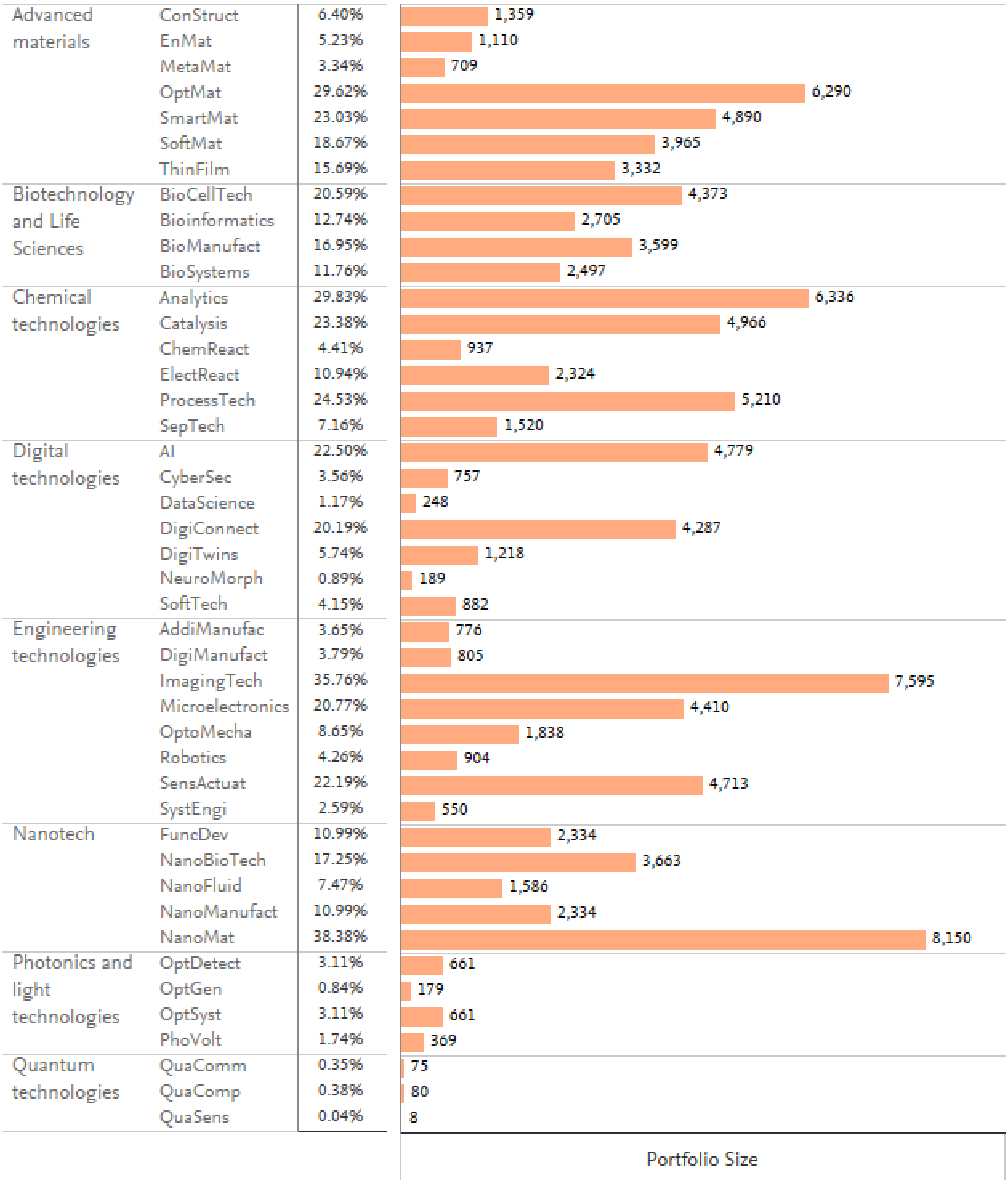


FIGURE 3-3
Portfolio size (orange bars and numbers on the right) and share (percentages) of all key technology patents per key technology for NLD, for the period 2013–2022.
Source: PatentSight

The economic and technological value of Dutch inventors' patents is high, as shown in the previous section, with a focus on NANOTECHNOLOGIES and BIOTECHNOLOGY AND LIFE SCIENCES. These domains exhibit a high market coverage and a high technology relevance (FIGURE 3-4), but the differences with the other fields are not very large. Overall, the portfolio of Dutch inventors is highly valuable with high market coverage and high technological impact.

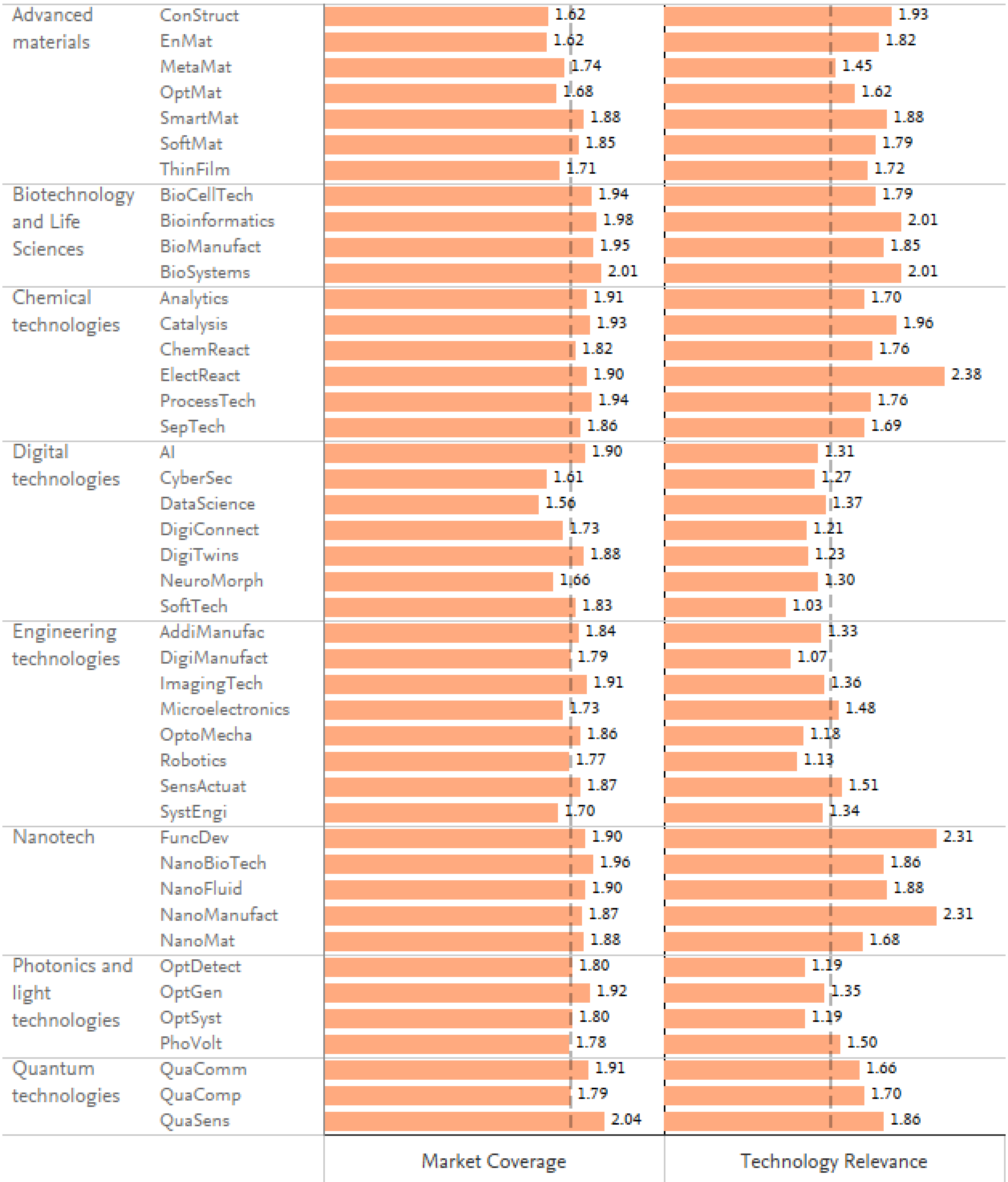


FIGURE 3-4
Market coverage and technology relevance per key technology for NLD, for the period 2013–2022
Source: PatentSight

Benchmarked with the comparators (FIGURE 3-5), the value of Dutch patents seems to relatively high within Eu-15, but no clear pattern is visible.

	AUT	BEL	DEU	DNK	ESP	FIN	FRA	GBR	GRC	IRL	ITA	LUX	NLD	POR	SWE
ConStruct	1.95	3.84	1.86	3.03	1.69	6.07	2.06	3.00	1.70	2.65	2.12	1.73	3.17	1.91	2.80
EnMat	1.78	3.51	1.88	2.74	1.89	5.12	2.07	3.26	2.38	3.21	2.09	1.69	3.04	1.78	2.46
MetaMat	2.77	2.50	2.18	2.75	2.52	3.82	2.21	3.42	7.10	2.48	2.00	2.10	2.87	1.14	3.65
OptMat	2.27	3.46	2.25	3.44	2.58	4.09	2.31	3.32	3.45	2.74	2.64	2.33	3.02	2.07	3.13
SmartMat	3.72	4.08	3.38	4.02	2.83	4.70	3.23	4.26	4.80	3.40	2.98	3.32	3.85	2.57	3.66
SoftMat	3.80	4.01	3.59	4.48	2.53	2.99	3.29	4.35	3.53	3.73	2.77	3.26	3.80	2.67	3.80
ThinFilm	2.89	3.93	2.58	3.62	2.88	4.83	2.69	3.80	6.44	2.85	2.76	2.99	3.22	2.46	3.45
BioCellTech	3.95	4.29	3.87	4.55	2.70	2.71	3.48	4.56	3.33	3.93	2.94	3.33	3.91	2.69	3.97
Bioinformatics	4.68	4.35	4.49	4.73	3.05	2.80	3.82	4.59	5.21	4.03	3.49	3.79	4.48	3.82	4.36
BioManufact	4.09	4.18	3.96	4.63	2.63	2.78	3.51	4.47	3.81	3.82	2.89	3.62	4.06	2.80	4.01
BioSystems	3.97	3.91	4.01	4.46	2.41	3.07	3.55	4.31	4.58	3.98	3.02	3.64	4.47	3.52	4.22
Analytics	3.64	3.96	3.18	4.29	2.64	3.65	3.10	4.18	4.02	3.59	2.76	3.03	3.58	2.48	3.57
Catalysis	4.13	4.34	3.70	4.61	2.83	4.76	3.39	4.73	3.80	3.79	3.03	3.33	4.08	2.67	4.18
ChemReact	1.94	2.97	2.37	4.03	1.61	2.64	2.28	3.46	1.20	3.25	1.58	3.08	3.34	2.03	2.84
ElectReact	3.49	4.69	3.51	4.31	2.96	5.48	3.57	4.31	6.07	3.91	3.30	3.37	4.81	2.60	4.28
ProcessTech	4.17	3.94	3.76	4.60	2.76	3.49	3.37	4.68	3.84	4.20	2.97	3.45	3.79	2.68	4.07
SepTech	3.47	3.74	3.00	4.77	1.91	3.26	2.83	3.91	1.79	2.92	2.50	2.51	3.32	3.00	4.36
AI	2.67	2.98	2.43	3.01	2.17	2.68	2.37	2.63	4.24	2.40	2.33	2.34	2.68	2.77	2.97
CyberSec	2.92	2.08	1.94	2.22	3.12	2.42	1.68	2.51	5.77	2.00	2.60	2.66	2.28	2.17	2.62
DataScience	1.99	1.66	1.33	1.98	2.08	1.83	1.64	2.19	1.72	1.33	1.76	0.63	2.53	4.38	2.20
DigiConnect	2.06	1.94	1.70	2.01	2.54	2.34	1.55	2.12	4.55	1.90	2.03	2.56	2.26	2.35	2.11
DigiTwins	4.81	2.57	2.22	2.66	2.65	3.03	2.35	2.69	6.70	2.03	1.71	2.16	2.44	2.38	2.71
NeuroMorph	2.31	1.85	1.39	1.69	2.27	1.87	1.47	1.85	1.94	1.67	1.67	0.44	2.34	5.42	1.87
SoftTech	2.47	2.08	1.57	1.67	1.96	1.79	1.66	1.97	1.77	1.59	1.46	1.20	2.00	2.91	1.79
AddiManufac	2.23	2.46	2.05	3.49	1.93	2.42	2.06	3.59	1.46	2.61	2.21	2.22	2.62	1.42	5.32
DigiManufact	3.97	1.97	2.04	1.78	3.05	2.44	2.05	2.33	5.52	1.75	1.37	1.12	2.01	2.48	2.67
ImagingTech	2.84	3.13	2.41	3.39	2.12	2.92	2.49	3.14	4.74	2.87	2.44	2.99	2.83	2.49	3.05
Microelectronics	2.18	3.23	1.96	2.69	2.94	3.87	2.02	2.91	4.90	2.43	2.31	2.13	2.65	1.74	2.77
OptoMecha	2.87	2.36	1.99	2.11	2.38	3.37	2.11	2.68	5.96	1.92	2.13	2.64	2.31	2.04	2.66
Robotics	3.32	2.12	2.00	2.68	2.73	2.37	1.81	2.58	5.25	1.87	1.40	1.18	2.10	2.22	2.65
SensActuat	2.59	3.50	2.14	3.28	2.18	3.82	2.28	3.10	5.68	3.40	2.20	2.91	2.89	1.99	3.20
SystEngi	2.39	2.29	1.79	3.06	1.94	1.84	1.78	2.96	0.77	2.54	1.19	2.01	2.39	1.84	2.69
FuncDev	3.12	4.21	3.35	3.81	2.51	5.22	3.04	3.70	6.38	3.21	3.10	3.38	4.73	3.01	3.79
NanoBioTech	3.85	4.17	3.63	4.17	2.60	3.11	3.36	4.39	2.99	3.75	2.78	3.28	4.11	2.58	3.95
NanoFluid	3.55	3.58	3.74	3.80	2.24	2.38	3.54	3.94	8.79	3.19	3.22	3.64	4.06	2.40	4.34
NanoManufact	3.39	4.62	3.66	4.04	2.63	5.52	3.40	4.10	6.88	3.59	3.19	3.63	4.69	2.92	3.79
NanoMat	3.22	3.80	2.78	3.72	2.50	4.07	2.82	3.97	3.51	3.29	2.66	3.00	3.44	2.33	3.47
OptDetect	2.76	1.97	2.02	2.30	3.09	3.72	1.99	2.65	6.85	1.84	1.89	2.30	2.35	1.25	2.85
OptGen	1.52	2.11	1.78	3.16	1.66	5.60	1.97	3.26	1.78	1.79	2.69	5.74	2.78	1.14	1.92
OptSyst	2.76	1.97	2.02	2.30	3.09	3.72	1.99	2.65	6.85	1.84	1.89	2.30	2.35	1.25	2.85
PhoVolt	3.91	2.53	2.40	2.06	3.27	4.23	2.31	3.25	8.14	1.50	2.33	2.52	2.96	1.37	3.10
QuaComm	1.70	1.91	1.83	1.11	1.47	4.49	1.52	2.41	2.89	1.30	1.68		3.36	1.44	0.91
QuaComp	1.94	2.37	1.70	1.09	1.25	3.96	1.30	2.16	2.85	1.41	1.65	0.20	3.36	2.43	1.08
QuaSens	16.44	1.77	2.63			3.05	1.04	2.59			0.62		4.08	2.13	2.63

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FIGURE 3-5
Competitive impact (numbers) and patent asset index (colr coding) of NLD and comparators per key technology.
Source: PatentSight

Chapter 4

Emerging topics within key technologies

4.1 Introduction into topics of prominence

Topics of prominence are a granular approach to grouping research publications that can identify high-performing or emerging research clusters.

While analyses at subject area level are an established way to codify research topics, these remain highly dependent on a journal-level analysis, given that publications are traditionally assigned to subject areas based on the journal published in. The journal-level approach works well for publications where the journal coverage is highly specific, but less so for the increasing number of multidisciplinary journals, which lack the same specificity. Complementary to this would be a more granular approach on the publications level. Based on citation links between individual publications, clusters of publications addressing the same research area can be calculated and represented. This approach has been taken using **topics of prominence** and **topic clusters**.

Topics of prominence

Of all articles in Scopus, 95% can be clustered into roughly 100,000 global and unique research topics based on direct citation analysis. Topics are meant to be aligned to the research-question level, created by clustering articles with strong citation linkages. Topic (as opposed to subject) names are derived from the keywords used in the abstracts of the articles constituting the topic. The relationship between potential topics can be identified by looking at where the citation links are weak. Weak links enable clusters to be split into separate topics.

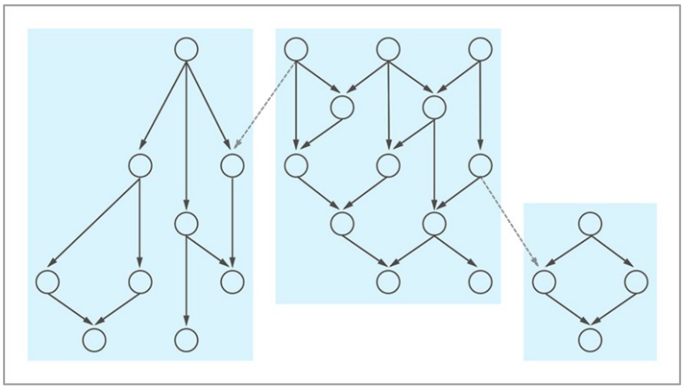

FIGURE 4-1
Depiction of publications being clustered into topics.
Source: SciVal website

Topic clusters are formed by aggregating individual topics with similar research interests together to form a broader, higher-level area of research. Topic clusters are formed using the same direct citation algorithm that creates the topics. When the strength of the citation links between different topics reaches a threshold, a topic cluster is formed. Each of the 96,000 topics can be classified within 1,500 topic clusters.

Topics and topic prominence analysis builds on the academic research conducted by Richard Klavans and Kevin W. Boyack (Klavans & Boyack, 2017; Small et al., 2014). Topics of prominence indicate the **momentum** in a particular field through ranking of topics according to prominence.

Topic prominence

Calculating a topic's prominence combines three metrics to indicate the momentum of the topic:

- **Citation count** in year n to papers published in n and n-1
- **Scopus views count** in year n to papers published in n and n-1
- **Average CiteScore** for year n

Prominence was developed as an indicator that would capture the momentum of topics and therefore has the potential to predict whether a topic will grow or decline in the near future, regardless of whether the topic is considered to be emergent or not. In the context of the current report, momentum therefore provides an indication where a research topic is more visible in terms of the attention it has received from the academic peers group. Prominence, however, should not be equated with importance, innovativeness, or newness.

Linking topics to key technologies

Since the key technologies are defined in this report through publications, it is possible to identify topic clusters within these publications set. As publications may relate to diffreent key technologies, topics may appear in different key technologies.

Emerging research topics

The analysis of the *burst score* is a further step on top of the *prominence score*. It can be considered a good method to predict the emerging research *topics* for each of the 44 key technologies, because their level of prominence in the most recent year is relatively higher than in the past 5 years with respect to other *topics* that map onto the same key technology.

4.2 Emerging topics

Burst analysis reveals for most of the domains and key technologies a rather mixed picture of emerging topics. BIOTECHNOLOGY AND LIFE SCIENCES, one of the focus areas for the Netherlands, has some emerging topics more on the biological side of BioCellTech rather on the technological side. EnMat is interesting, as it purely sees emerging topics in car battery technologies.

As mentioned in the previous section, topics are clusters of publications around the same research question. Usually, the three most relevant keywords are used to describe a topic, e.g. "*Object Detection; Deep Learning, IOU*" or "*Bioprinting; Three-Dimensional Printing; Tissue Engineering*". Given the large number of topics, these keywords are mostly high-level and it may be difficult to gain a deeper understanding of topics contributing to a key technology.

Therefore, the following analyses are in no way meant to be exhaustive but shall provide a high-level overview of topics that are emerging.

The burst score is an approximation of the trend of these topics, whether their prominence score is above other topics or not.

It should also be noted that usually there is a very long tail of topics that have only very few publications (but may have a high burst score). For this reason, FIGURE 4-2 limits the topics to a positive burst score and at least 50 publications from the Netherlands on that particular topic, in order to focus on research that is contributing already to topics.

The figure depicts the overall publications output versus the burst score, color-coded according to the key technology groups. Topics within the BIOTECHNOLOGY AND LIFE SCIENCES domain display a relatively high publication output, but burst scores are relatively low (except for two topics with a score between 8 and 10). ADVANCED MATERIALS, on the other hand, shows moderate output, but some emerging topics—a trend that seems to be similar for CHEMICAL TECHNOLOGIES.

One topic within the DIGITAL TECHNOLOGIES domain, *Object Detection; Deep Learning, IOU,* has the highest output of all topics plus a relatively high burst score (8.75), which may signal a field that is already high recognized, but still growing.

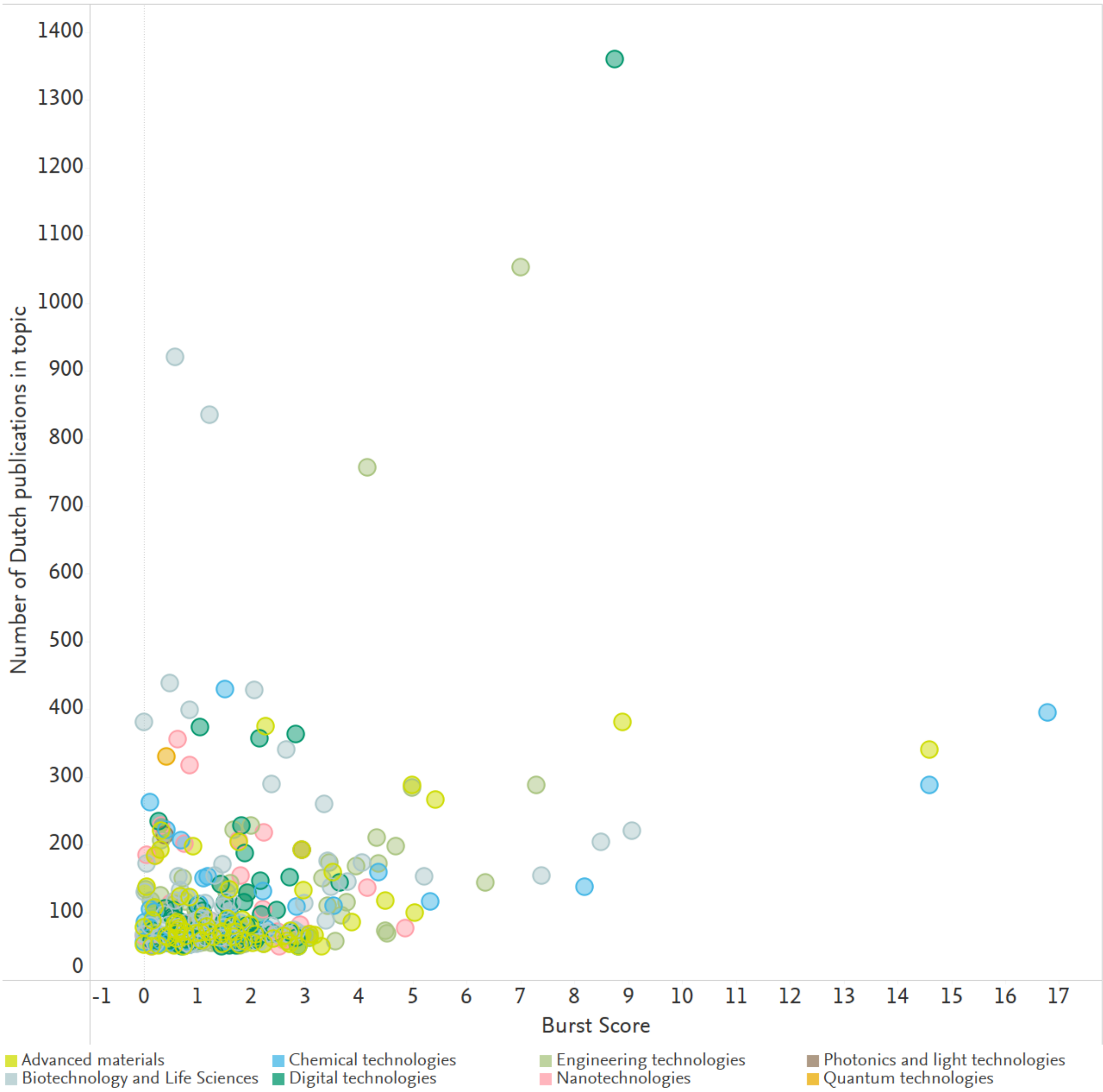

FIGURE 4-2
Number of NLD publications per topic (y-axis) and burst score (x-axis) for topics with at least 50 NLD publications and a positive burst score, 2013–2022. Color coding indicates technology domains.
Source: Scopus

The figures below give an overview of the topics with the highest burst score per key technology for the eight main technology domains. Again, a filter has been set for at least 50 publications from the Netherlands, and in addition the topics need to be amongst the top 10 topics by burst score. Therefore, not all key technologies may display 10 topics, as the filter criteria have not been met for all.

The topics are described by the three most relevant keywords appearing, which enables a rough description of the area of focus for the research. The keywords in the figures indicate though the content of the topics, while the middle numbers refer to as well as the number of Dutch publications (to focus on topics in which the Netherlands are already active) and the respective burst score (right hand column).

ADVANCED MATERIALS

Within ADVANCED MATERIALS, *Microcapsula; Urea Formaldehyde; Exchangeable Bond* appears as the topic with the highest burst score in three of the key technologies, which sounds be a bit surprising initially, but in fact this is used for self-healing elastomers and epoxy materials. In addition, it is proof of the overlap of key technologies since many publications classified as within one technology may appear in others, too. For EnMat, the burst score indicates a growing area of interest in battery technologies for cars and mobility, which would make sense given the "policy push" for these technologies.

ConStruct	Microcapsule;Urea Formaldehyde;Exchangeable Bond	88	4.87
	Shear Walls;Reinforced Concrete;Shear Strength	86	3.87
	Offshore Pipelines;Finite Element Analysis;Hyperbaric Chambers	50	3.30
	Silicic Acid;Hydration;Calcium Silicates	66	3.18
	High-entropy Alloys;Laves Phases;Entropy	68	3.08
EnMat	Plug-in Hybrid Vehicles;Energy Conservation;Energy Management	117	4.49
	Automobile;Alternative Fuel Vehicles;Electric Car	159	3.52
	Battery Pack;Electrode;Thermal Management	63	3.08
	Electric Vehicle;Vehicle-To-Grid;Charging	192	2.94
OptMat	Elastomers;Actuator;Nematic	69	2.87
	Demagnetization;Terahertz;Magnetic Switching	162	2.23
	Berry Phase;Holograms;Optics	50	2.22
	Power MOSFET;Heavy Ion;NAND	53	1.97
	Thermal Sensor;CMOS;All-Digital	82	1.81
	Superconductivity;Pseudogap;Charge Density Waves	52	1.78
	Qubits;Josephson Junctions;Microwave	64	1.67
	Strain Sensor;Flexible Electronics;Sensor	91	1.57
	Converter;Phase Locked Loops;Jitter	59	1.07
SmartMat	Microcapsule;Urea Formaldehyde;Exchangeable Bond	167	4.87
SoftMat	Membrane;Ultrafiltration;Chemical Cleaning	58	2.66
	Nucleus Pulposus;Intervertebral Disc Degeneration;Apoptosis	65	2.60
	Magnesium Alloys;Biodegradable Implant;Corrosion	50	2.52
ThinFilm	Microcapsule;Urea Formaldehyde;Exchangeable Bond	85	4.87
	Elastomers;Actuator;Nematic	103	2.22
	Demagnetization;Terahertz;Magnetic Switching	54	1.81

FIGURE 4-3
Top topics by burst score for ADVANCED MATERIALS, number of NLD publications and burst score, 2013–2022.
Source: Scopus

Biotechnology and Life Sciences

BioCellTech has the highest number of bursting topics and given that this key technology is the most prolific, this may not be surprising. It seems, however, that these topics relate more to the biological aspects of BioCellTech and less to the technological side.

BioCellTech	Single-Cell Analysis;Small Cytoplasmic RNA;Single Cell RNA Seq	125	4.53
	Bacteriophages;Phycodnaviridae;Microorganisms	102	4.25
	Bioinformatics;Biological Networks;Omics	77	3.70
	Nucleus Pulposus;Intervertebral Disc Degeneration;Apoptosis	76	3.39
	Acidobacterium;Chloroflexi;Microbial Communities	88	2.98
	Rhizosphere;Microorganisms;Mycobiome	113	2.84
	Anaerobic Ammonium Oxidation;Wastewater Treatment;Nitrogen ..	71	2.79
	Mendelian Randomization Analysis;Single Nucleotide Polymorphis..	74	2.69
	Bacterioplankton;Polynucleobacter;Bacteria	67	2.60
	Cellular Senescence;Cancer;Lipofuscin	80	2.37
Bioinformatics	Single-Cell Analysis;Small Cytoplasmic RNA;Single Cell RNA Seq	95	4.53
	Bacteriophages;Phycodnaviridae;Microorganisms	102	4.25
	Bioinformatics;Biological Networks;Omics	77	3.79
	Clinical Reasoning;Medical Education;Diagnostic Errors	145	3.70
	Health Level Seven;Electronic Medical Record;Clinical Trials	56	2.14
BioManufact	Nucleus Pulposus;Intervertebral Disc Degeneration;Apoptosis	77	2.60
	Microstructure;Titanium Alloy (TiAl6V4);Inconel (Trademark)	67	2.49

FIGURE 4-4
Top topics by burst score for Biotechnology and Life Sciences, number of NLD publications and burst score, 2013–2022.
Source: Scopus

Chemical technologies

Within Chemical technologies the key technologies again display a high level of overlap, since *Eutectics; Choline; Electroplating* appears for all key technologies in this cluster.

Analytics	Eutectics;Choline;Electroplating	87	4.87
	Microcapsule;Urea Formaldehyde;Exchangeable Bond	69	3.36
	Silicon Dioxide;Scorch;Treads	75	2.28
	Elastomers;Actuator;Nematic	131	2.22
	Strain Sensor;Flexible Electronics;Sensor	58	1.57
Catalysis	Eutectics;Choline;Electroplating	60	4.87
	Microcapsule;Urea Formaldehyde;Exchangeable Bond	114	4.10
	Peroxygenase;Enzymes;Marasmius	83	3.36
	Methane Production;Catalyst;Synthesis Gas	57	1.87
	Ziegler Catalyst;Ethylene;Magnesium Chlorides	55	1.76
ChemReact	Eutectics;Choline;Electroplating	87	3.36
	Membrane;Ultrafiltration;Chemical Cleaning	58	2.84
	Anaerobic Ammonium Oxidation;Wastewater Treatment;Nitrogen ..	109	2.66
ElectReact	Eutectics;Choline;Electroplating	87	3.36
	Battery Pack;Electrode;Thermal Management	63	3.08
ProcessTech	Eutectics;Choline;Electroplating	74	4.87
	Microcapsule;Urea Formaldehyde;Exchangeable Bond	105	4.10
	Peroxygenase;Enzymes;Marasmius	55	3.36
	Membrane;Ultrafiltration;Chemical Cleaning	58	2.66

FIGURE 4-5
Top topics by burst score for Chemical technologies, number of NLD publications and burst score, 2013–2022.
Source: Scopus

DIGITAL TECHNOLOGIES

Within DIGITAL TECHNOLOGIES, AI was the key technology with the highest number of topics, with a relatively wide range of topics. *Privacy Concerns; Online Shopping; Electronic Commerce* in CyberSec and *Triggered Event; Networked Control Systems; Multi-agent Systems* in DigiTwins stood out a bit for their high output for Dutch research.

AI	Music Information Retrieval;Music;Emotion Recognition	62	2.85
	Collaborative Filtering;Recommender Systems;Factorization	103	2.48
	Action Recognition;Convolutional Neural Network;Video Surveillance	97	2.18
	Activity Recognition;Wearable Sensors;Sensor	66	2.16
	Emotion Recognition;Facial Expression;Emotion	65	2.10
	Human-Robot Interaction;Humanoid Robot;Man-Machine Systems	60	2.08
CyberSec	Privacy Concerns;Online Shopping;Electronic Commerce	146	2.17
DigiConnect	Berry Phase;Holograms;Optics	50	2.87
	Antenna Arrays;Sidelobes;Sparse	65	1.88
DigiTwins	Triggered Event;Networked Control Systems;Multi-agent Systems	144	3.65
SoftTech	Scrum;Agile Software Development;Project Management	70	2.71
	Debt;Team Development;Software	69	2.41

FIGURE 4-6
Top topics by burst score for DIGITAL TECHNOLOGIES, number of NLD publications and burst score, 2013–2022.
Source: Scopus

ENGINEERING TECHNOLOGIES

SystEngi had the most bursting topics, as well as some relatively prolific topics with more than 100 publications. The topic *Object Detection; Deep Learning, IOU* was exceptional, with more than 600 Dutch publications within ImagingTech. This topic appears as well in other key technologies, but with a much lower publication output.

AddiManufac	Negative;Honeycomb Cores;Metamaterials	57	3.55
ImagingTech	Action Recognition;Convolutional Neural Network;Video Surveillance	75	2.18
	Object Detection;Deep Learning;IOU	647	1.93
	Breast Neoplasms;Cancer Classification;Histopathology	129	1.91
	Texture Analysis;Cancer;Fluorodeoxyglucose F 18	61	1.75
Microelectron..	Object Detection;Deep Learning;IOU	80	2.23
	Power MOSFET;Heavy Ion;NAND	53	1.97
	Thermal Sensor;CMOS;All-Digital	82	1.75
OptoMecha	Action Recognition;Convolutional Neural Network;Video Surveillance	97	2.18
Robotics	Elastic;Collision Detection;Human-Robot Interaction	72	3.17
	Pneumatic Actuators;Grippers;Robot	99	2.34
SensActuat	Triggered Event;Networked Control Systems;Multi-agent Systems	144	3.65
SystEngi	Triggered Event;Networked Control Systems;Multi-agent Systems	144	4.52
	Elastic;Collision Detection;Human-Robot Interaction	72	4.49
	Balanced Truncation;Model Reduction;Linear System	69	3.77
	Plug-in Hybrid Vehicles;Energy Conservation;Energy Management	73	3.67
	Trailing Edges;Airfoils;Aeroacoustics	115	3.65
	Adaptive Cruise Control;Connected Vehicles;Controller	95	3.17
	Nonlinear Dynamics;Contraction;Synchronization	66	2.99

FIGURE 4-7
Top topics by burst score for ENGINEERING TECHNOLOGIES, number of NLD publications and burst score, 2013–2022.
Source: Scopus

NANOTECHNOLOGIES

Previous chapters have already revealed that some key technologies within the NANOTECHNOLOGIES domain might be considered an area of strength for Dutch research. Within this domain, NanoMat has eight topics which match the selection criteria, with a rather wide range of topics. NanoMat is as well the key technology with the highest output (see section 2.2)

FuncDev	Demagnetization;Terahertz;Magnetic Switching	154	1.81
NanoBioTech	Nucleus Pulposus;Intervertebral Disc Degeneration;Apoptosis	59	2.60
	Magnesium Alloys;Biodegradable Implant;Corrosion	50	2.52
	Microstructure;Titanium Alloy (TiAl6V4);Inconel (Trademark)	71	2.49
NanoMat	Microcapsule;Urea Formaldehyde;Exchangeable Bond	77	4.87
	High-entropy Alloys;Laves Phases;Entropy	68	3.08
	Nanocrystal;Emulsions;Oil-Water Interface	82	2.91
	Elastomers;Actuator;Nematic	104	2.22
	Electrospinning;Nanofibers;Fiber	68	2.08
	Strain Sensor;Flexible Electronics;Sensor	61	1.57
	Nanobubbles;Bubble;Henry Law	59	1.07
	Scaffold;Polyethylene Glycol Dimethacrylate Hydrogel;Hyaluronic A..	76	0.88

FIGURE 4-8
Top topics by burst score for NANOTECHNOLOGIES, number of NLD publications and burst score, 2013–2022.
Source: Scopus

Photonics and light technologies and Quantum technologies

Both these technology domains displayed only one topic. In the Photonics and light technologies domain, for OptDetect it is again *Object Detection; Deep Learning, IOU,* and in the Quantum technologies domain, for QuaComm, it is *Qubits; Josephson Junctions; Microwave.*

OptDetect	Object Detection;Deep Learning;IOU	52	1.75
QuaComm	Qubits;Josephson Junctions;Microwave	52	1.67

FIGURE 4-9
Top topics by burst score for Photonics and light technologies (upper row) and Quantum technologies (lower row), number of NLD publications and burst score, 2013–2022.
Source: Scopus

Overall, the analysis of bursting topics does not reveal any surprising insights, but it supports a general sense of upcoming or growing niche areas, such as car battery technologies within EnMat.

It is necessary to remember, though, that prominence is not a measure of impact or quality, but of current attention to a particular research question. It may give an indication of future growth or decline but does not necessarily do so.

Conclusion

Although Dutch research has lower research activity on key technologies than comparator countries, its citation impact and breadth of excellent research position it among the leading countries in Europe and globally. Nevertheless, even greater focus and creating synergies with other European countries would be required to balance the research powers of China and the US.

This report was commissioned by the Dutch Ministry of Economic Affairs and Climate to conduct an objective, bibliometrics-based assessment of the Netherlands research base across 44 key technologies. This analysis supports the Dutch Ministry of Economic Affairs and Climate (Ministerie van Economische Zaken en Klimaat, MinEZK) in its development of a National Technology Strategy (NTS). The aim of the NTS is to form a vision as a basis for the allocation of resources to key technologies, thereby contributing to more efficient and targeted investment choices.

Overall Dutch research is highly productive, comprising almost 2% of the total research output of the world. Dutch research accrued 75% more citations than the global average and the breadth of excellent research is indicated by a share of 3% of the top 1% most highly cited publications in the period 2013 to 2022. This was the highest share across all European comparators.

Key technology research

Less than a third of Dutch total output was related to key technology research, which is lower than any comparator in this report. The citation impact and share of most highly cited publications was topped, however, only by Denmark and Luxembourg, signaling the high quality of Dutch research. Key technology research across the world was mainly driven in this period by China, which dedicated more than half of its research output to key technologies. Given the steep increase in China's research output, this may pose the threat of a monopoly, but the assessment of the technology monopoly risk revealed only few key technologies with a medium risk. Nevertheless, European countries should put more effort into this and consider gaining efficiency by using potential synergies on key technology research.

Focus areas

BIOTECHNOLOGY AND LIFE SCIENCES, DIGITAL TECHNOLOGIES, and QUANTUM TECHNOLOGIES are key domains with a relative activity above global average, strong citation performance and highly valuable patents, although it should be noted that Dutch research is strong across most of the key technologies. The enumerated domains, though, seem to already have a strong foundation for further development and focus. Within these domains, some of the key technologies stand out by number of publications or growth rates. BioCellTech is the most prolific key technology overall with more than 40,000 publications and BioInformatiocs displays an annual growth rate of almost 5%. Within QUANTUM TECHNOLOGIES, QuaComp and QuaComm grew by more than 6% annually (QuaSens with even 8% but based on only few publications overall). All of these key technologies display a relative activity above world and EU-15 level, and these are highly impactful.

Complex technologies

Based on the preliminary analyses on complexity and relatedness, it seems that Dutch research is already quite strong in rather complex technologies like within the

BIOTECHNOLOGY AND LIFE SCIENCES and parts of the DIGITAL TECHNOLOGIES (DataScience and SoftTech stand out with its relative activity already). The already mentioned QUANTUM TECHNOLOGIES appear to be quite complex, too, and might give the Netherlands a competitive edge.

Innovation potential

The Netherlands holds a strong position amongst the EU-15 countries with its patenting activities in the key technologies. BIOTECHNOLOGY AND LIFE SCIENCES and parts of the NANOTECHNOLOGIES seem to be focus areas with large portfolios and highly valuable patents.

Emerging topics

Within the key technologies, specific sub-topics may be of specific interest for Dutch research—like battery technologies within EnMat or self-healing elastomers and epoxy materials, which appears in various ADVANCED MATERIALS key technologies.

Conclusion

Overall, Dutch research has a strong impact on global research given its relatively small research base. Nevertheless, it should continue to create synergies with other European countries to balance the research powers of China and the United States.

Appendix A

Definition of key technologies

The concept of key technologies is defined in the Knowledge and Innovation Agenda for Key Technologies ("Kennis- en Innovatieagenda Sleuteltechnologieen", KIA-ST) as follows: "[Key technologies] encompass both Key Enabling Technologies (KETs) and the Future and Emerging Technologies from the European programs Horizon 2020 and its successor Horizon Europe. Key technologies are characterized by a broad scope of application or impact on innovations and/or sectors. They will significantly change the way we live, learn, innovate, work, and produce, offering opportunities to solve societal problems.[26]"

The Ministry of EZK requested advice from NWO and TNO to reevaluate the 2018 list of key technologies. The reevaluation process included desk research and expert consultation through written input, online group meetings, and physical meetings. The goal was to obtain a representative view for all key technology clusters. NWO and TNO developed a revised list based on initial research, which was refined through feedback from experts. The final version was discussed in physical meetings. The final summary of this process was published in March 2023 (van Bree et al., 2023).

The result was a list of 44 key technologies, grouped into 8 clusters. The clusters remained the same as in the previous iteration while the individual key technologies we comprised from 50 to 44 with some key technologies being changed or merged, some not changed at all. The eight domains are:

- Advanced materials
- Photonics and optical technologies
- Quantum technologies
- Digital and information technologies
- Chemical technologies
- Nanotechnologies
- Biotechnology and Life Science technologies
- Engineering and fabrication technologies

For visual reasons the key technologies are abbreviated throughout the report. The eight technology domains and their respective key technologies and abbreviations are presented in TABLE 4-1.

[26] Translated from van Bree et al., 2023.

Key technology group	Abbreviation	Key technology
Advanced materials	EnMat	Energy materials
	OptMat	Optical, electronic, magnetic and nanomechanical materials
	MetaMat	Meta materials
	SoftMat	Soft/bio materials
	ThinFilms	Thin films and coatings
	ConStruct	Construction and Structural materials
	SmaMat	Smart materials
Photonics and optical technologies	PhoVolt	Photovoltaics
	OptSystems	Optical systems and integrated photonics
	PhoDetect	Photonic/Optical detection and processing
	PhoGen	Photon generation technologies
Quantum Technology	QuaComp	Quantum computing
	QuaComm	Quantum communication
	QuaSens	Quantum sensing
Digital and information technologies	AI	Artificial intelligence
	DataScience	Data science, data analytics and data spaces
	CyberSec	Cyber security technologies
	SoftTech	Software technologies and computing
	DigiConnect	Digital connectivity technologies
	DigiTwins	Digital Twinning and Immersive technologies
	NeurMorph	Neuromorphic technologies
Chemical technologies	ProcessTech	(Bio)Process technology, including process intensification
	ReactEngi	(Advanced) Reactor engineering
	SepTech	Separation technology
	Catalysis	Catalysis
	AnalyticsTech	Analytical technologies
	ElectReact	Electricity-driven chemical reactor technologies
Nanotechnology	NanoManufac	Nanomanufacturing
	Nanomat	Nanomaterials
	FuncDevice	Functional devices and structures (on nanoscale)
	NanoFluid	Micro- and nanofluidics
	NanoBioTech	Nanobiotechnology / Bionanotechnology
Life science and biotechnologies	BioCellTech	Biomolecular and cell technologies
	BioSystems	Biosystems and organoids
	BioManufact	Biomanufacturing and bioprocessing
	BioInformatics	Bioinformatics
Engineering and fabrication technologies	SensActuat	Sensor and actuator technologies
	ImagingTech	Imaging technologies
	OptoMecha	Mechatronics and Opto-mechatronics
	AddiManufact	Additive manufacturing
	Robotics	Robotics
	DigiManufactTech	Digital manufacturing technologies
	MicroElectro	Micro electronics
	SystEngi	Systems engineering

TABLE 4-1
Technology domains, key technologies and abbreviations used in this report.

Publication set for each key technology

For each key technology a publication set covering all relevant publications was created.

In the previous report, these publications sets were defined through keyword- and concept-driven search queries in Scopus. Defining key technologies through keywords, however, poses some significant challenges (MacFarlane et al., 2022). A strict demarcation of key technologies is hardly possible, e.g., "Thin Films and Coatings" may (and certainly will) will overlap with other areas like "Nanotechnologies" or "Nanomaterials." Additionally, key technologies may influence each other, as developments in one key technology can lead to breakthroughs in others. And lastly, keywords used to describe a key technology or concept may be used in other contexts as well, which happens especially with rather broad terms. As an example, "Neural Network" may be used in the key technology "Artificial Intelligence" but as well in brain research (which may not be related to any key technology). A purely keyword-driven search query may not be distinctive between these fields.

Additonally, although a definition of a key technology can be (but is not necessarily) quite specific, the underlying keywords may be subjective based on the understanding of an expert on the field. While some experts may include some niche areas (with the respective keywords) into a key technology, others may exclude them. As another example, a broad keyword like "Artificial Intelligence" (or its acronym "AI") can appear not only in the description of the related key technology (provided that "Artificial Intelligence" is one of the 44 key technologies), but also in the description of several other key technologies (such as "Software technologies and computing" , "Digital Twinning and immersive technologies", "Neuromorphic technologies", "Systems engineering", "Bio-informatics", "Robotics", etc.). When dealing with broad keywords, it is important to restrict the search within relevant fields only, to avoid retrieving irrelevant results.

To further complicate the task, the above (as well as other) cases often appear together, i.e., the description of a given key technology can contain both very specific and very broad terms, can encompass or overlap with the descriptions of other key technologies, can have duplicated or hierarchical terms (for the latter, searching for the more general term automatically retrieves the more specific ones as is the case, for example, of the terms "AI" and "AI model"). In certain other cases, the description may also miss important keywords that are often used in relevant publications (e.g., in quantum computing the term "qubit" often appears in the titles and abstract of relevant publications, even when no other search terms among those selected to describe that key technology is present).

Other challenges for this process, given the number of key technologies, were timing and workload. The process used usually to define thematic areas through keyword-driven queries is time consuming and requires multiple rounds of feedback (with domain experts). To be able to define 44 key technologies in a rather short time, the approach used for this report had to be adjusted. Basically, the adjusted methodology could be split into four phases:

- Step 1. Precise core publication set through regex search, reviews, sources, and topics
- Step 2. Expanding through direct citations to get final publication set
- Step 3. Review by domain experts to assess precision (and recall, if possible)
- Step 4. Refinement of the final publications set, based on feedback from step 3.

Below follows a short description of these steps:

Step 1

Based on keywords defined in the joint process of NOW and TNO, a basic regex query[27] was created to search for a very precise set of core publications (through title, keywords and abstracts), identifying the most relevant journals titles and topics of prominence[28], i.e. the ones with at least 25% of the publications appearing in journal or topic. Publications from these sources have been included in the set. Once these relevant sources and topics have been identified, we searched for other similar sources and topics based on strong direct citation linkages (e.g., citations to or from the initial core set) with the initial set of sources and topics. From these similar sources and topics, the top 10% sources and the top 5% top topics (by share of direct citations) have been included. To further enrich the initial precise core, we identified all the review articles (as review is a separate document type in Scopus) included in the core and identified papers that are highly cited from these reviews, based on the assumption that reviews constitute a collection of relevant references for the field [29].

Step 2

To further increase recall, the set of publications created at Step 1 was expanded by direct citation links to and from other research outputs. A citation threshold of at least 25% of all citations to and from a core publication[30] was applied to retrieve related publications. Thresholds and parameters like the above-mentioned 25% are usually set through calibration throughout the application of a methodology by looking at precision and recall. For this project, internal simulations were performed to determine these heuristically, because of the mentioned time-sensitivity and scoping challenges.

Step 3

Precision and recall are basic components of bibliometric assessments based on publications sets. **Precision** (or “specificity”) gives the share of relevant out of all retrieved publications for a given key technology, e.g., if amongst 100 retrieved publications 98 are relevant and 2 are deemed irrelevant, the precision could be calculated as 98% (number of relevant = 98 / number of all retrieved = 100). **Recall** (or “sensitivity”) gives an estimate of the number or relevant articles retrieved as a proportion of all possible articles. Since the number of all possible publications is not known, it can only be estimated by a sample set of well-known publications. If 100 well-known and relevant publications are available and the publication sets includes 90 of these, recall can be calculated as 90% (90 included publications / 100 total possible publications). Recall and precision are always in a balance, a higher precision will result in lower recall and vice versa. To capture the key technologies as broadly as possible (similar to the rather broad keywords used to describe the key technologies), a 66% threshold for precision was used for the definition of the key technologies. Setting the threshold to two thirds of the randomly sampled checks was a choice made to counterbalance the variability in the expert feedback described below, because a more stringent threshold would not have fit with the range of different cases and opinions received by a control group of experts that does not necessarily coincide with the group of experts that created the definitions.

Random samples of the publication set (25 publications per set and per expert) were sent to domain experts (selected by MinEZK, NWO, and TNO) with the request to review the set and assign a relevance score. Additionally, the experts were asked to provide input on highly relevant articles, active authors, or active

[27] For a short introduction into regular expressions, see: https://en.wikipedia.org/wiki/Regular_expression

[28] I.e., where the precise core included at least 25% of the total publications appearing in the source or the topic, respectively. For additional details on topics of prominence, see: https://www.elsevier.com/solutions/scival/features/topic-prominence-in-science

[29] By considering all the reviews in the precise core and looking for top-cited papers from all these reviews, we benefited from the robustness of the aggregated effect of having multiple reviews pointing to these highly-cited papers, which can reasonably be assumed to be relevant for the field.

[30] I.e., at least 25% of the references of a publication citing publications in the set defined at Step 1, or at least 25% of the citations received by a publication coming from publications in Step 1.

institutions within their 'specific' key technology to assess recall. Although a definition of a key technology can be (but is not necessarily) quite specific, there is still a level of subjectivity within this definition. While some experts may include some niche areas (with the respective keywords) into a key technology, others may exclude them. This led to a few cases, when e.g., one expert rated 95% of the randomly selected publications as relevant, while another expert rated publications for the same key technology at only 60%. If several ratings per key technology were available, the arithmetic mean of precision scores was used. Another potential arose with the random set of articles, as some reviewers were expecting the most relevant (most highly cited or landmark publications), and their task was not absolutely clear to them. This understanding issue was solved by two virtual "walk-in" sessions in which the task and the methodology were explained to the attending experts. If the experts deemed the precision below 66%, additional refinements of the search query were carried out. If experts provided relevant publications, journal names or authors, it was checked whether these appeared in the final publication set.

It is worth noting that the experts who reviewed the results are not necessarily the same as those who created the description of the key technologies, hence they might have judged the results not in relation to the description given by NWO/TNO, but rather according to their own perception of the field.

On one hand, this characteristic created additional complexity, because the evaluation was not always performed with respect to the definition, but rather according to the personal judgment of the expert. Also, the concept of "relevance" of a randomly selected paper could have been misinterpreted (e.g., despite the guidance, in some cases the relevance was intended not as "is this paper related to the key technology?" but as "is this paper impactful for this technology?", thus yielding low precision scores to papers which were actually relevant for the key technology but judged of low quality by the expert).

On the other hand, despite the expected lower precision than a description-driven evaluation, the robustness of the feedback was higher, provided that—in such cases—the experts were not biased by the definition of the key technology given by NWO/TNO, but rather judged according to their own perception of the field. In this regard, a low precision score given to a randomly selected paper does not necessarily mean that the result retrieved is incorrect (hence it is not necessarily a "technical" error) but could also mean that the experience/perception of the expert is not necessarily aligned with the description given by NWO/TNO.

Step 4

For six key technologies (QuaComp, QuaSens, Nanofluid, Robotics, DigiManufact, SystEngi), even after refinement of the query, the threshold for precision could not be met. For these technologies, the selection criteria to determine the precise core were tightened (i.e., the thresholds used to select the topics, sources and reviews were increased) and, downstream, we also increased the above-mentioned direct citation threshold of 25% to 50%. This resulted in sufficient precision but lowered the recall as expected. Overall, the precision across all key technologies has been calculated at 81%.

Limitations of the methodology

As indicated already above, the definition of thematic areas (in this case key technologies) is a difficult task and many different approaches can be followed—each with its own limitations and challenges. For a good overview on various approaches, see Chapter 2.3 of the Handbook of Science and Technology Indicators (Glänzel et al., 2019).

The approach utilized in this report was employed taking various considerations into account. First of all, time and scoping were considered. Usually, although often connected with a subjective bias, the approach to use keyword-based search queries is deemed to result in the highest precision. It is, however, very time-consuming and results in a high workload for domain experts (for review) and evaluator due to multiple feedback rounds and the requirement to refine the queries multiple times. Therefore, this is a process not scalable to the creation of many thematic areas (i.e., key technologies) in a short period of time. More automated approaches usually tend to favor recall over precision, resulting in a high number of publications while including some publications outside the core of the key technology. This may limit the clear demarcation of key technologies, but on the other hand enables a broad overview of a field—which may be in line with the scope of the assessment.

The current methodology uses a similar balance, favoring recall over precision. This was reflected in the assessment of the experts, with an average precision of 81%, but a range between 68% and 100%. Increasing precision resulted in a lower recall. As an example, QuaSens had in the initial assessment a precision of only 56% with, in total, 31,000 publications. Refining the approach resulted in a precision score of 84% but reduced the recall to only 2,720 publications.

While this may be a relatively extreme example, this balance between precision and recall is one of the biggest limitations of any bibliometric assessment of key technologies. A very sharp delineation of key technologies using a very narrow and precise definition will likely increase the precision but lower the recall.

It needs to be noted, however, that the publications sets were defined at a global scale. Therefore, an assessment of key technologies across different countries will likely give reasonable results and insights generated are valid pointers into trends.

To give an idea on the size and precision of key technologies, TABLE 4-2 below summarizes the total number of publications and average precision score for each key technology. It highlights the different scope of key technologies via the different size of the publication sets as well.

Key Technology	Publication count	Precision score
EnMat	1074869	78%
OptMat	1755774	75%
MetaMat	113305	84%
SoftMat	488351	80%
ThinFilms	1243421	91%
ConStruct	1399627	83%
SmaMat	591537	100%
PhoVolt	321540	68%
OptSystems	164205	85%
PhoDetect	152658	72%
PhoGen	71631	76%
QuaComp	18995	92%
QuaComm	97283	68%
QuaSens	2720	84%
AI	1069218	92%
DataScience	42491	100%
CyberSec	285813	76%
SoftTech	219603	92%
DigiConnect	1748589	72%
DigiTwins	280159	72%
NeurMorph	51594	80%
ProcessTech	573853	88%

Key Technology	Publication count	Precision score
ReactEngi	620656	88%
SepTech	266387	66%
Catalysis	1039486	69%
AnalyticsTech	1472784	82%
ElectReact	737432	74%
NanoManufac	280659	69%
Nanomat	2376862	80%
FuncDevice	291390	84%
NanoFluid	95272	96%
NanoBioTech	559514	76%
BioCellTech	1407267	80%
BioSystems	106266	77%
BioManufact	324658	80%
BioInformatics	357420	71%
SensActuat	174175	76%
ImagingTech	777599	83%
OptoMecha	320623	88%
AddiManufact	148304	100%
Robotics	353890	88%
DigiManufactTech	156805	76%
MicroElectro	1023387	84%
SystEngi	1541313	96%

TABLE 4-2
Publication counts and assessment precision scores per key technology.

Appendix B

Comparators

This report benchmarks the Netherlands with 15 European countries, China, and the United States.

As wider benchmarks the aggregated group of EU-15 and the World are used.

Country or region	Abbreviation	Group
Austria	AUT	EU-15
Belgium	BEL	EU-15
China	CHN	CHN
Denmark	DNK	EU-15
Finland	FIN	EU-15
France	FRA	EU-15
Germany	DEU	EU-15
Greece	GRC	EU-15
Ireland	IRL	EU-15
Italy	ITA	EU-15
Luxembourg	LUX	EU-15
Netherlands	NLD	EU-15
Portugal	POR	EU-15
Spain	ESP	EU-15
Sweden	SWE	EU-15
United Kingdom	GBR	EU-15
United States	USA	USA
World	WLD	WLD

TABLE 4-3
Comparator countries and benchmarks used in this report with abbreviations.

Appendix C

Methodology and rationale

Our methodology is based on the theoretical principles and best practices developed in the field of quantitative science and technology studies, particularly in science and technology indicators research. The *Handbook of Quantitative Science and Technology Research: The Use of Publication and Patent Statistics in Studies of S&T Systems* (Moed et al., 2004) gives a good overview of this field. It is based on the pioneering work of Derek de Solla Price (De Solla Price, 1977), Eugene Garfield (Garfield, 1979) and Francis Narin (Pinski & Narin, 1976) in the United States, Christopher Freeman, Ben Martin, and John Irvine in the United Kingdom (Irvine et al., 1987) and researchers in several European institutions including the Centre for Science and Technology Studies at Leiden University, the Netherlands, and the Library of the Academy of Sciences in Budapest, Hungary.

The analyses of bibliometric data in this report are based upon recognized advanced indicators (e.g., the concept of relative citation impact rates). Our base assumption is that such indicators are useful and valid, though imperfect and partial measures, in the sense that their numerical values are determined by research performance and related concepts, but also by other, influencing factors that may cause systematic biases. In the past decade, the field of indicators research has developed best practices that state how indicator results should be interpreted and which influencing factors should be considered. Our methodology builds on these practices.

Throughout this report, analyses are limited to Scopus-indexed articles, reviews, and conference papers. We include these three publication types because they are an important and integral part of the research cycle: conference papers result from conferences where research ideas are first presented; these may then lead to original research that is published in articles; finally, original research is collated and summarized in reviews.

All analyses make use of whole counting rather than fractional counting. For example, if a paper has been co-authored by one author from the Netherlands and one author from Germany, then that paper counts towards both the publication count of the Netherlands and the publication count of Germany. Total counts for each country are the unique count of publications.

Glossary of terms

Citation is a formal reference to earlier work made in an article or patent, frequently to journal publications. A citation is used to credit the originator of an idea or finding. The number of citations received by a publication or patent from subsequently published articles is a proxy for the influence or impact of the publication. In this report, "citations" refer to citations by any Scopus-indexed publication, whereas citations made by other types of documents (e.g., patents, clinical guidelines) specifically reference the type of document that the citation was made in (e.g., as "patent citations" or "citations in clinical guidelines").

Competitive Impact measures the quality or usefulness of the patent to create a sustainable competitive advantage (Ernst & Omland, 2011). Thus, both the potential to create competitive advantage through important technologies (the impact of the patents as measured by Patents: Technology Relevance) and the potential to exploit that competitive advantage in large markets (the effectiveness of the patents to avoid imitation as measured by Patents: Market Coverage) must be considered simultaneously. High Technology Relevance combined with a large Market Coverage yields highly Competitive Impact, and advantage for the owner. A technology, however, is worth much less without a large market to exploit it. Likewise, broad international patent protection for weak technologies is of lower value too. The level of a patent's Competitive Impact should therefore be determined based on the combination of Technology Relevance and Market Coverage. Competitive Impact is defined as the product of a patent's Technology Relevance and its Market Coverage.

Compound annual growth rate (CAGR) is defined as the year-over-year constant growth rate over a specified period of time. Starting with the first value in any series and applying this rate for each of the time intervals yields the amount in the final value of the series.

Field-Weighted Citation Impact (FWCI) is an indicator of the citation impact of a publication (Purkayastha et al., 2019). It is calculated by comparing the number of citations actually received by a publication with the number of citations expected for a publication of the same document type, publication year, and subject. An FWCI of more than 1.00 indicates that the entity’s publications have been cited more than would be expected based on the global average for similar publications (by document type, year, and subject); for example, a score of 2.11 means the entity's publications have been cited 111% more than the world average. An FWCI of less than 1.00 indicates that the entity’s publications have been cited less than would be expected based on the global average for similar publications; for example, an FWCI score of 0.87 means the publications have been cited 13% less than the world average.

Market Coverage is a measure of the total size of the worldwide markets in which patent protection exists. The more patents a patentee (in this case an institution or a country the patent owners are affiliated with) owns in important markets, the more valuable the patents are estimated to be. This is because innovators spend more effort and resources on protection in multiple (global) markets via patents if they believe an invention is more valuable.

Market Coverage is calculated based on granted and pending patents, hence valid patents per country are adjusted for each market's size, as opposed to simple country counts. The size of each market is estimated using the sum of countries' gross national income (GNI) relative to the US GNI (as the largest global economy). A Market Coverage of 2 means that the protected markets are in total twice as large as the US market alone.

Patent portfolio is a collection of patents in a particular discipline which may represent parts of the accumulated knowledge in science and technology within that discipline. Growth in the number of patents of a given technology provides a good indication of its state of development.

Patent Asset Index is an objective measure of technological strength and innovation. It considers the entire patent portfolio and takes into account both the number of patent-protected inventions and their quality or value. The Patent Asset Index™ is defined as the aggregated Competitive Impact of all patents in a portfolio (Ernst & Omland, 2011).

Prominence Score is an indication of the momentum related to a particular topic. The Prominence Score is calculated by taking into account three metrics:

- Citation count in year n to papers published in n and n-1
- Scopus Views count in year n to papers published in n and n-1
- Average CiteScore for year n

Publication (unless otherwise indicated) denotes the main type of peer-reviewed documents published in journals: articles, reviews, and conference papers. It is used interchangeably with scholarly output in this report.

Relative activity index (RAI) is defined as the share of an entity's article output in a subject or topic relative to the global share of articles in the same subject or topic. For example, Dutch researchers published 15% of its articles in 2021 in chemistry, while globally 10%% of all articles published were in chemistry. The Relative Activity Index for the Netherlands in Chemistry is calculated as 15 / 10% = 1.5. A value of 1.0 indicates that an entity's research activity in a field corresponds exactly with the global activity in that field; a value higher than 1.0 implies a greater emphasis; and a value lower than 1.0 suggests a lesser focus.

Technology Relevance is based on forward citations. Technology Relevance measures whether a patent has been more often cited than other patents from the same technology field and year. The total number of patent citations received not only depends on the technology field of the patented invention but also on the time that has passed since the patent was published. Patents only recently published tend to have received much fewer citations than older patents. The time-dependency of citations is corrected by dividing the number of citations received by a patent by the average number of citations received by all patents published in the same year. **Technology Relevance** also considers that international patent offices follow different citation rules. Therefore, the number of patent citations is corrected for age, patent office citation practice, and technology field. It is a relative measure comparing one patent to other patents. A value of 2 means that the patent is twice as relevant for subsequent developments as an average patent in the same technology field and of the same age. Patent citations are divided into two main classes: backward citations and forward citations. Backward citations are those made to earlier patents (or publications) cited by a focal patent; they are often used as measures of knowledge transfer. In contrast, forward citations are those linked to a focal patent by patents filed after it and that list the focal patent as a backward citation. The number of forward citations a patent receives accumulates over time and appears to be correlated to the patent's (i.e., its underlying invention's) technological impact. Forward citations indicate the existence of downstream research efforts, suggesting that money is being invested in the development of the technology. Also, the fact that a given patent has been cited by subsequent patent applications suggests that it has been used by patent examiners to limit the scope of protection claimed by a subsequent patentee, to the benefit of society. In this sense, forward citations indicate both the private and the social value of inventions. Forward citations are commonly used to measure the technological impact of innovation (Aristodemou & Tietze, 2018).

TopX most highly cited publications are those among the top X% based on the FWCI of all articles published and cited in a given period. An institution's number or share of highly cited articles is treated as indicative of the excellence of their research. In this report, we present data on the top 10% and top 1% most cited articles.

Topics (as pertaining to Topics of Prominence) refer to nearly 96,000 research Topics created using the citation patterns of Scopus-indexed publications. The methodology for using citation patterns to define research Topics was developed through an Elsevier collaboration with research partners (Klavans & Boyack, 2017). The advantage of taking a citation-based approach to identify research Topics is that one need not rely on identifying all the relevant keywords to define a research area. Rather, the research area is delineated by citation patterns in the Topic, whereby research that appears in the same citation network is clustered together in the same Topic. This approach provides a more nuanced definition of the research Topic.

Appendix D

Data sources

Scopus

Scopus is a comprehensive, source-neutral abstract and citation database curated by independent subject matter experts who are recognized leaders in their fields. 91+ million items include data from 7,000+ publishers, 94,000+ affiliation profiles and 17+ million authors. Scopus puts powerful discovery and analytics tools in the hands of researchers, librarians, research managers and funders to promote ideas, people and institutions.

Delivering a comprehensive overview of the world's research output in the fields of science, technology, medicine social sciences and arts and humanities, our state-of-the-art search tools and filters help uncover relevant information, monitor research trends, track newly published research and identify subject experts. Worldwide, Scopus is used by more than 3,000 academic, government and corporate institutions and is the main data source that supports the Elsevier Research Intelligence portfolio.

LexisNexis PatentSight

LexisNexis IP is a LexisNexis company. It provides best-in-class information-based solutions and services to meet the needs of the intellectual property (IP) market, government agencies, and the life sciences industry.

PatentSight compiles bibliographic patent data from over 95 authorities worldwide and has the most comprehensive full-text patent data, with over 100 million patent documents in English, approximately 700 million drawings and illustrations of inventions, and nearly 100 million PDFs that are searchable (OCR) and quickly downloadable. Expert legal status determination enables analysis on only those patents that are still active—that is, pending patent applications and valid patents. This information is tracked over time, and using the Reporting Date concept PatentSight can also track the active portfolio of any set of patents from the year 2000 to today.

PatentSight identifies patent ownership based on extensive research on corporate structure, M&A, spin-offs, company name changes, and patent transactions, among others. To ensure state-of-the-art data quality, PatentSight's highly skilled team of experts focuses entirely on this task. The multilingual team ensures the highest data quality on patents filed in many languages, including English, Chinese, French, German, Japanese, Korean, and Russian.

The Patent Asset Index, PatentSight's scientifically developed proprietary patent evaluation metric, is used to identify leading or even disruptive technologies from the plethora of patents available.

Appendix E

Composite indicator and Complexity/Relatedness

Composite indicator

As mentioned in the report, composite indicators which compare country performance are increasingly recognized as a useful tool in policy analysis and public communication. They integrate various indicators and therefore may enable a rather quick overview across various dimensions. On the other hand, "their 'big picture' results may invite users (especially policymakers) to draw simplistic analytical or policy conclusions. In fact, composite indicators must be seen as a means of initiating discussion and stimulating public interest. Their relevance should be gauged with respect to constituencies affected by the composite index."[31] Best practice for creation of composite indicators including a ten point checklist can be found in the *Handbook on Constructing Composite Indicators: Methodology and User Guide* (OECD et al., 2008).

In general, the composite indicator utilized in this report integrated relative activity index (RAI) and field-weigted citation index (FWCI). Both individual indicators may be connected, but they have no direct correlation (i.e., a higher RAI does not lead automatically to a higher FWCI), which is relevant for the theoretical framework behind.

The most basic construction for composite indicator of just two variables would be the average of the underlying indicators. Assessing Spearman[32] and Pearson correlation matrizes of this calculation indicated that the FWCI would drive the composite indicator quite heavily, so this approach was discarded. Various tests revealed that sqarerooting resulted in an effective equalization of the contributions of FWCI and RAI to the composite indicator. Therefore, this route was taken in creating the composite indicator.

The chosen indicators (RAI_sqrt, FWCI_sqrt) have then been subsequently normalized and re-scaled to make them fit for purpose. Standardization was performed using the z-score method. It is calculated by subtracting the population mean from an individual raw score and then dividing the difference by the population standard deviation, in this case by (('RAI_sqrt') – ('mean_RAI_sqrt')) / ('stddev_RAI_sqrt').

The absolutes of the min standardized scores are added to the standardized scores so they are all on the positive side. Re-scaling between 0 and 1 would re-introduce unequal variance across indicators. Instead, the min scores are added and later (post-aggregation) the values are bound to 1 (or 100) as the max scores. This maintains the gain in terms of equilibrating the contribution of each variable to the composite score.

Finally, the average of both transformed indicators was calculated to result the final composite indicator. Composite = ('RAI_scaled' + 'FWCI_scaled')/2.

Further tests showed that the contribution of both indicators appears to be rather equal (instead of favoring one indicator over the other).

31 (OECD et al., 2008)

32 The Spearman correlation between two variables is equal to the Pearson correlation between the rank values of those two variables; while Pearson's correlation assesses linear relationships, Spearman's correlation assesses monotonic relationships (whether linear or not). For further reading on this, see https://en.wikipedia.org/wiki/Spearman%27s_rank_correlation_coefficient

Complexity and Relatedness

Based on previous work by Balland and Boschma (Balland et al., 2019; Balland & Boschma, 2020), a new approach was tested for complexity and relatedness. The concept of the above paper was to use technometric (later in combination with scientometric) data to inform a data driven policy framework to inform smart specialization (or diversification) strategies.

The idea is to advise a given entity (e.g., typically a region) on new areas (technologies/research topics) of high complexity in which it would be best placed to diversify its activities because it can build on other local related capabilities in which it has strength. Because expertise in areas of high complexity are known to be more difficult to replicate, such a diversification strategy would therefore provide a region with a strong competitive advantage to help it reap the economic benefits of its R&I activities by leveraging its existing strengths.

The concepts have so far been applied on patent data and on a regional level. For this report, it is required to use publication data on a national level. Therefore, it needs to be noted that the current analysis is an exploratory analysis which requires additainal validation. The results, however, are according to preliminary tests sound and in line with the results retrieved by Balland and Boschma. Balland and Boschma utilized co-occurrence analysis in their approach to define relatedness and measured the complexity of a technology based on the combinations with other technologies mentioned in a patent. Both comcepts have similarities with concepts used in bibliometric analyses. Relatedness can be estimated as a network indicator showing the similarity (or closeness in a network) while complexity seems to relate to specialization (similar to relative activity but based on all key technologies).

The specializations were log-transformed into a matrix of countries and technologies and subsequently into a pearson correlation matrix. Further transformations resulted in the network parameters (used to depict FIGURE 2-18).

Complexity was calculated by transformations into eigenvectors and eigenvalues of the country/technology matrix and subsequent normalization and re-scaling.

In addition to the relatedness itself, the relatedness density was calculated. While the relatedness indicates the general relatedness of key technologies across global publications, the relatedness density[33] for a region or country gives insights into the regional availability of knowledge and capabilities. The higher the value of relatedness density, the higher the number of other technologies related to a particular technology in which a given country shows revealed technological advantage.

33 The relatedness around a key technology in a region is measured by dividing the sum of the relatedness of the key technology with all other technologies in which the region specializes by the sum of the relatedness of the key technology with all technologies in the world as a whole.

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