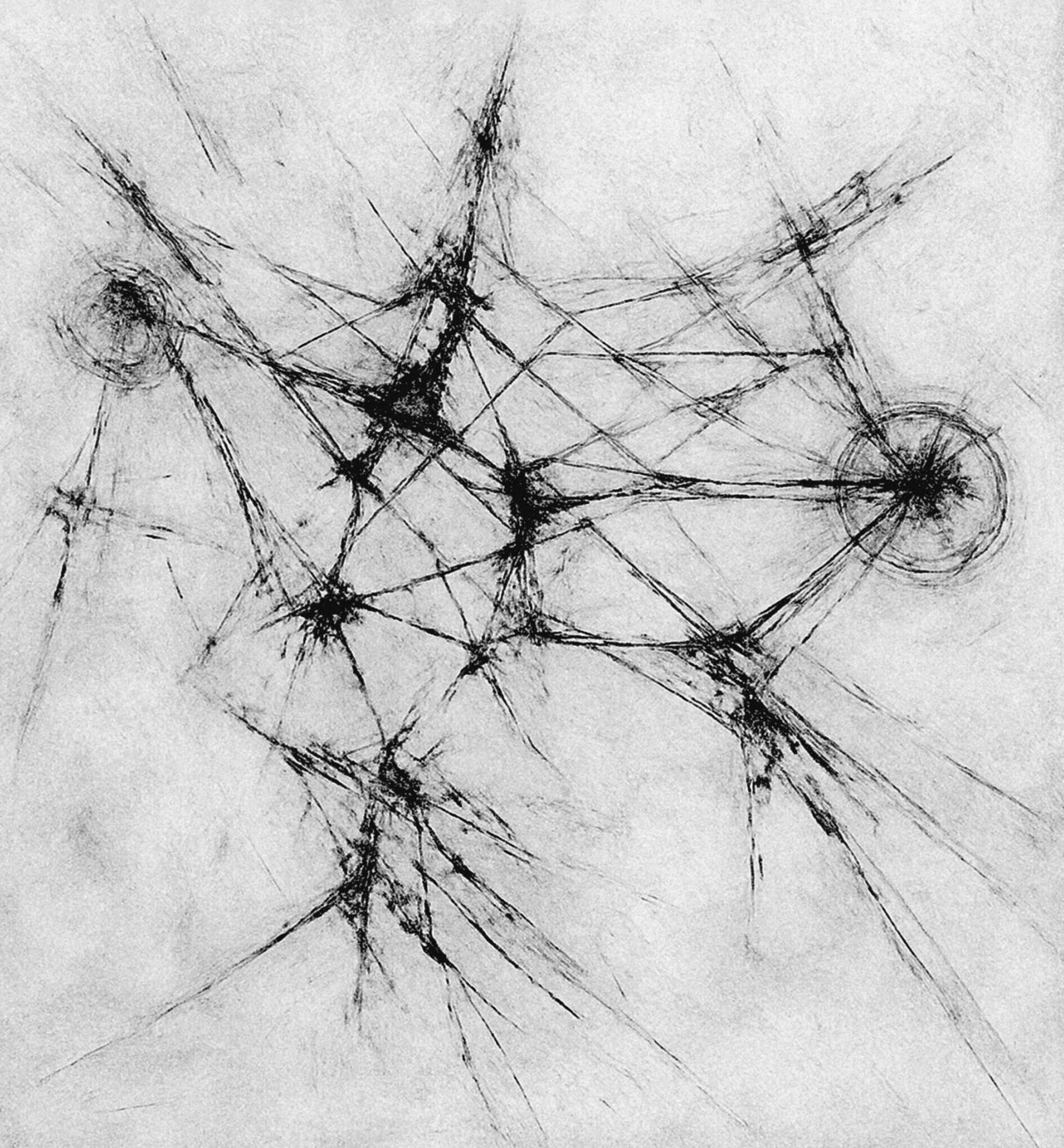
Transcending The Disciplinary Divide



Aalborg University – Copenhagen

Title: Transcending the Disciplinary Divide

Subtitle: Digital Methods? Interactional Expertise!

Programme: Techno-Anthropology – 6th Semester (TAN6)

Date: May 28, 2025

Project Type: Bachelor Project (P6)

Supervisor: Morten Falch

Co-supervisor: Frederick Sebastian Marcus Stender

Group 1:
Andreas Sommer Thastum / 20222147
Lasse Ørgård Slot / 20223520
Nicolaj Stevnsborg / 20225022
Thomas Julsgaard / 20222144

Characters (incl. spaces): 125981

Pages: 52.5

Appendices: 23

Abstract

This report explores various strategies for employing digital methods to inform our interactional expertise. We investigate: (1) intradisciplinary nuances within seemingly homogeneous disciplines, (2) interdisciplinary languages, (3) interdisciplinary blind spots, and opportunities for interdisciplinary collaboration. Our methodology combines detailed network analyses of academic literature on Bitcoin mining with a qualitative expert group interview focusing on epistemological differences. Through this approach, we demonstrate how a set of quali-quantitative methods can be used to strengthen our interactional expertise. Additionally, our research points to an unexplored area in the Scopus literature: the use of digital methods to inform interactional expertise within interdisciplinary and intradisciplinary contexts. By addressing this gap, we aim to inspire further exploration and development of digital methodological approaches, while explicitly acknowledging that our scope is limited to interactions between experts; other relevant actors should also be considered in broader analyses.

Table of Contents

1 Introduction: A Reflection

As contemporary challenges have resulted in an increased need for cooperation between multiple fields, there is an increased need for interdisciplinary experts who tie scientific communities together (Botin & Børsen, 2013: 37-39). Techno-Anthropology deals with problems that affect multiple fields; its interdisciplinary scope is used to handle, understand, and manage them accordingly (ibid.: 37-39). The core aspect of the techno-anthropological effort is visualised in the techno-anthropological triangle:

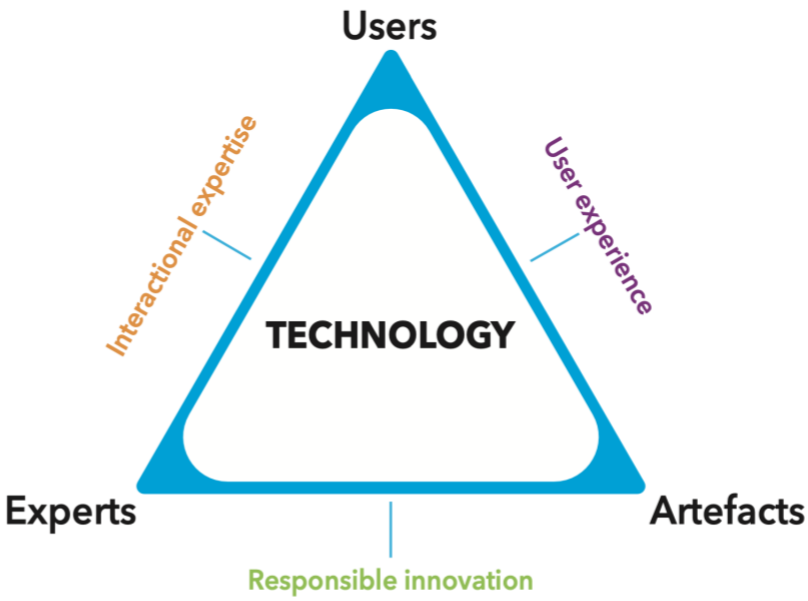


Figure 1: *The techno-anthropological triangle* (Børsen, 2020: 220)

The triangle represents the techno-anthropological domain, emphasising facilitation of communication between various actors: users/stakeholders, procedures, and artifacts, and experts. It points to one of our central competencies as techno-anthropologists: *Interactional expertise*, that is, facilitating communication between two domains that do not speak the same professional language. This can be between users and experts, as well as between experts and experts (ibid.: 49-50). Techno-anthropology is about translating between domains so that they can collaborate and generate an understanding of new perspectives to incorporate in their practices (ibid.: 50). Put briefly, Interactional expertise is the ability to master the language of a domain without being able to practise it – e.g., you understand the language and practice of the geneticist, but he would not let you run his lab; you understand how the farmer works, but he would not let you milk his cows. By mastering two such languages, techno-anthropologists help bridge gaps between domains, disciplines, expert cultures, or other stakeholders. As we, societally, encounter complex, pressing challenges (see section 2.1 on the *Cynefin framework*), this facilitation between actors is crucial because it allows for better problem-solving as insights from more fields are integrated (ibid.: 39-50). Dealing with these complex issues, the ease of collaboration between disciplines is paramount. Here, our techno-anthropological interactional expertise functions as lubrication, making, for example, interdisciplinary collaborations run more smoothly.

In recent years, Techno-Anthropology has undergone a significant bifurcation, with a growing number of researchers interested in pioneering the use of digital methods in Social Science studies. Digital methods are not solely practised by techno-anthropologists, and cannot be said to belong to any single discipline (Birkbark & Munk, 2017: 22). Rather, digital methods represent a powerful set of tools that enable researchers from different fields to study emerging phenomena of the digital world. Whereas conventional anthropological methods rely on fieldwork through interviews, observations, and local engagement, digital methods enable the study of online phenomena, such as social media dynamics, algorithmic systems, and online communities, thereby expanding the anthropological domain into virtual and networked spaces (Birkbark & Munk, 2017: 27-64).

The Aalborg University-based TANTlab (The Techno-Anthropology Lab) is at the forefront of this methodological and epistemological shift, experimenting with new tools and collaborative formats that reimagine how knowledge is produced, visualised, and shared (Aalborg University, nd). This is what sparked our initial interest in digital methods. Motivated by this interest, we were curious to explore how digital methods might inform our interactional expertise: a new approach that we, through a literature review, found to be unexplored. Plaisance writes in her 2020 paper:

> *We currently lack well-developed frameworks for thinking about how we should engage other expert communities and what the epistemic benefits are of doing so* (Plaisance, 2020: 53)

With Plaisances' quote in mind, we were curious to explore how a digital methods approach could inform alternative strategies for interactional expertise. It is with these considerations that we laid the groundwork for the following research questions, which will guide the premise of our enquiry:

> *How can we, as techno-anthropologists, utilise digital methods to guide our interactional expertise when dealing with experts?*
>
> - *i.) How can we reveal intradisciplinary nuances within seemingly homogeneous disciplines?*
> - *ii.) How can we identify an interdisciplinary language through mapping scientific literature as a network?*
> - *iii.) How can we reveal disciplinary blind spots and potentials for interdisciplinary collaborations?*

In the domain section, we introduce the term *post-normal science* and argue that Bitcoin mining can be understood as part of several wicked problems. We quickly explain what Bitcoin mining is and show a concrete example of how it overlaps with environmental sustainability. We then turn to Techno-Anthropology and one of its key competencies – interactional expertise. A short literature review reveals that, although interactional expertise is well theorised, almost no studies pair it with digital methods. In the methods section, we address how we set up a meeting with five energy system engineers and later scraped keywords from 1500 Scopus articles and made them into interpretable networks. In the theory section, we introduce the reader to the theoretical pillars we build the analysis on: Venturini and Munks' seven commitments of controversy mapping; Collins and Evans' taxonomy of expertise and *trading-zone* metaphor; and Marres' idea that issues spark publics into being. The analysis unfolds in three steps: (1) How can we reveal intradisciplinary nuances within seemingly homogeneous disciplines? (2) How can we identify an interdisciplinary language through mapping scientific literature as a network? (3) How can we reveal disciplinary blind spots and potentials for interdisciplinary collaborations? In the discussion, we reflect on the practical implications of this work for techno-anthropologists and on our use of AI. We then discuss the implications of weighing data and the limitations of keywords, and, finally, we show how we adhere to six of the seven commitments of controversy mapping.

2 Domain

2.1 Post-Normal Science and Bitcoin Mining as a Wicked Problem

According to Funtowicz & Ravetz (1993), we live in a post-normal scientific era. This post-normality comes into play for decision-making when:

> (...) *facts are uncertain, values in dispute, stakes high, and decisions urgent* (ibid.: 774).

In a recent blog post, Funtowicz (2021) exemplifies this post-normality by pointing to the actions needed to mitigate sea-level rises as a consequence of global climate change:

> *All the causal elements are uncertain in the extreme; at stake is much of the built environment and the settlement patterns of people, what to save and what to sacrifice is in dispute, and the window for decision-making is shrinking* (Funtowicz, 2021).

He argues that in such situations, normal science (as described by Kuhn, 1997) is necessary but no longer sufficient (ibid.) and relates the notion of post-normal science to more traditional problem-solving strategies. Firstly, *Systems uncertainties*, the idea that a problem cannot be solved solely through the discovery of a particular fact, but with the comprehension or management of an inherently complex reality (ibid.). Finally, *Decision stakes,* concerning the various costs, benefits, and value commitments involved in the issue through stakeholders (ibid.).

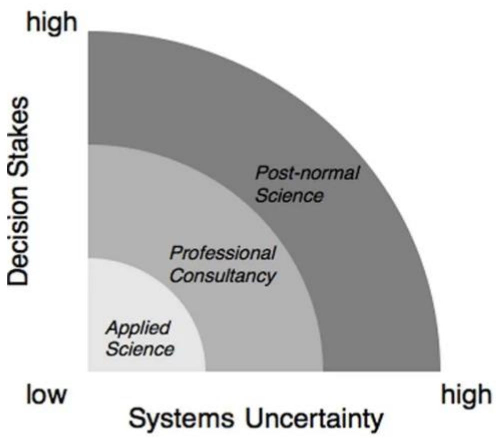


Figure 2: *Problem-solving strategies* (Funtowicz and Ravetz, 1993: 750)

The figure shows how we, in *Funtowiczian* terms, will move from *normal science* (*applied* science) through *professional consultancy* to *post-normal science* as both the system uncertainties and decision stakes rise (Funtowicz & Ravetz, 1993: 750). In post-normal science, it is the criteria of the affected broader communities that set the problems and evaluate the solutions (Funtowicz, 2021). However, this does not render *science* invalid in terms of epistemic enquiry as the post-normal era does not replace, but rather complements, traditional forms of science (ibid.). Within this perspective, different ways of knowing become crucial (ibid.).

Funtowicz & Ravetz (1993) use their framework to emphasise how decision-making in a post-normal era requires extended peer communities, that is, the inclusion of a wider array of legitimate participants in the process of qualifying scientific inputs (Funtowicz, 2021). While we agree with this participatory epistemology, we argue that post-normal science also points to the importance of interdisciplinary collaborations. We acknowledge that scientific expertise alone – interdisciplinary or not – is not sufficient to deal with these complex situations. Nonetheless, we maintain that thorough interdisciplinary collaborations remain important sites of knowledge production that can then be guided by, e.g., contextual societal values and ethics. As techno-anthropologists, we are trained in addressing these complex, at times called *wicked,* problems (Bertelsen & Petersen, 2021: 48). These problems might be of societal, ethical, environmental, or political nature (ibid.).

Let us briefly introduce the Cynefin framework to elaborate on what we mean by *wicked problems*. The framework was formed by Snowden and Boone (2007) to deal with leadership and decision-making, as it helps executives sort issues into five contexts (ibid.: 2): (1) Firstly, they describe *simple contexts*. These situations are characterised by stability and transparent cause-and-effect relations. The answer is often self-evident and is the realm of *known-knowns* (ibid.: 2-3). Snowden and Boone write that leaders must deal with this situation by *sensing, categorising,* and *responding* (ibid.). (2) Secondly, they elaborate on *complicated contexts.* These situations might contain multiple right answers, and while there is a clear relationship between cause and effect, it is not evident to everyone. It is the realm of *known unknowns*, and leaders must, in this case, *sense, analyse,* and *respond* (ibid.: 3-5). (3) In a complex context – what we sometimes refer to as *wicked problems* – right answers cannot be sought out at all. Instead, instructive patterns emerge if the leader conducts experiments that can safely fail (ibid.: 5). We are here dealing with the realm of *unknown unknowns.* They argue that leaders in these situations need to *probe, sense,* and then *respond* (ibid.). (4) Finally, they describe the *chaotic context* in which the search for answers is pointless, as it is impossible to establish any meaningful relationship between cause and effect. This is the realm of *unknowables.* A leader must, in this situation, *act* to establish order, *sense* where stability is, and then attempt to *transform* the situation from chaos to complex (ibid.: 5-6).

One might be wondering how this is relevant to our techno-anthropological practice, specifically our effort as interactional experts (we will elaborate on this concept in section 2.4.1). Let us briefly argue our case: As we are schooled in how to deal with emerging technologies, we are often situated in complex situations as we engage with the socio-technical aspects of these wicked problems. In the previous section, we maintained that interdisciplinary collaborations are crucial in the post-normal scientific era. Likewise, we argue that such interdisciplinarity is equally essential when dealing with *wicked problems.* We do not think that interdisciplinary collaborations alone can solve these problems, however, we think that they are detrimental points of departure when we *probe, sense,* and *respond* to these complex affairs. With these two considerations articulated – that is, (1) the post-normal era, and (2) wicked problems – we can now proceed to explain how Bitcoin mining might be thought of as a symptom of this era as well as an example of such a wicked problem. Firstly, as an emerging technology, Bitcoin mining extends into various societal domains: finance and economy, energy infrastructure, environmental sustainability, legal and regulatory frameworks, and socio-political governance. While we do not claim that all of these domains are located in what might be termed a complex situation, some undoubtedly are. Take, for example, finance and economy: Within this context, there is not necessarily *a* good answer as to how Bitcoin mining and Bitcoin should be integrated into the monetary economy. For instance, we understand the United States' establishment of a strategic national Bitcoin reserve (The White House, 2025) as a way of *probing*. As we are dealing with an emergent technology, the *sensing* is a contemporary affair. Likewise, we argue that Bitcoin mining in the context of environmental sustainability can equally be understood as a wicked problem, because, again, there are no good answers. The *probing* is taking place as multiple countries *experiment* with integrating Bitcoin mining into the electricity grid to improve their infrastructure (see section 2.3).

In the following, we will introduce the reader to Bitcoin mining to provide a preliminary understanding of what the technology is. We think that this introduction is important to understand how and why Bitcoin mining can be thought of as a technology that extends into various complex contexts (as argued above). This introduction is by no means technically exhaustive but will hopefully lay the foundation to better understand our subsequent literature review on Bitcoin mining as a complex case.

2.2 Bitcoin Mining: A Brief Introduction

2.2.1 History

In late 2008, the pseudonymous Satoshi Nakamoto released a white paper titled: *Bitcoin: A Peer-to-Peer Electronic Cash System* (Nakamoto 2008). Nakamoto proposed a purely peer-to-peer electronic cash system allowing online payments to be transferred directly from one party to another, thus disintermediating and operating without third parties such as financial institutions or central banks. Instead, Bitcoin relies on its peer-to-peer network (and cryptography) to maintain the public ledger of transactions, also known as the blockchain. Every transaction since the *genesis block* (first block ever mined) is recorded on this ledger and maintained collectively by the network's nodes. This ensures a decentralised network with no single authority or point of failure; rather, the nodes of the network achieve consensus on the ledger's state. While we do not expect the reader to develop a deeper technical understanding of the technology, we will still present some concepts to better familiarise the reader with our case.

2.2.2 What is Mining?

To understand why Bitcoin mining is the subject of an ongoing academic dispute, it is crucial to understand the concept of proof-of-work. The main takeaway is that computational power, which requires electricity, is essential to sustain the integrity of the Bitcoin network.

Proof-of-work is a fundamental mechanism for Bitcoin mining. It is a process that converts electrical energy into a digital proof of work on the blockchain (Nakamoto, 2008: 3). This ensures that *miners* must expend computational power, which requires energy, to earn Bitcoin. This work is performed by specialised computers – ASICs (Application-specific integrated circuit), whose only task is to find a specific number for each block: the nonce. This number is part of the solution to the cryptographic equation, which gives a miner the right to process the block, earning Bitcoin (ibid.). The crucial point for the reader to understand is that the maintenance and security of the Bitcoin network require large quantities of electrical energy, and that this requirement makes the network secure. This significant energy consumption is also one of the central aspects of the dispute over Bitcoin mining.

Now that the reader hopefully has a better preliminary understanding of Bitcoin mining, we will continue to conduct a literature review on Bitcoin mining in an environmental context. Through our review, we show that Bitcoin mining is a highly contested subject in the literature; we argue that this dispute underlines our claim that Bitcoin mining is situated in a complex context, and therefore a relevant case for our research.

2.3 Bitcoin Mining as a Complex Issue

Through this deep dive into the academic literature on the environmental implications of Bitcoin mining, we hope to support our argument that Bitcoin mining is a technology that is embedded in complex contexts. The environmental aspect is therefore one of various examples of how Bitcoin mining extends into such complex contexts.

While we present these articles, we want to emphasise the polemic nature of Bitcoin. By this, we mean that Bitcoin is a highly disputed subject that can be rather polarising in terms of perspectives and analyses (Treiblmaier, 2023: 8). We recognise this, and will therefore approach the following review with caution, keeping in mind the strong incentives sometimes blurring the lines between science and ideology (ibid.).

Let us start by diving into some of the more Bitcoin-sceptic articles to highlight our point above. In a highly-cited article from Nature Climate Change, Mora et al. (2018) conclude that *Bitcoin emissions alone could push global warming above 2°C* (which is also the title of the article). However this conclusion has been disputed by multiple scholars such as: Masanet et al. (2019), Houy (2019) and Treiblmaier (2023) who all point out that Mora's et al. (2018) predictions are flawed because they highly overestimate the amount of Bitcoin transactions that can be made per year (Treiblmaier, 2023: 7). Both Masanet et al. and Houy – also published in Nature Climate Change as a direct response to Mora et al. (2018) – point out serious flaws in the design and execution of the study, e.g.:

(...) had the authors avoided the errors we described above, their own study design would have yielded much different — and far less alarming — projections of future Bitcoin CO_2 emissions (Masanet et al., 2019: 654).

This is not to say that justified and sound critique of Bitcoin mining is never valid; quite the contrary. However, the above controversy emphasises that we are dealing with a highly contested (and equally complex) issue.

An important consideration to keep in mind when discussing the energy consumption of Bitcoin mining, is the primary source of the electricity that is being used; this can vary a lot depending on multiple factors such as composition of energy, price, geographical location, grid flexibility and possible alternative uses (Treiblmaier, 2023: 11).

Continuing on emissions, Calvo-Pardo et al. (2022) aim to measure the carbon footprint of Bitcoin mining using feed-forward neural networks. While the authors emphasise that such measurement is controversial and subject to significant uncertainty (ibid: 1), they estimate the yearly CO_2 footprint for Bitcoin mining at 2.77Mt in 2017, 16.08Mt in 2018, and 14.99Mt in 2019. The 2017 estimate is 25-fold lower than the corresponding estimation by Mora et. al (at 69Mt in 2017). Nonetheless, this discrepancy should not shift the focus from a legitimate concern about the CO_2 footprint of Bitcoin mining. For comparison, the estimate for 2018 (16.08Mt) is higher than the annual levels of emissions of Bolivia, Sudan, or Lebanon (Calvo-Pardo et al., 2022: 21).

Interestingly, similar analyses (cf. De vries, 2018; De Vries 2020; Stoll et al., 2019) have been disputed by Sai and Vraken in their paper *Promoting rigor in blockchain energy and environmental footprint research: A systematic literature review* (2023: 11). They conclude: *that a majority of these studies lack the scientific rigor expected from a mature scientific field* (ibid.: 17). Bitcoin – as a technological system – is a highly contested and disputed subject. We are in the midst of an ongoing scientific dispute – some might say a battleground – and it is therefore difficult to say anything conclusive about the *actual* implications of Bitcoin mining.

Let us now present some of the potential positive use cases of Bitcoin mining concerning renewable energy.

Lal et al. (2024) investigate how the implementation of Bitcoin mining can help the transition from a fossil to a green energy system, by showing different profitable use cases (based in the US) of implementing ASICs on renewable energy-powered grids.

Similarly, Hallinan et al. (2023) describe the global need to reduce CO_2 emissions, while also meeting the UN's goals to achieve sustainability with equity (ibid.: 2). While microgrid projects have been deployed to provide electricity to disadvantaged communities (e.g. in India and Indonesia), kWh-pricing reaching upwards of USD 1-1.5 often make such projects financially unsustainable (ibid.). To mitigate this, Halliman et al. bring up the term *productive use of energy* (PUE): *this notion of adding income-generating systems to mini- and micro-grids* (ibid.: 2). Through six cases (ibid.: 12; 15) they assess the potential impact of Bitcoin mining integrated with microgrids and find that such an income-generating system can promote the investment worthiness of the grids while also lowering the kWh costs for the communities (ibid.: 16). Ibañez & Freier (2023) mention that Bitcoin mining could incentivise the expansion of renewable energy (RE). They describe different synergies between Bitcoin and RE, including but not limited to:

(a) A reduction of CO_2 emissions in grids oversaturated with wind power by decreasing reliance on natural gas for energy intermittency (ibid: 14).

(b) A 77.7% reduction of GHG emission by pairing solar plants with cryptocurrency mining facilities (ibid.).

(c) Maintenance of grid resilience during periods of heightened demand by reducing hashrate (ibid.).

(d) Combining batteries, solar, and Bitcoin mining could cater to 99% of the grid's needs (ibid.).

Altogether, Ibañez & Freier conclude that Bitcoin mining can potentially play a role in grid decarbonisation as a flexible load resource (2023: 18). However, they emphasise that a willingness of Bitcoin loads to be adaptable is needed if the technology is to significantly support the deployment of RE.

To conclude, some studies (De Vries, 2018; De Vries, 2020; Stoll et al., 2019) present concerning results regarding the emissions of Bitcoin, other studies (Sai and Vraken, 2024; Masanet et al., 2019) refute these claims as they criticise both the data and methods. On the other side, we presented some positive potentials, such as (1) Lal et al. (2023) with its multiple profitable RE use-cases, (2) Haliman et al. showed how mini grids could provide disadvantaged communities with access to electricity and (3) Ibañez & Freier (2023) identifies examples like the aforementioned *a, b, c*, and *d*, and investigate how the synergy between Bitcoin and RE could provide environmental positive outcomes.

We argue that Bitcoin mining is a good case to investigate interdisciplinary collaborations, because the ambiguity represented in the above literature indicates that Bitcoin mining is embedded in a complex context. However, while this ambiguity gives us little guidance in how to understand the technological potentials of Bitcoin mining, it points to an interesting socio-technical point: As the academic war rages, facts (re)shift in and out of existence; new papers render older ones invalid, but eventually the scientific community will approach some type of consensus that can *then* guide the technological development. In this mess, our role as techno-anthropologists is to find out where the translation between different communities is needed to deal with such wicked problems. If we can point out interdisciplinary blindspots, we might (just might) facilitate a better dialogue between the different camps; this is where our competencies in interactional expertise become relevant. However, this cannot be accomplished through this relatively eclectic literature review, but rather through a thorough network analysis.

In the following section, we will therefore introduce the reader to the techno-anthropological *raison d'être*, that is, why are *we* equipped to deal with such interdisciplinary challenges? We hope to provide the reader with a better understanding of what we do as techno-anthropologists.

2.4 On Techno-Anthropology

To better follow the techno-anthropological implications of our argument, we must first clarify what Techno-Anthropology is about. While this sounds like a trivial task, we want to note that it took our dear teachers 483 pages to do so in their anthology: *What is Techno-Anthropology* (Botin & Børsen, 2013) (and they are not done, as another body of work titled *This is Techno-Anthropology* is in the making and will be published in the years to come). So, bear with us as we present to you what *Techno-Anthropology* is to us and which of its aspects we find relevant to tackle our intellectual puzzle.

2.4.1 What Does Techno-Anthropology Mean?

Techno-Anthropology consists of two words that imply what the programme entails. *Techno-* for technology; representing the field's focus on machines and technique. Additionally, the hyphen underlines its connectedness to Anthropology, pointing to the human-technology relation (Botin & Børsen, 2013: 7-8). It is in this very relation that we are dealing with. As Botin & Børsen write:

> *Anthropology becomes a proxy for different humanistic and social scientific research approaches that in their multitudes reveal different aspects of technology and techno-science. Technologies, themselves interdisciplinary monsters, can accordingly be perceived as amorphous objects of these studies* (ibid.: 8).

This means that Techno-Anthropology is neither about humans nor technology, but rather about the bridging of both and how they affect one another in a constantly dynamic and ever-developing relationship; technology is constantly evolving, giving birth to new use(r)s as well as abuse(r)s (ibid.).

To practise Techno-Anthropology we must engage with a broad spectrum of disciplines, making it a hybridisation of multiple epistemologies to better bridge the gap between humans and technology (ibid.: 36). This makes the endeavour inherently interdisciplinary by combining elements from the social, natural and technical sciences (ibid.: 36-37). This approach is not to be confused with multi- or trans-disciplinarity. This distinction is important, as these approaches imply different ways of studying. To avoid confusion, we will briefly define each of the approaches in the following section.

2.4.2 Multidisciplinarity

With a multidisciplinary approach, respective disciplines are used independently, side by side, but the different approaches are neither synthesised nor combined (ibid.: 39). For example, while a multidisciplinary analysis might compare outcomes from different approaches as well as identify similarities, it will not integrate neither method nor theory (ibid.: 38-39).

2.4.3 Interdisciplinarity

As contemporary challenges have resulted in an increased need for cooperation between multiple fields, the term interdisciplinarity has become somewhat of a buzzword. The term describes the inclusion and integration of *elements* between at least two disciplinary perspectives (ibid.: 38). As Techno-Anthropology deals with problems that affect multiple fields, the interdisciplinary approach is used to handle, understand, and manage these challenges accordingly (ibid.: 37-39). The term is conceptually divided into methodological and theoretical interdisciplinarity: The former relates to how methods from different disciplines are integrated, while the latter concerns the integration of theories or conceptual frameworks from different disciplines (ibid.).

2.4.4 Transdisciplinarity

Similar to interdisciplinarity in its integration of perspectives from multiple fields, transdisciplinarity takes it one step further by calling for new unified analytical strategies: In transdisciplinary work, disciplines merge or hybridise. Botin and Børsen use Kuhn's notion of how scientific revolutions challenge the normal science, eventually giving birth to a new paradigm. In this perspective, transdisciplinarity is a move towards restoring a new scientific order (ibid.: 40). Botin and Børsen claim that Techno-Anthropology is only trans-sectorial trans-disciplinary, meaning it involves different ways of thinking across various sectors and professions (ibid.: 39-41).

Another cornerstone of Techno-Anthropology is the *Techno-Anthropological Triangle*, which highlights the different central competencies Techno-Anthropology comprises. The triangle is shown in the next section.

2.4.5 The Techno-Anthropological Triangle

To fully grasp what the triangle entails, we will go through each connection and explain what it means.

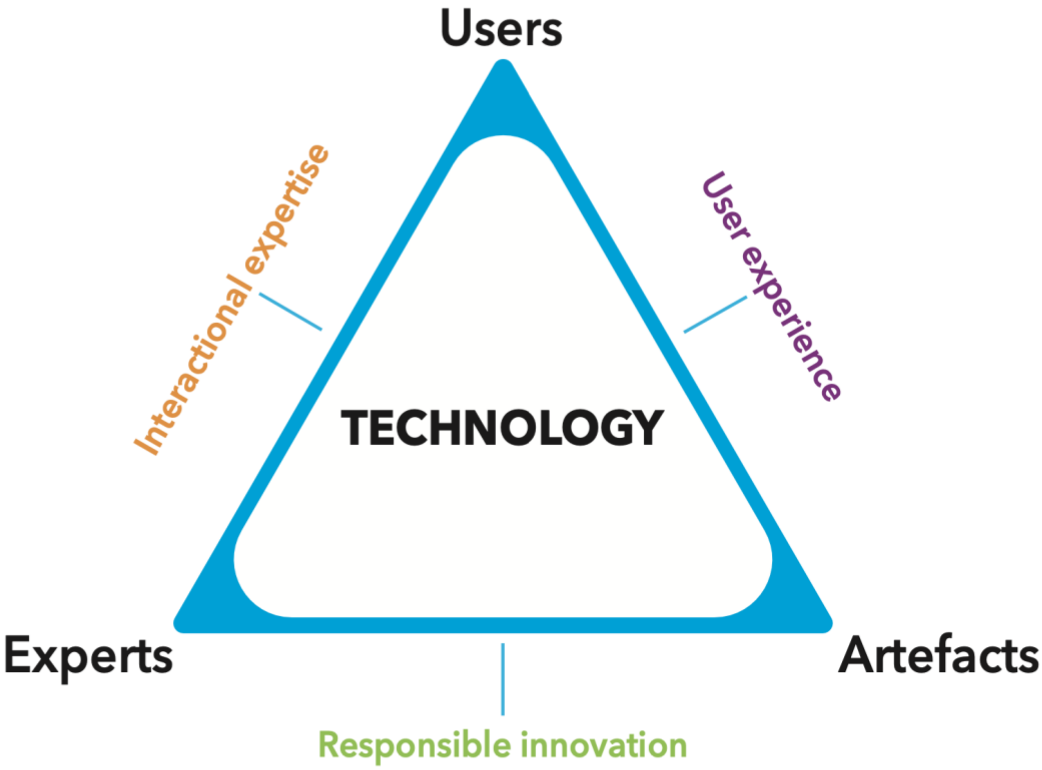


Figure 1: The Techno-Anthropological triangle (Børsen, 2020: 220)

2.4.5.1 User-Artefact

This connection describes the design-oriented techno-anthropological qualities. Herein lies the *value-sensitive innovative* approach: working with observations, models, and experiments to create user-friendly and practical design solutions. This transcends the traditional anthropological approach by focusing on change through action-oriented research and the field's affiliation with the natural sciences (Botin & Børsen, 2013: 51).

2.4.5.2 Expert-Artifact

This connection represents the ethical and socially responsible commitments that Techno-Anthropology has made. It is through these competencies that techno-anthropological studies can make informed judgements about the specific dangers concerning long-term, and often unintended, cultural and biological consequences. This means that the techno-anthropologist can identify cultural clashes, which often occur as the experts often operate in an *interdisciplinary* space (ibid.: 49-51).

2.4.5.3 Expert-User

This connection is essential to our project, as it is here that interactional expertise is emphasised. This competency is described as having the ability to mediate and *fix* the lack of understanding between users and experts, as well as between experts and experts. Botin and Børsen draw inspiration from C.P. Snow's *Two Cultures* (1959), wherein Snow identifies and describes the clash between the humanities and hard sciences, stemming from a reciprocal lack of understanding. Botin and Børsen use this example to describe how a techno-anthropologist would be able to map and identify the intrinsic differences in cultures to further develop a common understanding between two groups (Botin & Børsen, 2013: 49-50). Our interactional expertise will be the focal point of this research as we navigate the different disciplines of science. It is this competency that we will treat methodically throughout this paper to see how it might be informed by digital methods.

2.4.6 Digital Methods

In its broadest sense, digital methods refer to working systematically with digital tools on digital data with the ambition of saying something beyond the digital domain (Birkbak & Munk: 27, 2017). Rather than being a methodological tradition, digital methods can be understood as a series of practical challenges and pragmatic approaches found when working within the digital domain. Researchers must ask themselves: *what works and makes sense digitally?* (ibid.: 30-31). Just as there is no fixed methodology in digital methods, it also does not belong to any specific discipline. However, many of the disciplines engaging with digital methods are rooted in Science and Technology Studies (STS) and Actor-Network Theory (ibid.: 23). Lastly, a key ambition within digital methods has been to use digital data to map scientific controversies making them available to the public (ibid.: 24).

So far, we have established that we, techno-anthropologists, are taught how to deal with complex issues by facilitating interdisciplinary collaboration aided by our interactional expertise. We then argue that Bitcoin mining is embedded in such a complex context and is therefore a relevant case for our enquiry. However, it is important to note that Bitcoin mining is not a matter that we want to *solve*. Our argument of bitcoin mining as a wicked problem is merely to use it as a steppingstone for our methodological puzzle, which is:

> *How can we, as techno-anthropologists, utilise digital methods to guide our interactional expertise when dealing with experts?*

To continue this enquiry, we wanted to find inspiration in the established literature to learn how other scholars have tackled this methodical issue. Therefore, we conducted the following literature review.

2.5 Literature Review: Interactional Expertise and Digital Methods

The table below shows our incremental search with corresponding hits.

#	Advanced search	Hits
1	"Interactional expertise"	135
2	**Limit to:** Interactional Expertise as a keyword	74
3	**AND** Interdisciplinary	11
4	REMOVE "**Limit to:** Interactional Expertise as a keyword"	20
5	**AND** "Digital Methods"	0

Table 1: Systematic Scopus search results

To review the current literature on interactional expertise, we conducted a systematic search on Scopus. Our first search was "Interactional expertise"; the apostrophes were important as the search engine would otherwise search for articles including "Interactional" AND "Expertise". We then limited the search to articles containing the keywords "Interactional Expertise". However, as we consider interdisciplinarity an essential part of our inquiry, we added "Interdisciplinarity" to our search. While this narrowed our search to 11 articles, it was still limited to articles containing the keyword "Interactional Expertise", and we therefore chose to remove the limit. This combination of search criteria resulted in 20 articles. As our research intends to utilise digital methods, we tried adding "Digital Methods" to see if anyone else had used digital methods within this context. To our surprise, the search netted no results. We tried limiting the search to "Interactional expertise" **AND** "Digital Methods", but still no results were found. This surprised us as we saw it as an obvious opportunity to better understand *where* the interactional expertise is needed in interdisciplinary work.

We meticulously reviewed each of the 20 articles to see exactly how they went about the topic. We were particularly interested in seeing if any of them discussed methods on how to identify *where* the interactional expertise is needed in interdisciplinary collaborations. We found that the articles primarily discussed methods on *how* to use interactional expertise in practice and *why* to use it, but none of them discussed methods to identify *where* to apply the approach.

In this review, we find no papers discussing Interactional expertise in relation to digital methods (or vice versa). We are somewhat intrigued, as it seems that no one (published in Scopus) has dealt with the subject from this specific perspective. This means that we will have to establish an exploratory approach, since we have no literature to draw inspiration from. This concludes our domain section, and to put a final nail in the coffin, let us quickly summarise its contents: As techno-anthropologists, we are guided by our interactional expertise to approach complex issues interdisciplinarily, but we do not necessarily know how to locate these blind spots. We will use the literature on Bitcoin mining (which we have established as a complex technology) to explore how digital methods might give us interesting insight that we can use to inform our interactional efforts.

3 Method

In the following section, we will elaborate on our method. We start by presenting the practicalities of the meeting we conducted between five energy systems engineers. We will then address Scopus as our data source. Subsequently, we will highlight how we handle this data in our data-processing section and then continue to comment on our use of the data visualisation program Gephi.

3.1 The Meeting

As we have previously argued, Bitcoin mining can be understood as a technology that extends into complex domains, e.g., environmental sustainability. Inspired by our modularity analysis (see section 5.1.1), we thought it would be interesting to further investigate this intradisciplinary point. We wondered what would happen if we arranged a meeting between experts from the same disciplines to discuss this subject matter. Our choice of discipline was based off of (1) an analytical consideration as well as (2) a practical coincidence: (1) The modularity score for the discipline *Energy* was categorised as high, indicating that the discipline was somewhat heterogenous. (2) As our university offers multiple careers in various forms of energy engineering (AAU, n.d.), we have access to experts in this field within the vicinity of our university. We therefore invited various energy systems engineers to participate in our (online) meeting. Five of our invitees agreed to participate in the meeting:

(1) Peter Johansen: Senior energy specialist with over 20 years of experience at the World Bank, where he has worked with implementing RE into countries' energy infrastructure, from the Caribbean to Southeast Asia.
(2) Poul Alberg Østergaard: Professor of the Institute of Sustainability and Planning at Aalborg University, with 285 publications and 25 projects spanning six different continents, at the time of writing.
(3) Mads Ville Flinch Markussen: Board member of Bornholms Energi og Forsyning, the sole energy distribution company of Bornholm.
(4) William Kristian Krogh Vergo: Industrial PhD student, working with Energistyrelsen, developing tools for predicting energy technologies.
(5) Frederick Sebastian Marcus Stender: Research assistant in energy planning at the Institute of Sustainability and Planning, and our co-advisor.

As we have described the context for our expert meeting, we will now begin to unwrap our approach to digital methods. The following section explains the origin of our data, the platform Scopus, and what it entails.

3.2 Data Curation on Scopus

We accessed scientific articles on Bitcoin mining through Scopus: the world's biggest citation database with records dating back to 1788 for peer-reviewed literature from more than 7000 publishers, including scientific journals, books, and conference proceedings (Scopus, 2024). Another reason that we accessed our literature through Scopus is that it categorises articles in scientific disciplines. This categorisation is based on the journal in which the literature was published (Elsevier, nd).

Regarding the data scraping, we searched the terms "Bitcoin" *AND* "Mining" – indicating that both the keywords "Bitcoin" and "Mining" had to be present in each article. We got 1504 matches across 21 disciplines; of these 21, we chose to scrape the 15 largest disciplines, measured by the number of articles available on the issue of Bitcoin Mining, for which we used Scopus' built-in export tool. The data we were looking for was keywords, both author and indexed keywords. Author keywords are chosen by the author(s) to best reflect the content of their paper, while indexed keywords are standardised keywords provided by Scopus to account for synonyms, various spellings, and plurals (Scopus, nd). While Scopus standardises the keywords provided by the authors, it also adds new keywords to papers to better describe their content.

We chose to export both types of keywords as they each have their strengths and weaknesses, which we will later discuss (see section 6.3). Therefore, we chose to export both types and merged them into one cell. As a direct result of this merging, some cells (articles) had keyword duplicates, as the keyword would be present in both the author and the indexed keyword. Therefore, we cleaned duplicates from cells using Excel's integrated data cleaning tools.

> *Computer Science, – Engineering, – Mathematics, – Decision Sciences, – Economics, Econometrics and Finance, – Business, Management and Accounting, – Social Sciences, – Energy, – Materials Science, – Physics and Astronomy, – Environmental Science, – Medicine, – Multidisciplinary, – Arts and Humanities, – Chemical Engineering.*

Now that the reader has been introduced to Scopus and why we chose it as our data source, we will move on to exactly how we processed and handled said data.

3.3 Data Processing

After our data collection, we had index- and author keywords from 1504 papers across 15 disciplines. We knew that our data processing should amount to three different types of networks, each revealing different aspects of our academic inquiry. We wanted (1) 15 keyword co-occurrence networks, one representing each discipline; (2) a bipartite keyword co-occurrence network; and (3) a modified keyword co-occurrence network of sorts, in which we remove the keyword-to-keyword relationship, but instead construct a keyword-to-article-to-keyword relation. This is called a bipartite network, as it has two types of nodes. This seemingly minor nuance may seem insignificant, but it has a substantial impact on how the network unfolds as it allows for visualising the terminological overlaps, while still preserving the disciplinary origins of each article. Our keyword co-occurrence network containing all keywords from all 15 disciplines would – in contrast to the previous network – reveal how the keywords gravitate towards each other, without us projecting any predefined structure onto the data, i.e., disciplinary categorisations. Co-occurrence networks suit our needs as this type of network visualises the relationship between terms (such as keywords found in articles) and helps us find clusters and common themes (Birkbak & Munk, 2017: 155). We generated the two large networks containing all our keywords using table2net, an online platform that converts tabular data (CSV files) into networks (.gexf files). For the 15 smaller keyword networks, each representing a discipline, we used CorText Manager v2. We will elaborate on this process in the two following sections.

3.3.1 Step 1: Terms Extraction

To work with our dataset in CorText, we first had to convert it to a standard corpus database file. To do this, we uploaded our CSV files in zipped format and ran CorText's data-parsing script, after which we could start the terms extraction script. We set the minimum frequency of terms per dataset to one. In addition, we set the term list length to a maximum of 500 terms per extraction. We allow each term to contain a maximum of five words. This allowed for greater context without compromising the readability of the network. We had the script extract words at the *document level* instead of the default *sentence level*. This setting ensures that the script contextualises terms based on the document as a whole. This process transformed our dataset from a list of keywords attached to papers into a ranked list of the most frequent terms, as well as the relationship between them.

3.3.1 Step 2: Network-Mapping Script

After the terms extraction, we ran the processed data through CorText's network-mapping script. We used the script's maximum of 500 nodes per network. This resulted in 15 .gexf files that were ready to be visualised in Gephi.

Now that we have briefly touched on our data handling, we will use the following section to characterise the program Gephi and describe how we utilise it in our project.

3.4 Gephi

Gephi is an open-source software used for network analysis and data visualisation. Gephi visualises data in interactive networks, which makes it especially useful for making large datasets possible to comprehend and visually interpret (Bastian et. al. 2009). In this project, we use its Force Atlas 2 algorithm – a force-directed layout algorithm. This algorithm simulates a physical system where nodes repel each other, like two particles with the same charge, while edges attract the nodes at each end like an elastic band (Jacomy, 2014). When running the simulation, these attractive and repulsive forces balance each other out. This creates a network of nodes with a lot of connections close together and nodes without connections that are far apart due to the repulsive forces (ibid). This also means that the algorithm is not deterministic, as the map will not always have the same layout even though it has the same data.

As discussed earlier, we specifically work with co-occurrence networks. A co-occurrence network is a way to visualise words and/or groups of words that frequently appear together in a dataset (Levallois, 2023). This should help us identify clusters, relationships, and themes in data that could otherwise be easily overlooked. Let us provide an example by looking at the following network of Facebook friends:

Figure 3: *Visualised Facebook friend-list* (Ognyanova, 2014)

In the picture, we see a network of a Facebook user's friends list. Each picture represents a profile, and each line symbolises that the two profiles at each end are friends. We can see two large and two small clusters forming on the network, with lines between some of them. Each cluster represents a 'friend group' with so many connections between them that the connections flow together into distinct grey masses. At the edges of the clusters, we see that some of the profiles have connections to profiles from the other clusters, which means that these (despite being part of a relatively distinct friend group) also have friends in one or more of the other groups.

Now, imagine that instead of friends appearing in friend lists, it is the words from our terms extraction that constitute the nodes in the network. Instead of the connections indicating friendship, they indicate which words are mentioned together. Let us look at the example below to better understand this mechanism:

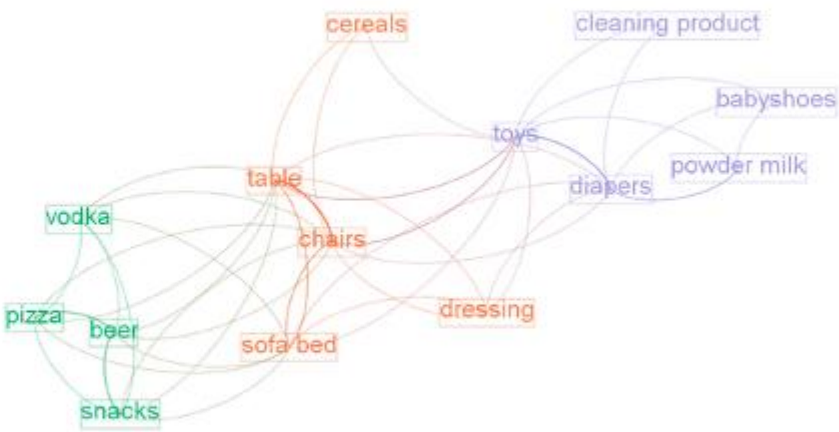


Figure 4: *Visualised terms extraction* (Levallois, 2023)

Just like the Facebook example, we see distinct clusters being formed and visualised with colours in the network. There is a cluster with the words *vodka, pizza, beer, and snacks*, a cluster with *cereals, table, chairs, sofa bed,* and *dressing*, and finally a cluster with the words *cleaning product, toys, babyshoes, powder milk, and diapers*. These clusters have been formed on the basis that words that co-occur most are placed together. The connections between the words show that the words appear together in the dataset. In our case, these are the index and author keywords.

Now that we have explained some of Gephi's functions and briefly introduced the algorithm ForceAtlas 2, we hope that the reader is now better equipped to understand the basic mechanisms behind our network maps that will be introduced later in our analyses (see section 5). We will now turn to some theoretical foundations that will need attention before we can proceed with our analyses.

4 Theory

In the following sections, we will elaborate on the theoretical foundations that inform our analyses. We start by clarifying the context and theoretical commitments to controversy mapping, highlighting its Actor-Network Theoretical origins. We then dwell on the foundations of the Interactional Expertise that we have continuously referred to throughout this paper. To further contextualise this notion of Interactional Expertise, we present the concept of trading zones, as described by Collins et al. (2007). We end this section by introducing Marres' (2005) idea of how *issues spark a public into being* – we will draw on this idea in our third analysis.

4.1 Controversy Mapping: Context and Theoretical Commitments

Controversy mapping is a set of methods and techniques for exploring and visualising social issues (Venturini, 2021: 258). The aim is to unfold socio-technical controversies in a conceptual space where actors and disputes can be weighed against each other (Venturini & Munk, 2021: 25). The methodical index was developed by Bruno Latour at the École des Mines de Paris as a didactic version of actor-network theory (ANT) to train university students in the study of current socio-technical debates (Venturini, 2021: 258). Since its introduction, controversy mapping has thus functioned as an educational version of Actor-Network Theory, but unlike ANT, it avoids conceptual complications and is therefore more accessible to students. Venturini describes controversy mapping as an actor-network-theoretical practice free from theoretical subtleties (ibid.). Munk and Venturini describe seven obligations that the cartographer – i.e., the one who prepares the controversy mapping – must commit to, see the table below (Venturini & Munk, 2021: 26-27):

1	I will follow the actors. I will not presume to know better than the people I am studying. I will learn from them what is relevant and important, what belongs to the controversy, and what does not. I will not silence the voices I do not agree with or that I find off topic.

2	I will provide weighting. I will grant visibility to actors in a way that is proportional to the difference they make in the debate. I will not represent all viewpoints as equally important, but take responsibility for weighing their influence and importance.
3	I will state my position. I will not pretend to be disinterested. I will not hide my opinion about the subject I am studying. I will make clear how my stakes in the debate influence how I explore and represent it.
4	I will stay with the trouble. I will not avoid the complexity of the controversy by means of methodical or theoretical shortcuts. I will not use my explanatory framework to take refuge from the incongruity and bewildering richness of social situations.
5	I will follow the medium. I will take advantage of the fact that controversies are made public, and thus mediated and recorded, by digital technologies. While investigating these records, I will also investigate the sociotechnical infrastructures that produce them and consider the specific ways in which they act upon the situation they mediate.
6	I will draw legible maps. In order to provide an overview and facilitate navigation, maps are necessarily simplifications of the territory they represent. Making legible maps of sociotechnical debates is the only legitimate reason for reducing the complexity of a controversy. Yet, my simplification will be cautious, transparent, respectful, and leave others the possibility to reverse it.
7	I will open my inquiry to others. Whenever possible, I will make publicly available the data 1 collect, the code I develop, and the text and images I produce. I will share my investigation with the people who have stakes in it and invite them to participate.

Tabel 2: *The seven commitments* (Venturini & Munk, 2021: 26-27)

These commitments point to the fact that controversy mapping has its theoretical origin within the Actor-Network Theory (ibid.) To consolidate our theoretical stance, we will therefore briefly dwell on the relational ontology of Actor-Network Theory. In the concrete digital-ethnographic work, we do not refer directly to the actor-network theoretical ontology; we nevertheless hope that this brief review will make our central argument clearer to the reader, because it becomes clear where we draw our ontological, epistemological, and methodological inspiration from. The actor-network theoretical relational ontology is based on the idea that the world is best understood by examining the relationships that exist between people, machines, statements, materials, texts, etc. (Jensen, 2021: 83). It operates with a flat ontology, which means that no actor – human or non-human – can *a priori* be assumed to be more important than other actors (ibid.: 86-89). Each actor is defined in relation to other actors in this network of heterogeneous relations. This concept of material semiotics is inspired by post-structuralist semiotics, where the meaning of a word is entirely defined in relation to other words. A central point is that an ANT analysis – as a consequence of its flat, relational ontology and material semiotics – does not assume a distinction between micro and macro, or that certain types of actors exist *a priori*. The actor network is always analysed on the same terms, regardless of the scope, format, or size of the network (ibid.: 89).

We hope to have familiarised the reader with the theoretical and ethical implications of controversy mapping, as we will now move on to elaborate on Interactional expertise. In the following section, we will explain Collins' and Evans' (2007) terminology, which will later inform our analytical scope.

4.2 Foundations for Interactional Expertise

As previously argued, Interactional Expertise is an essential part of our techno-anthropological effort as translators between various domains. We will therefore briefly present the notion of *Interactional Expertise* as conceptualised in Colins & Evans (2007): *The Periodic Table of Expertise 1: Ubiquitous and Specialist Expertises.* Collins and Evans present their taxonomy of knowledge, starting with the lowest level: *Beer-mat Knowledge.* This level of knowledge is defined through the following example:

> *(...) Jew or religious catholic might know how to recite certain prayers in Hebrew or Latin, respectively, without knowing their meaning* (ibid.: 19).

Thus, meaning that the person knows about the concept, but does not comprehend its deeper meaning. Following, the next level of expertise is termed *Popular Understanding* (ibid.: 20). This level contains a stronger understanding of the contents, and the person might be able to refer to basic notions gathered from mass media and popular books (ibid.). Next in the taxonomy is *Primary Source Knowledge*, which is gathered by – as the name suggests – reading primary sources. This endeavour can often lead to a false sense of mastery, as the primary source texts are technical and embedded in a complex field that might not yet have established a scientific consensus (ibid.: 22-23). Next, we have *interactional expertise*. This level of expertise implies that the person has knowledge and understanding of the field's language, but without the capacity to practise it: *you know the talk but cannot walk the walk.* This level of expertise is often used in large-scale projects, where solutions come from multiple different fields of knowledge. As techno-anthropologists, this level of expertise is essential in the pursuit of creating interdisciplinary understanding. Collins and Evans note that this interactional expertise is dependent on *interactive* and *reflective ability.* The former refers to the skills needed to interact with others, while the latter is the ability to reflect, for instance, by considering the epistemic foundations of any type of knowledge (Collins & Evans, 2007: 38-39). Finally, the highest ranking type of expertise is termed *contributory expertise* and is characterised by a level of knowledge that *contributes* to a particular field of interest, i.e., the particle physicist will (likely) possess this type of knowledge when she formulates theories about the elementary particles (ibid.: 28).

While Interactional Expertise is essential to understand *how* to engage in translation between various actors that need to collaborate but do not share a common language, the concept of trading zones is great for contextualising *where* to focus this interactional effort. We will therefore present this idea as conceptualised by Collins et al. (2007).

4.3 Trading Zones

The term *trading zone* was introduced to the social studies of science by Peter Galison as he tried to resolve the problem of incommensurability between Kuhnian paradigms (Collins et al., 2007: 657). His enquiry was quite simple: *How do scientists communicate if paradigms are incommensurable?* Galison's argument is twofold: Firstly, he denies that paradigms are as monolithic as stated by Kuhn. Secondly, he uses the metaphor of trading zones to explain how communication is handled between incommensurable actors (ibid.). Collins et al. only deal with the second leg of Galison's argument. They present *trading zones* as metaphysical spaces where dissimilar groups find ways to work and communicate with each other:

> *We define 'trading zones' as locations in which communities with a deep problem of communication manage to communicate* (ibid.: 658).

If there is no problem of communication, we are simply dealing with 'trade' as trading zones indicate difficulties of communication (ibid. 658). Collins et al. describe four types of trading zones, see figure below:

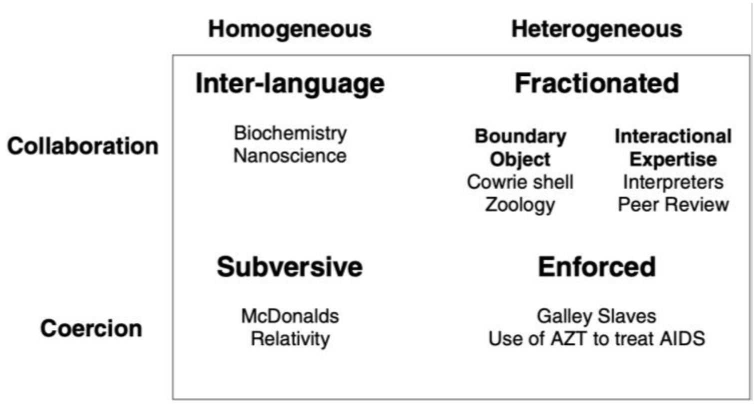


Figure 5: *A general model of trading zones* (Collins et al., 2007: 659).

The vertical dimension represents the extent to which power is used to enforce trade, while the horizontal dimension represents the extent to which trade leads to a homogeneous new culture (ibid. 658).

In the *Inter-language* trading zone, the problem is solved by developing 'in-between' vocabularies that allow actors to communicate (ibid.: 658). 'Jargon' is the simplest of these inter-languages; 'pidgin' represents a higher complexity, while a 'creole' refers to a new language (ibid.). They use biochemistry as an example of such an inter-language trading zone, because it is now an established scientific discipline arising out of biology and chemistry (ibid.).

In *Enforced trading zones,* the levels of coercion and heterogeneity are high. We are dealing with a one-sided bargain, where no cultural exchange is attempted (ibid.: 658-659). Slavery is a clear example of such a trading zone: the slave masters get work done, in return, the slaves get some food, water, and relief from beatings or execution (ibid.).

While Inter-language trading zones merge components from both parties to trade, communication can also happen when one party's language replaces the other's (ibid.: 660). In such a *Subversive* trading zone, two languages are gradually being replaced by that of one of the parties. In this trading zone, coercion and homogeneity are high. For instance, as Einsteinian physics became more established, Newtonian terms slowly faded out of the language, and those that remain are *de facto* Einsteinian sentences in disguise (ibid.).

Lastly, and most importantly for our techno-anthropological practice, Collins et al. describe the *Fractionated* trading zone. This type of trading zone occupies the top-right corner of the figure; here, collaboration and heterogeneity are high (ibid.). They describe two types of fractionated trading zones: *boundary object* trading zones, which are mediated by material culture in the absence of linguistic interchange, and *interactional expertise* trading zones, which are mediated by language in the absence of material culture (ibid.). We will only dwell on the interactional expertise trading zone. By being able to translate between heterogeneous collaborators without a shared language, the interactional experts make it possible for communication to take place within this trading zone. It is this zone that we, techno-anthropologists, are situated in.

This elaboration on trading zones is thought of as a contextualisation of our claim that interactional expertise remains important in interdisciplinary collaborations, because we are (often) dealing with heterogeneous collaborators who share no common language.

We are now ready to momentarily turn our attention to Marres' (2005) idea of how publics are sparked into being.

4.4 Nortje Marres*: Issues Spark a Public into Being*

Noortje Marres is Professor in Science, Technology and Society in the Centre for Interdisciplinary Methodologies at the University of Warwick (Marres, nd). In her PhD thesis (Marres, 2005a), she outlines an issue-oriented concept of public participation in technological societies, drawing on American pragmatism and Actor-Network Theory (Marres, nd). Taking her intellectual point of departure from the famous Lippman-Dewey debate, she develops the idea that complex issues enable public involvement in politics (Marres, 2005b: 2). Her main argument is that *issues spark a public into being*, rejecting an *a priori* concept of a public (Marres, 2005b; Marres, 2007). Simply put, there is no public *out there* as publics only momentarily exist around contemporary issues. Paraphrasing Dewey, Marres describes this concept of a public as *a community of strangers* (Marres, 2005b: 10). With this notion, a public consists of actors who are jointly implicated in an issue, but do not (necessarily) belong to the same social world (ibid.). We will draw on this concept to show that issues might also spark *scientific communities* into being and that we can use this knowledge to guide our interactional expertise.

As we conclude the theoretical segment of our paper, we hope that the reader is now well-equipped to better understand the premise on which our analyses are built.

5 Analyses

The following segment will consist of three analyses. In the first analysis, we will analyse the modularity of 15 networks. Secondly, we will analyse our expert meeting to show interesting differences in ways of approaching the issue in question. We then proceed to analyse a bipartite network with all 15 disciplines, focusing on co-occurrent overlaps of terminology as signifiers of a shared language between disciplines. In our third analysis, we shift focus from the disciplinary categories to the commonalities between disciplines.

5.1 First Analysis

As techno-anthropologists, we need to decide where to exercise our interactional expertise. In Collins et al. (2007): *Trading zones and interactional expertise*, the authors argue that interactional expertise is especially urgent in the *fractioned* trading zone (as explained in section 4.3). This zone is often described as being constituted of fractions of cultures as the medium of exchange, e.g., an interdisciplinary team of scientists working together to solve a specific issue. While we agree that interactional expertise is needed in this type of trading zone, we want to challenge that scientific disciplines always contain homogeneous groups of scientists. In the following analysis, we want to show how seemingly homogenous disciplines, when mapped in a network, are not so homogenous after all. This points to an important techno-anthropological consideration: we must also practice our interactional expertise *intra*disciplinarily, that is, *within* a discipline. By analysing 15 network maps, we show that the disciplines exist on a spectrum that spans from homo- to heterogenous.

5.1.1 Disciplinary Modularity Analysis

When visualising our networks in Gephi, we can calculate a modularity score for each network. Modularity indicates the degree of well-defined clusters in a network. It analyses the degree of internal and external connections of clusters. In other words, a network with low modularity has clusters that merge, while a network with high modularity has clusters that are well-defined and stand alone, cut off from the rest of the clusters in the network. In the following analysis, we will categorise the networks into three degrees of modularity: high, medium, and low. In this analysis, we will link a high network modularity with higher degrees of heterogeneity, while a low modularity indicates higher levels of homogeneity. In practice, this means that a low modularity indicates that a discipline shares a lot of the same keywords, making it more homogenous. Contrarily, a high modularity indicates that fewer keywords are shared across a certain discipline, thus making it more heterogeneous.

In the picture below, each of the 15 disciplines has been visualised as keyword co-occurrence networks ranked from highest to lowest according to their modularity score.

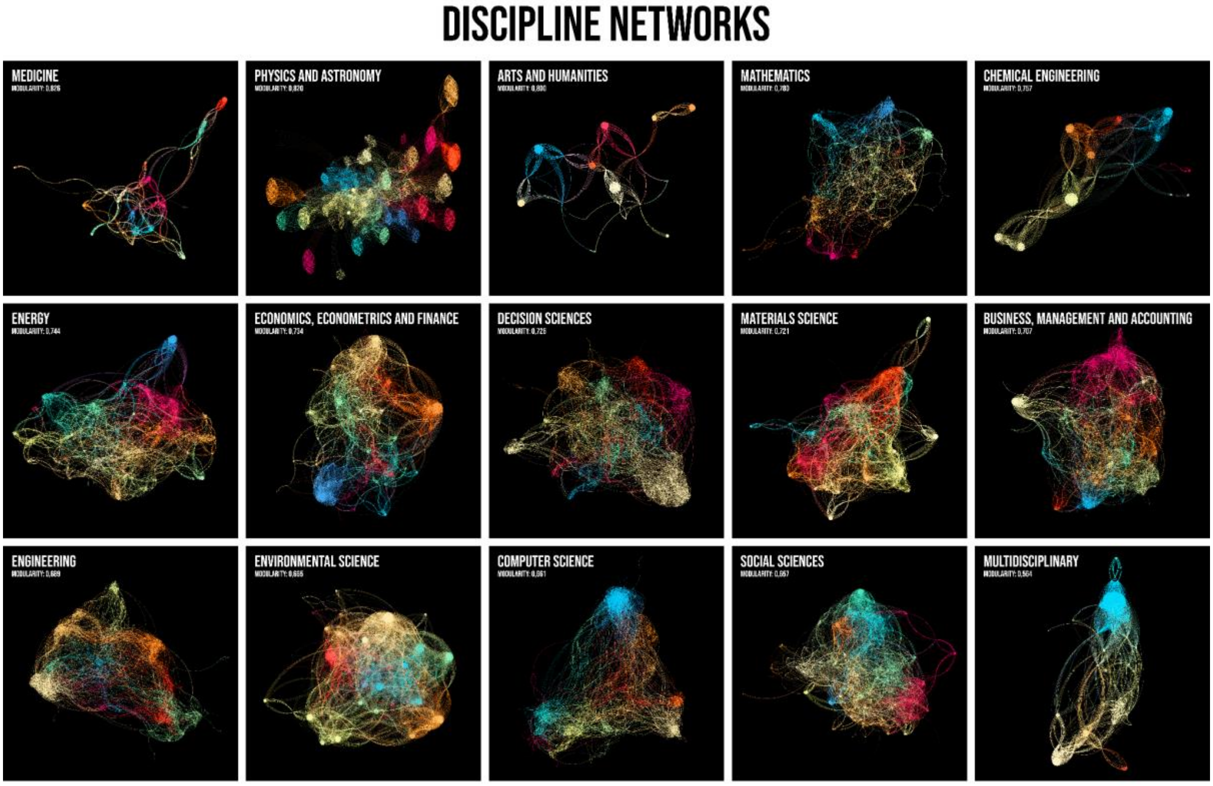


Figure 6: Modularity networks of the 15 disciplines

A glance at the networks reveals that some disciplines exhibit fewer edges (links) between clusters, making them appear separated and isolated. Conversely, other networks have far more edges between clusters, thus appearing intertwined – almost fused. For practical reasons, we categorise the networks into two groups, respectively: high and low modularity. Where high modularity networks have a value above 0,74 and low modularity networks have a value below 0,74. It should be noted that this threshold is not a universal standard for modularity classification, but serves as a useful distinction within the context of our study. Using these relative thresholds, the disciplines fall into the following groups:

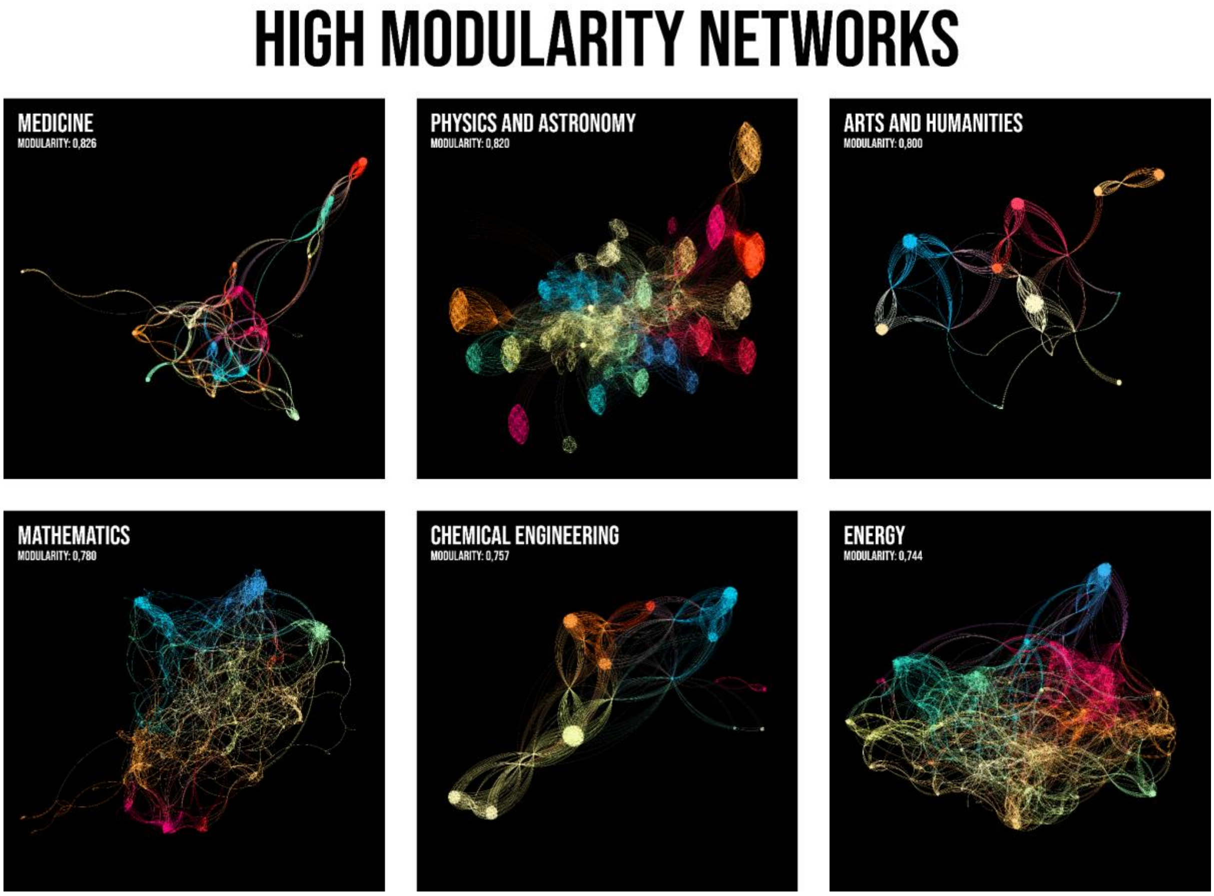


Figure 7: High modularity score networks

When looking at the networks, we see several well-defined clusters with high internal node and edge density, with few long edges between clusters. If we zoom in on *Physics and Astronomy,* we see several clusters without any outside connections. This tells us that topic areas operate in isolation from each other and seldom use the same keywords as the other areas in their discipline.

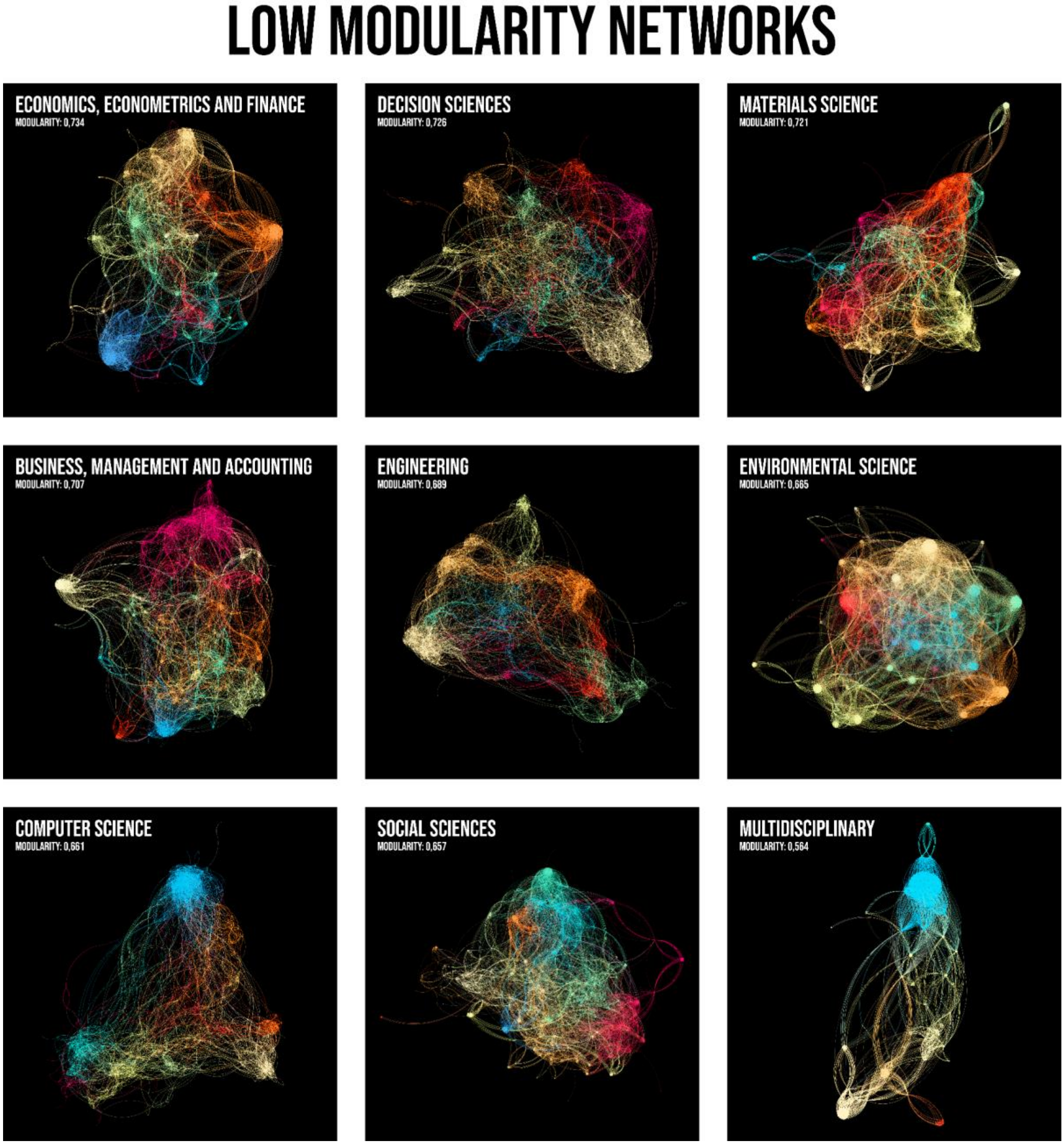


Figure 8: Low modularity score networks

The networks with a low modularity score are more entangled and show densely connected, unclear clusters with a lot of cross-cluster edges. Many keywords co-occur across the literature in these disciplines, indicating a shared language. An interesting find is the fact that *Multidisciplinary* is the network with the lowest modularity score. Upon further inspection of Scopus' categorisation (see section 3.2), we found a disagreement with what the search entailed. The reason that the Multidisciplinary network has the lowest modularity might be that this network is no longer categorised by a single discipline. Rather, it is grouped by the particular focus that the multidisciplinary publishers have, which appears to trend towards very connected topics within articles on Bitcoin mining; this inadvertently results in a low modularity network. By using each network's modularity score, we have shown the degree of disciplinary hetero and homogeneity within each discipline, based on keywords within the context of Bitcoin mining.

Let us try to see this through the lens of Collins' et. al. (2007) idea of fractionated trading zones. Within this framework, we interpret high modularity as the empirical manifestation of a fractionated trading zone: these trading zones require mediation in the form of interactional expertise. Without such mediation, the potential for shared understanding remains constrained by the internal fragmentation of the discipline.

5.1.2 Analysis of the Meeting

While our modularity analysis only expresses whether or not a discipline utilises the same language, it does not reflect whether they agree on a certain subject. For instance, a low modularity network might be the result of researchers in a discipline who strongly disagree on the *same* subject. Based on our modularity analysis alone, we cannot conclude whether disciplines need interactional expertise. To conclude this, we will need a qualitative and nuanced understanding of the communication between actors in a given discipline – keyword co-occurrence is not sufficient. Therefore, we arranged a meeting between five experts in energy systems engineering (see section 3.1) as this would allow us to qualitatively explore how different actors from the same discipline communicate on a given subject. Our idea was to analyse how these experts would tackle the issue in question: Bitcoin mining in the electricity grid. In a sense, we sparked a *synthetic* scientific community into being by arranging this meeting. However, contrary to Marres' notion of *a community of strangers,* this community seemed homogenous as all its members were from the same discipline. We argue that our interactional expertise – specifically what Collins and Evans call *reflective ability* (2007: 28) – can also be useful when dealing with seemingly homogenous groups of collaborators.

While we did not observe any ontological disagreements between the engineers, our participants *did* express different starting points to solve the issue in question, i.e., how Bitcoin mining can be integrated into the electricity grid. We understand these different starting points as different epistemological grounds. While this observation might be true, it is not surprising: different practices (see section 3.1) of the same science (Energy Systems Engineering) result in different starting points. *Then, what is our point?!* To put it shortly, one should not assume *a priori* that members of the same discipline can communicate effortlessly on all matters. In the following, we will try to analyse the meeting to show the concrete techno-anthropological implications of this point.

Our onto-epistemological point is simply that while the participants agreed on the nature of the problem, they differed in the means of solving it. We understand these different approaches to solving the problem as epistemological nuances – it has to do with *where* they acquire the knowledge to solve the issue in question.

We encountered three overall epistemological nuances (approaches) that recurred throughout the meeting.

(1) Broader societal value (technical prism).
(2) Broader societal economic value.
(3) Micro-scale profit value.

Firstly, we encountered a recurring standpoint relating to the (lack of) broader societal value of Bitcoin mining when compared to other technical alternatives. This standpoint emphasised the technical aspect of how else we might make better use of the electricity. But, it did not definitively deny the potential value of Bitcoin mining in the electricity grid. Secondly, we identified an inherently macroscale-focused viewpoint regarding how society can use Bitcoin mining to push *the green transition* forward. While these two standpoints are highly linked and, in many aspects, indistinguishable, one perceives the problem to be solved through a *technical prism,* while the other is motivated by *economic dynamics*. As techno-anthropologists, we must be able to identify such subtle epistemological differences, as they prove to be detrimental to the different ways respective members of a discipline conduct science. Thirdly, the last viewpoint was centred around how the *micro actor*, e.g., smaller private enterprises, might benefit from integrating Bitcoin mining into the electricity grid. This standpoint mainly differs from the latter in terms of scale, which, for us – the techno-anthropologists – informs an entirely different analytical approach.

This meeting exemplifies that while members of the same discipline might be able to communicate on a shared ontological basis, they will likely have different epistemological assumptions about how to solve the problem(s) at hand. It might sound like a trivial point: different people think differently about how to approach the same problems. However, we want to emphasise the importance of being able to identify these subtle epistemological differences, because it allows us to better synthesise and analyse their perspectives.
If we fail to identify these epistemological differences, we might not appreciate that we are being presented with different standpoints because they, at first glance, seem indistinguishable. By turning our attention to these subtle differences, we now see how (1) one group understands the solution as a matter of technical utility, (2) another focuses on the wider economic implications for society, (3) while a third seem to focus on what economic implications it might have for the small actor. It is this reflective ability – that we have developed through extensive analysis informed by the Philosophy of Science – that allows us to identify these subtle nuances. Now, where does this leave us as techno-anthropologists, and what implications does it have for the way we engage with experts?

As we argue, interactional expertise is crucial for our techno-anthropological practice. However, we think that this notion overlooks that we will also sometimes need to engage with members of the same discipline who do not necessarily share assumptions about how to approach the world. This is our epistemological argument. We argue that this bridging is also essential *within* a discipline, and is thereby also an *intra*disciplinary exercise. If we acknowledge that people within the same discipline might (and most likely will) have diverging epistemological grounds as a result of the specific way they operate within their discipline, we open up for this new way of techno-anthropological bridging. It is not a radical point, but one we cannot emphasise enough. It is even less radical if we think deeper about how the disciplinary boundaries are demarcated. In *the Logic of the Social Sciences,* the late Austrian-British philosopher of science Sir Karl Popper touches on this exact point in his ninth thesis:

> *A so-called scientific subject is merely a conglomerate of problems and attempted solutions, demarcated in an artificial way. What really exists are problems and solutions, and scientific traditions* (Popper, 1962: 92).

We are now able to understand why the techno-anthropological bridging is equally essential *intra*disciplinarily, as each discipline merely consists (according to Popper) of problems and solutions. This explains why our meeting participants expressed different epistemological grounds despite being 'members' of the same discipline. By being sensitive to these subtle epistemological differences, we are better suited to understand the complexities of the particular field of interest.

We hoped to have opened up for a broader understanding of the techno-anthropological practice by showing that we do not only engage with *inter*disciplinary but also *intra*disciplinary matters.

5.1.3 First Conclusion

In the modularity analysis, we argue that low-modularity networks represent disciplines with a greater degree of shared language, while networks with a higher modularity can be understood as disciplines with a lesser degree of shared language. Then, by analysing the meeting, we pursue the idea that our interactional expertise is not only needed to facilitate collaboration between disciplines, but that it can also be useful when dealing with groups of collaborators from the same discipline. Through this analysis, we show that our group of energy systems engineers approached the issue in question from different epistemological grounds: While agreeing on the nature of the issue, they differed in *where* to acquire their knowledge to solve it. Thus, we learn that one should not *a priori* assume that members of the same discipline can always communicate effortlessly on all matters. However, it is important to note that members might not be aware that they express different epistemological points of departure. This is why we argue that our interactional expertise – specifically our reflective ability – can *also* be crucial when dealing with seemingly homogenous groups of experts. By making explicit these subtle epistemological nuances, we allow for greater intradisciplinary collaboration because it becomes evident that we are dealing with a multitude of approaches to solving the issue.

5.2 Second Analysis

In the following analysis, we map all 15 disciplines' keywords in one network while still maintaining the disciplinary divide (shown by colour palette). In this way, we can see how the different disciplines relate to each other (or not).

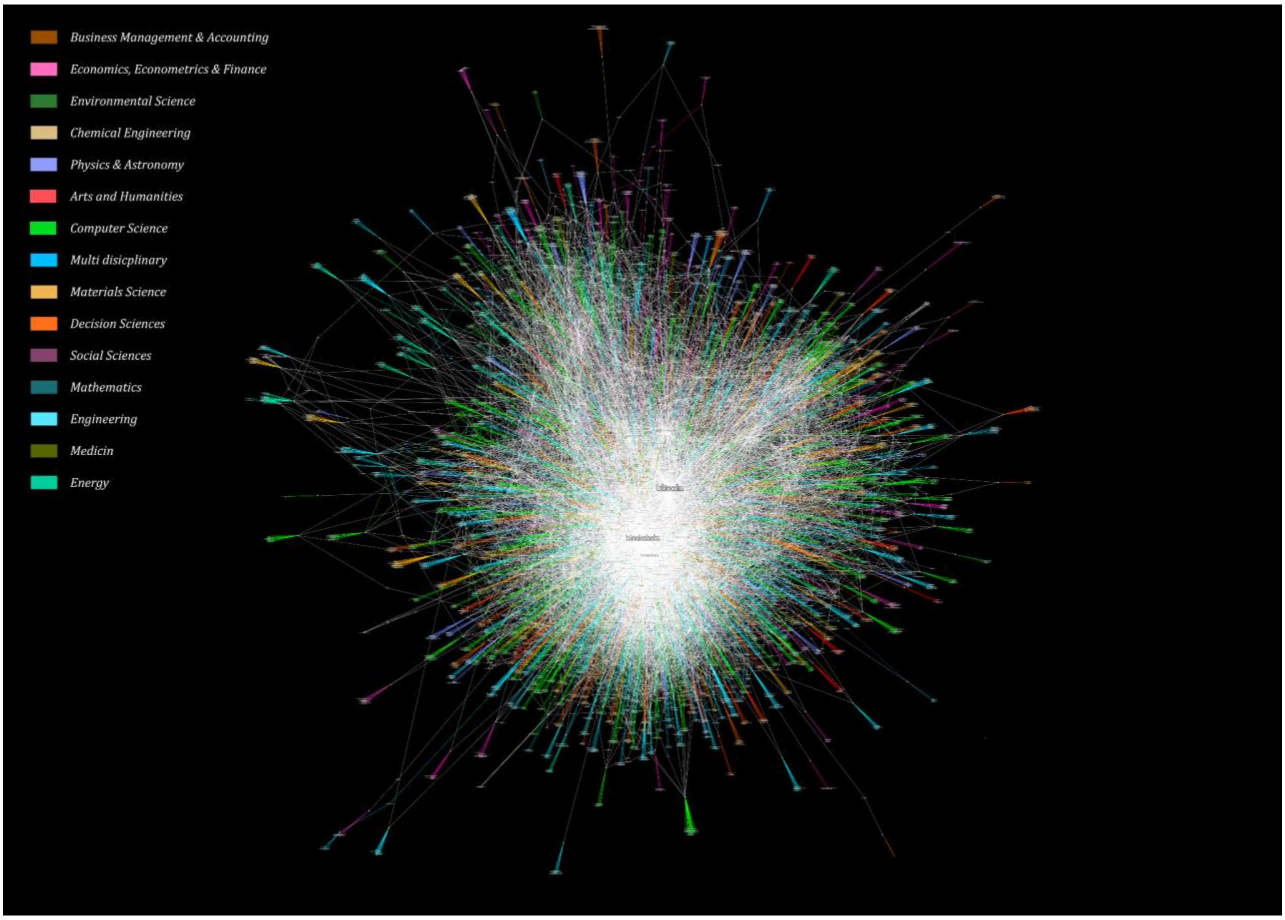


Figure 9: The bipartite network

The network consists of two types of nodes, making it a bipartite network. One type is the scientific articles (represented as a unique ID); the second is all keywords used in each article. Whenever two articles use the same keyword, they create an edge through that shared keyword. These nodes (and their subsequent edge) are then coloured white, as we have left no palette instruction for Gephi on how to colour keywords that share two or more disciplines. This allows us to observe not only the differences between disciplines but also the similarities. We observe the differences through the coloured keywords, which make up 76,66% (5512 nodes) of the nodes in the network, whereas we observe the similarities through the white nodes, which comprise 23,34% (1677 nodes) of the network's nodes. The former represents the discipline's individuality, and the latter represents the language shared among the disciplines. As we move further from the centre of the network, the disciplines become more segmented or specialised; the language they use is more niche, as their keywords are not found in other disciplines – the narrower a focus is, the more a discipline branches out.

However, it is inaccurate to claim that 23,34% of the keywords represent shared language, as it only takes at least two disciplines to share a keyword for it to become categorised as shared language (white node/edge). In actuality, only 0,6% of keywords are found across all disciplines. But what percentage of keywords do any two disciplines share? By visualising the degree to which any two disciplines share keywords, we can show which disciplines have the most shared language:

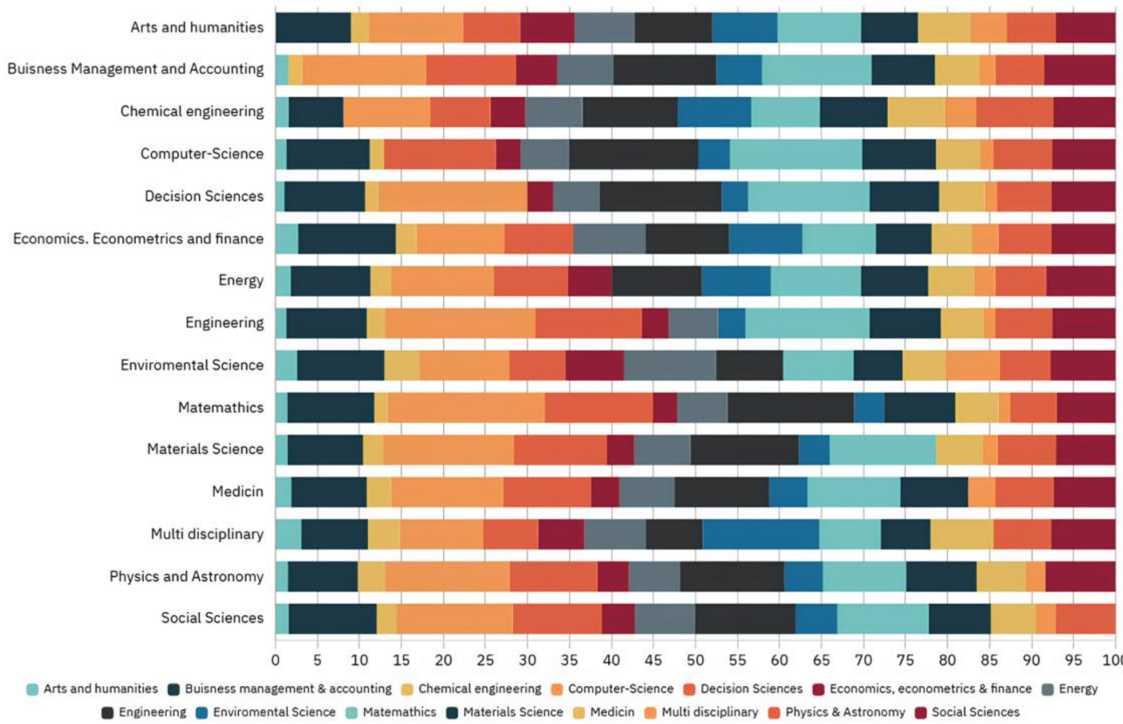


Figure 10: *Stacked bar chart of shared keywords between disciplines*

By reading the chart horizontally, we can see the amount of shared language between the two disciplines. Let us take a look at *Arts and Humanities*: This discipline shares approximately 8% shared language with Business Management & Accounting, and 3% with Chemical Engineering, 10% with Computer Science, etc. This allows us to quickly see the degree to which any two disciplines share keywords. For disciplines with a low percentage of shared language, we interpret this lack of a shared language as an example of a *fractionated trading zone*, where the disciplines cannot meaningfully communicate without external facilitation by either a *boundary object* or an *interactional expert.*

5.2.1 Second Conclusion

In the second part of our analysis, we wanted to experiment with plotting all disciplines in the same network to analyse how they might relate to one another. While this network represents the discreteness of each discipline as fragmented clusters in the vicinity, the white centre indicates some sort of shared language between the disciplines. The further we move away from the centre, the more specialised and discrete the disciplines become; at these 'suburban' sites, the language is simply more niche and is therefore used less by other disciplines. Notably, the shared language across all disciplines only accounts for 0.6% of the total nodes, while a shared language between two or more disciplines accounts for 23,34% of the nodes. We therefore argue that these heterogeneous collaborators are still in need of developing a shared language to facilitate communication, though it appears that some disciplines actively use this shared language more than others. As an interactional expert, one needs to identify *where* the potential for a shared language lies; we argue that the shared keywords (white nodes) are points of departure that we can draw on when translating between domains in new contexts. Finally, we want to emphasise that it might be more useful to isolate the specific disciplines one is dealing with (as an interactional expert) and *then* analyse their specific shared language.

5.3 Third Analysis

In the above analyses, we were analytically dependent on the disciplinary labels (sub-fields) as we analysed (1) how they can each express varying degrees of heterogeneity despite being *one discipline*, and (2) how these seemingly discrete fields might lack a shared language as visualised in our network map. In the following analysis, we will map the keywords in a co-occurrence network to see how they distribute themselves when they are no longer confined to these disciplinary boundaries. We hope to convince the reader that this mapping will better allow us to decide *where* to focus our interactional expertise. We argue that by mapping the keywords from all 15 disciplines, we can focus on *how* they approach the issue, transcending the disciplinary divide. To support and develop our argument, we will analyse our network map through the prism of an issue-based (here: scientific) public, as conceptualised in Marres (2005a). Let us start our analysis by programmatically describing and categorising the topography of the co-occurrence network map.

5.3.1 Thematic Categorisation

The keywords form six interesting clusters. Since each cluster contains more keywords (ranging from 398 to 2205) than we could meaningfully categorise thematically, we fed the keywords of each cluster to ChatGPT and prompted it to identify the overarching theme as represented by the keywords, see prompt below:

> I need your help identifying the overarching theme represented by the following keywords. These keywords originate from a cluster identified in my network analysis. Your task is to analyse all the keywords carefully and determine what unites them conceptually. Based on this, suggest a concise and meaningful name for the cluster, and provide a short rationale explaining why this name fits the group of keywords. Please ensure that you read and consider all the keywords when forming your interpretation.

Based on this prompt, ChatGPT suggested a cluster name followed by a detailed rationale for this name. For the turquoise cluster, the output looked like this (see the appendix 3.3 for all outputs):

> *Suggested Cluster Name:* ***'Cryptographic Hardware and Computational Efficiency'***
>
> *This keyword cluster revolves around the intersection of cryptographic systems, hardware technologies, and computational performance optimization. Key themes emerge from the following domains:*
>
> *1.* ***Cryptographic Infrastructure & Blockchain***
> *Keywords like bitcoin mining machine, blockchain headers, secure hash algorithm, merkle trees, and ethereum platform show a strong focus on the architecture and protocols of blockchain and cryptocurrencies.*
>
> *2.* ***Hardware & Accelerated Computing***
> *Terms such as AI chip, ASIC, FPGA, GPU, superconducting circuit, system-on-chip, and hardware accelerators emphasize high-performance hardware implementations of cryptographic tasks.*
>
> *3.* ***Energy & Efficiency Concerns***
> *Phrases like low-power consumption, energy-efficient, dark silicon, e-waste, and waste management highlight concerns about sustainability and computational efficiency in mining and related activities.*
>
> *4.* ***Error Handling & Optimization***

Inclusion of terms like error correcting codes, timing error detection, delay circuits, and pipeline techniques point to design-level optimization in digital systems to ensure performance and reliability.

5. ***Emerging & Alternative Technologies***

The presence of reversible computing, approximate computing, unconventional computing, and near-threshold voltage suggests experimentation with cutting-edge techniques to address efficiency bottlenecks.

This blend of ***hardware development, cryptographic protocol design, and environmental/efficiency considerations*** *supports the proposed cluster name, reflecting both the technical core and the practical implications of crypto-centric high-performance computing.*

Following this method, we categorised *the turquoise cluster* as: *Cryptographic Hardware and Computational Efficiency,* as it represents hardware development, cryptographic protocol design, and environmental and efficiency considerations (as described by ChatGPT above).

The red cluster is thematically centred around blockchain; More specifically, how agents behave strategically within blockchain systems and how protocols are designed to optimise or secure these interactions. We categorised it: *Blockchain, Game Theory, and Security Mechanisms.*

We termed *the pink cluster: Graph-Based Forensics and Financial Crime Detection* because the cluster is thematically focused on using advanced data analysis techniques, in particular graph mining and network analysis, for detecting financial fraud, cybercrime, and illicit behaviour in digital and blockchain-based systems.

As *the green cluster* is centred around cryptocurrencies' energy use and its environmental impact and regulation, we termed it: *Crypto-Energy and Environmental Sustainability.*

The blue cluster represents a broad array of concepts from machine learning, data science, financial modelling, and cryptocurrency market behaviour. These are conceptually connected through the application of advanced predictive techniques and AI models to understand, forecast, and respond to behaviours and trends within crypto-related environments. We termed it: *Machine Learning and Predictive Modelling in Cryptocurrency Analytics.*

Finally, we termed *the orange cluster: Socio-Technical Architectures of Crypto-economics,* as the cluster represents how currency, trust, governance, and social behaviour are encoded in software and algorithms.

Below, we have visualised our network with the corresponding cluster categorisation:

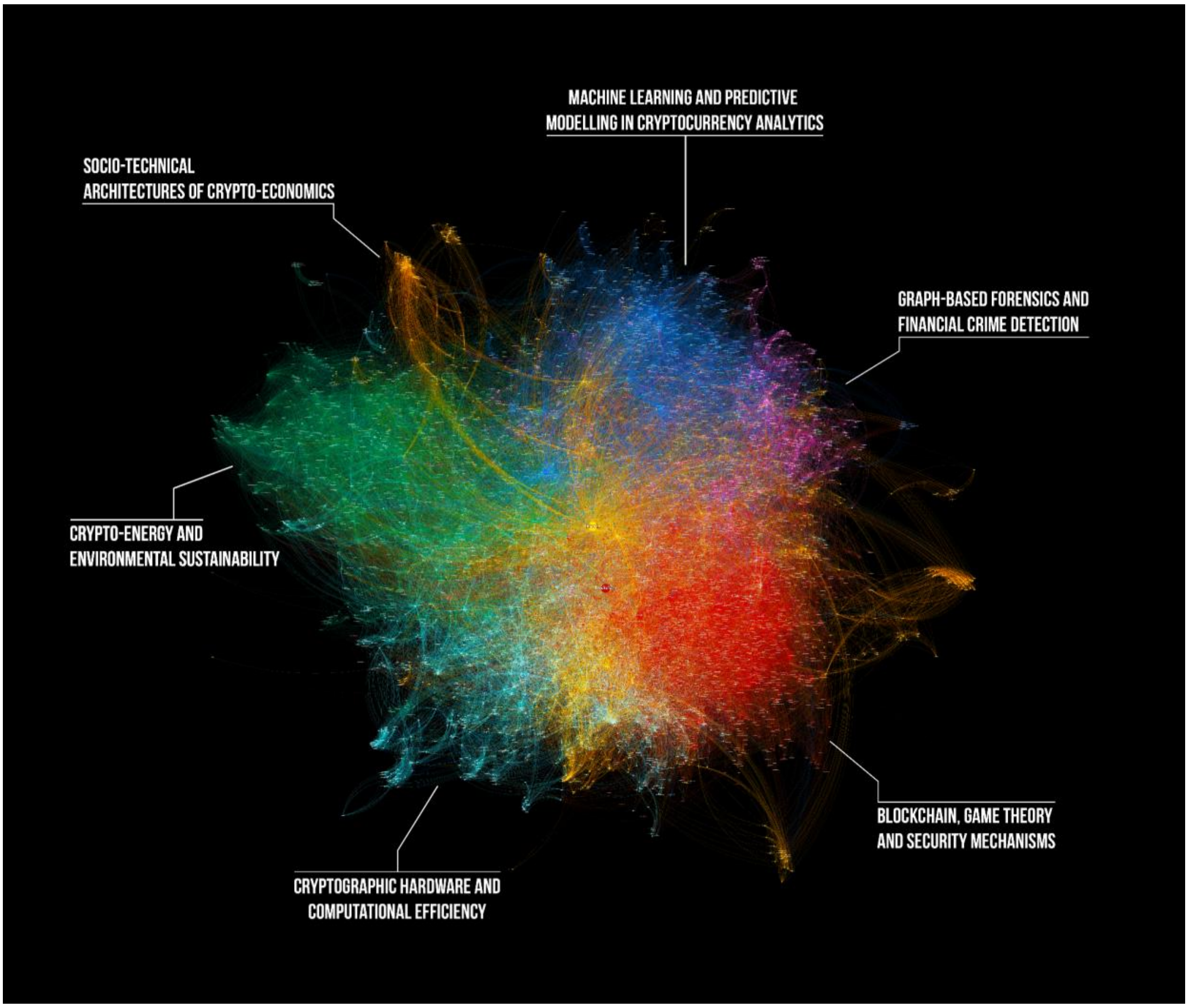


Figure 11: Issue-based co-occurrence network

We are now ready to build our analytical points.

5.3.2 First Analytical Point

Issues spark scientific communities into being

By allowing the keywords to distribute themselves without confinement to disciplinary boundaries, we can interpret and analyse our data from a new perspective. A trivial, but interesting observation is that the keywords form six (significant) clusters, not 15, which is the number of disciplines we have scraped the Scopus articles from. If that had been the case, we would have simply shown that each discipline deploys its own extremely niche vocabulary. Anyone superficially familiar with how science is practised will not be surprised that this is *not* what our network shows: Clearly, different disciplines will have overlapping language, e.g., in terms of shared notions, concepts, and theories. Luckily for us, this is not our point. While it might be self-evident that different disciplines will deploy overlapping language, it is not self-evident precisely *where* this shared language occurs. What we are grappling with in this analysis is the reason why these clusters form the way they do, that is, *what is their intellectual centre of gravity?*

To better develop this argument, we will draw on Marres' (2005b) concept of an issue-based public (see section 4.4). By ignoring the *a priori* notion that characterises each discipline, we allow for a greater sensitivity to *how* these disciplines tackle certain intellectual issues. Marres understands a public as a community of strangers who are all affected by, and thereby engaged in, a certain contemporary issue. We understand a scientific community as a community of scientists who are all intellectually invested in – and thereby relate to each other through – a concrete contemporary issue. It is Bitcoin mining – a concrete intellectual centre of gravity, an issue – that sparks this scientific community into being. Disciplinary boundaries *can* be helpful, but we want to argue that shifting our attention from *disciplinary categories* to how these disciplines engage with concrete issues might be a helpful heuristic for our interactional expertise (we will elaborate on this point in the next section).

Through this issue-based, constructivist prism, our network can be understood as a visual representation of this contemporary scientific community. The clusters represent different scientific approaches to engaging with the issue. However, while these clusters do not reflect any disciplinary boundaries, we might learn that some disciplines tend to engage more with the issue through certain approaches than other disciplines. Our point is that we can only learn this *a posteriori*, as the issue defines the practice *across* disciplines. By mapping the articles without incorporating their disciplines of origin, we can identify which approaches are applied *across* these disciplines (as visualised in the above network): (1) Cryptographic Hardware and Computational Efficiency, (2) Blockchain, Game Theory and Security Mechanisms, (3) Graph-Based Forensics and Financial Crime Detection, (4) Crypto-Energy and Environmental sustainability, (5) Machine Learning and Predictive Modelling in Cryptocurrency Analytics, and (6) Socio-Technical Architectures of Crypto-economics.

Let us end this section by summarising our analytical point: By shifting our focus from the disciplinary boundaries to contemporary issues that spark the scientific community into being, we allow for a greater sensitivity to understand *how* these disciplines engage with the issue in question. An important nuance of this analytical point is that one discipline will often apply multiple approaches when engaging with the issue. This prism allows for a more flexible understanding of what has traditionally been called a discipline. Within this perspective, such *disciplines* are rarely confined to the arbitrary boundaries they are preconceived to operate. Our point can easily be exemplified when observing an interdisciplinary team of scientists because it is the concrete project goal that defines how each scientist approaches the issue. As previously stated by Sir Karl Popper:

> *A so-called scientific subject is merely a conglomerate of problems and attempted solutions, demarcated in an artificial way. What really exists are problems and solutions, and scientific traditions* (Popper, 1962: 92).

In the following section, we will analyse which disciplines are present in the respective clusters. This analysis will allow us to identify *how* the disciplines collaborate and thereby guide our effort as interactional experts.

5.3.3 Second Analytical Point

Where to build the bridge?

In the previous analysis, we emphasised the importance of paying attention to the issues at the centre of scientific communities rather than relying on preconceived notions of academic disciplines. In the following section, we will connect this analytical point with the idea of interactional expertise. We have previously argued that this capability is a fundamental part of our techno-anthropological practice, and we intend to guide *where* to focus this expertise. While we have already categorised the six clusters, we have not yet identified which disciplines are present in the clusters. If we momentarily reapply the disciplinary origins of each keyword to the network – by colouring the nodes according to their discipline rather than their keyword cluster – we can visually observe how the disciplines are distributed across the clusters. This visualisation can be seen below:

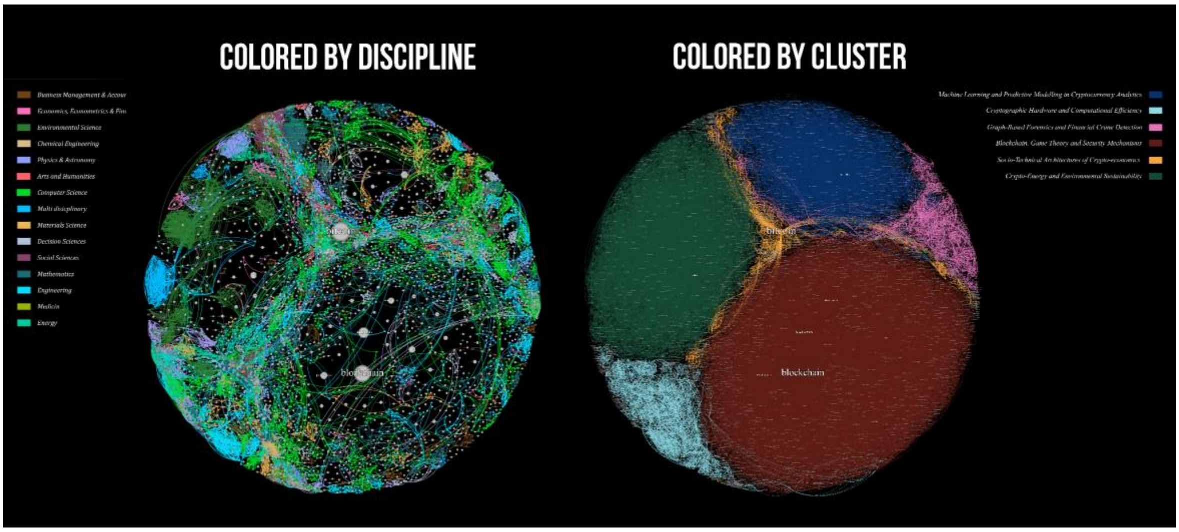


Figure 11: Issue-based co-occurrence network, with high gravity coloured by cluster and discipline

First, we must address that a network visualisation is not the most efficient way of deriving any meaningful analytical points. We will therefore, in the following section, quantify this information to present it in a more accessible form – specifically through radar charts. Before doing so, we must consider that the disciplines are not equally represented in our data. Therefore, we recalculated the distribution based on a weighted percentage, we multiplied the percentage of each discipline by a weight factor to account for this uneven representation in our data (see appendix 3.2). Below we have visualised each of the six clusters in their own radar diagram, allowing us. Furthermore, as a courtesy to the reader, we have also visualised how each discipline distributes itself among the clusters. To enhance readability, each of the six vertices has been coloured to match the issues from the colours in Figure 12.

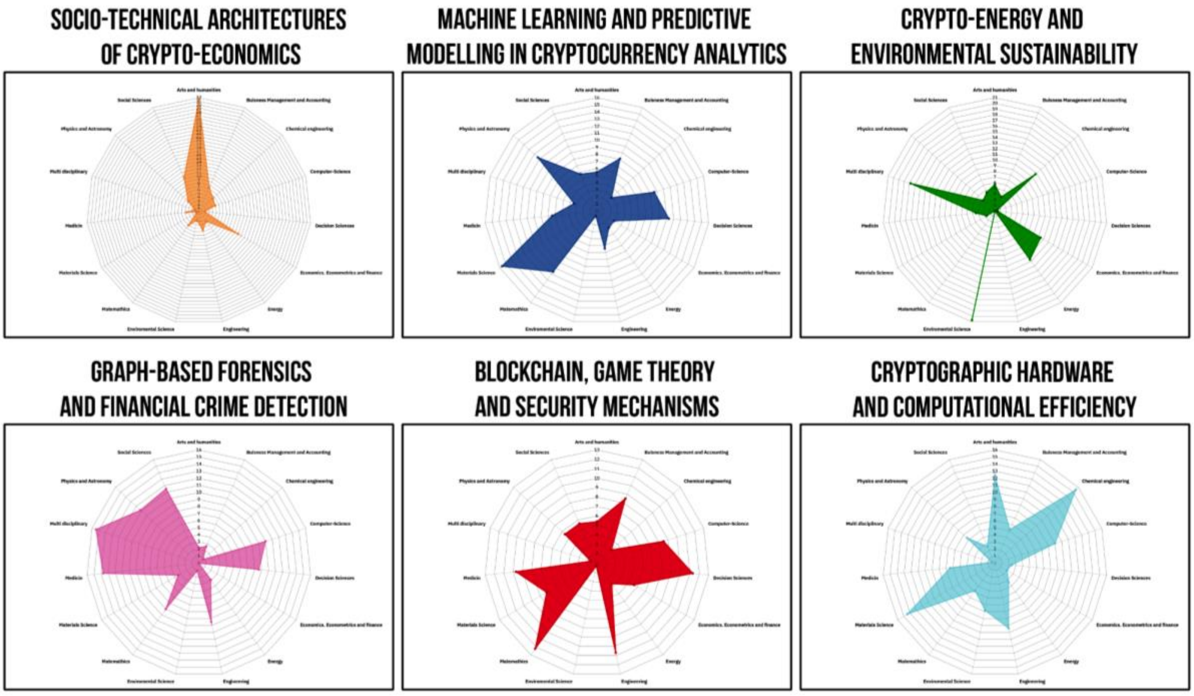


Figure 12: Issue-based radar charts sorted by issues

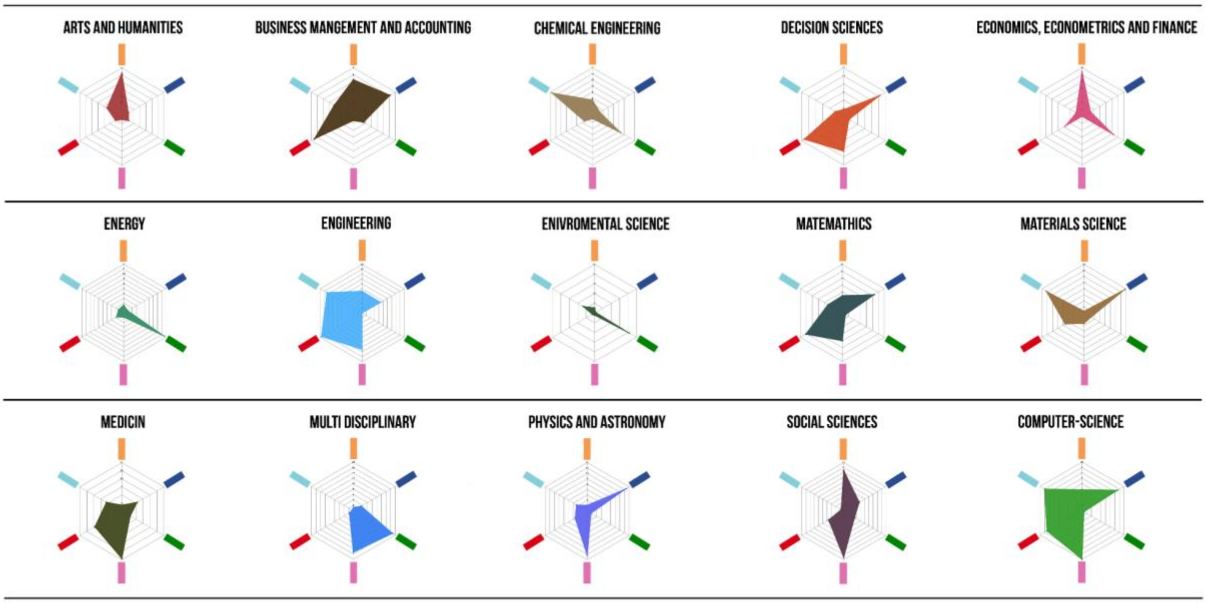


Figure 13: Issue-based radar charts sorted by discipline

Remember that each of the clusters represents a particular approach to engaging with Bitcoin mining. Thus, if a discipline has a high percentage count after weighing, it means that its keywords are relatively more present in this particular cluster than keywords from other disciplines. By identifying how the disciplines are distributed in the clusters, we can point to where we need to focus our interactional expertise. We need to briefly summarise how we have arrived at this analytical site before we continue our argument: By ignoring the disciplinary boundaries, we have been able to visualise how the disciplines are better understood as dynamic entities that engage with the issue through six different approaches. This point was informed by Marres' *a priori* rejection of a public. What we intend to do next is to *reintroduce* the disciplinary boundaries to identify how the different disciplines are distributed between the six approaches. This will allow us to point to potentially blind angles and thereby inform our interactional expertise as to where the bridge(s) need(s) to be built.

Let us start by commenting on those of our cluster distributions that we think are most coherent with our expectations, and therefore least analytically interesting. For example, we are not surprised by the disciplinary distributions of *Blockchain, Game Theory, and Security Mechanisms* as our results indicate a relatively high presence of, for example, mathematics, decisions, and computer science. Likewise, we are not surprised that social sciences, computer science, mathematics, and medicine are all relatively more present in *Graph-Based Forensics and Financial Crime Detection* than, e.g., Chemical Engineering or Arts and Humanities.

Conversely, we must admit that we are surprised by the disciplinary distribution of *Cryptographic Hardware and Computational Efficiency*. While most of the disciplinary distributions in this cluster make intuitive sense to us (a relatively high presence of e.g., materials science and engineering), we are surprised by the significant presence of Arts and Humanities. We find it difficult to connect the typical disciplinary traits of Arts and Humanities with this seemingly *hard-science* cluster. However, we must not only acknowledge but also celebrate that our data might tell stories that we cannot always necessarily comprehend. We find this discrepancy interesting and would have probably overlooked it had we conducted a conventional literature review. A humble attempt at explaining this (to us) counterintuitive observation could simply be that we underestimated the amount of interdisciplinary effort represented in this specific approach: Maybe this cluster is a prime example of the interdisciplinary coordination that exists across the disciplines. We simply cannot know without further research, but this speculation exemplifies how our network analysis can help challenge our preconceived understanding concerning how the disciplines engage with one another.

Let us continue to develop our analytical point by turning to two particularly interesting distributions: (1) Crypto-Energy and Environmental Sustainability, and (2) Socio-Technical Architecture of Crypto-Economics.

While the former cluster is coherent with our expectations, as we find it intuitive that Environmental Science is strongly engaged in this approach, we want to point out the *absence* of both social and economic sustainability. Throughout our studies, we have been taught to always consider sustainability as a tripartite concept: one needs to always consider both the environmental, social, and economic aspects as they relate to and depend on one another. It is not *sustainable* to isolate any of the three elements. We went through the keywords of this cluster and concluded that it did not contain anything pointing to either social or economic sustainability. As interactional experts, we would therefore focus our expertise on integrating greater social and economic sensitivity, e.g., by building bridges to both social science and arts and humanities, as we would expect these disciplines to have valuable insights that the other disciplines might benefit from. This point exemplifies how we can utilise our network map to localise the sites on which to build the bridges.

Likewise, we observe an interesting disciplinary distribution in the cluster: *Socio-Technical Architectures of Crypto-Economics,* as it is significantly dominated by Arts and Humanities. Even without knowing the exact contents of this cluster, it indicates that (what has traditionally been termed) *hard sciences* do not engage in socio-technical matters (at least not in this cluster). In a sense, this discrepancy is what provoked the formation of our study programme (Techno-Anthropology) and why the need for our interactional expertise is urgent. It is therefore neither surprising to us that this cluster might need a few bridges nor where they need to be built: By connecting, e.g., Engineering, Computer and Materials Science with Arts and Humanities, we allow for a greater sensitivity to how the social and technical relate to each other. Simply put, by drawing on the insight from an array of disciplines, we can design better technology(systems). This is essentially the idea of interdisciplinary collaboration. We argue that by identifying such missed potentials (blind angles) between disciplines, we can improve the conditions for interdisciplinary collaboration by knowing *where* to exercise our interactional expertise.

5.3.4 Third Conclusion

Finally, in this last analysis, we take a different approach as we see what happens if we ignore the disciplinary boundaries and let the disciplines rearrange themselves based on keywords. Our network shows six interesting clusters that represent different approaches to engaging with the issue. We draw on Marres' (2005b) concept of an issue-based public to explain how

Bitcoin mining can be understood as an issue that sparks a heterogeneous community of scientists into being. By applying this philosophical trick, we dissolve the *a priori* notion of a discipline, thus allowing us to focus on how the issue engages different approaches, transcending the disciplinary boundaries. In line with our prior analytical points (see section 5.1.2), these six approaches might represent different epistemological grounds, that is, where does one acquire knowledge to solve the issue? However, by reintroducing the disciplinary boundaries, we quantified how the disciplines were distributed in the respective clusters. This allowed us to point to clusters (approaches) that might benefit from the insights of certain other disciplines that were not represented in this particular cluster. For example, we argue that building a bridge between the arts and humanities and the hard sciences in the cluster: Socio-Technical Architecture of Crypto-Economics might benefit the overall approach, as the latter disciplines are absent in this cluster. Through this network analysis, we have shown how to identify where to focus our interactional ability, that is, *where to build the bridge*.

5.4 Analyses Conclusion

As this concludes our tripartite analysis, let us briefly summarise what we have argued thus far: We start by analysing the modularities of each of the 15 networks representing the respective disciplines. From this analysis, we found that some disciplines express varying levels of heterogeneity. Inspired by this finding, we arranged a meeting between five experts from the same discipline to analyse their degree of hetero- or homogeneity. By analysing this meeting, we showed that the engineers had different approaches to solving the issue in question – we argue that these epistemological nuances indicate a degree of heterogeneity. Our first two analyses thereby relate to each other because the first informs and inspires the second: We would have had no interest in arranging the meeting if our networks had all had low modularity scores. With this analysis, we argue that our interactional expertise can also be crucial within a discipline. In our second analysis, we map all disciplines in the same network to see how their keywords relate to one another. We find that some of the disciplines have varying degrees of a shared language, but we argue that this overlap is small and might indicate the need for *interactional expertise.* In our third and final analysis, we map the keywords' co-occurrence without confinement to their disciplinary origins. By shifting our focus from the disciplinary categories to the *issue* that sparks this scientific community into being, it allows us to better understand which approaches are being pursued across disciplines. We can thereby identify potential blind spots in the respective approaches as visualised in Figure 12.

6 Discussion

First, we discuss how our analytical points can inform our techno-anthropological practice, that is, what implications do they have for our interactional expertise? Following this, we will reflect on our use of artificial intelligence and the implications thereof. Afterwards, we will debate how we have chosen to handle our data, concretely how we have weighed it, and what that implies. Then we discuss the limitations of keywords. Lastly, we justify how we have abided by the seven commitments.

6.1 Techno-Anthropological Implications

In the following section, we will discuss how these analytical points can inform our techno-anthropological practice, that is, what implications do they have for our interactional expertise?

To better develop this discussion, we want to introduce a hypothetical situation of a newly graduated techno-anthropologist (Tage). He has been hired as one of two project managers at a large interdisciplinary research project that aims to assess whether or not to integrate Bitcoin mining into the Danish electricity grid. The other project manager (Per) has a background in political science and is thus used to utilising some of the same methods as the techno-anthropologist. The research group consists of many disciplines: Energy- and Material Engineers, Mathematicians, Decision Scientists, Environmental Scientists, Anthropologists, Sociologists, Economists, Computer Scientists, et cetera. It is because of this disciplinary heterogeneity that the board of directors thought it might be a good idea to hire the two project managers to steer the project.

Before the project is initiated, Tage (the techno-anthropologist) and Per (the political scientist) discuss how to approach the group of scientists. Per argues that they need to focus on how to facilitate dialogue between such distinct disciplines. He is worried that the sociologists will find it hard to understand the language of the engineers, while the engineers might not acknowledge the *soft knowledge* generated by the sociologists. Tage agrees but emphasises that they will first need to approach the group at an even smaller scale: one discipline at a time. Per is confused as he thought the point of their job was to facilitate dialogue between disciplines. Nonetheless, Tage convinces Per that they should arrange meetings with scientists from all disciplines independently – and they do. By analysing the meetings, Tage and Per discover interesting epistemological nuances within some of the disciplines. While Per is surprised, he quickly realises that these nuances are important as they will allow for the two project managers to better facilitate the teamwork *within* each discipline. By identifying these different approaches (epistemological nuances) to solving the issue in question, they are better equipped to discuss with the scientists how to acquire knowledge. Our first analytical point thereby informs the interactional expertise of Tage and Per by making evident the intradisciplinary epistemological diversity that might exist in some of the disciplines. They can utilise this information to avoid miscommunication between scientists from the same discipline, because they are now aware that not *all engineers are epistemologically calibrated*. Simply put, it enriches their epistemological vocabulary, allowing them to make better decisions not only *within* but also *across* disciplines.

After the meetings, Per acknowledges the practical utility of this first techno-anthropological trick, but insists that they must now deal with the interdisciplinary communication. However, he finds it difficult to approach this task. Tage suggests that they conduct a literature review to learn about how other scientists from the same disciplines communicate interdisciplinarily. Per is sceptical and argues it is too big a task as they will need thousands of articles to learn anything interesting. Tage agrees that it is a big task, but presents his idea of mapping all these articles into a singular network in Gephi. While Per is not fully convinced, he agrees to try it out. The two project managers proceed to select, scrape, digest, and finally map relevant literature representing the disciplines in their interdisciplinary group. All articles originate from a big interdisciplinary project on Bitcoin mining in Texas. By identifying disciplinary overlaps – that is, when two or more disciplines use the same keywords – they can gradually point to a shared language between the disciplines. They can also isolate certain disciplines, e.g., engineering and sociology, to specifically learn about their commonalities. Maybe they learn that engineers and sociologists from the project in Texas did, in fact, share some assumptions about the world, or maybe that they expressed coherent values. They can then use these disciplinary precedent commonalities as points of departure to catalyse the formation of a shared language in their research group. Our second analytical point thereby contributes to the interactional expertise of the two project managers, by allowing them to identify shared language between disciplines from earlier projects. With this precedent shared language, Tage and Per can now utilise these insights to start facilitating communication in their research group.

Tage and Per have now gradually started to get a grip on their rowdy group of scientists. However, while they did gain important insights from the second techno-anthropological trick, they still find it difficult to know where to build the bridge *between* disciplines. Reflecting on their work, Tage considers if combining the insights from the above tricks could prove useful: *What would happen if we let go of the disciplinary categorisation and instead looked at how they engage with the issue in question? How might another network map help accomplish this task?* By letting the keywords arrange themselves without confinement to their disciplinary boundaries, Tage and Per learn that they might be dealing with fewer approaches than the disciplines would indicate. In the project from Texas, they found that 15 disciplines represented six overall approaches to solving the issue. After identifying the different approaches, they reintroduce the disciplines into the network to see how they distribute. They learn that some disciplines deal with the issue in similar ways, while they also see that some disciplines are fully absent from some approaches. For example, they note that the social scientists are not represented when dealing with the issue through an environmental approach. Through this network analysis, they have learned that it can be useful to sometimes pay more attention to the issue in question and less to one's preconceived notion of a particular discipline. This shift allows for a greater sensitivity to the actual work being done. However, Tage and Per do not agree on the utility of this last method, as Per is confused by the continual shifting of focus. He does, however, acknowledge that paying more attention to which approaches to dealing with the issue can be helpful. On the contrary, Tage maintains that it is helpful to visualise these blind angles within the disciplines, as they can help point to where they need to focus when exercising their interactional expertise. Thus, our third analytical point can guide the interactional expertise of the two project managers by (1) visualising which approaches exist around similar issues in question (the precedent from Texas), and (2) by pointing to blind angles, that is, unexploited interdisciplinary potentials.

The reader now hopefully has a more concrete idea of how our project could help in promoting interdisciplinary work. The following section will reflect on how we used generative AI throughout our analysis and its implications for our project.

6.2 Reflections on our Use of Artificial Intelligence

In this section, we will discuss our use of generative artificial intelligence. Specifically, we used ChatGPT to thematically categorise six clusters in our third analysis (see section 5.3.1) and to assist in naming these clusters based on their respective keywords. While there is established precedent in the digital methods literature, notably by our former teachers Anders Munk, Matilde Ficozzi, and Torben Elgaard Jensen (Munk et al. 2024), we still find it important to be reflexive about our application of it. The most intriguing question to discuss might not be whether we use it, but *how* we use it.

The first thing we wish to address is the opaque nature of the AI algorithm. This means that the rationale behind the algorithm's answers remains hidden from us, compromising transparency and accuracy if employed without adequate scrutiny. We do not know what data the AI is trained on, what methods were used, and whether or not it has any biases we are unaware of – the AI algorithm is a black box. This could be problematic if not carefully managed. An unreflexive use could lead to incorrect conclusions about our data and a diminished level of transparency. To mitigate this risk, we included a request in our prompt for the AI to provide a concise rationale for each cluster name:

> *...provide a short rationale explaining why this name fits the group of keywords,*

This provided us with a partial insight into the AI's reasoning process. Importantly, this method allowed us to double-check whether the AI was hallucinating keywords by manually going back to our data and verifying that the keywords existed in their respective cluster.

This verification strategy still has its limitations. While it enables us to confirm the presence of the keywords in our dataset, it does not guarantee that the theme identified by the algorithm is the only interesting theme in the cluster. To investigate whether the AI simply chose a random theme from the cluster, we tried using the prompt on the same data on another ChatGPT account on a different computer: We got the same answer on both instances. While this might just show that a potential bias is consistent, it did boost our confidence in the validity of the AI-generated results. If we had had access to a premium subscription account on another AI service, we would have fed our data to their model and prompted it to see if it would identify the same themes, further boosting the validity.

While it is reasonable, and maybe natural, to be cautious about embracing black-boxed generative AI due to its inherent lack of transparency, it is equally important to acknowledge the opaqueness and capability accompanying human judgment. Researchers regularly emphasise certain aspects of a dataset while neglecting others, typically without fully articulating the rationale behind each minute interpretive decision (Liu et al., 2020). Human interpretations are inevitably influenced by cognitive biases and underlying disciplinary assumptions, which often remain implicit and unexplored, as Haraway puts it: *There is no view from nowhere* (Harraway, 1988). Combine this with the fact that some of our clusters contained thousands of keywords it would be, although not impossible, a task more time-consuming than we had the resources to do manually.

6.3 Weights and Realities

An issue that is worth discussing is the fact that we scraped an uneven number of keywords from each discipline, stemming from the imbalanced disciplinary distribution of articles. However, is this a problem? It is a question of whether weighing data is correct or not. There is no straightforward answer, as weighing data is neither right nor wrong – it depends on the context. When we use unweighed data, it reflects reality as it is. For example, Scopus has significantly more articles published by Computer Science than Arts and Humanities, making it hard to compare them without weighing the data. At times, weighing our data is appropriate, e.g., when we are examining the relations between disciplines, rather than their raw, unfiltered presence. In these cases, normalising our data helps visualise these connections. Whether to weigh data or not is not a question of correctness, but rather a question of what specific kind of insights we want to gain.

However, there may be a deeper data issue that weighing will not fix; when a discipline has contributed with a small number of articles, we may end up relying – and thus over-generalising – on a narrow slice of work to represent an entire discipline. For instance, chemical engineering only contains 211 keywords, distributed between 15 articles. In this case, no matter how we manipulate the data – e.g., through weighing – these articles will never capture the full complexity within Chemical Engineering. Doing so would contradict our analytical point that disciplines are not uniform; therefore, over-generalising based on a small data set risks drawing misleading conclusions. Well, that is not our goal. We must convey that our analysis only reflects insights specific to the context of Bitcoin mining, as represented within the scope of Scopus. Therefore, we must remain aware that our data and subsequent analysis cannot make general claims about these disciplines. Now that our scope has been re-established, we can return to the previous point on whether small sample sets are valid or not. As long as we operate within our scope, a strong argument can be made that our data is representative of each discipline, within the confines of this scope. Yes, some disciplines are small (data-wise), but this reflects the empirical reality. We are not removing or altering anything; contrarily, we are including all available data within our scope.

Weighing our data is similar to adjusting the scale on a graph. It is not about changing the data; it is about allowing new patterns to emerge visually and analytically. This ties into the second commitment guiding our approach:

> *I will provide weighting. I will grant visibility to actors in a way that is proportional to the difference they make in the debate. I will not represent all viewpoints as equally important, but take responsibility for weighing their influence and importance.* (Venturini & Munk, 2021: 26-27).

As we acknowledge the limitations of what we know, our approach is primarily exploratory and inductive; we avoid firm assumptions on which disciplines carry the most weight in the debate. Therefore, we cannot impose normative assertions about which viewpoints are more or less valuable in this field – instead, we let the data guide us.

So, when we avoid applying weights, what we are doing is letting volume speak for itself: the more a field contributes, the more visible it becomes in the network. But when we do weigh the data to normalise differences in volume, it is because we recognise that sheer quantity does not automatically equate to greater relevance or impact. In such cases, we act on the idea that we *do not know* who the key actors are, and that we should not and cannot be the arbitrators of who deserves more or less representation.

6.4 Limitations of Keywords

When doing digital methods, we must stay reflective in regards to what our data is capable of conveying and vice versa. There are certain shortcomings concerning keywords that we must address:

(1.) There is no guarantee that different authors use keywords in the same way; some might focus on the methods used in the paper, some on the theories, and others on the empirical topic in question. This means that two almost identical papers might seem entirely different when only looking at their author keywords. Indexed keywords, on the other hand, use a standardised vocabulary when assigning the keywords to papers, which recognises the similarity between the two aforementioned papers. However, indexed keywords might miss intentional nuances from the author keywords. The bias of each author is thereby mitigated, perhaps – some would argue – replaced by another sort of bias.

(2) Another slight variation of this issue is that keywords are reductionistic and relational in their nature; two articles could use the same term, e.g., *sustainability,* but vary widely in whether they found Bitcoin mining sustainable or not. While these facts of data may seem problematic, it can be argued that it does not necessarily undermine our analytical points. The variation in keyword usage still reveals meaningful differences in how Bitcoin mining is approached across disciplines.

(3) Several articles can use the same keyword but ascribe different meanings to it depending on their epistemological grounding. Take, for example, the term *efficiency*: in engineering, the term might refer to the energy input to output in a technical system; in social sciences, it might relate to how a policy or intervention achieves social goals, while in economics, it would supposedly relate to the distribution of scarce resources. This particular fallacy of keywords is hard to argue against, as the problem itself is rooted in not only epistemological differences but also ontological ones.

6.5 The Seven Commitments

As described in our theoretical segment regarding controversy mapping, we listed seven commitments to stand by when utilising digital methods (see section 4.1). We will systematically go through each commitment that we have chosen to adhere to and argue how we have done this.

First commitment:

> *I will follow the actors. I will not presume to know better than the people I am studying. I will learn from them what is relevant and important, what belongs to the controversy, and what does not. I will not silence the voices I do not agree with or that I find off topic* (Venturini & Munk, 2021: 26-27).

As the commitment states, we never once take a stance in which we either presume that we know better than what is expressed by our data or silence any viewpoints in our dataset by tampering with it. Quite to the contrary, we admit that some data maps were incomprehensible to us, as the data was either (1) too complex and grand, or (2) the results took us by surprise. However, this does not mean we convict the data to be *wrong* or *worth less*. We embraced that such is the experience when using an explorative methodology. If we were not taken by surprise or had trouble understanding our field at times, it could be argued that we had been too unambitious in our scale.

Second commitment:

> *I will provide weighting. I will grant visibility to actors in a way that is proportional to the difference they make in the debate. I will not represent all viewpoints as equally important, but take responsibility for weighing their influence and importance* (ibid.).

This commitment has already been meticulously discussed in the previous segment (see section 6.3). But to put it briefly – for the sake of removing any confusion – yes, we do comply with what the commitment entails.

Third commitment:

> *I will state my position. I will not pretend to be disinterested. I will not hide my opinion about the subject I am studying. I will make clear how my stakes in the debate influence how I explore and represent it* (ibid.).

A big part of our domain section consists of us explaining and detailing the implications of our background as students. We concretely state our interests by showing how we are guided by our belief in interdisciplinarity, given our educational background as techno-anthropologists. This belief plays a central part in our methodology, theoretical lens, and scientific puzzle. We will, however, argue that this does not have any negative or unfair impact on the contents of the research, as we remain introspective throughout the entire project. We have been critical of our data by repeatedly questioning its nature and how we should handle it.

Fourth commitment:

> *I will stay with the trouble. I will not avoid the complexity of the controversy by means of methodical or theoretical shortcuts. I will not use my explanatory framework to take refuge from the incongruity and bewildering richness of social situations* (ibid.).

As stated in our discussion concerning the *first commitment,* we admit that some findings from the networks perplexed us, i.e., the significant presence of Arts and Humanities in the *Cryptographic Hardware and Computational Efficiency* cluster (see section 5.2). Although we do not necessarily expand on why these complexities take place, we do not hide them or steer clear of them as if they were unwelcome parts of the data. We, conversely, celebrate them and, to some extent, seek them out as these surprises in our data are what help consolidate it. Furthermore, the appearance of these complexities is a general indication that our approach to the field is just and not warped by our beliefs.

Sixth commitment:

> *I will draw legible maps. In order to provide an overview and facilitate navigation, maps are necessarily simplifications of the territory they represent. Making legible maps of sociotechnical debates is the only legitimate reason for reducing the complexity of a controversy. Yet, my simplification will be cautious, transparent, respectful, and leave others the possibility to reverse it* (ibid.).

We want to showcase our networks as manifestations of the empirical reality of the field, and can only do so by handling them attentively. Although this indubitably also results in a simplification of this reality, we argue that it does not make it any less meaningful in what we are trying to achieve. Therefore, we argue that we have operated honestly, and not carelessly favoured any one viewpoint in our chosen *public*, as we have extensively contemplated how we have visualised and handled our data.

Seventh commitment:

> *I will open my inquiry to others. Whenever possible, I will make publicly available the data 1 collect, the code I develop, and the text and images I produce. I will share my investigation with the people who have stakes in it and invite them to participate* (ibid.).

As all handling, collection, and analysis of our data has been made (1) public through attaching it as an appendix, (2) discussed in text, or (3) showcased, we believe that we have acted with full transparency and opened our inquiry to anyone interested. By doing so, we have made it more accessible to replicate our methodology and get the same result as ours. Even though we employ tools like Photoshop to better express our data, i.e., colour filters and text overlays. We do not remove, tamper or manipulate any important features of the original images, which would otherwise render the replicability impossible.

With this, we have now concluded the discussion. We hope now that the reader is ready and equipped to understand our final conclusion and the insights gained throughout the project

7 Conclusion

Finally, let us connect our analytical points to answer our research question:

> *How can we, as techno-anthropologists, utilise digital methods to guide our interactional expertise when dealing with experts?*
>
> - *i.) How can we reveal intradisciplinary nuances within seemingly homogeneous disciplines?*
> - *ii.) How can we identify an interdisciplinary language through mapping scientific literature as a network?*
> - *iii.) How can we reveal disciplinary blind spots and potentials for interdisciplinary collaborations?*

Firstly, we reveal intradisciplinary nuances within seemingly homogeneous disciplines through (1) our modularity analysis of 15 co-occurrence network and (2) our meeting: Through our modularity analysis, we argue that modularity correlates with the degree of heterogeneity of a discipline: lower modularity network represents disciplines with a greater degree of shared language, while networks with higher modularity can be understood as disciplines with a lesser degree of shared language. By analysing the meeting, we show that one should not *a priori* assume that members of the same discipline can always communicate effortlessly on all matters, as they might not be aware that they express different epistemological points of departure. While the meeting allowed for greater qualitative sensitivity, the modularity analysis enabled a broader, though more surface-level, exploration of intradisciplinary variation.

Secondly, we identify the shared language between disciplines through a bipartite network. The shared language is revealed in our network as *white nodes* and *edges*. It is this shared language that we, as techno-anthropologists, could potentially use to learn the most essential vocabulary that ties them together. As indicated by our network, the shared language only amounts to between 0,60-23,34%, and we therefore argue that these disciplines, when working interdisciplinarily, might still be in communicative trouble and will therefore need our interactional expertise. Finally, we find it more useful to isolate the specific disciplines we are dealing with (as interactional experts) and *then* analyse their specific shared language.

Thirdly, we show that shifting analytical focus from disciplinary categorisation to issue-based clustering of disciplines (in a co-occurrence network) reveals disciplinary blind spots and potential for interdisciplinary collaborations. By momentarily dissolving the *a priori* categorisation of a discipline, we can focus on *how* Bitcoin mining engages six approaches that transcend disciplinary boundaries. We then reintroduce the disciplinary boundaries to quantify how they distribute throughout the network. By identifying the absence of certain disciplines, it allows us to point to disciplinary blind spots in clusters (approaches).

Finally, we utilised digital methods to guide our interactional expertise by applying the different analytical approaches as evident in our analyses. Through this exploratory enquiry, we have shown that digital methods do show promising potential of informing this techno-anthropological practice. We argue that by following these methods, we can identify where to focus our interactional ability, that is, *where* to build the bridge.

8 References

Aalborg University. (nd). *The Techno-Anthropology Lab (TANTlab).* Retrieved 2025, from https://www.en.culture.aau.dk/research/research-groups/tantlab#more-about-tantlab

AAU. *Find din bachelor- og professions-bachelor-uddannelse.* aau.dk. https://www.aau.dk/uddannelser/bachelor/liste

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: an open source software for exploring and manipulating networks. Paper presented at the *Proceedings of the International AAAI Conference on Web and Social Media, , 3*(1) 361–362.

Birkbak, A. M., Anders. (2017). *Digitale metoder* (1st ed.). Hans Reitzel.

Bertelsen & Petersen (2021) in: Botin, L., & Børsen, T. H. (2021). Technology assessment in techno-anthropological perspective.

Børsen, T. (2020). Bridging Critical Constructivism and Postphenomenology at Techno-Anthropology. *Techne: Research in Philosophy & Technology, 24*

Børsen, T., & Botin, L. (2013). *What is Techno-Anthropology?*. Aalborg University Press.

Calvo-Pardo, H. F., Mancini, T., & Olmo, J. (2022). Machine learning the carbon footprint of bitcoin mining. *Journal of Risk and Financial Management, 15*(2), 71. https://www.mdpi.com/1911-8074/15/2/71

Collins, H., & Evans, R. (2007). The Periodic Table of Expertises 1: Ubiquitous and Specialist Expertise. *HM Collins and Robert Evans*, 13–43.

Collins, H., Evans, R., & Gorman, M. (2007). Trading zones and interactional expertise. *Studies in History and Philosophy of Science Part A, 38*(4), 657–666.

De Vries, A. (2018). Bitcoin's growing energy problem. *Joule, 2*(5), 801–805. https://www.cell.com/joule/fulltext/S2542-4351(18)30177-6?ref=blog.holochain.org

De Vries, A. (2020). Bitcoin's energy consumption is underestimated: A market dynamics approach. *Energy Research & Social Science, 70*, 101721. https://www.sciencedirect.com/science/article/pii/S2214629620302966

De Vries, A., & Stoll, C. (2021). Bitcoin's growing e-waste problem. *Resources, Conservation and Recycling, 175*, 105901. https://www.sciencedirect.com/science/article/pii/S0921344921005103

Elgaard Jensen, T. (2021) 'Aktør-netværksteori'. I Danholt, P. & Gad, C. (red.) Introduktion til STS: videnskab, teknologi og samfund i en kompleks verden. Hans Reitzels Forlag

Elsevier. (, nd). *Scopus Content.* https://www.elsevier.com/products/scopus/content#0-content-coverage

Funtowicz, S. O., & Ravetz, J. R. (1993). Science for the post-normal age. *Futures, 25*(7), 739–755.

Hallinan, K. P., Hao, L., Mulford, R., Bower, L., Russell, K., Mitchell, A., & Schroeder, A. (2023). Review and demonstration of the potential of bitcoin mining as a productive use of energy (PUE) to aid equitable investment in solar micro-and mini-grids worldwide. *Energies, 16*(3), 1200. https://www.mdpi.com/1996-1073/16/3/1200

Haraway, D. (2013). Situated knowledges: The science question in feminism and the privilege of partial perspective 1. *Women, science, and technology* (pp. 455–472). Routledge.

Houy, N. (2019). Rational mining limits Bitcoin emissions. *Nature Climate Change, 9*(9), 655.

Ibañez, J. I., & Freier, A. (2023). Bitcoin's carbon footprint revisited: Proof of Work mining for renewable energy expansion. *Challenges, 14*(3), 35. https://www.mdpi.com/2078-1547/14/4/47

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PloS One, 9*(6), e98679.

Kuhn, T. S. (1997). *The structure of scientific revolutions*. University of Chicago press Chicago.

Lal, A., Niaz, H., Liu, J. J., & You, F. (2024). Can bitcoin mining empower energy transition and fuel sustainable development goals in the US? *Journal of Cleaner Production, 439*, 140799. https://www.mdpi.com/1996-1073/16/3/1200

Lal, A., Zhu, J., & You, F. (2023). From mining to mitigation: How Bitcoin can support renewable energy development and climate action. *ACS Sustainable Chemistry & Engineering, 11*(45), 16330–16340. https://pubs.acs.org/doi/full/10.1021/acssuschemeng.3c05445

Levallois, C. (2023). Working with text in Gephi. https://seinecle.github.io/gephi-tutorials/generated-pdf/working-with-text-en.pdf

Liu, Y., Althoff, T., & Heer, J. (2020). Paths explored, paths omitted, paths obscured: Decision points & selective reporting in end-to-end data analysis. Paper presented at the *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems,* 1–14.

Marres, N. (2005). Issues spark a public into being: A key but often forgotten point of the Lippmann-Dewey debate. *Making Things Public: Atmospheres of Democracy,* , 208–217.

Marres, N. (2007). The issues deserve more credit: Pragmatist contributions to the study of public involvement in controversy. *Social Studies of Science, 37*(5), 759–780.

Marres, N. S. (2005). *No issue, no public: Democratic deficits after the displacement of politics*. Amsterdam.

Masanet, E., Shehabi, A., Lei, N., Vranken, H., Koomey, J., & Malmodin, J. (2019). Implausible projections overestimate near-term Bitcoin CO2 emissions. *Nature Climate Change, 9*(9), 653–654. https://www.nature.com/articles/s41558-019-0535-4

Mora, C., Rollins, R. L., Taladay, K., Kantar, M. B., Chock, M. K., Shimada, M., & Franklin, E. C. (2018). Bitcoin emissions alone could push global warming above 2 C. *Nature Climate Change, 8*(11), 931–933. https://www.nature.com/articles/s41558-018-0321-8

Munk, A. K., Jacomy, M., Ficozzi, M., & Jensen, T. E. (2024). Beyond artificial intelligence controversies: What are algorithms doing in the scientific literature? *Big Data & Society, 11*(3), 20539517241255107.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. http://dx.doi.org/10.2139/ssrn.3440802

Noortje Marres. *About.* noortjemarres.net. https://noortjemarres.net/index.php/about/

Ognyanova, K. (2014). *Facebook data collection and photo network visualization with Gephi and R.* Kateto.net. https://kateto.net/facebook-data-collection-and-photo-network-visualization-with-gephi-and-r/

Plaisance, K. S. (2020). The benefits of acquiring interactional expertise: Why (some) philosophers of science should engage scientific communities. *Studies in History and Philosophy of Science Part A, 83*, 53–62. 10.1016/j.shpsa.2020.03.002

Popper, K. (1962). *THE LOGIC OF THE SOCIAL SCIENCES. First Contribution to the Symposium.*

Sai, A. R., & Vranken, H. (2024). Promoting rigor in blockchain energy and environmental footprint research: A systematic literature review. *Blockchain: Research and Applications, 5*(1), 100169. https://www.sciencedirect.com/science/article/pii/S2096720923000441

Scopus. (nd). *How do Author keywords and Indexed keywords work?* https://service.elsevier.com/app/answers/detail/a_id/21730/supporthub/scopus/

Scopus. (2024). *What is Scopus about.* service.elsevier.com. https://service.elsevier.com/app/answers/detail/a_id/15100/supporthub/scopus/

Sedlmeir, J., Buhl, H. U., Fridgen, G., & Keller, R. (2020). The energy consumption of blockchain technology: Beyond myth. *Business & Information Systems Engineering, 62*(6), 599–608. https://link.springer.com/article/10.1007/s12599-020-00656-x

Silvio Funtowicz. (2021). *A quick guide to post-normal science.* https://i2insights.org/. https://i2insights.org/2021/10/19/guide-to-post-normal-science/

Snow, C. P. (1959). Two cultures. *Science, 130*(3373), 419.

Snowden, D. J., & Boone, M. E. (2007). A leader's framework for decision making. *Harvard Business Review, 85*(11), 68.

Stoll, C., Klaaßen, L., & Gallersdörfer, U. (2019). The carbon footprint of bitcoin. *Joule, 3*(7), 1647–1661. https://www.cell.com/joule/fulltext/S2542-4351(19)30255-7

The White House. (2025). *ESTABLISHMENT OF THE STRATEGIC BITCOIN RESERVE AND UNITED STATES DIGITAL ASSET STOCKPILE.* The White House. https://www.whitehouse.gov/presidential-actions/2025/03/establishment-of-the-strategic-bitcoin-reserve-and-united-states-digital-asset-stockpile/

Treiblmaier, H. (2023). A comprehensive research framework for Bitcoin's energy use: Fundamentals, economic rationale, and a pinch of thermodynamics. *Blockchain: Research and Applications, 4*(3), 100149. https://www.sciencedirect.com/science/article/pii/S2096720923000246

Venturini, T. (2010). Diving in magma: how to explore controversies with actor-network theory. *Public Understanding of Science, 19*(3), 258–273.

Venturini, T., & Munk, A. K. (2021). *Controversy mapping: A field guide*. John Wiley & Sons.