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Introducing a methodological approach to determine value shares in Digital Ecosystems

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Research Paper

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Abstract. Motivated by the critical yet unsolved task of fair value distribution in digital ecosystems (DEs), this study presents a methodological approach that allows us to determine ecosystem components' value share to the total co-created value. Our method takes a holistic perspective on DEs. It suggests that when viewing DEs as complex networks, the value share of a component to the total co-created value stems from the network size and the interaction between the network participants. We demonstrate the applicability of the proposed method in a simulation of a Smart Living service ecosystem. Our simulation shows that our method is suitable for unraveling hitherto hidden interconnectedness between value-co-creating ecosystem components. Components that offer a low structural contribution to the total value can still play a crucial role in the network and have the most significant value share to the whole network.

Keywords: *Value Decomposition, Value Share, Co-created Value, Digital Ecosystem, Network Theory*

1 Introduction

In today's highly competitive business environment, companies increasingly recognize the importance of Digital Ecosystems (DEs) as a pathway to success and growth (Subramaniam et al., 2019). DEs are dynamic multi-agent environments in which interconnected digital services, goods, and platforms interact to create unique better products and services for their clients (Wang, 2021). One of the biggest appeals of DEs is that they enable their participants to generate unique value that otherwise would not materialize (therein *co-created value*). Specifically, in DEs, the participants jointly contribute to the ecosystem's success by creating technologies, services, or tools that other ecosystem participants can recombine with other components to generate new complementary products and services (Floetgen et al., 2022).

Because in DEs co-created value emerges only through resource sharing and recombination of data and services, successful DEs demand extensive collaboration among their participants (Floetgen et al., 2022; Valdez-De-Leon, 2019). Yet, to keep participants motivated to contribute, DEs must have adequate mechanisms for fair revenue allocation across partners (Valdez-De-Leon, 2019). If the co-created value of the DE is not fairly distributed across contributing partners, the ecosystem is unattractive for new actors and, thus likely to fail (Valdez-De-Leon, 2019; Wang, 2021). Surprisingly, despite the importance of fair value distribution for DE's success, currently, it remains unclear how to achieve a fair value sharing mechanism.

Prior literature focuses predominantly on the value creation in DEs but remains silent on the distribution of the co-created value across the involved participants. One of the most probable reasons for this gap in the literature is the recombinant yet partly opaque nature of DEs. Although co-created value arises from the interconnectedness of the assets of various ecosystem participants, these interconnections often remain hidden. Accordingly, each participant's contribution to the total co-created value remains concealed. Viewing co-created value as the sum of value shares contributed by a variety of ecosystem components (e.g., products, data, services), a fair distribution of the total co-created value requires us to identify and quantify the contribution share of each participant. As of now, the critical task of determining each participant's value contribution share to the total of parts of the co-created value has yet to be solved. Our paper addresses this literature gap by addressing the question: *[RQ]: How can we determine the value shares of each contributor to the co-created value in DEs?*

2 Theoretical Background and Related Work

As the literature on DEs continues to develop across various disciplines, there is no widely established vocabulary to theorize various aspects of DEs. To avoid jingle-jangle fallacies stemming from the ambiguous use of our focal terms (e.g., participant, co-created value), in this section, we present insights from prior literature while clarifying the central terminology in our paper. First of all, for the sake of simplicity, we refer to any actors involved in the value-creation process as *participants*. Participants are typically providers of *components*. Depending on the DE domain, such components can be data, software artifacts, or hardware (e.g., Internet of Things devices). Whether participants are companies, organizations, independent developers, or individuals is not essential at this point. Similarly, whether a component is a data source, a trained Artificial Intelligence (AI) model, or a complex service is also unimportant. After all, we understand the *allocation of value to be fair* when it is not based on actors' size or available resources but rather based on the value that a component brings when it is combined with other components. Analogous to new products developments in a firm, where extant core-components of previous products are used for the development of new products and services (Mihale-Wilson et al., 2022), in digital ecosystems companies effectively integrate the functionalities and essential components of other products and services into their new offerings. This deliberate approach significantly shortens their time to market while substantially mitigating the risks of failure (Mihale-Wilson et al., 2022).

The most important characteristic of *components* is that they are tangible assets that can exist independently but simultaneously be part of a larger system. To illustrate the concept of components, let us assume an exemplary DE for AI-based services in Smart Living. The Smart Living concept (also often referred to as “smart home”) envisions that by integrating technology (e.g., wearables, home sensors, intelligent transportation systems, and other AI-based systems), we can automate and optimize daily routines and activities to improve humans’ comfort and quality of life. Hence, within the context of smart living DEs, various components are working together and form new complex products and services such as improved predictive maintenance of housing infrastructure (e.g., Lowin et al., 2021; Lowin & Mihale-Wilson, 2021), or AI-based personal assistance (Mihale-Wilson et al., 2019, 2017). AI-based assistants can help individuals fulfill their personal and professional obligations easier. In the future, AI-based assistants will be able to perform tasks on their users' behalf, freeing up time for more meaningful activities (Meurisch et al., 2020). To this end, the ecosystem might, for instance, encompass an AI model that forecasts anomalous behavior in a heat sensor (call it <AI model>). This <AI model> can function on its own and predict heat sensor failures. Simultaneously, the same <AI model> can be combined with a particular dataset <dataset> and trained to generate a service <service> that predicts failures in more than one type of sensor and device. Based on our definition above, all three assets <AI model>, <dataset>, and <service> represent components. After all, <dataset> and <service> can again exist as independent entities on their own. Simultaneously, <dataset> and <service> can be combined with other data sets and services to generate more complex services. These examples illustrate the hierarchical relationship between components and, ultimately the participants in a DE. The fact that each component can exist in more than one version and is combinable with a multitude of other components which can also exist in more than one version complicates these relationships even further. Case in point: the <AI model> can exist in an initial version <_v_1> which is trained on a relatively small set of sensor data. Additionally, more elaborate versions of the <AI model> may exist <v_x>. Analogously, there might also be varios versions of <dataset_v_x> and <service_v_x>. Assuming that there exist three versions <v_1>,<v_2>, and <v_3> of each of the three components <AI model>, <dataset>, and <service>, there are 27 possible recombinations. Clearly, in practice, there are more than three components and versions available to recombine with each other to co-create value. Against this background, we follow Kortum et al. (2022) and suggest modeling and analyzing the complexly interwoven relationship between the components of a DE based on **network theory**.

Nascent in the field of mathematics network theory can be used to model and analyze a wide range of phenomena, including social networks, biological systems (Albert & Barabási, 2002; Newman, 2003), product and service systems (Hagen et al., 2019), and technological networks (Kortum, Hagen, et al., 2022). The core idea of network theory is that actors within a network influence each other. Hence, the overall performance and behavior of the network depend not only on network size but also on the interactions in the network.

Following Newman (2003), a network consists of a set of items (in our case, components, which are also referred to as *nodes*) and the connections between them (also referred to as *edges*). Networks are often represented as graphs. The most parsimonious network entails a set of nodes joined by edges. More complex and sophisticated networks, however, can distinguish between more than one type of node and edges (Newman, 2003). Circling back to our exemplary components (<AI model>, <dataset>, and <service>) and the network they build: The simplest form of the network would be to list the three components and link them to each other. More sophisticated representation of the network, however, would incorporate, for instance, the class of the AI model (i.e., decision tree, neural network), or directed or weighted edges to better describe the relationships between the nodes they connect.

While graphs allow visual investigations and inferences when the network under investigation is small and parsimonious, they are less visually informative as the number of nodes and edges and the level of detail increase (Newman, 2003). Against this background, network theorists have developed various models and statistical methods to quantify large and complex networks. We use extant methods to model and document the **value chain within a DE**–i.e., the path of how independent components contribute to the total co-created value.

Central to the idea of *value chains* is that new value is generated when adding components to the chain. A value chain starts with an organic component—i.e., a component that is not the product of combining other components. We refer to the value - added when combining another component with the organic component as *Value Share (V*S). We must clarify the term **value** at this stage, as it has several connotations across different research disciplines (Jimenez & Arenas, 2021).

In essence, *value* can be defined in economic or more abstract terms. Most of the extant work investigating value contributions in complex networks such as DEs gravitates around economic value like revenue or pricing (e.g., Fricker & Maksimov, 2017; Nguyen & Paczos, 2020; Stoppel & Roth, 2016). Nguyen and Paczos (2020), for instance, discuss approaches to measure the economic value of data, data monetization strategies for new business models, and how the value of data can be conceptualized and measured from a business perspective. Fricker and Maksimov (2017) analyze mechanisms used to evaluate the pricing of data products in data marketplaces. Stoppel and Roth (2016) transfer value-based pricing from the product to the service-oriented perspective. We acknowledge that the economic perspective on value is helpful on numerous occasions. However, for the purpose of this study, a more comprehensive perspective is needed. In this vein, revenue and pricing capture only the financial performance of the ecosystem, whereas a more abstract understanding of value can also entail non-financial, intangible benefits. Most recently, Jimenez and Arenas (2021) built on Grover and Kohli (2012) and used IT-based value to refer to the value generated when companies collaborate to implement joint IT-based products and services. In this study, we follow these scholars and comprehend *co-created value* as an abstract concept that can incorporate all types of utility generated through component recombination.

3 Methodological Approach for Value Decomposition in DEs

We process the various streams of literature to develop a method that allows us to decompose the co-created value in DEs. Our method exploits one of the many advantages of DEs—that they typically reveal (machine-readable) information on the relationships between individual components. Applying network theory to DEs and using the previously discussed nomenclatures, we can visualize components as nodes that are related

to each other via directed edges. Components can form subnetworks. This representation allows new ways of calculating the value share each component contributes to the network or subnetwork (denoted by τ). Due to the network representation of the DE, one would immediately be tempted to determine that a node contributes to τ based on the node's position in the network (e.g., centrality) and other parameters. Although this approach is per se correct, it is incomplete, as it disregards the fact that nodes are recombinant, and thus the value of a node also depends on the value it generates for the subsequent nodes. Following this logic, our proposed method postulates that the value share that a node contributes to τ depends on *(i) the network size*—i.e., the amount of nodes and edges in the network and *(ii) its recombinant (or recursive) nature*.
We distinguish between *contributions* and *weights* of a node to τ. Contributions are generally computed within a (sub-)network while weights are typically parameters provided by domain experts. Besides, we also distinguish between the *structural* and *value-added* worth of a node within the entire network. The value-added stems from any value chains' central assumption that each component within the chain needs to add value to subsequent components of the chain. The structural value of a node, however, reflects that within a network there are interdependencies of components that need to be accounted for. After all, the interdependencies between components imply that the failure or malfunctioning of one component can have dire consequences for the entire network. We use this nomenclature to **describe the value shares that a node can have in a network.** We introduce **four core constructs**: *Structural Contributions (SC), Value-added Contributions (VC), Structural Weights (SW), and Value-added Weights (VW).* We elaborate on these core constructs individually.
The structural contribution (SC) of a component (i.e., node) is based on its location within the network. We explain based on a simplified example: A component that is located at the periphery (call it *periphery node*) of a network and thus has relatively few edges linking them with other components yields a comparatively small value for the network. In contrast, a component located at the center of the network (call it *central node*) with many edges that link it to various other components will yield a comparatively higher value to the network than the periphery node. The difference in value contribution of the exemplary periphery and central nodes stems from their relative importance for the network's overall performance. If the central node fails or malfunctions, large parts of the ecosystem will no longer be functional. In contrast, a failure of the periphery node is likely to have only minor effects on the overall performance of the ecosystem. Recently, Kortum et al. (2022) identified possible metrics from network theory suitable for quantifying the relevance of a node within an ecosystem. In this work, the authors mention that PageRank is a popular method suitable for this purpose. PageRank evaluates the structural importance of a node based on the number and dependencies of other nodes in the network. This way, it provides insights on the underlying structure and importance of a node in relation to the network as a whole. In particular, PageRank uses the incoming edges to a node for calculating the importance of that node relative to the network as a whole. Thus, PageRank yields a network importance and ranks the nodes in an 'inverse' order compared to the aforementioned value chain contemplation. A node with a higher number of incoming edges are considered more important than edges with a low number of incoming edges.

In contrast to the structural contribution, the *Value Contribution (VC)* of a component (i.e., node) does not depend on its position in the network. It is determined directly from its value for one (or more) specific subsequent node(s). In this sense, a single node sometimes has several value contributions depending on the number of nodes that follow it. In technical terms, the value contribution represents the amount a node adds to the fulfillment of the task of its successor. This can be nicely illustrated based on the example of an AI–based component for the prediction of a value, which uses as input several services that provide or manipulate data.

Reusing the introduced nomenclature, imagine the following: An <AI model> is used by two different Services <S_1> and <S_2>. In both cases, <AI model> uses the same <dataset> for its training. Now, for <S_1>, the <AI model> is the only input and thereby has a high VC for <S_1>. In contrast, <S_2> has many different inputs, one being <AI model>. Clearly, the VC of <AI model> will probably be lower. If we assume that two <AI models> with the same functionality but from different providers are present in the DE, their VC for a <Service> might be different. To quantify their respective VC, different approaches are applicable. For example, the VC can be measured via the mean squared error (*MSE*). Generally speaking, the lower the MSE, the better the AI service. In this case, the MSE depends on the inputs ('features') provided by the predecessor node(s), here the <dataset>. A feature's specific contribution to the forecast's quality can be quantified using state-of-the-art statistical methods and represents the VC of the predecessor node for the AI service. For AI-based components, we can use, for example, SHapley Additive exPlanations (SHAP) values, permutation feature importance, or feature importance for trees. For non-AI services, other forms of contribution determination can be used (e.g., coefficient magnitude method, variance inflation factor (VIF), partial regression coefficient method).

We now turn to the *Structural* (SW) and *Value Weights* (VW), which should currently be determined by domain experts, who can evaluate the relative importance of SW and VW for the particular DE and within a specific domain. After all, every DE is marked by specific characteristics or manners dictated by the encompassing domain (e.g., Smart Living, production, etc.). These specific characteristics need to be accounted for, especially because these weights can vary greatly from application domain to application domain. In ecosystems with close links between services and few redundancies, for example, structural weights play a more important role than in ecosystems in which many substitutes exist for a particular service. Since both weights express relative importance, they must sum up to one.

All previous things considered, we formally propose that the value share (*VS*) of a component (*c*) to the overall network value τ ($\sum_1^n VS$) is calculated as:

$$VS_c = \frac{1}{\sum_1^n VS} \left(SW \frac{1}{n} \sum_1^n SC_c + VW \frac{1}{n} \sum_1^n VC_c \right) \tag{1}$$

where:

VS	*denotes the value-added worth of a component (i.e., node) in the value chain to a related component (i.e., node)*
SW	*is the structural weight of a node (i.e., represents a context-dependent weighing of the structural contribution of a node). SW together with the value weight (VW) add up to 1.*

SC	*denotes the structural contribution of a node (i.e. the importance of a node in the value chain depending on its position in the (sub-) network)*
VW	*refers to the value weight (i.e., calculated as a context-dependent weighting of the value contribution). VW together with the structural weight (SW) add up to 1.*
VC	*is the value contribution of a node (i.e., the amount a component adds to the fulfillment of the task of its successor)*
c	*denotes the focal component (i.e., node) for which the value share is computed*
n	*is the number of components (i.e., nodes) in the DE (i.e., network)*

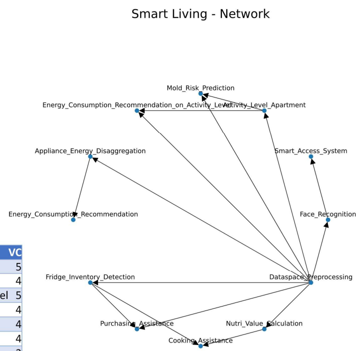
$SW\frac{1}{n}\sum_{1}^{n}SC_c$ denotes the structural contribution of the component multiplied by its importance weight. This value does not change unless the structure of the DE changes. In contrast, $VW\frac{1}{n}\sum_{1}^{n}VC_c$ captures the value contribution of a component depending on the subnetwork evaluated. This value contribution might change in accordance with the value that that particular node adds to other services.

4 Simulation Study to Demonstrate Applicability

To demonstrate the applicability of the proposed method, we conduct a simulation study mimicking a DE in the Smart Living industry. The network was built with the Python package NetworkX (https://networkx.org/) and contains the relationships of components in the domain of Smart Living—e.g., *energy optimization* (i.e, appliance energy disaggregation, energy consumption recommendations), *user assistance* (e.g., smart access system, cooking assistance, nutrition value calculation, fridge inventory detection) and other *generic components* (e.g., face recognition, dataspace preprocessing, activity recognition or mold risk recognition). We generated a representation of the mentioned components (nodes) and their relations to each other (edges) and implemented equation (1) in Python. Figure 1 illustrates the simulated network and the assumed components and edges.
For our simulations, we randomly assume edge values (VC) between [0 to 5]—see Table lower left of Figure 1. In a real DE, VCs can be estimated by using model-agnostic determined values such as SHAP. To calculate each node's structural contribution (SC) we used the previously mentioned PageRank method. To calculate the value shares of components such as services that do not offer any direct value to subsequent nodes in the network, we need only the structural contribution (SC)—in our case their PageRank. To calculate the value share (VS) of a node, we need the value and structural weights of the DE under scrutiny. Domain experts in Smart Living estimated the structural weight (SW) to 0.7 and the value weight (VW) to 0.3. Based on these parameters and equation (1), we first calculate each node's corresponding **value share (*VS*) to the co-created value in the entire network**. Table 1 presents the estimated value shares within the postulated network. As the VCs in the table reveal, the dataspace prepro-

cessing component has the highest value share to the total network (VS=0.178), followed by the cooking assistance component (VS=0.096). The smart access system and energy consumption recommendations are on par (VS=0.077).

Node	Pagerank
Face_Recognition	0.063029
Smart_Access_System	0.110549
Activity_Level_Apartment	0.063029
Mold_Risk_Prediction	0.089816
Energy_Consumption_Recommendation_on_Activity_Level	0.089816
Appliance_Energy_Disaggregation	0.063029
Energy_Consumption_Recommendation	0.110549
Fridge_Inventory_Detection	0.063029
Purchasing_Assistance	0.089816
Cooking_Assistance	0.137336
Nutri_Value_Calculation	0.063029
Dataspace_Preprocessing	0.056975



Source	Target	VC
Face_Recognition	Smart_Access_System	5
Activity_Level_Apartment	Mold_Risk_Prediction	4
Activity_Level_Apartment	Energy_Consumption_Recommendation_on_Activity_Level	5
Appliance_Energy_Disaggregation	Energy_Consumption_Recommendation	4
Fridge_Inventory_Detection	Purchasing_Assistance	4
Fridge_Inventory_Detection	Cooking_Assistance	4
Nutri_Value_Calculation	Cooking_Assistance	3
Dataspace_Preprocessing	Face_Recognition	4
Dataspace_Preprocessing	Mold_Risk_Prediction	4
Dataspace_Preprocessing	Activity_Level_Apartment	3
Dataspace_Preprocessing	Appliance_Energy_Disaggregation	3
Dataspace_Preprocessing	Fridge_Inventory_Detection	3
Dataspace_Preprocessing	Nutri_Value_Calculation	2
Dataspace_Preprocessing	Purchasing_Assistance	3
Dataspace_Preprocessing	Energy_Consumption_Recommendation_on_Activity_Level	3

Figure 1: Simulation of a DE for Smart Living services and assumed VC

Interestingly although we set the value weight to only 0.3, which should in theory, result in a network value distribution still close to other current approaches, we end up with the node *Dataspace_Preprocessing* (VS=0.178) having the highest value share contribution in the network. Even though, its structural importance is relatively small (SC = 0.056). This in turn, reiterates how important our methodology is to represent the added value in new DE. By giving a slight benefit to nodes that offer a high value to their subsequent nodes (VW=0.3), components such as "data preprocessing" reveal their impact to the total co-created network value. This is important to encourage nodes that offer added value (e.g., enriched, data, preprocessing steps) to subsequent components in the value chain.

To verify the plausibility of the estimated VS, we assess the instantiation of the node *Activity_Level_Apartment* in more detail. Precisely, we first calculate the inner term of our formula ($SW \frac{1}{n} \sum_1^n SC_c + VW \frac{1}{n} \sum_1^n VC_c$), which represents the value-added by the node before considering the overall network to create the value share (VS). With our structural weight (SW) set to 0.7, the node *Activity_Level_Apartment* has a structural contribution (SC)—i.e., PageRank of ~ 0.063. The VC is computed by considering the nodes' contribution to all connected nodes, divided by the sum of the VC in this smaller sub-network.

With our set value weight factor (VW) at 0.3, the VC of our node 'Activity_Level_Apartment' is ~ 0.167. Now we can calculate our inner term in the formula to get the value-added ~0.094. Note that this value-added is not yet in relation to the network.

$$VS_{node} = \frac{1}{\sum_1^n VS'}(0.7 * 0.063 + 0.3 * 0.167)$$

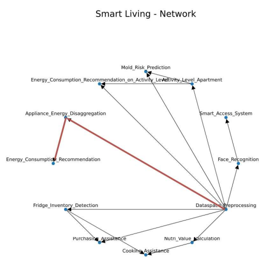
To compute our overall value share (VS), we calculate the relative share of the value-added ~0.0941 in relation to the value co-created to the entire network. To this end, we divide ~0.0941 through the sum of all inner terms of all nodes in the network. In our simulated network this results in the overall network value-added at ~ 1.0. We compute VS_{node} as 0.094 / 1.0 = 0.094.

Table 1. Value Share (VS) to the total co-created value (per node)

Node	VS per node (computed)
Face_Recognition	0.072
Smart_Access_System	0.077
Activity_Level_Apartment	0.094
Mold_Risk_Prediction	0.063
Energy_Consumption_Recommenda-tion_on_Activity_Level	0.063
Appliance_Energy_Disaggregation	0.066
Energy_Consumption_Recommendation	0.077
Fridge_Inventory_Detection	0.089
Purchasing_Assistance	0.063
Cooking_Assistance	0.096
Nutri_Value_Calculation	0.061
Dataspace_Preprocessing	0.179
Cumulated Value	1.0

Next, we focus next on each node's **value share (*VS*) to the total co-created value within a sub-network—i.e., a node's corresponding value chain(s)**. Let us consider the value chain of the component *Energy_Consumption_Recommendation*. Figure 2 highlights this path in red. In this example, the biggest contribution to creating the focal component *Energy_Consumption_Recommendation* comes from the *Appliance_Energy_Disaggregation* component. Next to the graphical network in Figure 2, each network value chain is listed with its internal value shares for the nodes in its corresponding sub-network. These are also calculated based on equation (1). However, the co-created value under consideration is that of a sub-network rather than the entire network. This implies that to calculate the VC of a node, only subsequent nodes inside the value chain are considered. Likewise, to calculate the VS's of all nodes in the value chain, again, only the sum of the added value of the nodes inside this sub-network is considered. However, this approach allows for more in-depth analyses of specific value chains. Additionally, it can offer insights into diversifying a specific value chain.

To demonstrate the usefulness and functionality of the weights we also simulated other, contrary or more extreme allocations. In many occasions this leads the first and last node in the network to 'switch' importance, which is expected due to the underlying methods for value calculation. For the intermediary nodes it depends, obviously, on the structure of the network and their individual VC, but in general the changes are less significant compared to the first and last nodes. In the example given above these results are plausible and also in general suggest the comprehensiveness of the approach.



Value Chain from 'Dataspace_Preprocessing' to 'Mold_Risk_Prediction':
Dataspace_Preprocessing: 0.5164585054472713
Mold_Risk_Prediction: 0.14069069530118683
Activity_Level_Apartment: 0.3428507992515419

Value Chain from 'Dataspace_Preprocessing' to 'Purchasing_Assistance':
Fridge_Inventory_Detection: 0.36726282298553786
Dataspace_Preprocessing: 0.4920464817132753
Purchasing_Assistance: 0.14069069530118683

Value Chain from 'Dataspace_Preprocessing' to 'Energy_Consumption_Recommendation_on_Activity_Level':
Energy_Consumption_Recommendation_on_Activity_Level: 0.14069069530118686
Activity_Level_Apartment: 0.4038808585865318
Dataspace_Preprocessing: 0.45542844611228134

Value Chain from 'Dataspace_Preprocessing' to 'Smart_Access_System':
Face_Recognition: 0.4568544707334519
Smart_Access_System: 0.16772116562453326
Dataspace_Preprocessing: 0.3754243636420148

Value Chain from 'Dataspace_Preprocessing' to 'Energy_Consumption_Recommendation':
Energy_Consumption_Recommendation: 0.16772116562453326
Appliance_Energy_Disaggregation: 0.4671753159222947
Dataspace_Preprocessing: 0.36510351845317207

Value Chain from 'Dataspace_Preprocessing' to 'Cooking_Assistance':
Cooking_Assistance: 0.183373928395919
Fridge_Inventory_Detection: 0.27490295339805226
Dataspace_Preprocessing: 0.31450660361185095
Nutri_Value_Calculation: 0.22721651459417783

Figure 2: Value Distribution per Value Chain in the network

5 Discussion

In rhis work, we develop and present a methodological approach suitable to decompose the co-created value in (sub)networks. We demonstrate the applicability of the proposed methodology in a simulation with a Smart Living service ecosystem. This way, we present various contributions to theory and practice.

We highlight three of this study's main theoretical contributions. Firstly, our research closes the gap in the literature surrounding the question of how to achieve fair value allocation. Although various scholars (e.g., Valdez-De-Leon, 2019; Wang, 2021) emphasize the importance of fair value distribution across the ecosystem contributors for the DEs' long-term success, the corpus of literature presents a "blindspot" on this topic. The second main contribution of our work is its holistic perspective on co-created value. We suggest viewing DEs as complex entities for which we can model the value creation and relationship between its components based on constructs from network theory. This is not new per se. What is new, however, is our proposition to leverage the strengths of the network representation of the DE to account not only for structural interconnected relationships between DE components but also for the recombinant, recursive nature of these relationships. Earlier, we noted that components can exist alone and are part of more complex components. These more complex components can provide input and can be recombined with other components to generate even more sophisticated components. The recursive nature of DE components implies that the value contribution of a component is determined not only by its direct successors but also recursively by those components that build on the successors, and so on.

Based on the described recursivity and Wang's (2021) idea that DEs should be investigated not only in their parts but also as a whole, we argue that considering only structural interconnectivity would yield an incomplete and thus erroneous quantification of the contributors' value shares in the ecosystem. In contrast, our holistic approach will generate more accurate quantifications of components' value shares the co-created value. Ultimately, we contribute to the current corpus of literature by presenting a domain and component-agnostic approach to value decomposition. Extant literature investigated primarily data and value in economic terms (e.g., Fricker & Maksimov, 2017; Nguyen & Paczos, 2020). While we agree that the economic perspective on value is valuable in various contexts, the economic perspective is incomplete for complex and heterogenous DEs that entail many types of digital species (e.g., data, software, and hardware). Our work rests upon the notion that fair value contribution implies that all types of tangible assets within an ecosystem need to be considered. In this vein, our method uses "component" as one of its core constructs. Thereby it is not crucial whether these components are data, hard- or software.

From a pure practice perspective, our methods represent a novel approach (1) to generate transparency of value contributions within an ecosystem, (2) to allocate the co-created value fairly across participants, and (3) ultimately increase the attractiveness of the DE for other potential contributors. Starting with the dual consideration of structural and value-added contributions to total co-created value: our approach will generate more accurate quantifications of components' individual shares on the total value created. Further, by considering each component's structural and value-added contribution (i.e., the value a component adds to the subsequent component), we can better understand the overall value distribution within the focal (sub-) network. By incorporating the structural and value contributions in our approach, we can also identify the value shares of components within a specific value chain. This can in turn, help us identify components that may be undervalued or underutilized. As mentioned, a common problem in DEs is that interconnections between components and their value contributions often remain hidden. Our approach allows us to unravel the previously hidden interconnections between contributors and generate hitherto unachieved transparency on value flows. Together, the transparency and the accurate quantification of components' value shares to the co-created value will enable DEs to distribute value equitably among all its participants. Because "fair" distribution of value will continuously attract potential new contributors into the ecosystem (Valdez-De-Leon, 2019), our proposed method is essential to ensuring DE's long-term success.

Despite the numerous benefits our methodological approach affords, our work also features some **limitations** that can be addressed in **future research**. The most significant limitation of our proposed method is its "good faith" character which assumes provider honesty about the components a provider recombines to generate new components. Because this information is essential to compute VC, DEs need mechanisms to ensure the traceability of component recombination. Certifications, change logs, and audit trails can be helpful tools to motivate providers to be honest about the components they combine. This is particularly the case for established DEs but also for those in their inception. However, for the latter, DE designers should consider implementing dependency management tools (that track the recombination of components in a network), component metadata management, or component monitoring and logging. These tools will help increase transparency on recombining components within the DE without solely relying on stakeholders' honesty. Nonetheless, future research should develop other methods to ensure that the information needed to compute VC is derived automatically without providers' involvement.

One major challenge of formalizing the VC of a component is the discoverability of the value-added through each node for the subsequent nodes. This discoverability is directly linked to the accessibility of relevant data for the value determination of the subsequent nodes. For AI services, this could be based on model-agnostic determined values over the input variables. However, this would require fully open access to data concerning the inner workings of each service node. Such open access to such information is, in practice, unrealistic. Thus, our approach highlights the importance of data accessibility and discoverability for data ecosystems in determining their value contribution.

The domain experts' involvement in setting the structural and value weights as another potential limitation of our method. However, given the complexity and relative novelty of DEs in practice, reliance on domain experts is, at this stage, appropriate. In our simulation study, domain experts set the structural weight (SW) to 0.7 and the value weight (VW) to 0.3. As our discussion in section 4 reveals, our method yields plausible value shares. We believe that domain experts can gauge the SW and VW values appropriate to describe the weights of the structural and value-added contributions. In the future, we encourage scholars to develop human-in-the-loop-based approaches to support domain experts in setting the SW and VW values. However, as long as these weights need to be defined by domain experts alone, we suggest that it is highly important to ensure the reliability and validity of the structural and value weights by (1) finding the right experts and (2) and deriving the correct weights by consolidating experts' opinions. On finding the right experts: it is important that these are familiar with the domain of the DE and the market developments within this domain. In this vein we deem experts to be appropriate if they are operating the ecosystem, they are part of a public entity or associations involved in the development and/or operation of the DE. Related to deriving the correct weights by consolidating experts' opinions: suitable methods include the Delphi method, structured workshops, and discussion rounds. Further, we note that our approach envisions only rigid values for the weights for all components of the network. Future research should try to develop methods or extend our approach to allow for varying weights across all different components entering the calculation of the value share. Ultimately, we like to mention that our simulation study was based on an exemplary smart service network in the Smart Living domain. However, our method is scalable and transferable to more complex and other types of DEs (e.g., AI-based components, libraries, data) in other domains. Future investigations should seek to extend our proposed method to more complex network structures from real-world ecosystems. Overall, given the importance of "fair" value distribution across participants as a driver for the long-term success of ecosystems, we expect to see significantly more research on the topic in the future.

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