Analyzing Smart Services from a (Data-) Ecosystem Perspective: Utilizing Network Theory for a graph-based Software Tool in the Domain Smart Living

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Abstract: There has long been a trend away from monolithic solutions toward integrated service systems that combine technical services and product functionalities across different manufacturers. This is especially true for the Smart Living domain, where interconnected products and services are used in one of the most private areas. However, there is a lack of tools to manage these complex systems. This work represents the second iteration of an ongoing research project in which we are developing an analysis and management tool in response to specific requirements of various stakeholder groups of the Smart Living domain. We interpret the services and products of the data ecosystem as nodes of a network graph, which we analyze using established methods of network theory, e.g., to identify weak points and bottlenecks in the service systems. The metrics provided help domain experts and managers from the domain to perform concrete tasks and provide a business benefit.

Keywords: Smart Service System, Data Ecosystem, Network Theory, Smart Living, Design Science

1 Introduction

The demand for highly integrated services is growing steadily. Digitalization can act as this integrator by bundling offerings that have so far often been considered reclusively. Thereby it is creating increasing opportunities to realize additional value for consumers and producers [Va15]. This is illustrated for examples in the domain of Smart Living, which can be seen as an advancement of Smart Home. By connecting and integrating currently individual products and services, like single sensors or actuators, it enables autonomous service systems. In the Smart Living domain, these offerings concern by definition one of the most private sectors: Everyone's private apartment. Thus, characteristics such as comfort and security [Eb21] as well as context sensitivity [Ba20] have a significant impact on the attractiveness of Smart Living services and are only made possible by the integration of different components. The use case of the Intelligent Gatekeeper [Re22] illustrates these challenges prominently: Tangible and intangible goods with partly different, identical or overlapping functions of different manufacturers must work seamlessly together to provide the expected functionality [Ha19]. Therefore, the proliferation of Smart Living applications is still very limited, often due to its complexity. Nevertheless, the growth potential due to the increasing demand for this market [SF20] is correspondingly high.

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In the scientific community, especially in Information Systems and several Engineering disciplines, the offerings are often referred to as “product-service systems” or, through the now data-driven focus, as Smart Service (Systems) [Ko22]. Due to their integrative nature, they often have to incorporate several disciplines and overcome the heterogeneity of stakeholders involved in development and operation [La16]. Since the start of research into service bundling, their representation has been of great interest and thus been examined often [BT13]. Based on the consideration of individual components, e.g. the process perspective through process modelling [Ka19] or physical components through CAD design [Kl19], overarching approaches are becoming increasingly important [HKT18]. Publications can already be found in the scientific context, ranging from linking individual components, as Schoormann et al. [Sc20] propose for processes and business models, to thoroughly (meta) models of product-service systems (e.g. [MBB18]). However, no approach has yet been widely adopted allowing automated production and maintenance of these models. In addition, the previously outlined interplay of different actors combining their services, products and data sources leads to the emergence of a data ecosystem. In ecosystems, the data shared between actors and their services are an important resource with great potential for economic value creation. The management of this resource and of the entire data ecosystem is therefore of great importance but has not been adequately pursued to date.

Our research interest is generated by this fact and was initially met with the development of a prototype for the German Digital Summit 2020[2] [Re21], which provides a tool to gather, persist and represent (technical) self-descriptions of services and their relations and thereby acts as a Service Registry. Based on feedback from practitioners, the idea arose to use the resulting digital representation of the ecosystem for analytic purposes, e.g. to identify most critical services on which many others rely on. We have therefore systematically imposed requirements for such functionality and used them to further develop our tool. This paper thus focuses on developing a concept and implementing a prototype for analyzing ecosystems according to digital representations of the elements using graphs. Data ecosystems can be understood as networks [AB02] whose entities are represented as nodes, which are linked to each other via edges in a variety of relationships, forming complex graph structures. To analyze these graph structures, we use metrics and analytic methods from network theory and adapt them to our business-oriented use case. Because the proposed analysis is performed in real-time, we chose to use labeled property graphs instead of the established Resource Description Framework for their increased performance [DYB00]. We call this tool ‘Smart Service Analyzer’.

In order to describe our approach thoroughly the paper is structured as follows. In Section 2 the scientific methods used are outlined and set into context of the overall research framework, which this paper is the second iteration of. Section 3 thus briefly illustrates our previous work and is followed by the description of the requirement elicitation (Section 4). The transfer from requirements into a functional and technical concept is explained in Section 5 and followed by the description of the implementation. Lastly, we discuss our work and point our future work opportunities in Section 7.

[2] https://www.de.digital/DIGITAL/Redaktion/DE/Dossier/digital-gipfel-2020.html

2 Methodical Approach

As stated before this paper represents the second iteration of a design science research (DSR) [He04] prototype development within ForeSight[3], a research project in the domain of Smart Living. In a previous paper [Re21], requirements for the Service Registry were elicited and a prototype was implemented based on these requirements. In the present paper we describe the evaluation of this prototype, which at the same time represents the requirements elicitation for the next iteration stage and the current status of the ongoing development process. Our methodological research approach thus follows the Design Science Research methodology (DSRM) of Peffers et al. [Pe07]. In this paper we focus primarily on the first three steps suggested in DSRM: problem identification, conceptualization of the solution and improvement of the solution artifact. The subsequent steps of demonstration and evaluation are not part of this work. Our DSRM oriented approach is outlined in Fig. 1.

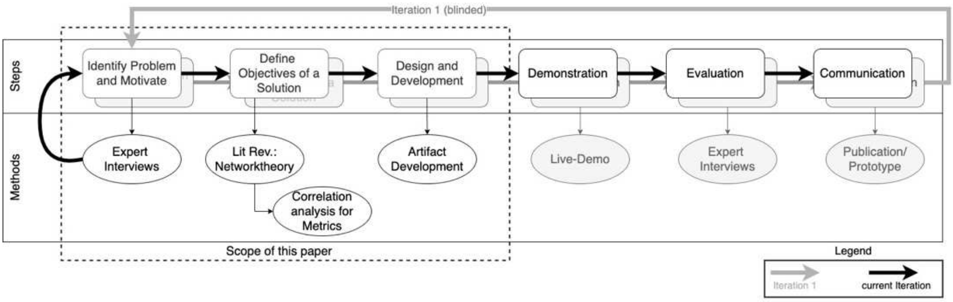

Fig. 1: Our DSRM [Pe07] oriented research approach

Since the evaluation of the prototype of the first iteration revealed the demand for an analysis function, we collected detailed requirements for such a function. These requirements enable us to incorporate domain knowledge into the development process, as suggested by [GH13]. For this purpose, we conducted focus groups with experts from different companies. All interviewed persons are experts in the sense of Bogner et al. [BLM09], hold a managerial position in their company and have several years of professional experience in the field of Smart Living. The results of the individual focus groups were subsequently consolidated in a workshop with all experts and are presented in section 4.

In a second step, we derive literature-based relevant methods and metrics for the realization of the analysis scenarios and the fulfilment of the previously identified requirements. Specifically, we draw on approaches from network theory, which we map to business problems in the Smart Living ecosystem. The selection of metrics is flanked by a correlation analysis, which helps us to identify metrics with identical meaning. Building on the insights gained here, we develop our solution artifact - the Smart Service Analyzer, a tool for analyzing data ecosystems.

[3] https://foresight-plattform.de

3 Representing the Smart Living Ecosystems

To enable innovative and secure service offerings, a transparent ecosystem maintaining interoperability and trust is needed. Within the beforementioned research project thus tools were implemented supporting these values and empowering companies utilizing the available services to build upon them or offer completely new services. One of these tools is the Service Registry, which was designed and developed as a catalog for collecting and presenting (digital) services. Therefor a standardized self-description for services was defined, which is a representation of individual services in the form of JSON-LD files. The definition is based on the W3C Web of Things standard[4] and was extended with Smart Living specific attributes. Services are stored in two levels of abstraction that build upon each other. 'Base Services' describe services in an abstract manner and focus their characteristics, while 'Service Instances' represent concrete instantiations of individual Base Services and contain, for example, information about specific endpoints. Base Services can be understood as building instructions for Service Instances. The Service Registry provides an interface to create and manage the services, both visually via a GUI and programmatically via an API. A similar approach was used for the standardized descriptions of Smart Home devices. These are stored in another catalog, the Thing Registry [Al21]. Together these tools provide information regarding elements in the ecosystem: physical goods, intangible services, datasets and their respective providers and thereby stakeholders.

4 Identifying Practical Needs and Potentials through Personas

The representation of entire ecosystems introduces a whole new level of complexity and thus barriers for wide adoption. To tackle these, focus groups with experts aimed at identifying ways to dissolve them and, most importantly, to gain insights on which benefits can arise from this integrated representation and analysis of an ecosystem, consisting e.g. of the self-descriptions in the Service Registry. Therefore, we chose an explorative and creative approach within the focus groups to discover aspects unthought of yet for different roles in the business context. As stated above, we firstly asked the participants to come up with personas for whom the tool can be beneficial, and secondly specify potentials in using it. In each focus group between one and three employees from the respective company shared their thoughts on requirements and potentials. In total we talked to 9 companies via video calls lasting about 45-60 minutes each. The participants cover all relevant areas of the Smart Living ecosystem, such as the housing industry, IoT and product manufacturers, ML developers, infrastructure providers, research institutes and service provider. During the focus groups, the respondents were asked to identify personas for whom an analysis function of the service graph is relevant and to derive concrete use cases and information needs for these personas.

[4] https://www.w3.org/WoT/

In Tab. 1 we present the personas and potentials we gathered. After we obtained the raw results, we grouped and aggregated them into the final list of most relevant aspects. In the first column the different roles are named. It was interesting to see, that the spread reached from technical (software development / data scientist) over business (product management / sales) to managerial (management) groups. Even though the tool can be of different importance for each group, it is promising that a wide target group exists. Assigned to each role are the stated potentials. One has to notice, that they partially have been associated with multiple roles by the experts. For simplicity we assigned it to the role it was most often mentioned with.

Business Role	**#**	**Potentials**
Product Manager	1.1	Identify gaps in the product portfolio
	1.2	Define product requirements
	1.3	„Supply chain“ monitoring
	1.4	Evaluate usage of offered services
	1.5	Calculate fair compensation
Software Developer	2.1	Risk assessment (e.g. failures on dependent services) 2.1a: Risk for the Network 2.1b: Risk for the Node
	2.2	Examining relationships
	2.3	Simplify troubleshooting
	2.4	Contact information
	2.5	Insights on technical feasibility
Data Scientist	3.1	Overview of present data sources
	3.2	Support in ensuring data quality
Sales	4.1	Identify potential customers
Management	5.1	Outline of portfolio
	5.2	Synopsis of business model (and opportunities)
	5.3	Review needs for certification
	5.4	Identify standard processes etc.
Operator / Ecosystem	6.1	Standardization
	6.2	Ensure privacy
	6.3	Ensure data sovereignty
	6.4	Identify / expand basis technology
	6.5	Overview over the ecosystem

Tab. 1: Potentials and thus functional requirements for the Smart Service Analyzer

5 Transforming Requirements into a technical Concept

5.1 Network Theory and Analysis in Data Ecosystems

In order to map the complex relationships between different entities of a data ecosystem (e.g. services, products, data, stakeholders), we use a graph representation and persistence of information in a graph database. In the same way that many complex systems can be described as networks of interacting entities [FS03], data ecosystems can also be understood as complex networks [AB02] whose entities are represented as nodes, linked to each other via edges in a variety of relationships, e.g. hierarchical. In our case the ecosystem comprises various Smart Service Systems, which consist of different entities like Smart Services, data sources, products, or stakeholder thus, in the context of network theory, the ecosystem represents the entire network graph, individual Smart Services are subnetworks, and the previously mentioned entities represent individual nodes of various types. Fig. 2 illustrates the relations within the overall network.

This form of representing data ecosystems enables the use of statistical methods of network topology and dynamics, which provide conclusions about the characteristics of the system. In this paper, we are mainly interested in the relationships between Smart Services, which is why we limit our further analysis to the entity class “Services”. In this way, various metrics [AS15] can be calculated, which allow statements about the robustness of the network to failures [AB02, BTL09] and provide starting points for its optimization. As different actors in data ecosystems develop and operate their services mainly independently, there is often no holistic view of the ecosystem as a whole. Although the services are dependent on each other, too little attention has been paid to this fact [Ko22]. As a result, critical dependencies on individual services can arise, so that their failure leads to a cascade of further service failures that affect sub-networks or even the entire ecosystem. From an economic perspective, such a failure is associated with high costs for the affected actors, which is why measures must be taken to avoid it. In addition to these relatively simple statistical metrics, more complex techniques, such as unsupervised machine learning methods, can also be used to identify patterns in the network structures of data ecosystems [Lo06] and to detect anomalies [ATK15].

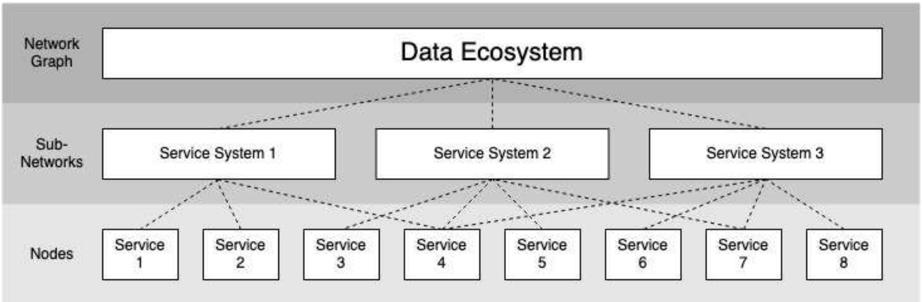

Fig. 2: Nodes and subnetworks in data ecosystems

5.2 Used Metrics and Methods

Metrics can be calculated at multiple levels of a data ecosystem. Firstly, for the entire data ecosystem, secondly, for individual, self-contained Smart Service Systems within the ecosystem and thirdly, at the level of individual services. In the literature of graph theory, there are a multitude of metrics that allow statements about the graph as a whole, subgraphs and individual nodes. To identify suitable metrics for meeting the business requirements identified in section 4, the relevant literature in this area was searched. Many of the identified metrics have a strong overlap in content. Harmonic centrality, for example, is a variant of closeness centrality which solves the problem of dealing with disconnected graphs. Both metrics aim to determine the centrality of nodes in the network and can be used to identify services that are critical for the ecosystem. To avoid redundancies within the Analyzer and to counteract a cognitive overload of its users, we performed a correlation analysis on a test data set that served as a basis for decision-making for the selection of KPIs for the Smart Service Analyzer. Since the amount of data currently available from the Smart Living data ecosystem is not sufficient to make a significant statement about the correlation of metrics, we resorted to a sample of the Python package repository Python Package Index (PyPI). The sample consists of 2,179 packages and their relationships to each other.

The packages (services) are connected as nodes by their dependencies via edges and thus form a graph that can be interpreted in the same way as our Smart Living graph. Metrics with a Pearson correlation coefficient of more than 0.9 or less than -0.9 were examined for overlap in content, and in the case of a technically identical interpretation for the Smart Living Data Ecosystem, one of the metrics was removed. The results of the correlation analysis are shown in Fig. 3.

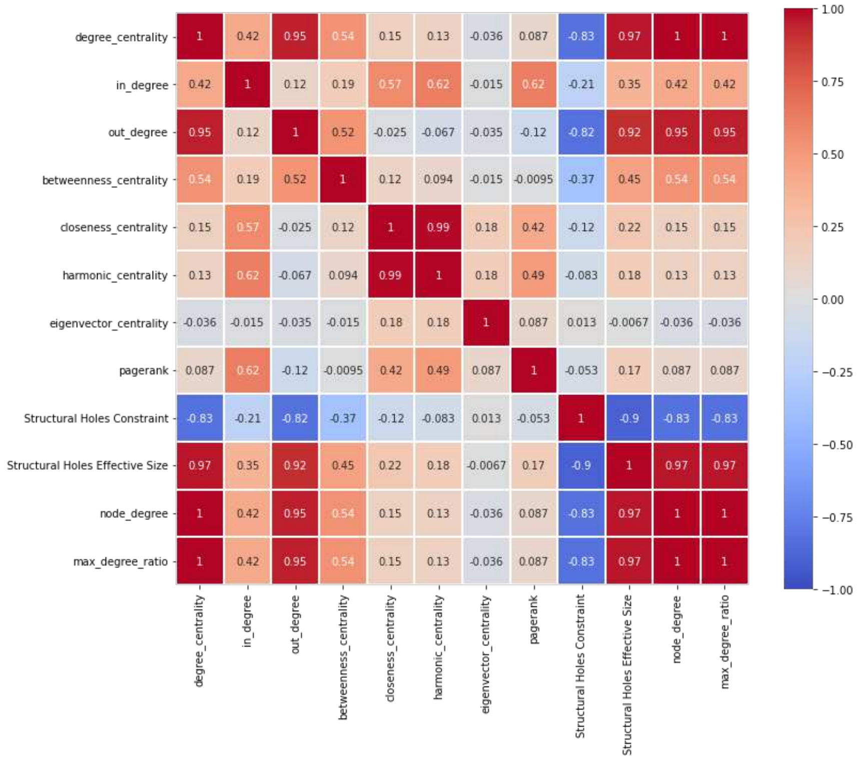

Fig. 3: Correlation matrix of tested metrics

The remaining metrics were evaluated by researchers with expertise in Smart Living and data ecosystems to obtain a domain specific interpretation of the metrics. Subsequently, a workshop was conducted to map the individual metrics to the requirements elicited through the focus groups. The results of this process are summarized in Tab. 2.

Req.	**Metric**	**Description**	**Domain Specific Interpretation for the Smart Living Data Ecosystem**
		Dimension: Services/Nodes	
1.2, 2.1b, 2.2	Indegree	Number of incoming edges of a node.	Number of services consumed by a service.
1.4, 2.1a, 2.2, 4.1, 5.2, 6.2, 6.3	Outdegree	Number of outgoing edges of a node.	Number of services that consume a service.
1.4, 1.5, 2.1a, 2.1b	(Normalized) Degree Centrality	Measures the number of direct relationships a node has, normalized by the maximum possible degree.	Allows information about how strongly interconnected a service is in relation to the size of the ecosystem.
1.4, 1.5, 2.1a, 5.2, 6.4	Betweenness centrality	Measures sum of the fraction of all-pairs shortest paths passing through a node [Br08].	Indicates how many shortest paths exist through the ecosystem via a given service. Enables the identification of important bridge services that connect other services of the service system.
1.5, 2.1a, 2.1b	PageRank	The PageRank is a variant of the Eigenvector metric, also taking link direction and weight into account. It mainly uses the indegree to estimate the influence level of nodes, thus applies to directed graphs [Pa99].	Allows conclusions to be drawn about the importance of a service to the data ecosystem. In addition to the number of services that Consume a given service, the number of services that consume the consuming services is also considered.
1.4, 1.5, 2.1a	Closeness centrality (Wasserman and Faust)	Calculates the inverse of the average shortest path between a node and all other nodes. Wasserman and Faust proposed an improved formula for usage with multi component graphs [WF94].	Allows conclusions to be drawn about how central and thus how important a service is for an isolated service system. The metric is suitable for our case because it works for data ecosystems in which not all nodes are connected, either directly or indirectly.

Dimension: Sub-Networks/Services Systems, Network Graph/Data Ecosystem			
1.1, 1.4, 2.2, 5.2, 6.2, 6.3	Structural Holes (Constraint)	Measures how strongly a given node is connected to nodes that are themselves connected to its neighbors [Bu04].	The occurrence of structural holes indicates that the connections between services in a system are unbalanced. This means that there are services with exclusive connections that link individual service systems in an ecosystem and whose failure could be critical for the data ecosystem as a whole.
2.1a	Max Degree Ratio	The Max Degree Ratio is the maximum degree of any node in the graph normalized by the highest possible degree [Il07].	Allows statements about whether there is at least one service node in the ecosystem with very high impact/damage potential in case of failure.
2.1a	Density	The Density of a graph is measured on a 0-1 scale where 1 is equivalent to a graph where every possible edge between two nodes exists and 0 is equivalent to a graph without any edges.	Represents the proportion of possible relationships between services in the data ecosystem that actually exist. A high value indicates strong dependencies of the ecosystem on individual services and thus the existence of individual points of failure.
Addition-ally: 1.3, 2.3, 2.4,	Exploratory analysis of the visualized network graph	-	Visual explorative analysis of the data ecosystem helps stakeholders get an overview of the services, the stakeholders connected to them, and can help with troubleshooting.

Tab. 2: Relevant metrics for the node and graph dimensions

6 Implementation

Transforming all the required information into a form suitable for graph analysis requires various technologies and technical artifacts, which will be described in further detail in the following paragraphs and in the sequence diagram (See Fig. 4). The existing service descriptions, which were previously stored exclusively in the relational database of the Service Registry, are converted into a format that represents the services and their stakeholders as nodes and their dependencies as edges. Thus, these service and stakeholder nodes and their edges can be transferred from the Service Registry into a graph database, for which we chose Neo4J [Ne22]. Nodes and relationships representing Smart Things (sensors and actuators) and their stakeholders are stored in the graph database as well. Based on the service description, a service may depend on a certain number of entities. The visualization of the data ecosystem is based on the nodes and edges stored in the graph database and the Javascript library D3.js [BOH11]. The information of all nodes and edges are loaded from the Neo4j graph database into the Service Registry.

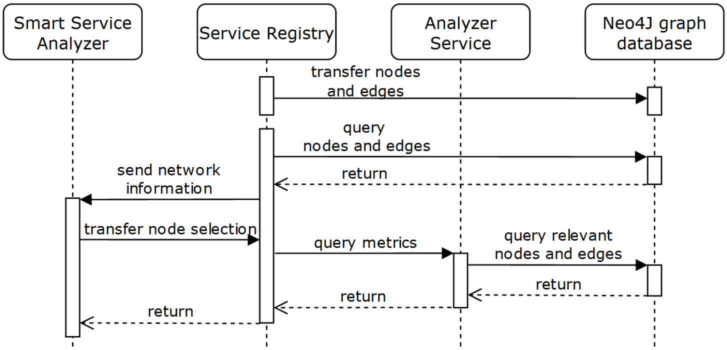

Fig. 4: Sequence diagram showing the Smart Service Analyzer and related technologies

Then these nodes and edges are systematically traversed and transformed using an algorithm to make them readable by D3.js. The Analyzer Service is a REST-full Python service that connects to the Neo4J database to retrieve the data for analysis. The service uses the Numpy and Pandas libraries for data manipulation and internal storage. Most of the network analysis is done with the open source library networkX [HSS00]. Upon receiving a generic request or a request containing a specific node ID the necessary information for the calculation of the metrics is loaded from the Neo4J graph database. While stakeholders and things are already represented in the graph database, they will not influence the analysis of the ecosystem as we solely focus on the service – service relationships in this work. Based on this information, the metrics are calculated and then sent back to the Service Registry via REST. This response is dynamically loaded into the web interface of the Smart Service Analyzer. Fig. 5 shows a screenshot of the Analyzer UI, illustrating how the data ecosystem graph and the metrics are displayed to users.

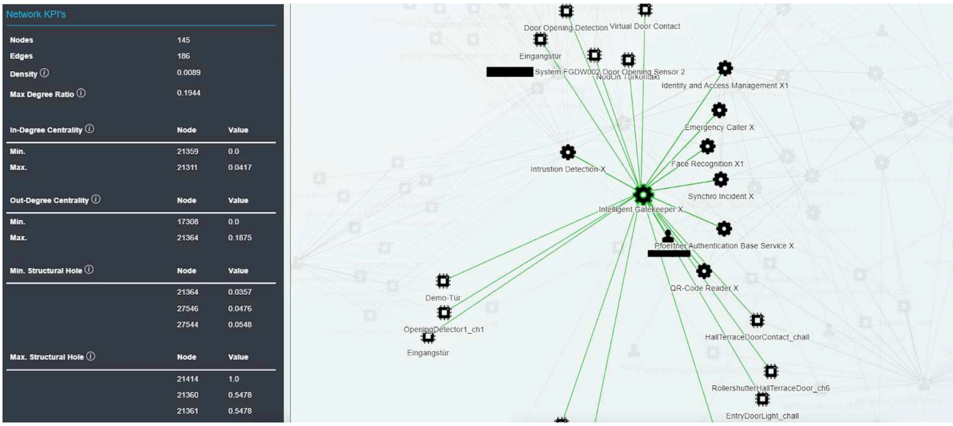

Fig. 5: Screenshot of the interface of the Smart Service Analyzer

7 Discussion, Limitations and Future Work

This paper presents a graph theory-based approach to analyze data ecosystems and a software tool demonstrating the approach, exemplarily in the domain Smart Living. Our proposition marks the second iteration of a design science research (DSR) cycle and thereby builds upon previous research insights and the corresponding prototype. The requirements were derived from focus groups and an aggregating workshop and mapped onto different established methods from graph analysis. It can take the different components data ecosystem currently encompass into account and thereby support companies offering highly integrated service offerings. By providing functionalities like planning, documenting, and analyzing services with respect to different metrics, our approach and thus the Service Registry and the Smart Service Analyzer provide a toolset for data ecosystems development.

However, in this paper we focus on the analysis of the relationships between services solely to demonstrate the approach. In future work it can be extended in several areas, e.g. including other ecosystem relevant entities, e.g., data sources, actors, or products as new node types. The introduction of new node classes would also result in new edge types to represent the relationships between the different nodes, giving the graph the additional property of being multi-relational. This can, for example, be integrated into the software with a toggle switching between the analysis of specific or all node types and edges. Also, the elements can be represented in greater detail (with more information). In addition, the set of metrics we have chosen for the Analyzer is only a snapshot covering the fulfilment of the collected requirements. In the course of time and with growing numbers of use cases, the requirements will change, and further metrics should be added to the Analyzer. The field of machine learning-based analysis methods was only briefly touched upon in this paper. In addition to using the previously described metrics, more complex machine learning and clustering methods can be used to analyze network graphs, especially in the context of data mining to uncover previously unknown structures and relationships between services. In our further research work we plan to transform the network graphs of the data ecosystem into numerical feature vectors using methods like Node2Vec [GL16] or Graph2Vec [Na17], in order to further analyze them with different machine learning methods, such as DBSCAN or different classifiers.

An automatically classification or clustering of services can also be utilized for new forms of revenue allocation. It can be dynamically measured and e.g. oriented at the importance of an offering for the overall ecosystem to achieve a fair compensation.

One has to note that our tool only provides numeric metrics which support companies in the decision process. They do not contain qualitative solutions to overcome certain problems and thus implicitly enable the propositions defined in Tab 1. Therefore, methods and skills need to be examined, which empower people and companies to build upon the analysis results. A starting point for this is provided by the work of [KRT22] in which skill requirements for AI domains were examined based on the analysis of job advertisements.

A big advantage of our approach lies in its broad applicability for all data ecosystems, assuming that their entities are represented in a corresponding graph structure. This also results in the potential for cross-domain use, within which service systems between different domains are analyzed. Here, we see added value for current initiatives to create transparent, interoperable ecosystems (e.g. GAIA-X) and would like to encourage practitioners and scientists to continue our work and use the Smart Service Analyzer.

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Bibliography

[Al21] Alberternst, S.; Anisimov, A.; Antakli, A.; Duppe, B.; Hoffmann, H.; Meiser, M.; Muaz, M.; Spieldenner, D.; Zinnikus, I.: Orchestrating Heterogeneous Devices and AI Services as Virtual Sensors for Secure Cloud-Based IoT Applications. In: Sensors vol. 21. MDPI, pp. 1-25, 2021.

[ATK15] Akoglu, L.; Tong, H.; Koutra, D.: Graph based anomaly detection and description: a survey. In: Data mining and knowledge discovery vol. 29. Springer, pp. 626–688, 2015.

[AB02] Albert, R.; Barabási, A.: Statistical mechanics of complex networks. In: Reviews of modern physics vol. 74. American Physical Society, pp. 47-97, 2002.

[AS15] Alenazi, M. J. F.; Sterbenz, J. P. G.: Comprehensive comparison and accuracy of graph metrics in predicting network resilience. In: 2015 11th International Conference on the Design of Reliable Communication Networks (DRCN). IEEE, pp. 157–164, 2015.

[Ba20] Bauer, J.; Hechtel, M.; Holzwarth, M.; Sessner, J.; Franke, J.; Wittenberg, T.; Waldhör, K.; Schena, A.; Falanga, A.; Ristok, B.; Böhle, F.: A Concept for Context Awareness in Smart Environments. In: Current Directions in Biomedical Engineering vol. 6. De Gruyter, pp. 380–383, 2020.

[BTL09] Bigdeli, A.; Tizghadam, A.; Leon-Garcia, A.: Comparison of network criticality, algebraic connectivity, and other graph metrics. In: Proceedings of the 1st Annual Workshop on Simplifying Complex Network for Practitioners. Association for Computing Machinery, pp. 1–6, 2009.

[BLM09] Bogner, A.; Littig, B.; Menz, W.: Introduction: Expert interviews—An introduction to a new methodological debate. In (Bogner, A., Littig, B., Menz, W, eds.): Interviewing experts. Palgrave Macmillan, London, pp. 1–13, 2009.

[BOH11] Bostock, M.; Ogievetsky, V.; Heer, J.: D3 Data-Driven Documents. In: IEEE Transactions on Visualization and Computer Graphics vol. 17. IEEE, pp. 2301–2309, 2011.

[BT13] Boehm, M.; Thomas, O.: Looking beyond the rim of one’s teacup: a multidisciplinary literature review of Product-Service Systems in Information Systems, Business

Management, and Engineering & Design. In: Journal of Cleaner Production vol. 51. Elsevier, pp. 245–260, 2013.

[Br08] Brandes, U.: On variants of shortest-path betweenness centrality and their generic computation. In: Social Networks vol. 30. Elsevier, pp. 136–145, 2008.

[Bu04] Burt, R. S.: Structural Holes and Good Ideas. In: American Journal of Sociology vol. 110. The University of Chicago Press, pp. 349–399, 2004.

[DYB00] Donkers, A. J. A.; Yang, D.; Baken, N.: Linked Data for Smart Homes: Comparing RDF and Labeled Property Graphs. In: LDAC2020—8th Linked Data in Architecture and Construction Workshop. Pp. 23-36, 2020.

[Eb21] Ebbers, F.; Zibuschka, J.; Zimmermann, C.; Hinz, O.: User preferences for privacy features in digital assistants. In: Electronic Markets vol. 31, pp. 411–426, 2021.

[FS03] Ferrer Cancho, R.; Solé Vicente, R.: Optimization in complex networks. In (Pastor-Satorras, R.; Rubi, M.; Diaz-Guilera, A, eds.): Statistical Mechanics of Complex Networks vol. 625. Springer, pp. 114–126, 2003.

[GH13] Gregor, S.; Hevner, A.: Positioning and Presenting Design Science Research for Maximum Impact. In: MIS Quarterly vol. 37. JSTOR, pp. 337–356, 2013.

[GL16] Grover, A.; Leskovec, J.: node2vec: Scalable feature learning for networks. In: Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining. Association for Computing Machinery, pp. 855–864, 2016.

[HKT18] Hagen, S.; Kammler, F.; Thomas, O.: Adapting Product-Service System methods for the digital era – requirements for Smart PSS engineering. In: Customization 4.0. Springer Proceedings in Business and Economics. Springer, Cham, 2018.

[Ha19] Hagen, S.; Brinker, J.; Gembarski, P.C.; Lachmayer, R.; Thomas, O.: Integration von Smarten Produkten und Dienstleistungen im IoT-Zeitalter: Ein Graph-basierter Entwicklungsansatz. In: HMD, vol. 56. Pp. 1220–1232, 2022.

[HSS00] Hagberg, A.; Schult, D.; Swart, P.: NetworkX

[He04] Hevner, A. R.; March, S. T.; Park, J.; Ram, S.: Design Science in Information Systems Research. In: Management Information Systems Quarterly vol. 28. Management Information Systems Research Center, University of Minnesota, pp. 75-105, 2004.

[Il07] Iliofotou, M.; Pappu, P.; Faloutsos, M.; Mitzenmacher, M.; Singh, S.; Varghese, G.: Network monitoring using traffic dispersion graphs (tdgs). In: Proceedings of the 7th ACM SIGCOMM Conference on Internet Measurement. Association for Computing Machinery, pp. 315-320, 2007.

[Kl19] Kloock-Schreiber, D.; Domarkas, L.; Gembarski, P.; Lachmayer, R.: Enrichment of Geometric CAD Models for Service Configuration. In: CEUR Workshop Proceedings 2467. Aachen, pp. 22-29, 2019.

[Ka19] Kammler, F.; Hagen, S.; Brinker, J.; Thomas, O.: LEVERAGING THE VALUE OF DATA- DRIVEN SERVICE SYSTEMS IN MANUFACTURING: A GRAPH-BASED APPROACH. In: Proceedings of the 27th European Conference on Information Systems (ECIS). Stockholm & Uppsala, pp. 1-15, 2019.

[KRT22] Kortum, H.; Rebstadt, J.; Thomas, O.: Dissection of AI Job Advertisements: A Text

Mining-based Analysis of Employee Skills in the Disciplines Computer Vision and Natural Language Processing. In: Proceedings of the 55th Hawaii International Conference on System Sciences. Pp. 5211-5220, 2022.

[Ko22] Kortum, H.; Rebstadt, J.; Hagen, S.; Thomas, O.: Integrating Data and Service Lifecycle for Smart Service Systems Engineering: Compilation of a Lifecycle Model for the Data Ecosystem of Smart Living. In: Proceedings of the 55th Hawaii International Conference on System Sciences. Pp. 2017-2026, 2022.

[La16] Larson, R. C.: Smart Service Systems: Bridging the Silos. In: Service Science 8(4). INFORMS, pp. 359–367, 2016.

[Lo06] Long, B.; Wu, X.; Zhang, Z.; Yu, P. S.: Unsupervised learning on k-partite graphs. In: Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining. Association for Computing Machinery, pp. 317–326, 2006.

[MBB18] Maleki, E.; Belkadi, F.; Bernard, A.: A Meta-model for Product-Service System based on Systems Engineering approach. In: Procedia CIRP vol. 73. Elsevier, pp. 39–44, 2018.

[Na17] Narayanan, A.; Chandramohan, M.; Venkatesan, R.; Chen, L.; Liu, Y.; Jaiswal, S.: graph2vec: Learning distributed representations of graphs. In: arXiv preprint arXiv:1707.05005 (2017)

[Ne22] Neo4j Graph Data Platform – The Leader in Graph Databases, https://neo4j.com/, accessed: 01/02/2022.

[Pa99] Page, L.; Brin, S.; Motwani, R.; Winograd, T.: The PageRank Citation Ranking: Bringing Order to the Web. URL http://ilpubs.stanford.edu:8090/422/. (2022-03-02)

[Pe07] Peffers, K.; Tuunanen, T.; Rothenberger, M. A.; Chatterjee, S.: A Design Science Research Methodology for Information Systems Research. In: Journal of Management Information Systems vol. 24. Routledge, pp. 45–77, 2007.

[Re22] Rebstadt, J.; Kortum, H.; Gravemeier, L.S.; Eberhardt, B.; Thomas, O.: Non-Discrimination-by-Design: Handlungsempfehlungen für die Entwicklung von vertrauenswürdigen KI-Services. In: HMD, vol. 59. Pp. 495–511, 2022.

[Re21] Rebstadt, J.; Kortum, H.; Hagen, S.; Thomas, O.: Towards a transparency-oriented and integrating Service Registry for the Smart Living Ecosystem. In: INFORMATIK 2021. Gesellschaft für Informatik, pp. 1425-1438, 2021.

[Sc20] Schoormann, T.; Hagen, S.; Brinker, J.; Wildau, S.; Thomas, O.; Knackstedt, R.: Towards Aligning Business Models with Business Processes: A Tool-based Approach. In (Bork, D.; Karagiannis, D.; Mayr, H. C., eds.): Modellierung 2020. Gesellschaft für Informatik e.V., pp. 13–27, 2020.

[SF20] Sovacool, B. K.; Furszyfer Del Rio, D. D.: Smart home technologies in Europe: A critical review of concepts, benefits, risks and policies. In: Renewable and Sustainable Energy Reviews vol. 120, 2020.

[Va15] Valencia, A.; Mugge, R.; Schoormans, J. P. L.; Schifferstein, H. N. J.: The design of smart product-service systems (PSSs): An exploration of design characteristics. In: International Journal of Design vol. 9. IJDesign, pp. 13–28, 2015.

[WF94] Wasserman, S.; Faust, K.: Social network analysis: Methods and applications. Cambridge University Press, New York, 1994.