Transdisciplinary Development of Neuromorphic Computing Hardware for Artificial Intelligence Applications: Technological, Economic, Societal, and Environmental Dimensions of Transformation in the NeuroSys Cluster4Future

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Abstract Artificial Intelligence (AI) promises economic growth and solutions to global problems but also raises societal concerns. Training AI models has a big carbon footprint due to data processing in fossil-fuel-reliant data centers. If the data centers are outside the European legal space, data processing incurs privacy risks. Besides, reliance on AI aggravates Europe's dependence on non-European chipmakers, whose supply chains can be disrupted. To address such concerns, NeuroSys develops energy-efficient neuromorphic hardware tailored to AI applications that protect privacy by processing data locally. NeuroSys aims to build a chip plant near Aachen in Germany to support Europe's technological sovereignty. This depends on an innovation ecosystem where socio-technical transformations emerge in transdisciplinary collaboration. This chapter introduces NeuroSys as a testbed for studying

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how transformation research can contribute to the sustainability and trustworthiness of AI Made in Europe.

Keywords Transformation research · Transdisciplinary collaboration · Innovation ecosystem · Neuromorphic computing · Artificial intelligence

1 Introduction

The promise of AI to transform society for the better has been promoted by tech-companies, scientists, and policymakers since the early 2010s. In the meantime, AI has become so efficient and fast in processing large amounts of data that it can be applied in many economic sectors. AI is not only considered to be the key technology for future economic growth across the globe (Aghion et al. 2018); it is also described as a driving force for achieving the United Nations Sustainable Development Goals by tackling global challenges related to the future of work, climate change, and health care (Vinuesa et al. 2020). AI systems can help companies and public administrations to reduce resource consumption, produce less waste, and optimize energy efficiency in production processes (Nishant et al. 2020). It can further monitor and predict environmental changes to support decision-making in precision agriculture and ecosystem management (Plattform Lernende Systeme 2022). The societal relevance of AI was recently emphasized during the Covid-19 pandemic, when it enabled contact tracing, provided diagnosis support, and contributed to workplace safety (Sipior 2020).

Yet, these promising narratives are accompanied by a growing critical discourse on the ethical, material, and political challenges that AI poses (for an overview, see Garvey 2021). Ethical concerns may refer to the transparency and reliability of AI (Campolo and Crawford 2020). While AI is a generic term used in diverse ways in the media and public discourses (Collins 2021; Nguyen and Herman 2022), technical experts usually use the term to refer to machine learning (algorithms build a model based on sample or training data to make predictions) and deep learning (a subset of machine learning whose algorithm structure mimics the human brain). As it is difficult to understand, even for experts, how deep learning algorithms transform input into output, concerns about transparency and reliability arise, especially in those cases where algorithms are involved in decision-making that affects human beings (e.g., advice on employment) (Campolo and Crawford 2020). This opacity may conceal the fact that automated decisions reinforce existing discrimination due to biases that an algorithm picks up from training data (Benjamin 2019; Chun 2021). In addition, the big data requirements for training algorithms lead to data protection and privacy considerations, for instance, in cases where the algorithms use personal data and make inferences about sensitive information (Hu 2020; Murdoch 2021). In response to these ethical concerns, the European Commission (2020) aims to build a regulatory framework for "trustworthy AI" (p. 10) that protects personal data, privacy, and non-discrimination.

While the socio-ethical impacts of AI applications have been widely discussed over the last decade, the material backbone of these applications has only recently gained attention (Coeckelbergh, 2021; Crawford 2021; Denkena 2021; Van Wynsberghe 2021). The materiality of AI is becoming increasingly relevant because high-performance applications, for example in natural language processing, rely on training large-scale models which takes weeks of computing time, costs hundreds of millions of dollars, and leaves a considerable carbon footprint. Moreover, the production of electronic devices on which AI runs consumes a lot of energy and makes extensive use of plastics as well as raw materials, such as cobalt and aluminum. AI-embedded short-lived end user devices require frequent replacement of these materials whose extraction and disposal incur environmental costs. In recognizing these costs, the European Green Deal suggests incorporating environmental impacts assessments into policies that incentivize sustainable AI applications (Gailhofer et al. 2021).

The material backbone of AI, in particular the production of semiconductor chips, also invokes political concerns. Global manufacturers of semiconductor chips are mainly located in Asia and the USA (Brown and Linden 2011). The global chip shortage during the Covid-19 pandemic revealed the vulnerability of supply chains (Hess and Kleinhans 2021). Moreover, in light of rising protectionism related to a "US-China trade war" (Bown 2020, p. 1), European access to computer chips is threatened (Varas and Varadarajan 2020). To increase resilience toward supply chain disruptions and to strengthen Europe's position in the semiconductor industry, the European Chips Act will provide public investment in support of regional chip design and production (Von Der Leyen 2022). A large part of this investment will feed into the development of energy-efficient transistors for AI applications (ibid.).

In line with European policy-making efforts to address the ethical, material, and political challenges posed by AI, the German Ministry of Research and Education (BMBF) funds the NeuroSys Cluster4Future, which was launched in 2022. NeuroSys is a high-tech innovation cluster that seeks to build an innovation ecosystem around the development of neuromorphic computing hardware for AI applications in the Aachen region of Germany. Neuromorphic computing denotes a computer chip architecture that emulates the neural network of the human brain. This chip architecture is expected to be more energy-efficient than computer hardware, which is based on graphic processing units that are commonly used for training AI models. Not only does energy-efficient neuromorphic hardware promise to reduce AI's carbon footprint, it can also foster data security and privacy because it can be used for mobile edge-computing devices, like sensors and smart watches. These devices process data locally rather than sending them to cloud services owned by foreign companies whose operations do not fall under European data protection laws. To develop neuromorphic computing hardware in tandem with AI applications that respect data protection and privacy concerns, NeuroSys bundles expertise from scientists, engineers, social scholars, industrial professionals, and municipal actors in an emerging innovation ecosystem. The innovation ecosystem consists in an interacting set of diverse actors whose collaboration facilitates the transfer of research results into business models and supports a long-term vision of the project: building a semiconductor chip plant in the Aachen region that will produce neuromorphic computing hardware tailored to specific AI applications for autonomous driving, personalized health care, smart cities, the Internet of Things, and digitalization. A local chip plant would support European sovereignty in the semiconductor industry and place European values (e.g., democracy, open innovation, responsible AI) at the center of chip development. To orient innovation processes toward European values and to incorporate societal considerations in research and development, NeuroSys pursues a transdisciplinary approach that builds structures for innovation ecosystem governance.

The aspirations of NeuroSys go beyond those of ordinary high-tech innovation initiatives because the cluster is not only committed to achieving technological excellence, but also to building an innovation ecosystem in which social, environmental, and economic considerations are integrated in research and development processes. The cluster is thus a prime example of the model of transformation research introduced in this edited volume. By bringing the model from theory into practice, NeuroSys will reveal the opportunities and challenges that emerge in the research process. In this way, it will make valuable contributions to discourses on transformation research (Kollmorgen et al. 2015; Wittmayer and Hölscher, 2017), Responsible Research and Innovation (Owen et al. 2012; Von Schomberg et al. 2013), and adjacent fields, such as integrative research (Fisher et al. 2015; Schikowitz and Maasen 2021), ELSI/A (Ethical, Legal & Social Impacts/Aspects) research (Balmer et al. 2016a; Zwart et al. 2014), and anticipatory governance (Barben et al. 2007; Guston 2014). NeuroSys will help to assess the practical feasibility of transdisciplinary transformation research for contributing to trustworthiness and sustainability of AI made in Europe.

This chapter presents the NeuroSys Cluster4Future as a practical implementation of the Aachen model of transformation research (Letmathe et al., this volume).[1] After introducing the technological background and organizational structure of NeuroSys in more detail, the chapter elucidates how NeuroSys addresses the technological, economic, societal, and environmental dimensions of the model. In this way, the chapter showcases the holistic transdisciplinary approach of NeuroSys, which treats social and technical transformations as being inextricably linked. While the chapter emphasizes the opportunities of such an approach, it also reveals the challenges that may emerge in the implementation phase.

[1] Letmathe et al. (this volume) use 'transformation research' as an umbrella term for three different positionings of research in the transformation process: (1) transformation research which observes and analyzes transformation processes, (2) transformational research that aims at shaping transformation processes, and (3) research transformation which refers to a change in research itself. We do not distinguish between these positionings in this chapter, because NeuroSys endorses all of them. The chapter is included in the section on transformational research in this edited volume because most of the research activities described here fall under this category.

2 Neuromorphic Computing

While the recent history of the semiconductor industry reveals that it has always been forced to adapt to various crises (Brown and Linden 2011), chipmakers now face a fundamental challenge: to explore new ways of organizing a chip that matches recent breakthroughs in AI. Training large AI models on modern microprocessors—central processing units (CPUs) and graphic processing units (GPUs)—consumes high amounts of energy (Prytkova and Vannuccini 2022). A major reason is the von Neumann architecture, in which processing and memory units are implemented as separate blocks interchanging data intensively and continuously on a computer chip (Von Neumann 1945). This data transfer is responsible for a large part of a chip's power consumption while also slowing down the processing speed of the system. These energy and speed costs associated with the continuous movement of data are commonly referred to as the *von Neumann bottleneck*. Recent analyses indicate that increasing demand for computing power in AI applications will likely outpace improvements of digital computing on modern microprocessors (Amodei and Hernandez 2018; Lohn and Musser 2022).

To meet the demands of AI, one possibility is to embrace different software-hardware system architectures, such as neuromorphic computing, which may offer advantages over digital computing for specific applications (Waldrop 2016). To develop neuromorphic computing chips, researchers take inspiration from the brain (Mehonic and Kenyon 2022). In contrast to the von Neumann architecture, there is no separation between data storage and processing in the brain since neurons and synapses perform both functions. Information processing in the neural network of the human brain consumes on average 20 watts; this is several orders of magnitude less energy than what an artificial neural network of the same size requires (ibid. citing Wong et al. 2012). The exceptional capabilities of the brain inspired electrical engineering already in the late 1980s, when Carver Mead at the California Institute of Technology coined the term "neuromorphic computing" to denote systems and devices that mimic some functions of biological neural systems (Mead 1998). As activities under the label have continued to evolve and diversify over the years, the precise definition of "neuromorphic computing" has become a matter of debate (Mehonic and Kenyon 2022; Schuman et al. 2022). In communities of chipmakers, neuromorphic computing generally refers to the engineering of brain-inspired modes of computing. Brain-inspired computer chips can evade the von Neumann bottleneck through in-memory computing. This means that, similarly to the human brain, a single device co-locates memory and processing, which eliminates constant data transfer and significantly improves the system efficiency (Fig. 1). Examples of neuromorphic chips are the Loihi from Intel (Davies et al. 2018) and the True North, a joint venture of IBM and DARPA (Merolla et al. 2014). The True North has a power density of 1/10.000 that of most modern microprocessors (Hsu 2014).

The True North and the Loihi are specialized chips. Whereas CPUs are used for general-purpose chips on which a range of programs can run, software needs to be tailor-made for neuromorphic computing hardware (Prytkova and Vannuccini 2022).

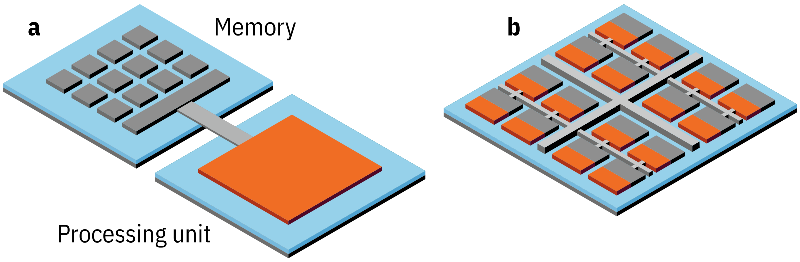

Fig. 1 **a** von Neumann architecture and bottleneck between memory and processing unit and **b** neuromorphic chip architecture

To develop software-hardware system architectures for neuromorphic computing, researchers from multiple disciplines (e.g., physics, material science, software engineering, computer science) need to work together. For these researchers, the following topics are of special interest: neuromorphic materials and devices, neuromorphic circuits, neuromorphic algorithms, applications, and ethics (Christensen et al. 2022). The NeuroSys Cluster4Future addresses these topics by organizing experts from various academic disciplines and industry sectors into distinct projects that engage in collaborative relationships with one another.

3 Organization of the NeuroSys Cluster4Future

The NeuroSys Cluster4Future consists of five projects A–E, each focusing on a different research topic. These topics correspond to the expertise of neuromorphic computing researchers at three prominent research institutes in the Aachen region of North Rhine-Westphalia: RWTH Aachen University, Research Center Jülich, and the non-profit enterprise AMO GmbH. These institutes have previously worked together in NEUROTEC, a research partnership funded by the BMBF since 2019 to develop energy-efficient neuromorphic computing hardware for AI applications in cooperation with industrial partners from the region. Several researchers and companies involved in NEUROTEC from the fields of physics, material science, neuroscience, computer science, and electrical engineering also participate in NeuroSys and have co-created the technical projects A–D (Fig. 2). These projects map onto the value chain of neuromorphic computing, ranging from research on material components of computer chips over the integration of such components in hardware-related circuit designs to case studies on applications of neuromorphic hardware.

Projects A and B focus on basic research. Project A studies the characteristics of memristors; these are material components which have the ability to change their resistance depending on the applied voltage or current. This ability makes them suitable for representing the weights between neurons in an artificial neural network. Memristors are thus important components for creating a hardware architecture that

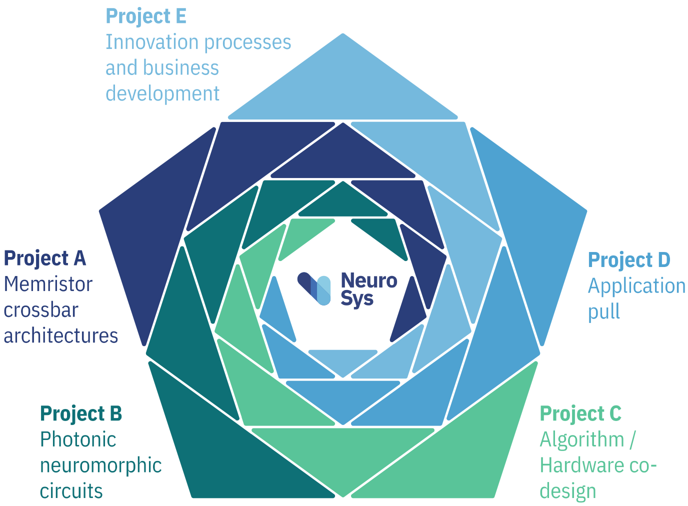

Fig. 2 Organization of the NeuroSys Cluster4Future

is inspired by the neural network of the human brain. While project A draws on microelectronics, project B examines optical signal transmission in neuromorphic hardware. That means that it focuses on using light, rather than electronics, to encode and transmit information. In comparison with electronic signal transmission, optical systems reduce latency and enable high data transmission rates. Researchers from projects A and B collaborate to study the combination of electronic and photonic approaches in neuromorphic hardware.

To exploit the technological potential of neuromorphic hardware for AI systems, project C brings together expertise from hardware-related circuit design, automated system design, and neuroscience. The aim is to develop innovative circuit architectures based on the properties of novel devices and material systems. By means of characterization and modeling, the complexity of the hardware is reduced to aspects that are relevant for exploration on an algorithmic level. In turn, the development of algorithms poses specific requirements for the device properties of neuromorphic hardware. Insights from neuroscience provide impulses for both hardware and software development.

With a focus on software development, project D investigates use cases of neuromorphic hardware. The goal is to prepare and optimize software from specific application areas for neuromorphic hardware. High-performance computing combined with relatively low energy consumption enables the processing of sensitive or time-critical data at the point of use (edge computing). Such potential benefits of neuromorphic hardware for specific AI applications will be evaluated with performance measures.

In addition to the technical projects, NeuroSys includes an additional project—project E—that works further along the value chain, examining the societal dimensions of neuromorphic computing research and development. Project E facilitates an economically viable, ethically robust, socially desirable, and environmentally sustainable development process for the innovations emerging from projects A to D. Economists develop business models and analyze value chains to support the successful market entry of these innovations. Professional management of patent licensing is provided so that the research institutions and industry partners of the cluster can benefit economically from the research results. Social scientists and ethicists study and contribute to the emergence of an innovation ecosystem around neuromorphic computing technologies that takes societal considerations and European values into account in research and innovation processes. As sustainability is considered as a key value, they also help NeuroSys project members to assess and address the environmental impacts of neuromorphic computing research and development.

While the basic outline of the NeuroSys project organization is expected to remain relatively stable, the work pursued within the projects will be dynamic, with actors, expertise, and interests joining the projects over the course of the nine-year funding period. For example, project E may recruit additional researchers with a background in sustainable development and life cycle assessment to deepen investigations on the environmental aspects of neuromorphic computing products. It may also strengthen collaborations with municipal officials from Aachen and neighboring towns as well as societal stakeholders (e.g., environmental groups) when the vision of a local chip plant comes closer to realization. Moreover, the Cluster4Future funding scheme requires NeuroSys to attract industry partners for participating in and financially supporting the cluster. The aim is to stimulate the market transfer of emerging technologies early in the research and development process.

Collaborations between NeuroSys projects, industrial actors, and societal stakeholders are an important condition for the realization of the project goals. As the spiral in Fig. 2 illustrates, these collaborations are intended to intensify over the course of the project duration so that research questions, activities, and outcomes from the different NeuroSys projects and partners will become more intertwined over time. The practical conditions necessary for such close intertwining to occur are regular meetings, joint seminars, and workshops (for examples of these, see Sect. 4.4.). In addition, NeuroSys researchers may have the opportunity to shadow the activities of a foreign project within the cluster to gain a better understanding of other disciplinary norms, practices, and cultures. Another example is the recently initiated NeuroSys Academy, a series of seminars in which early-career researchers explain the basics of their disciplinary fields to one another, discuss work-in-progress, and discover shared interests. The central objective is to cultivate communication, collaboration, and learning across disciplinary divides.

4 Transformation Research in NeuroSys

In considering the NeuroSys Cluster4Future as a whole, the orchestration of its diverse activities resembles project designs in the field of transformation research. The field spans various discourses and approaches rooted in the social sciences

(Heyen and Brohmann 2017). They range from sustainability transition studies and transition management (Geels and Schot 2007; Loorbach 2010; Rip et al. 1998), over innovation studies (Ömer-Rieder and Tötzer 2004; Smith et al. 2010), diffusion research (Rogers 1995; Wilson 2012), and change management (Boje et al. 2012), to literature on post-growth and sufficiency (De Saille et al. 2020; Jackson 2009; Stengel 2011). While there is little consensus on the definition of transformation (Feola 2015), the following examples tend to be associated with the term: the shift towards a low-carbon future (Foxon et al. 2013; Geels 2018), changes in media and communication sparked by the Internet and smart phones (Dolata and Schrape 2013; Küng et al. 2008), and "smart agenda[s]" (Köhler et al. 2019, p. 15) for mobility, urban development, and product manufacturing (Luque-Ayala and Marvin 2015; Manders et al. 2018; Van Agtmael and Bakker 2016). What these examples have in common is that they associate the introduction of new technologies with wider changes in society, economy, and geography. However, what makes a change transformative, whether transformation is radical and/or gradual, and how transformation relates to other concepts, such as transition, regime shift, resilience, and adaptation are topics of discussion in transformation research (Köhler et al. 2019).

This chapter sidesteps these discussions because transformation research in NeuroSys is not predominantly a social science endeavor. Although it resembles engaged social science approaches that initiate and shape transformation processes while describing and analyzing them at the same time (Herberg et al. 2021; see also Feola 2015; Heyen and Brohmann 2017), transformation research is considered as a transdisciplinary undertaking in NeuroSys in which all projects (see A–E in Sect. 3) participate. In NeuroSys, transformation research refers to science and technology development that is intertwined with societal, economic, and regional changes, while also reflexively engaging with processes and outcomes of change. Science and technology development can be considered as reflexive if the researchers involved can position themselves and their work within these wider changes to capture and anticipate how they themselves shape and are shaped by such changes (Stirling et al. 2006).

As these definitions are closely aligned with Letmathe et al.'s (this volume) model of transformation research, this chapter is structured according to the four dimensions of that model: technology, economics, society, and environment. In applying these dimensions to NeuroSys, the chapter demonstrates how a holistic transdisciplinary approach to transformation research can be put into practice. While the technological dimension elaborates on the kinds of technologies developed in the cluster, the economic dimension assesses their potential to enter and transform markets. The societal dimension discusses how building an innovation ecosystem around neuromorphic computing shapes—and is shaped by—structural, political, and cultural changes in the region. Both the societal and the environmental dimension further elucidate how an innovation ecosystem can be steered in order to support socially desirable, ethically acceptable, and environmentally benign research and innovation processes.

4.1 Technology

Technology development in NeuroSys is characterized by a co-design of neuromorphic hardware and tailor-made software. Whereas the design of hardware and software is split traditionally by a well-defined interface—the ISA (Instruction Set Architecture)—new processing principles in the neuromorphic computing domain promote a sequential approach: material and devices are defined first and inform the subsequent development of architectures, algorithms, and applications (Schuman et al. 2022). Quite differently, NeuroSys engages in a co-design process all across the design hierarchy (Fig. 3). In this co-design process, specific needs of algorithms and applications can influence the development of novel devices and material systems; at the same time, novel algorithms and learning models are developed that exploit the technical capabilities of neuromorphic hardware (Aimone 2021). Hence, the high performance of neuromorphic hardware at low energy consumption is a result of innovative connections between new materials and devices and the functions of entire AI systems (Chakraborty et al. 2020).

These connections are subject to a "technology push" and an "application pull" (Grunwald 2019, p. 76). On the one hand, results from basic research on materials and devices can push the development of algorithmic approaches. For example, emerging hardware devices inspired by the plasticity of the human brain can stimulate the development of new neuromorphic computing algorithms, which match how plasticity functions on these devices (Parsa et al. 2020). On the other hand, applications can pull hardware development into specific directions. The accuracy demands of applications can help to define the requirements of a specific crossbar implementation as well as the size and number of crossbars in a corresponding System-on-Chip. The push–pull dynamic requires hardware and software developers to engage in a continuous collaborative process of alignment, for instance,

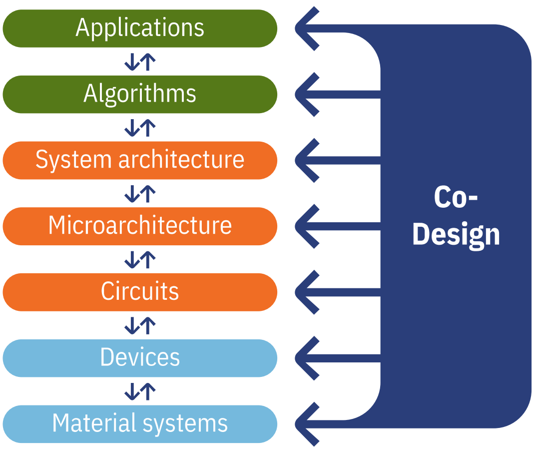

Fig. 3 Algorithm-hardware co-design

between the compute complexity required for highly-performant applications and the capabilities of neuromorphic hardware.

In NeuroSys, the application pull is stronger than in ordinary high-tech projects because industry actors are involved in early stages of the research and development process. Their involvement focuses on use cases of neuromorphic computing technology. Although there is currently no commercial neuromorphic computing technology available, Schuman et al. (2022) predict two wide areas of AI applications. First, neuromorphic computers could accelerate AI operations on personal computing devices, such as smartphones, laptops, and desktops. Neuromorphic accelerators improve battery life by realizing AI operations with significantly less power than today's state-of-the-art accelerators.

Second, low power consumption of neuromorphic hardware is also relevant for edge-computing applications. Edge computing refers to a type of computing where data analysis and processing are performed close to the points of data generation. Instead of sending data to a cloud service for remote processing, edge computing allows data to be processed locally, which supports data security and privacy by reducing network traffic (De Salvo 2018; Li and Huang 2021). These features are relevant for the following application areas: autonomous systems, such as vehicles and drones (Viale et al. 2021); remote sensors, especially in energy-constrained environments (Vanarse et al. 2017); robotics (Cheng et al. 2020); wearable technology and prostheses (Daus 2022; Osborn et al. 2018); and the Internet of Things, which is of particular interest in industrial contexts and smart homes (Fayyazi et al. 2018; Liu et al. 2017).

From this range of potential applications, four use cases are investigated in NeuroSys:

1. A *camera-based measurement device* will be developed for medical applications. The device will generate visual and thermal images of wounds whose diagnoses will be made with the help of neural networks. As the device is supposed to be mobile and light, it could be used in hospitals and care facilities.
2. A *speech recognition and translation system* will be built that relies on edge computing. The system will enable real-time language translation on mobile devices, such as smartphones.
3. A basic technology of *semantic video analysis* will be created for application in different domains. Examples are video editing on smartphones, segmentation of organs on medical images, and tracking of traffic participants in intelligent vehicles.
4. An *invasive medical controller* will be developed, which helps to adjust treatment measures to the changing biological measurements of a patient through reinforcement learning algorithms. Such a medical controller could be an artificial pancreas or a pacemaker.

These cases were selected because they all rely on energy-efficient hardware for mobile use but vary in terms of data: visual and thermal images, oral speech and written texts, video recordings, and biological measurements such as blood glucose concentration and heartbeat. These kinds of data have different features and their processing must satisfy specific demands. For example, the data rate of an artificial pancreas is low, but the device must be highly accurate in predicting treatment measures. Video segmentation systems, by contrast, must handle relatively large volumes of data, but the importance of accuracy varies per application (e.g., video editing for personal use vs. traffic tracking in autonomous cars). By tailoring algorithms to these use cases, NeuroSys tests the potential of neuromorphic computing hardware to satisfy diverging application demands. Moreover, speech recognition and language translation systems as well as semantic video analysis were selected as use cases because they depend on complex AI models which have high demands for their underpinning hardware. Hence, these technologies are "hard" use cases and could become prototypical benchmarks for the development of neuromorphic hardware.

NeuroSys researchers assess whether neuromorphic hardware is as performant as conventional hardware in working with hundreds of millions of parameters. Whereas neuromorphic computing hardware has been shown to outperform conventional microprocessors in terms of energy efficiency (Hsu 2014), Schuman et al. (2022) state that there is yet to appear an AI application for which neuromorphic computing is superior to other deep learning approaches in terms of accuracy (the number of an algorithm's correct predictions divided by the number of its total predictions). The authors anticipate a variety of challenges that could stifle the growth in neuromorphic algorithm and application development, for instance the lack of established benchmarks and metrics to evaluate which hardware system is most suitable for a given application and the integration of neuromorphic computing in a heterogenous computing environment. More specifically, Zidan et al. (2018) outline materials and device challenges of memristor-based neuromorphic hardware as it is developed in NeuroSys.

While enumerating the technical challenges of neuromorphic hardware development would go beyond the scope of this chapter, it is important to emphasize that they indicate a gap between expectations and reality. The history of microelectronic reveals that it can take a long time for such a gap to be closed. It took nearly four decades from the postulation of the memristor by Chua in 1971 until scientists from Hewlett Packard labs made the first operational memristor (Chua 2018; Mainzer 2022). Sometimes, the expectation-reality gap was never closed; several microelectronic devices (e.g., the Josephson junction and molecular electronics) promising to provide alternatives to the dominance of conventional silicon chips were studied for decades but failed to reach practical application and disappeared from view (Mody 2017).

Neuromorphic hardware is nowadays available in research communities, but it has not been used in real-world applications yet. However, market researchers and developers of neuromorphic computing technology predict that neuromorphic chips will be available on the market in about 3–5 years (La Barbera and Huang 2022; Yole Report 2021). Although these predictions are promising, NeuroSys has set itself an ambitious agenda. As the hardware systems and applications studied in NeuroSys primarily target prototype demonstrations in the first three years of the funding period, the cluster starts its activities on a mid-level technology readiness level. This means that the cluster seeks to facilitate an early market transfer of a technology under development whose commercial competitiveness is a topic of ongoing investigation—a task further advanced by the economic dimension of NeuroSys.

4.2 Economics

The economic dimension of NeuroSys supports one of the cluster's main objectives: achieving technological sovereignty for Europe in semiconductor and AI research, development, and production. This objective is aligned with the European Chips Act adopted in 2023. After years of decline in semiconductor investment (Fig. 4), the Chips Act aims to increase Europe's share of global chip production capacity to 20% from its current level of about 10% (Timmers 2022). As the global chip crisis exposed supply chain vulnerabilities which led to production stops (Pennisi 2022), the Chips Act strives to bring parts of the value chain to Europe.

In support of European technological independence, NeuroSys seeks to build an innovation ecosystem in the Aachen region, where neuromorphic computing chips will be designed and produced in close collaboration with companies that incorporate these chips in their products. To ensure the long-term usability of the innovations that will arise from NeuroSys, the economic dimension will evaluate possible business models. Moreover, the value chains of neuromorphic chips and associated products will be mapped to assess their feasibility with regard to its organization structure and the necessary competencies along the value chain. It is important for the establishment of neuromorphic hardware and software in the respective markets to identify possible cost savings, which can affect both the production and the use of the hardware. For this

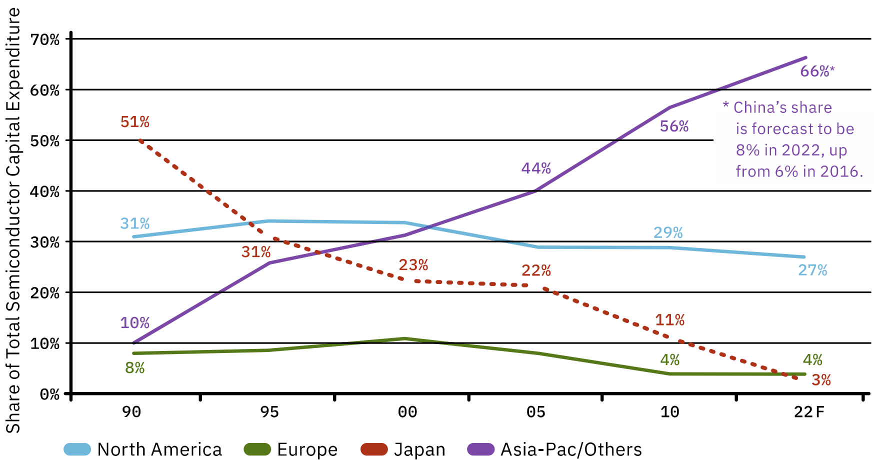

Fig. 4 Semiconductor capital expenditure by headquarter locations (IC Insights cited by European Commission 2022, p. 74)

reason, the study of the cost structures and value chains relevant to the production of neuromorphic hardware and software must be analyzed in detail. The same applies to the markets in which the resulting innovations are applied. This research is a prerequisite for commercializing NeuroSys innovations; it will also inform later analyses of external costs as well as quantifications of socio-environmental impacts.

To stimulate and inform entrepreneurial activities in and around NeuroSys, the economic dimension will quantify the target market potential of neuromorphic computing technologies. The market potential can be assessed on the basis of applications for which neuromorphic computing offers tailored solutions (see Sect. 4.1). However, the market potential of these applications is difficult to estimate at present because neuromorphic computing hardware has not yet reached market maturity. While the exact amount of neuromorphic computing hardware in future applications is still unknown, these applications can be organized into three categories. First, existing applications will be supplemented by neuromorphic hardware. Second, some applications will stimulate a production shift toward neuromorphic hardware because neuromorphic hardware is equally—or better—suited to performing a specific task. Here, the monetary benefit of the unique advantages of neuromorphic hardware will determine when the underlying technology of existing applications will be changed. Third, novel applications will emerge that are not possible or even conceivable with current hardware.

The first two categories target a certain share of existing markets. One of those markets is AI. According to a Statista (2022a) report (using the forecast from International Data Corporation), the global AI market is expected to reach up to 552.3 billion U.S. dollars by the year 2024. This includes hardware (server, storage), software (applications, software platforms, system infrastructure software, application development and deployment), and services (business services, IT services) (ibid.). The market size of machine learning, deep learning, supervised learning, unsupervised learning, reinforcement learning, natural language processing, context-aware computing, and computer vision is estimated to reach 227.46 billion U.S. dollars by 2024 and is expected to rise to 1,591 billion U.S. dollars by the year 2030 (ibid., using the forecast from GlobeNewswire). These estimates emphasize the growing demand for AI applications. Considering only the market for AI hardware, the market revenue is forecast to grow from 15.7 billion U.S. dollars in 2022 to 70.9 billion U.S. dollars by 2026 (Statista 2022b). A major customer of AI hardware will be the automotive industry, whose market size is expected to increase from 30 billion U.S. dollars in 2020 to 55 billion U.S. dollars by 2025 (Statista 2022c).

Although the specific market penetration of neuromorphic computing cannot be anticipated accurately at present, the general market predictions for neuromorphic applications are promising. Therefore, NeuroSys could have an impact on the competitive development of the wider high-tech sector and could transform the labor market in the Aachen region. Students, researchers, engineers, and other professionals will be attracted to the region both for education and employment in neuromorphic computing research, development, and production. To establish a platform for expert training, the university and further organizations involved in NeuroSys plan to develop and offer new fields of study as well as degree programs.

In this vein, university education will be complemented by learning opportunities for industry employees with the support of business development agencies, such as RWTH Innovation GmbH and the Chamber of Commerce and Industry Aachen. Hence, NeuroSys' investments in the local semiconductor workforce complement the high investments of the European Chips Act in semiconductor manufacturing (Heck 2022). This step is crucial to build an innovation ecosystem around neuromorphic computing technologies, which secures their long-term economic success.

4.3 Society

The societal dimension of NeuroSys focuses on the social order which enables and supports the emergence of an innovation ecosystem around the development of neuromorphic computing hardware in the Aachen region. Although the notion "innovation ecosystem" has been adopted with diverging meanings by academic, management, and policy-making discourses (Autio and Thomas 2021; Chhillar 2022), it is used here to denote an interacting set of actors who seek to realize the assumed beneficial outcomes of innovation (Adner 2017). The establishment of such an innovation ecosystem is an essential driving force for the socio-technical transformation process, which Van Agtmael and Bakker (2016) describe as a shift from "rustbelt" to "brainbelt" (p. 23). The authors use the American term "rustbelt" for areas in the USA and Europe which were once powerful industrial sectors but then experienced decline due to the elimination or outsourcing of manufacturing. They observe that some former rustbelts have become brainbelts: local research and development of smart products transform regions into innovation hubs. This transformation is driven by a collaborative ecosystem of universities, small and medium-sized companies, start-ups, local authorities, and a variety of supporters and suppliers. The reason is that one single research institute or company is not in a position to pursue the development of smart products, like computer chips, new materials, biotechnology, and medical devices. To tackle the complex tasks of developing smart products and transferring them into the market, transdisciplinary collaborations need to be established. An innovation ecosystem provides the social, material, and institutional conditions for such collaborations to emerge.

To transform the Aachen region—formerly a coal mining area—into an innovation hub, the NeuroSys project seeks to create an innovation ecosystem around the development of neuromorphic computing hardware. The NeuroSys cluster pools a transdisciplinary set of actors from RWTH Aachen University, Research Center Jülich, the non-profit Research and Technology Organization AMO GmbH, and regional technology companies as well as start-ups. The cluster is not a closed entity; it is the nucleus of an expanding innovation ecosystem. A resource for the organic growth of the ecosystem is the advisory board, which includes regional, national, and European members from science, industry, and society. All involved actors constitute a dynamic system which connects the research and development activities anchored in the cluster with innovation initiatives stimulated by external partners, such as the

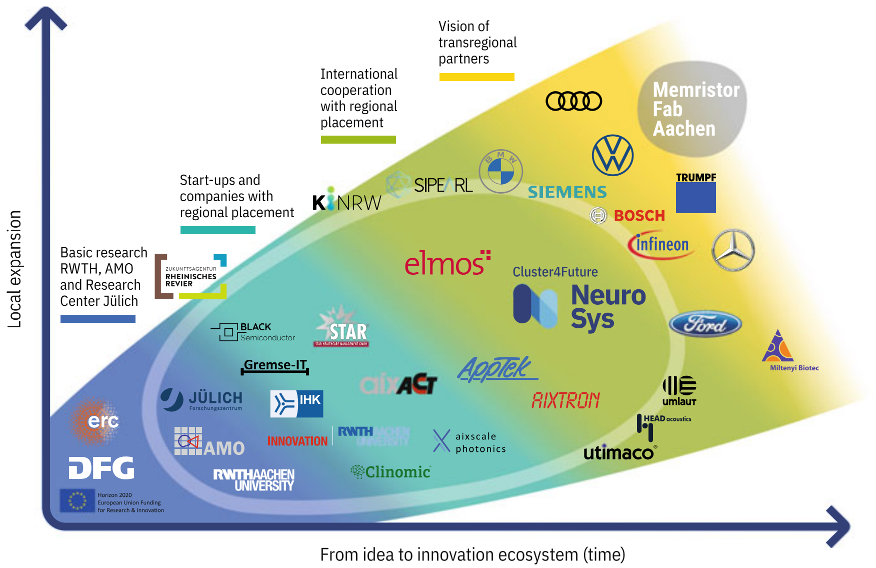

Fig. 5 Innovation ecosystem emerging around neuromorphic computing technology in the Aachen region[2]

City of Aachen, the regional competence platform KI.NRW, and European projects launched under Horizon 2020 and Horizon Europe. NeuroSys is thus a "connector" (Van Agtmael and Bakker 2016, p. 26): an organized group with the vision, the relationships, and the motivation for catalyzing the emergence and growth of an innovation ecosystem (Fig. 5).

To study the development of an innovation ecosystem from a social science perspective, different strands of literature are combined. The *multi-level perspective* is instructive for analyzing transformation processes of socio-technical systems (Geels 2004; Geels and Schot 2007). It distinguishes between three levels: a cultural, political, and material landscape, socio-technical regimes constituted by the practices of different actor groups, and the niche which is the nucleus of innovation. Climate change and associated political calls for sustainable AI, for example, in the European Green Deal (Gailhofer et al. 2021), can be regarded as pressures in the landscape. These pressures create instability in the regimes (e.g., technological and product regime, science regime, user and market regime) which preserve the existing socio-technical system around the use of GPU-based hardware for AI applications.

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[2] The figure displays the logos of companies who are a) official members of the NeuroSys Cluster4Future, b) members of the external advisory board, and c) potential cluster members. The following companies belong to the different groups: a) AiXscale Photonics, Black Semiconductor, Clinomic, Gremse-IT, AixACCT Systems, AppTek, RWTH Innovation, STAR Healthcare Management, AIXTRON, ELMOS Semiconductor; b) BMW, Bosch, ELMOS Semiconductor, Ford, HEAD acoustics, Infineon, Siemens, SiPearl, Utimaco, Umlaut; c) Audi, Mercedes-Benz, Trumpf, Miltenyi Biotec.

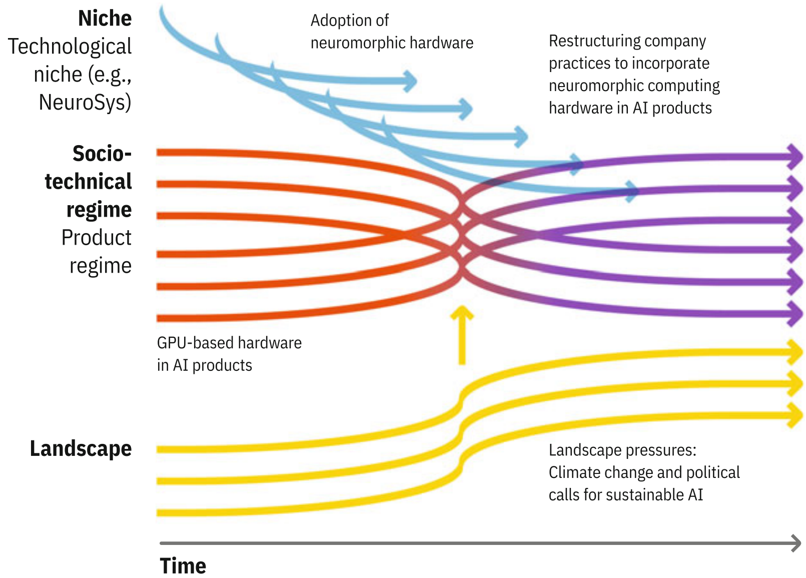

Fig. 6 Multi-level perspective on the transformation pathway of neuromorphic computing hardware (adapted from Geels and Schot 2007, p. 407)

Neuromorphic computing hardware may take advantage of such instability and may break through markets once it has been sufficiently developed in the technological niche of NeuroSys, i.e., a space protected by public subsidies and strategic company investments (Fig. 6).

For a new technology to move out from a niche into companies and markets, *quadruple helix collaborations* can support the transfer. Quadruple helix collaborations are a form of research and innovation in which actors from research institutes, industry, government, and civil society collaborate toward realizing a shared innovation goal (Carayannis and Campbell 2009). Such collaborations are important, especially if public subsidies for technology development come with high political and societal pressure on researchers to find a solution to a grand challenge. These pressures may induce researchers to continue working on the seemingly promising technological solution despite negative outcomes (Geels and Raven 2006). To avoid hype-backlash dynamics (Garud and Karnøe 2003), technological niches could incentivize researchers to flexibly adjust technology development and evaluation routines in response to continual feedback by users, policy makers, and special-interest groups. Such multi-stakeholder learning can occur in quadruple helix collaborations.

The opportunities and challenges that arise from bringing together diverse groups of actors in collaborative projects have been studied in historical and social science scholarship (Mody 2017; Nguyen and Marques 2021; Popa et al. 2020). Collaboration and networking provide support for knowledge sharing, but they depend on relationships of trust. The reason is that research groups and companies may fear the loss of competitive advantage due to knowledge leakage (Bogers 2011; Chesbrough 2003), especially in the current geopolitical climate of the semiconductor industry, where "technology theft" by Asian competitors is suspected (Li et al. 2021, p. 122). While non-disclosure agreements among universities and companies may be time-intensive and cumbersome (Berlin 2017; Parthasarathy 2017), the creation of legal and technological frameworks around a new technology can facilitate market entry in the long run. The development of reporting and benchmarking guidelines across research fields and streamlining quality, security, and sustainability standards across markets and national contexts supports the inclusion of the technology in existing infrastructures, processes, and products (Cheng et al. 2022; Van Den Ende and Kemp 1999).

Another aspect of quadruple helix collaborations is the *participation* of societal stakeholders. Participation has become a key concept in social science literature on the production of knowledge and innovation (Kimura and Kinchy 2019; Lezaun et al. 2017). It is often considered to be the defining feature of "transdisciplinary research," which denotes the collaboration between researchers and non-academic actors (Defila and Di Giulio 2015). Despite the ubiquitous talk about the importance of transdisciplinarity in academic and policy discourses, empirical research on practices of participation reveals that inputs from societal stakeholders and wider publics are often not included in innovation processes (Felt et al. 2012a, 2016; Irwin et al. 2012). One reason is that stakeholders have different interests, goals, and perspectives, which may be in tension with one another (Blok et al. 2015a, b). The tension between economic profit and socio-ethical considerations has been widely discussed in business ethics and responsible innovation literature (Garst et al. 2017; Hahn et al. 2018), and practical strategies to manage this tension have been proposed (Almquist et al. 2016; Long and Blok 2017; Porter and Kramer 2011).

Building on this literature, a holistic approach that takes socio-ethical considerations into account in the process of research and development is embedded in NeuroSys. The following list provides examples of such considerations:

- *Trust in AI:* Social acceptance of AI technologies is conditioned on trust in these technologies (O'Neill 2018; Thiebes et al. 2021). Trust is breached if AI output discriminates on the basis of race, gender, or age, or if data security cannot be warranted (Amoore 2020; Benjamin 2019; Chun 2021).
- *Human autonomy and AI:* Research has shown that users of AI systems are concerned about these systems violating their autonomy, for instance, by paternalistic nudging or impoverishing capacities for self-determination through increasing deferral of decision-making processes to algorithms (Laitinen and Sahlgren 2021; Nagel 2016).
- *Sustainability of AI:* The production of neuromorphic computing hardware is likely to have environmental costs, for example with regard to the extraction of minerals, water, and fossil fuels, which can be undergirded by pollution, extinction, depletion, and war (Crawford 2021; Letmathe and Wagner 2018).

The societal dimension of NeuroSys does not only study the socio-ethical aspects of neuromorphic computing but also helps to sensitize actors in the innovation ecosystem to these aspects. The aim is to facilitate the governance of a "responsible innovation ecosystem" (Smolka and Böschen 2023; Stahl 2022). Responsible innovation ecosystem governance is conceptualized as a "capacity" (Fisher 2007; Guston 2014; Guston and Sarewitz 2002) of actors to integrate the societal dimensions of research and innovation into their work. As capacities are shaped by wider political, institutional, and material structures, it needs to be investigated which socio-technical architecture of the innovation ecosystem supports socio-ethical reflection and responsible decision-making. The evolution of the innovation ecosystem around NeuroSys is thus a socio-technical transformation in which reflexive technology development, collaborative innovation, and responsible governance are intertwined. Instead of probing consumer and public reactions once a specific neuromorphic computing technology is ready for purchase, societal acceptance emerges in a collaborative process of "integrative" (Fisher et al. 2015) research and development. For this purpose, social and technoscientific experts continuously collaborate with one another, rather than engaging in a division of labor. A division of labor is common in technical projects with an add-on social science task force, such as in typical forms of *Begleitforschung* (Kromrey 2017; Schikowitz and Maasen 2021). NeuroSys, by contrast, builds an ecosystem linking social and technological innovation inextricably with each other. In adopting this approach, NeuroSys could become a role model for other regions, technologies, and research projects.

4.4 Environment

NeuroSys seeks to introduce neuromorphic computing to AI-dominated software domains, such as computer vision, speech recognition, and autonomous decision-making, where conventional computer hardware reaches its limits of performance and energy efficiency. High energy demands for training neural networks with deep learning methods are of environmental concern because energy is currently not derived from carbon–neutral sources in many locations, and, where renewable energy is available, it might be better allocated elsewhere (Strubell et al. 2019). Strubell et al. estimate that the process of training a deep-learning natural language processing model consumes roughly the same amount of energy as five cars over the cars' lifetimes (ibid., p. 1). In light of the global climate change crisis, algorithms that can perform mental tasks may not be worth the environmental costs. NeuroSys aims to create more "sustainable AI" (Van Wynsberghe 2021) which reduces the environmental impacts (e.g., carbon footprints) of developing and using AI models.

The environmental dimension of NeuroSys approaches sustainable AI holistically by not equating sustainability with energy efficiency but by adopting a broader view: critical interrogations of "techno-fix" narratives accompany technology development. Techno-fix narratives are based on a dominant rationality in society and policy-making according to which global challenges like climate change can be "fixed" by technological innovation that is advanced by technoscientific experts (Ludwig et al. 2021). Speculative technological innovations are cast as solutions to biodiversity, public health, and climate change crises (Thomas 2015). These narratives do not acknowledge that complex issues like climate change are "wicked problems" (Peters 2017; Rush 2019) that have neither a straightforward problem definition nor a solution because they can be approached from different disciplinary perspectives and may affect stakeholders in drastically different ways. A critical interrogation of a techno-fix narrative related to neuromorphic computing asks whether switching to more energy-efficient computer hardware will indeed reduce the carbon footprints of AI applications. To answer this question, the environmental dimension of NeuroSys follows Bratton's suggestion: "If we really want transformation, we have to slog through the hard stuff (history, economics, philosophy, art, ambiguities and contradictions). Bracketing it off to the side to focus just on technology, or just on innovation, actually *prevents* transformation" (Bratton cited in Thomas 2015, p. 93).

Historical, economic, and societal considerations need to be considered when exploring the relations between neuromorphic computing technology and carbon emissions because of the so-called "rebound effect" (Santarius 2012, 2015; Santarius et al. 2016). The concept denotes an increased energy demand that is driven by efficiency improvement. Santarius distinguishes between different types of rebound effects to explain why energy efficiency improvements often fail to translate into adequate absolute reductions of energy service demand. From the diversity of rebound effects that could be related to neuromorphic computing, two examples are presented here. A *financial rebound effect* may occur if neuromorphic computing hardware is used for new energy-intensive multi-feature AI applications rather than for making existing products more energy-efficient. *Material rebound effects* can result from (a) the energy consumed in the research, development, and production process of neuromorphic computing hardware, and (b) in building new capacities as well as infrastructures necessary for the implementation of this new type of hardware in products.

As neuromorphic computing hardware is still in its research and development phase, the aforementioned rebound effects are hypothetical. Yet, sensitizing researchers, technology developers, industrial actors, and societal stakeholders to potential rebound effects early on in the process helps them make decisions that are oriented toward sustainability goals. In light of financial, material, and structural rebound effects, it is important to balance the economic and social desirability of AI services and products against their environmental costs before investing in their development. An environmental outlook is not only relevant in the "upstream" design and "downstream" regulation of a technology, but also in the "midstream" of research and development (Fisher et al. 2006, p. 490). Välikangas' (2022) case study indicates that global challenges like climate change play an important role in the design and grant proposal writing of research projects, but that their relevance diminishes in later stages as other targets gain precedence, in particular academic excellence. The author suggests that one way of enhancing the interconnection between research and grand challenges is to encourage actors involved in research and development to reflect on the social, ethical, and environmental dimensions of their day-to-day work. Along these lines, NeuroSys incorporates reflexive exercises (i.e., dialogues, group discussions, multi-stakeholder workshops) in the midstream of research and development that probe actors to consider the environmental aspects of neuromorphic computing technology in everyday decision-making (cf. Fisher 2007). In approaching sustainable AI as a socio-technical phenomenon rather than as a technological fix, careful deliberation is required to decide what kinds of applications could be supported by neuromorphic computing in which contexts and at which social, environmental, and economic costs.

5 Conclusion

In applying Letmathe et al.'s model of transformation research to the NeuroSys Cluster4Future (Fig. 7), this chapter highlights that technological, economic, societal, and environmental dimensions of transformation are deeply intertwined. The technology development in NeuroSys introduces a shift away from conventional hardware for AI applications toward neuromorphic computing alternatives, whose emulation of the human brain promises significant energy efficiency and performance improvements. This technological transformation goes hand in hand with economic developments. Successful market entrance of neuromorphic hardware depends on the emergence of a competitive innovation ecosystem that can co-exist and merge with the current regime, sustaining the use of GPUs for AI applications (Dattée et al. 2018; Prytkova and Vannuccini 2022). At the same time, if neuromorphic computing hardware outperforms state-of-the-art technology, it may also accelerate the growth of such an innovation ecosystem. This will become visible in corresponding societal transformations in the Aachen region. NeuroSys plays into regional visions of transforming the Rhenish area into an "innovation valley" (ZRR 2021, p. 222) populated by skilled researchers, engineers, and professionals working at smart manufacturing plants or in co-working spaces within repurposed industrial buildings. The cluster is thus interlinked with the structural transformation of the Rhenish area, where the coal phase-out opens up "experimental spaces of transformation" (Böschen et al. 2021, p. 227) for innovative projects to participate in reshaping the region.

This chapter further emphasizes that active participation in shaping the technological, economic, societal, and environmental dimensions of transformation requires reflexive engagement with technology development and its wider contexts. Following Herberg et al. (2021), who claim that transformation research can only be scientifically grounded, fruitful for society, and ethically responsible if it engages in radical reflexivity,[3] a self-critical ethos is intended to become a defining feature of NeuroSys. To cultivate this ethos, stepping out of disciplinary and professional comfort zones and experiencing disconcerting differences (Hillersdal et al. 2020, p. 74; Smolka

[3] "Diese Ansätze [der Transformationsforschung] können jedoch nur wissenschaftlich fundiert, gesellschaftlich fruchtbar und ethisch verantwortungsvoll gestaltet werden, wenn sie mit einer radikalen Selbstreflexion verbunden sind." (Herberg et al. 2021, p. 7).

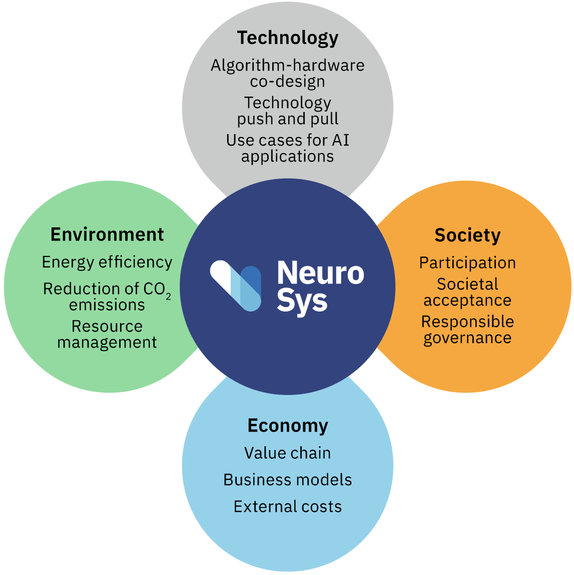

Fig. 7 Aachen model of transformation research applied to NeuroSys

et al. 2021) is a common practice in the cluster—not only across socio-technical divides but also within the technological domain where discussions between material scientists, physicists, neuroscientists, and computer scientists enable interrogations of disciplinary perspectives.

However, one may question whether socio-ethical reflexivity in transdisciplinary work can be cultivated if technoscientific project partners outnumber those with a background in the humanities and social sciences. Five projects within the NeuroSys cluster (see projects A–D in Sect. 3) are technoscientific in nature while only one project (project E) focuses on economic, socio-ethical, and environmental dimensions—an imbalance that is also reflected in funding and workforce. Therefore, the gray petal of the flower depicting transformation research in NeuroSys (Fig. 7) does not seem to be of an appropriate size. Yet, the equal size of all petals was a deliberate choice. It illustrates that reflexive engagement with the economic, societal, and environmental dimensions of neuromorphic computing research and development does not hinge on continuous collaboration with social scientists and humanities scholars. Instead, it is considered as a capacity of all project partners that can be activated and enhanced in such collaborations. In light of abundant literature on the challenges of transdisciplinary collaboration (Felt et al. 2012b; Schikowitz 2020; Viseu 2015) and of consortia resembling the NeuroSys cluster organization (Aicardi et al. 2018; Balmer et al. 2016b; Rabinow and Bennett 2012), the carriers and barriers of capacity building will be investigated. Hence, Fig. 7 illustrates the ambition rather than the actual state of NeuroSys. The ambition to give societal considerations, economic trade-offs, and sustainability concerns as much relevance as scientific and technological quests in everyday work practices will be put to the test in NeuroSys' research and development process.

Last but not least, readers may have noticed that the term "innovation ecosystem"—albeit frequently mentioned throughout the chapter—remains vaguely defined. The reason is that the innovation ecosystem is the object of transformation research in NeuroSys. The aforementioned socio-technical transformations associated with NeuroSys are in one way or another related to an innovation ecosystem emerging around neuromorphic computing technologies. Which shape this innovation ecosystem will take, how far it will reach geographically and institutionally, who will be involved in which role, function, and position are topics to be further explored. More specifically, the following questions will guide future research: What are the different ways to imagine the innovation ecosystem of neuromorphic computing? How do such imaginations shape and how are they shaped by socio-technical transformations? How do place-based factors influence transformation processes and ecosystem evolution? What are specific innovations in this ecosystem? Who could they benefit and who could they put at a disadvantage? How can the innovation ecosystem become both competitive and responsible? How do regional conditions, socio-material structures, and institutional contexts enable and constrain responsible innovation ecosystem governance? In answering these questions, NeuroSys will study and interrogate assumptions of "innovation" and "ecosystem" concepts (Oh et al. 2016; Von Schomberg and Blok 2021). In this way, NeuroSys will strengthen attempts to adopt an innovation ecosystem perspective in transformation research (Führ 2022) and in Responsible (Research and) Innovation discourses (Smolka and Böschen 2023; Stahl 2022).

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References

Adner R (2017) Ecosystem as structure: an actionable construct for strategy. JRM 43(1):39–58. https://doi.org/10.1177/0149206316678451

Aghion P, Jones BF, Jones CI (2018) Artificial intelligence and economic growth. In: Agrawal A, Gans J, Goldfarb A (eds) The economics of artificial intelligence: an agenda. University of Chicago Press, Chicago, pp 237–282

Aicardi C, Reinsborough M, Rose N (2018) The integrated ethics and society programme of the human brain project: reflecting on an ongoing experience. JRI 5(1):1–12. https://doi.org/10.1080/23299460.2017.1331101

Aimone JB (2021) A roadmap for reaching the potential of brain-derived computing. Adv Intell Syst 3:2000191. https://doi.org/10.1002/aisy.202000191

Almquist E, Senior J, Bloch N (2016) The elements of value. Measuring—and delivering—what consumers really want. HBR. Sept 2016. https://hbr.org/2016/09/the-elements-of-value. Accessed 10 April 10 2023

Amodei D, Hernandez D (2018) AI and compute. OpenAI Blog, 16 May. https://openai.com/research/ai-and-compute. Accessed 10 April 2023

Amoore L (2020) Cloud ethics. Algorithms and the attributes of ourselves and others. Duke University Press, Durham

Autio E, Thomas LDW (2021) Researching ecosystems in innovation contexts. INMR 19(1):12–25. https://doi.org/10.1108/INMR-08-2021-0151

Balmer AS, Calvert J, Marris C, Molyneux-Hodgson S, Frow E, Kearnes M et al (2016a) Five rules of thumb for post-ELSI interdisciplinary collaborations. JRI 3(1):73–80. https://doi.org/10.1080/23299460.2016.1177867

Balmer AS, Bulpin K, Molyneux-Hodgson S (2016b) Synthetic biology. A sociology of changing practices. Palgrave Macmillan, London

Barben D, Fisher SC, Guston DH (2007) Anticipatory governance of nanotechnology: foresight, engagement, and integration. In: Hackett EJ, Amsterdamska O, Lynch ME, Wajcman J (eds) The handbook of science and technology studies. MIT Press, Cambridge, pp 979–1000

Benjamin R (2019) Race after technology: abolitionist tools for the new jim code. Polity Press, Cambridge

Berlin L (2017) Troublemakers: silicon valley's coming of age. Simon & Schuster, New York

Blok V, Hoffmans L, Wubben EFM (2015a) Stakeholder engagement for responsible innovation in the private sector: critical issues and management practices. JCNS 15(2):147–164. https://doi.org/10.3920/JCNS2015.x003

Blok V, Lemmens P (2015b) The emerging concept of responsible innovation: three reasons why it is questionable and calls for a radical transformation of the concept of innovation. In: Koops B-J, Oosterlaken I, Romijn H, Swierstra T, Van Den Hoven J (eds) Responsible innovation 2: concepts, approaches, and applications. Springer, Dordrecht, pp 19–35

Bogers M (2011) The open innovation paradox: knowledge sharing and protection in R&D collaborations. EJIM 14(1):93–117. https://doi.org/10.1108/14601061111104715

Boje D, Burnes B, Hassard J (2012) The Routledge companion on organizational change. Routledge, London

Bown CP (2020) How the United States marched the semiconductor industry into its trade war with China. Working Paper. Peterson Institute for International Economics. https://www.piie.com/publications/working-papers/how-united-states-marched-semiconductor-industry-its-trade-war-china. Accessed 10 April 2023

Brown C, Linden G (2011) Chips and change. How crisis reshapes the semiconductor industry. The MIT Press, Cambridge

Böschen S, Förster A, Letmathe P, Paegert M, Strobel E (2021) Experiments matter: Strukturwandel als Netzwerk von Realexperimenten? In: Herberg J, Staemmler J, Nanz P (eds) Wissenschaft im Strukturwandel. Die paradoxe Praxis engagierter Transformationsforschung. Oekom Verlag, München, pp 213–238

Campolo A, Crawford K (2020) Enchanted determinism: power without responsibility in artificial intelligence. Engaging Sci Tech Soc 6:1–19. https://doi.org/10.17351/ests2020.277

Carayannis E, Campbell D (2009) 'Mode 3' and 'Quadruple Helix': toward a 21st century fractal innovation ecosystem. IJTM 46(3/4):201–234. https://doi.org/10.1504/IJTM.2009.023374

Chakraborty MA, Ankit A, Jain S, Roy S, Sridharan S, Agrawal A, Raghunathan A, Roy K (2020) Resistive crossbars as approximate hardware building blocks for machine learning: opportunities and challenges. Proc IEEE 108(12):2276–2310. https://doi.org/10.1109/JPROC.2020.3003007

Cheng R, Mirza KB, Nikolic K (2020) Neuromorphic robotic platform with visual input, processor and actuator, based on spiking neural networks. Appl Syst Innov 3:28. https://doi.org/10.3390/asi3020028

Cheng Z, Pang C-S, Wang P, Le ST, Wu Y, Shahrjerdi D, Radu I, Lemme MC, Peng L-M, Duan X, Chen Z, Appenzeller J, Koester SJ, Pop E, Franklin AD, Richter CA (2022) How to report and benchmark emerging field-effect transistors. Nat Electron 5:416–423. https://doi.org/10.1038/s41928-022-00798-8

Chesbrough HW (2003) Open innovation: the new imperative for creating and profiting from technology. Harvard Business School Press, Boston

Chhillar D (2022) Innovation ecosystem and its conceptualizations: a literature review. SSRN. https://doi.org/10.2139/ssrn.3994076

Christensen DV, Dittmann R, Linares-Barranco B, Sebastian A, Le Gallo M, Redaelli A, Slesazeck S et al (2022) 2022 roadmap on neuromorphic computing and engineering. Neuromorph Comput Eng 2:022501. https://doi.org/10.1088/2634-4386/ac4a83

Chua LO (2018) How we predicted the memristor. Nat Electron 1:322. https://doi.org/10.1038/s41928-018-0074-4

Chun WHK (2021) Discriminating data. Correlation, neighborhoods, and the new politics of recognition. MIT Press, Cambridge

Coeckelbergh (2021) AI for climate: freedom, justice, and other ethical and political challenges. AI and Ethics 1:57–72. https://doi.org/10.1007/s43681-020-00007-2

Collins H (2021) The science of artificial intelligence and its critics. Interdiscip Sci Rev 46(1–2):53–70. https://doi.org/10.1080/03080188.2020.1840821

Crawford K (2021) Atlas of AI. Power, Politics, and the planetary costs for artificial intelligence. Yale University Press, New Haven

Dattée B, Alexy O, Autio E (2018) Maneuvering in poor visibility: how firms play the ecosystem game when uncertainty is high. Acad Manag Journal 61(2):466–498. https://doi.org/10.5465/amj.2015.0869

Daus A (2022) Neuromorphic hardware meets flexible electronics—towards neuromorphic human-machine interfaces. Frontiers Workshop neuroAI^{x}, 18 Nov. https://www.neuroaix.de/en/frontier-workshop. Accessed 10 April 2023

Davies M, Srinivasa N, Lin T-H, Chinya G, Cao Y, Choday SH, Dimou G et al (2018) Loihi: a neuromorphic manycore processor with on-chip learning. IEEE Micro 38(1):82–99. https://doi.org/10.1109/MM.2018.112130359

De Salvo B (2018) Brain-Inspired technologies: towards chips that think? Proc IEEE Int Solid-State Circ Conf (ISSCC). https://doi.org/10.1109/ISSCC.2018.8310165

De Saille S, Medvecky F, Van Oudheusden M, Albertson K, Amanatidou E, Birabi T, Pansera M (2020) Responsibility beyond growth: a case for responsible stagnation. Bristol University Press, Bristol

Defila R, Di Giulio A (eds) (2015) Transdisziplinär und transformativ forschen. Eine Methodensammlung, vol 1. Springer, Basel

Denkena W (2021) Compute hubs—reassessing platform power at the hardware layer. Master thesis, University of Amsterdam

Dolata U, Schrape J-F (eds) (2013) Internet, mobile devices und die transformation der Medien. Radikaler Wandel als schrittweise Rekonfiguration. Edition Sigma, Berlin

European Commission (2020) White Paper on artificial intelligence: a European approach to excellence and trust. COM (2020) 65 final. https://ec.europa.eu/info/files/white-paper-artificial-intelligence-european-approach-excellence-and-trust_en. Accessed 10 April 2023

European Commission (2022) A chips act for Europe. Commission Staff Working Document SWD (2022) 147 final. https://digital-strategy.ec.europa.eu/en/library/european-chips-act-staff-working-document. Accessed 10 April 2023

Fayyazi A, Ansari M, Kamal M, Afzali-Kusha A, Pedram M (2018) An ultra low-power memristive neuromorphic circuit for internet of things smart sensors. IEEE Internet Things J 5:1011–1022. https://doi.org/10.1109/JIOT.2018.2799948

Felt U, Igelsböck J, Schikowitz S, Völker T (2012a) Challenging participation in sustainability research. DEMESCI 1(1):4–34

Felt U, Igelsböck J, Schikowitz A, Völker T (2012b) Growing into what? The (un-)disciplined socialization of early stage researchers in transdisciplinary research. High Educ 65(4):511–524. https://doi.org/10.1007/s10734-012-9560-1

Felt U, Igelsböck J, Schikowitz S, Völker T (2016) Transdisciplinary sustainability research in practice: between imaginaries of collective experimentation and entrenched academic value orders. ST&HV 41(4):732–761. https://doi.org/10.1177/0162243915626989

Feola G (2015) Societal transformation in response to global environmental change: a review of emerging concepts. Ambio 44(5):376–390. https://doi.org/10.1007/s13280-014-0582-z
Fisher E (2007) Ethnographic invention: probing the capacity of laboratory decisions. NanoEthics 1(2):155–165. https://doi.org/10.1007/s11569-007-0016-5
Fisher E, Mahajan RL, Mitcham C (2006) Midstream modulation of technology governance from within. Bull Sci Tech Soc 26(6):485–496. https://doi.org/10.1177/0270467606295402
Fisher E, O'Rourke M, Evans R, Kennedy EB, Gorman ME, Seager TP (2015) Mapping the integrative field: taking stock of socio-technical collaborations. JRI 2(1):39–61. https://doi.org/10.1080/23299460.2014.1001671
Foxon TJ, Pearson PJG, Arapostathis S, Carlsson-Hyslop A, Thornton J (2013) Branching points for transition pathways: assessing responses of actors to challenges on pathways to a low carbon future. Energy Policy 52:146–158. https://doi.org/10.1016/j.enpol.2012.04.030
Führ M (2022) Wie gelingen Systeminnovationen? Transfer als Lernprozess in der Region – Bilanz und Ausblick des Projects Systeminnovation für Nachhaltige Entwicklung. Schader Stiftung, 17 Oct. https://www.schader-stiftung.de/veranstaltungen/aktuell/artikel/abschlussveranstaltung-des-projekts-systeminnovation-fuer-nachhaltige-entwicklung-sne. Accessed 10 April 2023
Gailhofer P, Herold A, Schemmel JP, Scherf C-S, Urrutia C, Köhler AR, Braungardt S (2021) The role of artificial intelligence in the European green deal. Policy Department for Economic, Scientific and Quality of Life Policies Directorate-General for Internal Policies. http://www.europarl.europa.eu/supporting-analyses. Accessed 10 April 2023
Garst J, Blok V, Jansen L, Omta OSWF (2017) Responsibility versus profit: the motives of food firms for healthy product innovation. Sustainability 9:2286. https://doi.org/10.3390/su9122286
Garud R, Karnøe P (2003) Bricolage versus breakthrough: distributed and embedded agency in technology entrepreneurship. Res Policy 32(2):277–300. https://doi.org/10.1016/S0048-7333(02)00100-2
Garvey SC (2021) Unsavory medicine for technological civilization: introducing 'artificial intelligence & its discontents.' Interdiscip Sci Rev 46(1–2):1–18. https://doi.org/10.1080/03080188.2020.1840820
Geels FW (2004) From sectoral systems of innovation to socio-technical systems. Insights about dynamics and change from sociology and institutional theory. Res Policy 33:897–920. https://doi.org/10.1016/j.respol.2004.01.015
Geels FW (2018) Disruption and low-carbon system transformation: progress and new challenges in socio-technical transitions research and the multi-level perspective. Eneg Res Soc Sci 37:224–231. https://doi.org/10.1016/j.erss.2017.10.010
Geels FW, Raven R (2006) Non-linearity and expectations in niche-development trajectories: ups and downs in Dutch biogas development (1973–2003). Technol Anal Strateg Manag 18(3–4):375–392. https://doi.org/10.1080/09537320600777143
Geels FW, Schot J (2007) Typology of sociotechnical transition pathways. Res Policy 36:399–417. https://doi.org/10.1016/j.respol.2007.01.003
Grunwald A (2019) Technology assessment in practice and theory. Routledge, London
Guston DH (2014) Understanding 'anticipatory governance.' SSS 44(2):218–242. https://doi.org/10.1177/0306312713508669
Guston DH, Sarewitz D (2002) Real-time technology assessment. Tech Soc 24(1–2):93–109. https://doi.org/10.1016/S0160-791X(01)00047-1
Hahn T, Figge F, Pinske J, Preuss L (2018) A paradox perspective on corporate sustainability: descriptive, instrumental, and normative aspects. J Bus Ethics 148:235–248. https://doi.org/10.1007/s10551-017-3587-2
Heck M (2022) Where's the chips education act? Bits & Chips, 19 Oct. https://bits-chips.nl/artikel/wheres-the-chips-education-act/. Accessed 10 April 2023
Herberg J, Staemmler J, Nanz P (2021) Wenn Wandel Wissenschaft erfasst: Die paradoxe Praxis engagierter Forschung im Strukturwandel. In: Herberg J, Staemmler J, Nanz P (eds)

Wissenschaft im Strukturwandel. Die paradoxe Praxis engagierter Transformationsforschung. Oekom Verlag, München, pp 4–44

Hess J, Kleinhans J-P (2021) Understanding the global ship shortages. Policy Brief. Stiftung Neue Verantwortung. https://www.stiftung-nv.de/de/publikation/understanding-global-chip-shortages. Accessed 10 April 2023

Heyen DA, Brohmann B (2017) Konzepte grundlegenden gesellschaftlichen Wandels und seiner Gestaltung Richtung Nachhaltigkeit – ein Überblick über die aktuelle Transformationsliteratur. In: Rückert-John J, Schäfer M, Eds. Governance für eine Gesellschaftstransformation. Herausforderungen des Wandels in Richtung nachhaltige Entwicklung. Wiesbaden: Springer Fachmedien, pp 69–86

Hillersdal L, Jespersen AP, Oxlund B, Bruun B (2020) Affect and effect in interdisciplinary collaboration. STS 33(2):66–82. https://doi.org/10.23987/sts.63305

Hsu J (2014) IBM's new brain. IEEE Spectr 51:17–19. https://doi.org/10.1109/MSPEC.2014.6905473

Hu M (2020) Cambridge Analytica's black box. Big Data Soc 7(2). https://doi.org/10.1177/2053951720938091

Irwin A, Jensen TE, Jones KE (2012) The good, the bad and the perfect: criticizing engagement practice. SSS 43(1):118–135. https://doi.org/10.1177/0306312712462461

Jackson T (2009) Prosperity without Growth: Economics for a Finite Planet. Earthscan, London

Kimura AH, Kinchy A (2019) Science by the People: participation, power, and the politics of environmental knowledge. Rutgers University Press, New Brunswick

Köhler J, Geels FW, Kern F, Markard J, Onsongo E, Wieczorek A, Alkemade F et al (2019) An agenda for sustainability transitions research: state of the art and future directions. Environ Innov Soc Transit 31:1–32. https://doi.org/10.1016/j.eist.2019.01.004

Kollmorgen R, Merkel W, Wagener H-J (eds) (2015) Handbuch Transformationsforschung. Springer, Wiesbaden

Kromrey H (2017) Begleitforschung und Evaluation – fast das Gleiche, und doch etwas Anderes! In: Glaser M, Schuster S (eds) Evaluation präventiver Praxis gegen Rechtsextremismus. Deutsches Jungendinstitut , Halle, pp 113–135

Küng L, Picard RG, Towse R (eds) (2008) The internet and the mass media. Sage, London

La Barbera S, Huang C (2022) Impact of the global chip shortage on the development of in-memory chips. Nat Commun 13:4055. https://doi.org/10.1038/s41467-022-31598-5

Laitinen A, Sahlgren O (2021) AI systems and respect for human autonomy. Front Artif Intell 4:705164. https://doi.org/10.3389/frai.2021.705164

Letmathe P, Wagner S (2018) "Messy" marginal costs: Internal pricing of environmental aspects on the firm level. IJPE 201:41–52. https://doi.org/10.1016/j.ijpe.2018.04.016

Lezaun J, Marres N, Tironi M (2017) Experiments in participation. In: Felt U, Fouché R, Miller CA, Smith-Doerr L (eds) The handbook of science and technology studies, 4th edn. MIT Press, Cambridge, pp 195–222

Li Y (2021) The semiconductor industry: a strategic look at China's supply chain. In: Spigarelli F, McIntyre JR (eds) The new Chinese dream. Palgrave Macmillan, Cham, pp 121–136

Li J, Huang H (2021) Research study on edge computing. In: Proceedings of 2021 IEEE 6th International conference on smart cloud (SmartCloud), vol 9(23), pp 2347–23485. https://doi.org/10.1109/JIOT.2022.3200431

Liu CH, Zhong R (2017) Internet of things for manufacturing in the context of Industry 4.0. In: Chen CH, Trappey AC, Peruzzini M, Stjepandic J, Wognum N (eds) Transdisciplinary engineering: a paradigm shift. IOS Press, Singapore, pp 1013–1022

Lohn AJ, Musser M (2022) AI and compute. How much longer can computing power drive artificial intelligence? Center for Security and Emerging Technology (CSET) Issue Brief. https://cset.georgetown.edu/wp-content/uploads/AI-and-Compute-How-Much-Longer-Can-Computing-Power-Drive-Artificial-Intelligence-Progress.pdf. Accessed 10 April 2023

Long TB, Blok V (2017) Integrating the management of socio-ethical factors into industry innovation: towards a concept of Open Innovation 2.0. IFAMR 21(4):463–486. https://doi.org/10.22434/IFAMR2017.0040

Loorbach D (2010) Transition management for sustainable development. A prescriptive, complexity-based governance framework. Gov 23(1):161–183. https://doi.org/10.1111/j.1468-0491.2009.01471.x

Ludwig D, Blok V, Garnier M, Macnaghten P, Pols A (2021) What's wrong with global challenges? JRI 9(1):6–27. https://doi.org/10.1080/23299460.2021.2000130

Luque-Ayala A, Marvin S (2015) Developing a critical understanding of smart urbanism. Urban Stud 52(12):2105–2116. https://doi.org/10.1177/0042098015577319

Mainzer K (2022) Neuromorphe Computer und Künstliche Intelligenz. In: Mainzer K (ed) Philosophisches Handbuch Künstliche Intelligenz. Springer, Wiesbaden, pp 1–23

Manders TN, Wieczorek AJ, Verbong GPJ (2018) Understanding smart mobility experiments in the Dutch automobility system: Who is involved and what do they promise? Futures 96:90–103. https://doi.org/10.1016/j.futures.2017.12.003

Mead C (1998) Analog VLSI and neural systems. Addison-Wesley Longman Publishing, Boston

Mehonic A, Kenyon AJ (2022) Brain-inspired computing needs a master plan. Nature 604:255–260. https://doi.org/10.1038/s41586-021-04362-w

Merolla PA, Arthur JV, Alvarez-Icaza R, Cassidy AS, Sawada J, Akopyan F et al (2014) A million spiking-neuron integrated circuit with a scalable communication network and interface. Sci 345(6197):668–673. https://doi.org/10.1126/science.1254642

Mody CM (2017) The long arm of Moore's Law. Microelectronics and American science. MIT Press, Cambridge

Murdoch B (2021) Privacy and artificial intelligence: challenges for protecting health information in a new era. BMC Med Eth 22:122. https://doi.org/10.1186/s12910-021-00687-3

Nagel SK (2016) Algorithm anxiety—do decision-making algorithms pose a threat to autonomy? In: IEEE International symposium on ethics in engineering, science and technology (ETHICS 2016), 13–14 May 2016

Nguyen D, Herman E (2022) The news framing of artificial intelligence: a critical exploration of how media discourses make sense of automation. AI Soc. https://doi.org/10.1007/s00146-022-01511-1

Nguyen HT, Marques P (2021) The promise of living labs to the Quadruple Helix stakeholders: exploring the sources of (dis)satisfaction. Europ Plan Stud 30(6):1124–1143. https://doi.org/10.1080/09654313.2021.1968798

Nishant R, Kennedy M, Corbett J (2020) Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. IJIM 53:102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

O'Neill O (2018) Linking trust and trustworthiness. IJPS 26(2):293–300. https://doi.org/10.1080/09672559.2018.1454637

Oh D-S, Phillips F, Park S, Lee E (2016) Innovation ecosystems: a critical examination. Technovation 54:1–6. https://doi.org/10.1016/j.technovation.2016.02.004

Osborn LE, Dragomir A, Betthauser JL, Hunt CL, Nguyen HH, Kaliki RR, Thakor NV (2018) Prosthesis with neuromorphic multilayered e-dermis perceives touch and pain. Sci Robot 3:eaat3818. https://doi.org/10.1126/scirobotics.aat3818

Owen R, Macnaghten P, Stilgoe J (2012) Responsible research and innovation: from science in society to science for society, with society. In: Owen R, Bessant J, Heintz M (eds) Responsible innovation: managing the responsible emergence of science and innovation in society. Wiley, Chichester, pp 27–50

Ömer-Rieder B, Tötzer T (2004) Umweltinnovation als spezieller Innovationstyp. Seibersdorf: ARC Systems Research GmbH

Parsa M, Mitchell JP, Schuman CD, Patton RM, Potok TE, Roy K (2020) Bayesian multi-objective hyperparameter optimization for accurate, fast, and efficient neural network accelerator design. Front Neurosci 14:667. https://doi.org/10.3389/fnins.2020.00667

Parthasarathy S (2017) Patent politics. Life forms, markets, and the public interest in the United States and Europe. The University of Chicago Press, Chicago

Pennisi S (2022) Pandemic, shortages, and electronic engineering. IEEE Circuits Syst Mag 22(3):41–49. https://doi.org/10.1109/MCAS.2022.3189891

Peters BG (2017) What is so wicked about wicked problems? A conceptual analysis and a research program. Policy Soc 36(3):385–396. https://doi.org/10.1080/14494035.2017.1361633

Plattform Lernende Systeme (2022) Mit KI den nachhaltigen Wandel gestalten. https://doi.org/10.48669/pls_2022-05

Popa EV, Blok V, Wesselink R (2020) A processual approach to friction in quadruple helix collaborations. Sci Pub Policy 47(6):876–889. https://doi.org/10.1093/scipol/scaa054

Porter M, Kramer MR (2011) Creating shared value. How to reinvent capitalism—and unleash a wave of innovation and growth. HBR, January-February. https://hbr.org/2011/01/the-big-idea-creating-shared-value. Accessed 10 April 2023

Prytkova E, Vannuccini S (2022) On the basis of brain: neural-network-inspired changes in general-purpose chips. Ind Corp Change. https://doi.org/10.1093/icc/dtab077

Rabinow P, Bennett G (2012) Designing human practices: an experiment with synthetic biology. University of Chicago Press, Chicago

Rast AD, Adams SV, Davidson S, Davies S, Hopkins M, Rowley A, Stokes AB, Wennekers T, Furber S, Cangelosi A (2018) Behavioral learning in a cognitive neuromorphic robot: an integrative approach. IEEE Trans Neural Networks 29:6132–6144. https://doi.org/10.1109/TNNLS.2018.2816518

Rip A, Kemp R (1998) Technological change. In: Rayner S, Malone EL (eds) Human choice and climate change 2. Battelle Press, Ohio, pp 327–399

Rogers EM (1995) Diffusion of innovations, 4th edn. Simon and Schuster, New York

Rush E (2019) Wicked problems: The challenge of food safety versus food security—working towards the SDG goals? EJCN 73:1091–1094. https://doi.org/10.1038/s41430-018-0352-2

Santarius T (2012) Green growth unravelled. How rebound effects baffle sustainability targets when the economy keeps growing. Heinrich Böll Foundation and the Wuppertal Institute for Climate, Environment and Energy

Santarius T (2015) Der Rebound-Effekt. Ökonomische, psychische und soziale Herausforderungen für die Entkopplung von Wirtschaftswachstum und Energieverbrauch. Metropolis, Marburg

Santarius T, Walnum HJ, Aall C (eds) (2016) Rethinking climate and energy policies. New perspectives on the rebound phenomenon. Springer, Berlin

Schikowitz A (2020) Creating relevant knowledge in transdisciplinary research projects—coping with inherent tensions. JRI 7(2):217–237. https://doi.org/10.1080/23299460.2019.1653154

Schikowitz A, Maasen S (2021) Integrative Forschung. In: Schmohl T, Philipp T (eds) Handbuch Transdisziplinäre Didaktik. Bielefeld: Transcript, pp 151–162

Schuman CD, Kulkarni SR, Parsa M, Mitchell JP, Date P, Kay B (2022) Opportunities for neuromorphic computing algorithms and applications. Nat Comput Sci 2:10–19. https://doi.org/10.1038/s43588-021-00184-y

Sipior JC (2020) Considerations for development and use of AI in response to COVID-19. IJIM 55:102170. https://doi.org/10.1016/j.ijinfomgt.2020.102170

Smith A, Voß J-P, Grin J (2010) Innovation studies and sustainability transitions: the allure of the multi-level perspective and its challenges. Res Policy 39(4):435–448. https://doi.org/10.1016/j.respol.2010.01.023

Smolka M, Böschen S (2023) Responsible innovation ecosystem governance: socio-technical integration research for systems-level capacity building. JRI 10(1):2207937. https://doi.org/10.1080/23299460.2023.2207937

Smolka M, Fisher E, Hausstein A (2021) From affect to action: choices in attending to disconcertment in interdisciplinary collaboration. ST&HV 46(5):1076–1103. https://doi.org/10.1177/0162243920974088

Stahl BC (2022) Responsible innovation ecosystems: ethical implications of the application of the ecosystem concept to artificial intelligence. IJIM 62:102441. https://doi.org/10.1016/j.ijinfomgt.2021.102441

Statista (2022a) Market size and revenue comparison for artificial intelligence worldwide from 2018 to 2030. https://www.statista.com/statistics/941835/artificial-intelligence-market-size-revenue-comparisons/. Accessed 10 April 2023

Statista (2022b) Digital & trends AI chips. Statista dossier about the artificial intelligence (AI) chip market. https://www.statista.com/study/71650/artificial-intelligence-ai-chips/. Accessed 10 April 2023

Statista (2022c) Size of the global market for automotive sensors in 2020, with a forecast for 2025. https://www.statista.com/statistics/1011203/projected-global-automotive-sensor-market/. Accessed 10 April 2023

Stengel O (2011) Suffizienz: Die Konsumgesellschaft in der ökologischen Krise. Oekom, München

Stirling A (2006) Precaution, foresight, and sustainability: reflection and reflexivity in the governance of science and technology. In: Voß J-P, Bauknecht D, Kemp R (eds) Reflexive governance for sustainable development. Edward Elgar, Cheltenham, pp 225–272

Strubell E, Ganesh A, McCallum A (2019) Energy and policy considerations for deep learning in NLP. https://doi.org/10.48550/arXiv.1906.02243

Thiebes S, Lins S, Sunyaev A (2021) Trustworthy artificial intelligence. Electron Mark 31:447–464. https://doi.org/10.1007/s12525-020-00441-4

Thomas J (2015) Constructing a 'futurology from below': a civil society contribution toward a research agenda. JRI 2(1):92–95. https://doi.org/10.1080/23299460.2014.1002176

Timmers P (2022) How Europe aims to achieve strategic autonomy for semiconductors. Brookings, 9 Aug. https://www.brookings.edu/techstream/how-europe-aims-to-achieve-strategic-autonomy-for-semiconductors/. Accessed 10 April 2023

Välikangas A (2022) The use of grand challenges in research policy and university management: something for everyone. JRI 9(1):93–113. https://doi.org/10.1080/23299460.2022.2040870

Van Agtmael A, Bakker F (2016) The smartest places on earth. Why rustbelts are the emerging hotspots of global innovation. Public Affairs, New York

Van Den Ende J, Kemp R (1999) Technological transformations in history: how the computer regime grew out of existing computing regimes. Res Policy 28:833–851. https://doi.org/10.1016/S0048-7333(99)00027-X

Van Wynsberghe A (2021) Sustainable AI: AI for sustainability and the sustainability of AI. AI Ethics 1:213–218. https://doi.org/10.1007/s43681-021-00043-6

Vanarse A, Osseiran A, Rassau A (2017) An investigation into spike-based neuromorphic approaches for artificial olfactory systems. Sensors 17:2591. https://doi.org/10.3390/s17112591

Varas A, Varadarajan R (2020) How restricting trade with China Could End US Semiconductor Leadership. Boston Consulting Group, 9 Mar. https://www.bcg.com/publications/2020/restricting-trade-with-china-could-end-united-states-semiconductor-leadership. Accessed 10 April 2023

Viale A, Marchisio A, Martina M, Masera G, Shafique M (2021) CarSNN: an efficient spiking neural network for event-based autonomous cars on the Loihi Neuromorphic Research Processor. In: Proceedings of 2021 international joint conference on neural networks (IJCNN). https://doi.org/10.1109/ijcnn52387.2021.9533738

Vinuesa R, Azizpour H, Leite I, Balaam M, Dignum V, Domisch S, Felländer A, Langhans SD, Tegmark M, Fuso Nerini F (2020) The role of artificial intelligence in achieving the sustainable development goals. Nat Commun 11:233. https://doi.org/10.1038/s41467-019-14108-y

Viseu A (2015) Caring for nanotechnology? Being an integrated social scientist. SSS 45(5):643–664. https://doi.org/10.1177/0306312715598666

Von Der Leyen U (2022) Statement by President von der Leyen on the European Chips Act. European Commission Statement, 8 Feb. https://ec.europa.eu/commission/presscorner/detail/en/statement_22_866. Accessed 10 April 2023

Von Neumann J (1945) First draft of a report on the EDVAC. Moore School of Electrical Engineering, University of Pennsylvania. http://abelgo.cn/cs101/papers/Neumann.pdf

Von Schomberg R (2013) A vision of responsible research and innovation. In: Owen R, Bessant J, Heintz M (eds) Responsible innovation: managing the responsible emergence of science and innovation in society. Wiley, Chichester, pp 51–74

Von Schomberg L, Blok V (2021) The turbulent age of innovation. Synthese 198(Suppl 19):4667–4683. https://doi.org/10.1007/s11229-018-01950-8

Waldrop M (2016) More than Moore. Nat 530(11):145–147. https://www.nature.com/news/polopoly_fs/1.19338!/menu/main/topColumns/topLeftColumn/pdf/530144a.pdf. Accessed 10 April 2023

Wilson C (2012) Up-scaling, formative phases, and learning in the historical diffusion of energy technologies. Energy Policy 50:81–94. https://doi.org/10.1016/j.enpol.2012.04.077

Wittmayer J, Hölscher K (eds) (2017) Transformationsforschung. Definitionen, Ansätze, Methoden. Umweltbundesamt. http://www.umweltbundesamt.de/publikationen. Accessed 10 April 2023

Wong TM, Preissl R, Datta P, Flickner M, Singh R, Esser SK et al (2012) IBM research report 10^{14}. RJ10502(ALM1211-004), 13 Nov. https://dominoweb.draco.res.ibm.com/reports/RJ10502.pdf. Accessed 10 April, 2023

Yole Report (2021) Neuromorphic computing and sensing. Market and Technology Report. Yole Development. https://s3.i-micronews.com/uploads/2021/05/Yole-D%C3%A9veloppement-Neuromorphic-Computing-and-Sensing-2021-Sample.pdf. Accessed 10 April 2023

Zidan MA, Strachan JP, Lu WD (2018) The future of electronics based on memristive systems. Nat Electron 1:22–29. https://doi.org/10.1038/s41928-017-0006-8

ZRR (2021) Wirtschafts- und Strukturprogramm 1.1 für das Rheinische Revier. Zukunftsagentur Rheinisches Revier. https://www.rheinisches-revier.de/wp-content/uploads/2022/04/wsp_1.1.pdf. Accessed 10 April 2023

Zwart H, Landeweerd L, Van Rooij A (2014) Adapt or perish? Assessing the recent shift in the European research funding arena from 'ELSA' to 'RRI.' Life Sci Soc Policy 10(11):1–19. https://doi.org/10.1186/s40504-014-0011-x