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Institutional Framework for Hyper-Cooperation: Dynamics in the Digital Economy

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ABSTRACT

This paper examines the dynamics of the digital economy, focusing on decentralized data ecosystems in Europe compared to the centralized models of the US and Chinese hyperscalers. It addresses data's growing complexity and quantity and its implications for business models. The "Institutional Role Model" (IRM) is a system-dynamic instrument for promoting such hypercooperative decentralized approaches. The IRM serves as an economic system architecture to facilitate market integration, create trust, and reduce complexity. In the context of Gaia-X projects, it supports the development of a competitive digital infrastructure that reflects European values and standards.

1. INTRODUCTION

Decentrally organized data ecosystems are currently being developed in Europe, and it is hoped that they will prove to be competitive with centrally organized data ecosystems such as those operated by the American and Chinese hyperscalers [1, 2]. The objective of establishing these decentralized data ecosystems is, therefore, to reduce the dependency of the European economy on the centrally organized data ecosystems of the American and Chinese hyperscalers and to establish the competitiveness of the European economy in the digital age on the one hand and to expand it over time on the other [3, 4]. European efforts to establish a competitive digital infrastructure for Europe must be viewed in the context of the systems competition between the US, Europe, and China, each of which, with different strategic economic orientations, is seeking to achieve and enforce technological and economic superiority in the digital age over the other two. China focuses on improving the economic and technological results of its state-centered economic control activities, while the US relies on its private-sector hyperscalers and their scaling capacities. On the other hand, Europe is focusing on an approach derived from European values, taking into account the structure of European competition and finding its expression in precisely these decentralized data ecosystems. It is an attempt to lead the European economy into a successful future under digital conditions based on European values, data protection standards, and rights of self-determination, which is why the concept of decentralized data ecosystems is being developed and continuously refined for this purpose. Although the race for economic and technological superiority in the digital age between the US, Europe, and China has not yet been decided, it can be stated at this point that Europe is lagging behind the US and China, as it is only now just starting to develop decentralized data ecosystems. In contrast, the US and China are much further ahead in their strategic activities of aggregating and synthesizing data to improve business models [5-7]. It is, therefore, logical that the European economy's dependence on American and Chinese hyperscalers, which has existed to date and is likely to increase under the same conditions, is linked to the availability and operationalizability of data as a critical resource. This is because the hyperscalers can currently design new data-driven business models and thus expand their competitive position due to the versatile aggregation of data. This is not the case concerning European companies because they have numerous types of data about multiple different companies, which have not yet been put to any everyday use in the form of data exchange so that their competitive position can also be improved as a result of the improved availability and operationalizability of the data merged from different companies. Furthermore, the development of these decentralized data ecosystems is also extremely time-critical because the centralized data ecosystems are already well advanced in their aggregation and synthesis of data, both quantitatively and qualitatively, which is why the European decentralized data ecosystems should prove to be functional as quickly as possible so that a significant lead over time does not become an unassailable lead in favor of the hyperscalers. A further difficulty arises from the fact that the established concepts of the hyperscalers have already proven themselves empirically, whereas the decentralized data ecosystems have yet to be tested. More and more data is being collected and analyzed worldwide to derive benefits from it. This enormous growth in the amount of data is called Big Data. The term data volume refers to the characteristic of Big Data that more and more data is being generated and processed from increasingly heterogeneous sources [8-10].

This work presents an instrument used in the European decentralized data ecosystem Gaia-X as a cooperation-promoting economic system architecture. This is intended to counteract the increased complexity described below and to counter the hyperscaling approaches of competing systems with a hyper-cooperating approach. To this end, Chapter 2, after this introductory chapter, deals with the increase in data and the resulting potential. Building on this, Chapter 3 will examine the challenges that arise from these developments and how they lead to an increase in complexity that should be counteracted. Chapter 4 then provides an insight into the concept of hypercooperation and its significance. Building on this, Chapter 5 presents the Institutional Role Model (IRM) based on its four dimensions and explains the structure of the IRM matrix. In addition, an example results matrix from the Gaia-X 4 Future project family is presented in this chapter, and a selection of IRM application areas is introduced. Chapter six concludes with a summary and outlook.

2. HYPER-SCALING

On the one hand, the amount of data available today has grown massively, which is why the age of Big Data has already begun. On the other hand, it is still in its infancy because it can be assumed that the amount of data available will increase at an ever-faster rate in the near and more distant future, which is where its actual explosiveness lies [11, 12]. At the same time, the term "big" in big data not only refers to the already massively available and usable data volume and the accelerating growth of the data volume but also refers to the second essential characteristic of the age of Big Data, which is the fact that data sets have become so large that it is becoming increasingly challenging to manage them within a reasonable time and also within a reasonable monetary outlay [13]. Overall, three distinct phases can be distinguished concerning the Big Data era. The first phase of the Big Data era was initiated in the 1990s with the emergence of e-commerce. The second phase of the Big Data era resulted from social networks, which, for the first time, enabled Internet users to create and exchange their content and interact with websites. We are currently experiencing the third phase of the Big Data era, which is characterized by the fact that more and more data is coming from the Internet of Things (IoT) and is, in turn, impacting the achievements of the first two phases of the Big Data era, which are flourishing more than ever before, and causing the volume of data to be processed and evaluated to increase exorbitantly [14]. The driving factors behind this dynamic of increasing and accelerating the amount of data available in the third phase are, in addition to the Internet of Things (IoT), cloud computing and smart devices, which contribute to the global interconnectivity of heterogeneous data sources is expanding, resulting in more and more structured and unstructured data that can no longer be analyzed using tried and tested data analysis methods because these quickly reach an insurmountable limit [15, 16]. Big Data can be seen as one of the most important areas of future information technology, which is why companies need to build up capacities in the area of Big Data to operate competitively in the current and future market environment [14]. This chapter provides a differentiated analysis of the essential characteristics of the Big Data age, which goes far beyond these general statements in terms of depth of analysis by identifying and presenting the profound mechanisms that make the Big Data age so special and distinctive. In this context, 1) the process of datafication is presented to build on it and discuss the associated, 2) increase in the self-expressivity of data. Subsequently, both distinctive characteristics of the Big Data era are linked to present the concept of Algocracy. In the course of the argument, the special characteristics of the age of big data and the well-known characteristics of the increase in data volumes will be highlighted. It will also be shown how these characteristics function independently and interact in a mutual context to provide a profound and comprehensive overview of the mechanisms at work in the age of big data. Big data can be seen as an enabling technology for numerous other technologies, which is a major reason for the interest in its further development. The importance of big data is continuously increasing since it is in a symbiotic relationship of further development with other trend-setting technologies, such as the Internet of Things (IoT) or cloud computing, which in turn require big data as an operational basis so that they can be expanded. Initially, cloud computing technology was an immature and vague concept. It gradually gained maturity through its intensifying combination with big data over time, becoming a very profitable business model for companies such as Alphabet, Microsoft, Amazon, Meta, and Alibaba. Big data and cloud computing are two sides of the same coin. On the one hand, big data is the quintessential application for cloud computing. On the other hand, cloud computing provides the information technology infrastructure that big data requires to develop its potential further [17]. The American company Amazon, for example, has the competitive advantage of managing a global platform for purchasing all conceivable products and is the undisputed market leader. Strictly speaking, Amazon's competitive advantage results from the fact that it aggregates and evaluates the data on the usage behavior of prospective product buyers and the sales figures of the products of all retailers organized on the platform and, as a result, obtains a depth of insight that is denied to all other retailers. At the same time, they are implicitly forced to sell their products on the Amazon platform because there are numerous potential buyers on it. This ongoing and expanding aggregation and interpretation of data over time puts Amazon in a position to manufacture and market certain products itself because it can accurately estimate the demand and willingness to pay off all customers [18]. In contrast, Alphabet has the competitive advantage of managing a search engine platform called Google, which sells advertisements for industrial customers. Because Google records and evaluates all customer search queries based on data, it can target the prices for advertisements for certain search queries to increase its economic advantage. Since most online search queries take place via the Google platform, other search engines cannot implement an almost comparable level of detail in the findings on search query behavior and efficient ad pricing [19]. Another example in this context is Tesla, which sells electric vehicles worldwide. However, the special feature of Tesla's business model is that it not only sells roadworthy electric vehicles but also equips them with intelligent sensors and electronics to drive forward algorithms for improving automated driving based on all the data [20]. These examples impressively illustrate the competitive advantages that can be derived from a platform approach to hyperscaling and also show the need for the European economy to catch up in independent, functioning strategies to counter this enormous market power. Since numerous trend-setting technologies are increasingly dependent on the existence and usability of big data, it is important to bear in mind that big data itself is facing some challenges that need to be overcome so that it can serve as an increasingly useful basis for technologies such as artificial intelligence, cloud computing or the Internet of Things (IoT) and does not reach a point where it hinders rather than promotes their potential due to its technological immaturity. The increasing combination of big data with artificial intelligence, cloud computing, and the Internet of Things (IoT) leads to three new problems that must be solved.

3. INCREASE IN COMPLEXITY

The first problem to be solved is the increase in data complexity because not only is the amount of data to be processed and analyzed constantly increasing but so is the inherent degree of complexity of the data itself because the data to be processed and analyzed is not only becoming more numerous but also more diverse. Consequently, there is a simultaneous increase in the quantity and the variety of data, making up its complexity. As the double-conditioned data complexity increases, the challenge is to find out how to achieve the best possible results with the least possible computational effort. The second problem is closely related to the first problem of data complexity. The second problem is computational complexity. Traditional calculation methods need to be revised for processing and analyzing enormous amounts of data since they have to cope with the previously increased amount and variety of data and the property of data to change quickly and prospectively. New calculation methods must, therefore, break with assumptions that have proven successful in traditional calculation methods since they can no longer be applied to the challenges of Big Data in a way that is adequate to the complexity. Accordingly, this results in a high demand for innovation in modern calculation methods. The final problem is system complexity. This forms the third level of abstraction concerning data complexity and calculation complexity. The system's complexity draws attention to the fact that data complexity and calculation complexity can only develop if they are supplied with sufficient energy in the form of electricity and, in the future, with more energy. This is why ensuring the uninterrupted supply of energy is a further problem in the context of big data [17]. All three problems are closely interrelated.

It is tempting to define Big Data in terms of the massive and ever-increasing volume of data. However, this definition falls short because the concept of Big Data cannot be grasped without reference to the underlying process of datafication. The process of datafication indicates that more and more aspects of society can be subjected to quantitative observation and analysis, which in turn creates more and more fields of application for big data, increasing the available volume of data and the options for further datafication. Big data owes its relevance above all to the fact that the process of advancing datafication is spreading to and intensifying numerous aspects that previously could not be quantified [21]. Both Big Data and datafication are driven by technological innovations that focus on the collection, aggregation, and processing of data and that improve the status quo [22]. The process of datafication thus accelerates the volume of available data by tapping into and exploiting new and productive quantification potential, making reality accessible to an increasingly immersive data-based approach and form of analysis. Datafication is, in turn, subdivided into three interrelated concepts. Dematerialization means that it is possible to extract the information value from the real phenomenon virtually and in data form. In contrast, liquidation points out that information can be flexibly passed around virtually and bundled with information extracted from other places and times and then unbundled again once dematerialized. The final concept is density, which means that the dematerialized and liquidified information must be arranged in the best possible way regarding a defined goal so that value can be added that justifies the effort [23]. Consequently, the phenomenon of big data and the process of datafication are in a relationship of co-evolutionary mutual reinforcement. Whenever a new field of application invites quantification, more and more data will be aggregated over time. Whenever another field of application has been subjected to comprehensive and expanding quantification, the interest arises in extending the successful model of quantification to further fields of application, thereby initiating yet another iteration of the cycle. The effectiveness of this cycle results in the powerful relationship of powerful co-evolutionary mutual reinforcement. In this context, the statement that data is the new oil in economics and that it is driving the transition from a data-poor economy to a data-driven economy seems to need to be supplemented in that it is not only the use of big data that is important but also the development of new types of data aggregation and data value creation potential, as the term datafication suggests. Examples of novel fields of application in the course of the implementation of the process of datafication are creditworthiness checks, portfolio analysis, marketing campaigns, or consumer behavior, among many others, and many more options in the future [24]. The dematerialization, liquification, and compression of ever larger, more numerous, and more heterogeneous data sources are leading to a gradual normalization of the process of datafication in society, as it increasingly enters people's everyday lives in the form of the Internet of Things (IoT), for example, and is taken for granted [25]. The unpredictability of the medium- and long-term interaction of big data and datafication underlines the relevance of big data. Still, at the same time, it is becoming apparent that the direction of further development is by no means predetermined but is characterized by a high degree of openness, which should also prompt regulatory efforts [21].

Following these considerations, cooperation among the decentralized participants of a European data space is necessary to catch up with centralized systems and to present a functioning competing system. The increasing amount, variety, and complexity of data lead to increased computational and system complexity, creating a need for coordination that increases with datafication and ever-increasing data volumes. As shown in Chapter 5, this coordination requirement is controlled in parts of the European decentralized data ecosystem Gaia-X by using the Institutional Role Model (IRM), and the complexity is reduced to realize the data value creation potential [26]. In this way, a form of decentralized (hyper) cooperation is made possible in Gaia-X 4 Future Mobility, which is intended to offer competition to the hyperscaling system competitors. Before that, the concept of hypercooperation is discussed in chapter four, which follows now.

4. HYPER-COOPERATION

The American and Chinese hyperscalers are thus able to rapidly and purposefully scale their business models due to the accumulation, evaluation, and application of enormous data sets, which in turn leads to the emergence of new business models to which the same mechanism applies. In this way, the American and Chinese hyperscalers have a decisive competitive advantage over decentralized data ecosystems based on operationalizing the principle of hyperscalation [27]. Because of this, these companies themselves have been given the designation hyperscaler [28]. Consequently, the question arises as to what decentralized data ecosystems such as Gaia-X can do to counter this functional success mechanism of the hyperscalers of American and Chinese technology companies in order to be able to position themselves competitively in the market. In this respect, operationalizing the hypercooperation process is an obvious solution. The hypercooperation process is based on a large number of heterogeneous actors willingly exchanging information with each other as needed. On this basis, new business models can be designed and implemented. In the digital age, this needs-based information primarily involves specific and high-quality data sets that can be combined to derive promising new business models based on them. This process of hyper-cooperation is a suitable model for competing against the already proven and successful process of hyperscalability because it enables an expandable number of companies from a wide range of industries to combine enormous amounts of data in the form of data exchanges to design and then scale new business models. Accordingly, operationalizing the hypercooperation process results in the competitive advantage of decentralized data ecosystems over hyperscalers in that a heterogeneity of the most diverse business model ideas can be supplied with the data required for this. In contrast, the hyperscalers, with the collection, evaluation, and application of enormous amounts of data, only want to scale their own existing business models on the one hand and develop new business models for themselves on the other [29]. Consequently, the operationalization of the hypercooperation process results in a more diverse collection, evaluation, and application of data sets than is the case with the operationalization of the hyperscale process since the latter is one-sided and leaves no room for a diversity of business models to develop among the most diverse companies. However, answering the question of a suitable procedure as a competing model to the hyperscalers' hyperscalation procedure raises a derived question, which is how the hypercooperation procedure can best be implemented in decentralized data ecosystems so that it can be successfully developed and does not fail in real-world implementation. Chapter 5 is dedicated to solving this derived problem, in which the Institutional Role Model is presented as a proposed solution.

5. METHODOLOGY – INSTITUTIONAL ROLE MODEL

This chapter proposes a methodology to enable and facilitate the hyper-collaboration described above. The Institutional Role Model (IRM) is a tool for establishing cooperation in complex environments [30, 31]. For example, it is used in the Gaia-X 4 Future Mobility Lighthouse Project family as an economic system architecture to integrate the services developed there into the socio-economic environment of the market and thus facilitate market introduction and the development of business models in the pre-competitive area [26]. Particularly in complex undertakings with a high digital focus, such as Gaia-X [32], the IRM approach presented below can help to increase trust among the actors, synchronize the actors, and reduce complexity through role definition and assignment [33].

When creating an IRM, a flexible process is applied that relates four dimensions to each other (see Figure 1). This adaptability ensures that the IRM approach can be effectively applied in various contexts. First, the goal of the role model is defined. The IRM can cover different levels of detail, from small processes at the micro level to strategic decisions at the macro level [34]. For example, the goal may be to facilitate the market launch of developed services or products (as in Gaia-X), and the IRM can thus accelerate innovation. However, the IRM can also be used, for example, to improve processes or develop strategic corporate decisions. Once the goal of the IRM has been defined, the two eponymous dimensions are examined. First, the dimension of roles is used to determine which tasks (= roles) are necessary to achieve the goal. These can be technical or economic roles [35, 31], with Kleis [26] adding ecological roles. These roles are collected, categorized, and evaluated in terms of their contribution to achieving the goal and, if they complement each other, combined into consistent meta-roles if necessary. Meta roles thus combine logically congruent sub-roles so that the complexity of the model is reduced and overlapping roles do not appear redundantly in the model. In addition to this, sub-roles within a meta-role can contradict each other. This can lead to the need for a new meta-role so that the sub-roles within the meta-roles are congruent again. Meta-roles can, therefore, be understood as summarizing, superordinate roles, which in turn contain sub-roles to be executed. The structure and organization of the model can thus be flexibly refined and/or simplified. The next step is determining which institutions are essential for assuming the roles and successfully achieving the defined goal. In IRM, institutions are organizations such as companies, scientific institutions, or public authorities. Intraorganizationally, however, institutions can also be, for example, different employees with the same interests or company divisions. When institutions take on a role, they become actors in the sense of IRM [35]. The number of institutions within the model can be chosen flexibly, although the model becomes more complex as the number increases [36].

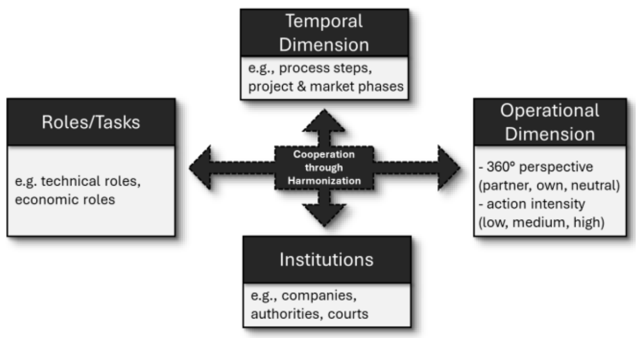

Figure 1. The four dimensions of IRM [26]

The temporal dimension integrates a temporal component into the IRM. Based on this dimension, the model can be flexibly differentiated into process steps, market phases, project phases, or development phases. This makes it possible to determine at which point in time a particular institution should take on a defined role and whether this applies only to a specific point in time. The operational dimension makes it possible to further differentiate (meta-)roles concerning their intensity of action and to integrate external perspectives into the model. In addition, AI can be used and included in the dimension of institutions as a role-taking institution and in the operational dimension as a neutral evaluating perspective [26, 30].

Once the content of the dimensions has been determined, a so-called IRM matrix can be created (see Figure 2). The structure of the matrix corresponds to the logic of Figure 1. On the left side of the matrix are the economic, technical, and ecological (meta-)roles, prioritized into Very Important Roles, Essential Roles, and Supporting Roles. In the case of Figure 2, these are the theoretically developed roles of Chief Innovation Officer, AI Manager, Sustainability Manager, and Remote Work Manager. These roles were developed for large digital projects. The institutions are on the bottom side of the matrix, categorized by branch and geographic origin. The upper side of the matrix consists of the development phases and the overarching, jointly defined goal of the role model. The operational dimension, with its various perspectives, can be found on the right-hand side. Artificial intelligence has been integrated into the matrix as a possible evaluative instance to supplement the perspectives [26]. Schulz et al. [30] add that this dimension can also differentiate the intensity of the role's action (e.g., weak/medium/strong).

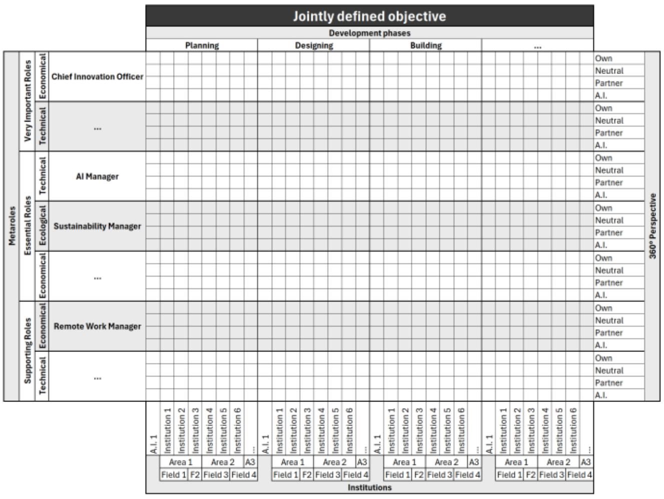

Figure 2. IRM matrix based on Schulz et al. [30] according to Kleis [26]

Once the IRM matrix has been developed, the next step is determining suitability. The participating institutions, external experts, and the AI are asked to what extent a particular institution is suitable for taking on the various roles at different points in time in the model. In doing so, the institutions evaluate themselves and each other. The evaluation can be based on a model-specific, flexibly selectable scale (e.g., 1-5). It should be emphasized that great importance is attached to the principle of anonymity in this process so that the respondents are free in their response behavior and reduce strategic response behavior. The data is collected and processed once the evaluation has been carried out. Subsequently, the findings are calculated based on mathematical calculations and visualized as a result matrix and various indices [35]. An example of the results of such a visualization can be seen in Figure 3. In this figure, a heat map indicates the suitability distribution within a consortium of the Gaia-X project lighthouse family 4 Future Mobility. For data protection reasons, the IRM matrix from Figure 3 is reduced and blacked out, and an operational dimension has been omitted for simplicity. The project phase and the market entry phase were analyzed.

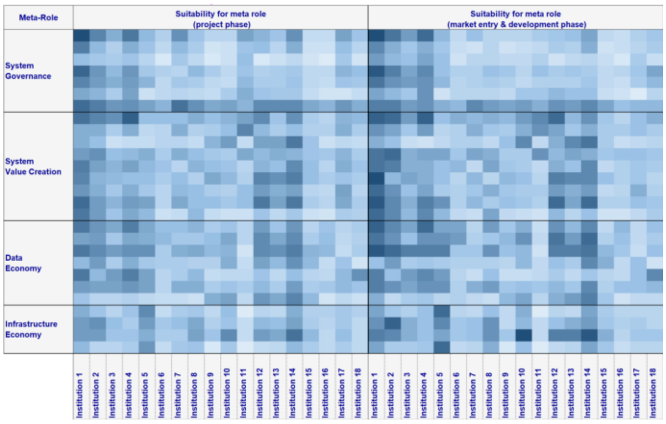

Figure 3. Reduced and blackened IRM matrix from the Gaia-X 4 Future Mobility project family [37]

Figure 3 shows the suitability clusters in the form of dark spots. This means that a darker blue stands for a higher suitability. Thus, for example, it quickly becomes apparent that equally high suitability was determined for the last sub-role in the first meta-role System Governance across the consortium, while a heterogeneous suitability distribution was identified in the first sub-role of the same meta-role. Furthermore, it can be determined whether the suitability of different institutions to take on a role decreases or differs over various periods and whether there are particularly risky roles that are important but can only be taken on by a few institutions. If it is determined that no institution is suitable for taking on a role, then further necessary institutions can be determined based on these findings. Finally, the institutions enter into negotiations to take on a role based on the findings of the IRM process. In this process, roles can be taken over by multiple institutions and traded between the actors, which gives rise to a coordination task between the actors. Finally, if desired by the actors, a binding framework in the form of a legal agreement can be integrated on the basis of the distribution [35]. For the application of the IRM as an economic system architecture in the Gaia-X lighthouse project family, the model was flexibly individualized for the respective projects, following the theory of IRM. As shown in Figure 3, two phases (project and market phase) were defined and examined concerning the temporal component of the model. With regard to the roles (=tasks) necessary to achieve the objectives, four economic meta-roles with a total of 27 economic sub-roles were developed. When developing the roles, the decentralized approach of Gaia-X was considered so that all actors involved were included in defining the roles. Attention was also paid to the sovereignty of the actors and interoperability within the roles and in the development of the respective technology. This is also reflected in the technical roles. Here, the technical standards of Gaia-X were integrated. A major challenge in developing the model was the necessary harmonization of technical and economic roles. Due to the novel decentralized approach of Gaia-X, comparatively few business models have been generated so far. Therefore, when developing the model, care was taken to integrate economic roles that favor business model development in the pre-competitive area. In addition to the use of the IRM as an economic system architecture in the Gaia-X lighthouse project family 4 Future Mobility to facilitate the market entry of the services developed there [26] and as a Governance instrument [38], the IRM has already been used, among other things, to integrate cooperative transport systems [30], to reduce complexity in projects [31, 33], reducing time to market in product development [39], evaluating critical infrastructure [40], and making strategic technological decisions [41]. This broad range of applications underlines the flexible character of IRM. By assigning competencies and tasks, it provides a controlling framework that promotes transparency and builds trust, which is based on evidence-based mathematical calculations.

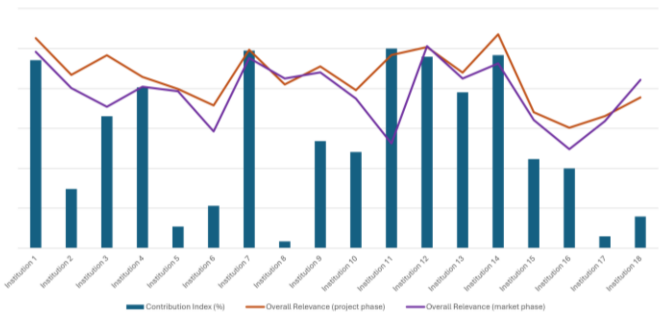

Figure 4. Simulated contribution index & overall relevance

Figure 4 shows an example of how the IRM results can be differentiated using the Contribution Index in combination with the overall relevance. This simulation shows how the IRM process can lead to insightful findings. The figure shows three central indicators for 18 institutions: the Contribution Index (percentage of completed surveys) and the Overall Relevance in two phases (project phase and market phase).

First, it is striking that the Contribution Index varies from only about 3% (Institution 8) to 100% (Institution 11). Some institutions stand out for their particularly high contribution (e.g., Institution 7, Institution 11, Institution 12, and Institution 14), which indicates above-average interest and possibly also sufficient resources or greater proximity to the subject of the study in terms of content. A high contribution index tends to indicate more intensive engagement with the survey topic and can thus contribute to the informative value of the study results. In contrast, survey contribution at other institutions (e.g., Institution 8 and Institution 17) is extremely low, with values below 6%. This very low level of engagement makes it difficult to gain consistent insights. Nevertheless, even isolated responses can provide valuable insights in special cases, especially if the respective institution has a unique specialization due to its orientation.

Regarding overall relevance in the two market phases (project vs. market phase), significant differences can be seen between the institutions. Institutions such as Institution 11 are particularly noteworthy, whose high relevance in the project phase (0.4032) correlates with a significant drop in the market phase (0.2185). This discrepancy indicates a specialization in the planning and development phase, while the institution's own competencies are less pronounced in the practical implementation on the market. Similarly, although less pronounced, institution 3 shows a significant decline in relevance from 0.4028 (project phase) to 0.2952 (market phase). Conversely, institution 8 has a marginally higher significance in the market phase (0.3543) than in the project phase (0.3416), which could indicate that it primarily encompasses specific implementation or marketing competencies.

Other institutions show a relatively balanced distribution between project and market phase relevance. Institution 12 (0.4196 vs. 0.4215) and Institution 14 (0.4463 vs. 0.3857) remain at a high level in both phases. The proximity of the values indicates a holistic spectrum of competencies that is useful both for the initial project planning and for the subsequent market launch. This balance can, among other things, indicate a smooth transfer from scientific concept development to realization in application contexts.

It should be noted that a combination of a high contribution index and high relevance in both phases can be particularly valuable: such institutions participate actively, provide a great deal of information, and, at the same time, contribute substantial expertise to all phases of the project. In the present evaluation, this particularly applies to institutions such as Institution 7, Institution 12, and Institution 14. For research, development, and market introduction strategies, targeted cooperation and funding approaches can be derived by specifically involving institutions with a high contribution and relevance rate in key roles. At the same time, it is crucial to consider institutions that may have a low level of participation but could potentially contribute indispensable specialist expertise. This approach allows for the best possible realization of synergies in both the planning and the market phase.

6. CONCLUSIONS

America, China, and Europe are currently competing in systems competition. Centralized ecosystems in America and China, which rely on hyperscaling and aggregate large amounts of data, can develop business models and expand their competitive position. The increase in data quality and data quantity further strengthens this circumstance. In Europe, a competing decentralized data ecosystem called Gaia-X is currently being developed to promote data exchange among participants by adhering to technical standards. The increase in heterogeneous data volumes, partly due to IoT, leads to increased data complexity, computational complexity, and system complexity within such systems. The process of datafication further accelerates this complication. To generate business models in this complex environment of Gaia-X or decentralized ecosystems, the parties involved must cooperate to a high degree. The concept of hypercooperation enables the competitiveness of decentralized ecosystems to be increased compared to hyperscalers, as it increases the availability and combinability of data sets for all ecosystem participants so that they can each scale their business models. To establish such hyper-cooperation, suitable instruments are necessary. One such suitable instrument can be the Institutional Role Model (IRM). It relates four dimensions to each other (Roles, Institutions, Temporal Dimension, Operational Dimension) and can be flexibly adapted. Through clear role definition and assignment, the identification of the necessary and appropriate institutions, and its temporal perspective, the IRM contributes to creating transparency, promoting trust, and thus enabling cooperation. To this end, an IRM matrix is developed based on the project or process requirements and the IRM approach, which is used to visualize the IRM results at the end of the process. This quickly reveals a suitability distribution of the institutions for role assumption. Further developed indices substantiate the results. The range of applications of IRM is flexible. It has been used, among other things, as an economic system architecture in Gaia-X lighthouse projects, for strategic decision-making, and in product development.

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NOMENCLATURE

IRM	Institutional Role Model