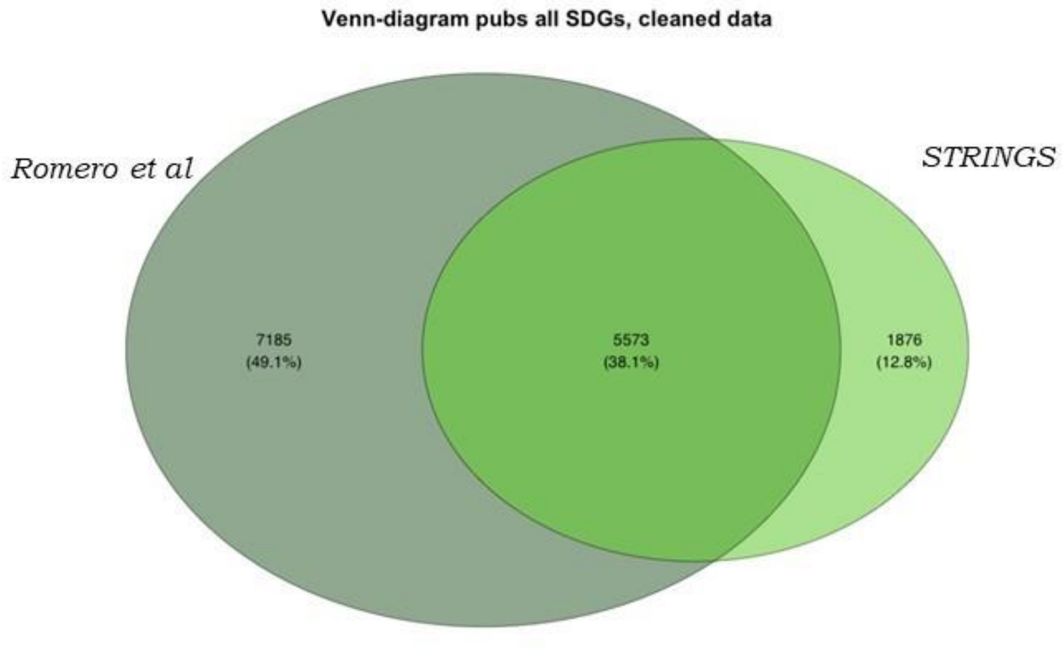
# Supplementary Material Note 1:
# Quantitative methods

### Understanding emergence of the Sustainable Development Goals Research.

### 1.1 Thesaurus robustness analysis.

The search results of the Romero et al. [1] and the STRINGS [2] thesauruses are compared in depth. The Romero et al. thesaurus consist of a total of 2155 keywords, describing the 17 SDGs. The STRINGS thesaurus consists of 3718 keywords, describing 16 SDGs (excluding SDG 17). Both thesauruses are used to find SDG publications in the dataset.

The Venn-diagram, which shows the interaction and difference between both datasets, is shown in S1. We see that of all publications retrieved by both the Romero and STRINGS keywords, 5573 publications are retrieved by both thesauruses. We also observe that the Romero keywords retrieve many more publications, a total of 12,758 (Romero) vs. 7,449 (STRINGS) publications. Of the publications that STRINGS retrieves, a large share of 75% is also found by the Romero keywords. This implies that the STRINGS thesaurus is more specific, resulting in a smaller dataset, but retrieves largely similar publications. The Romero keywords are less strict defined and therefore match more publications.




S1: Venn diagram of the overlapping publications between the Romero and the STRINGS datasets

Comparing the publications found in each SDG shows that the STRINGS thesaurus is more biased towards SDG 3, whereas the publications retrieved with the Romero et al. thesaurus are more evenly distributed across all SDGs. Figure shows the overlapping publications in each SDG. We see that many publications that are defined as SDG 3 using the STRINGS thesaurus are defined as SDG 1 or 2 using the Romero thesaurus. When we look at the distributions of the publications per SDG for each thesaurus in Figure. we observe that for the STRINGS thesaurus nearly 40% of the retrieved publications are in SDG 3. For the Romero et al. publications this number is half.

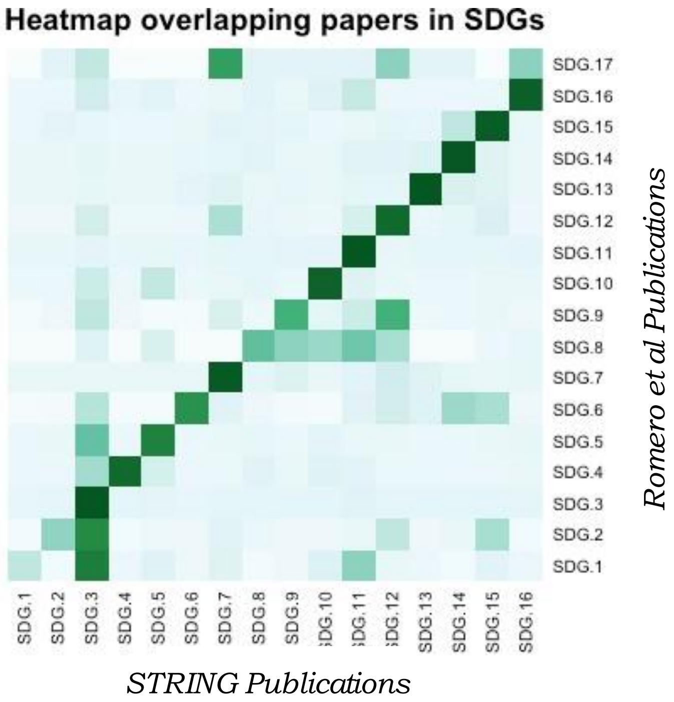



Figure S2: Heatmap with the overlapping publications per SDG for the Romero et al. and STRINGS thesaurus (matrix is scaled column-wise)

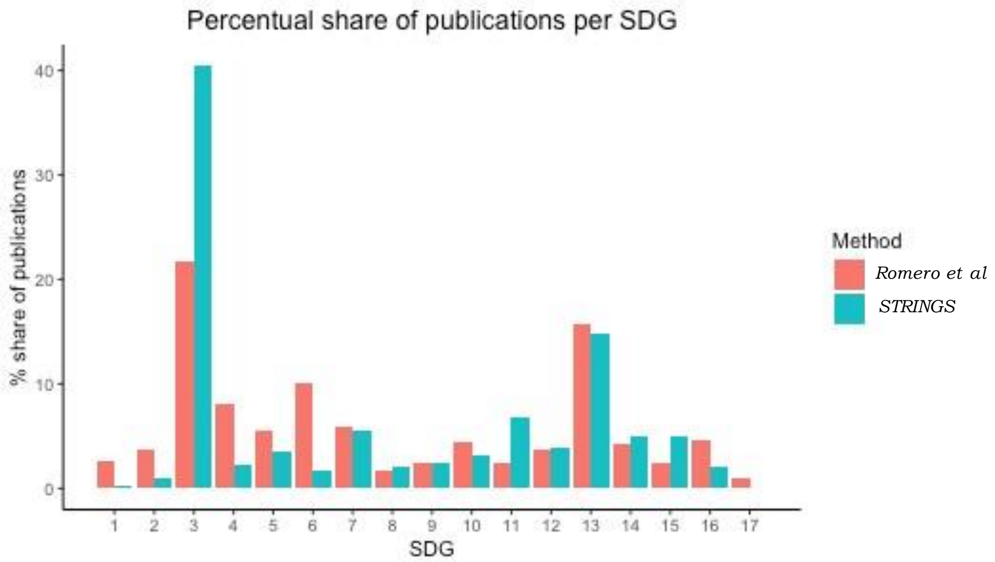



Figure S3: The percentual share of the publications per SDG, for the Romero et al. and STRINGS thesaurus

The Romero et al. thesaurus is developed to study the interactions between the SDGs and focusses on the transformative lens presented in the main manuscript, whereas the STRINGS thesaurus is developed with more focus on single SDGs. Due to the familiarity of the researchers with the Romero thesaurus, as well that it has been developed to study the interactions between the SDGs, this research uses the dataset of SDG publications as retrieved by the Romero et al. keywords. Combining both thesauruses was considered, but this would mean that two thesauruses developed for a very different research aim would be used together. Moreover, for most SDGs both thesauruses find publications in the same SDG. The differences are in SDG 1, 2 and 3 and SDG 8.

### 1.2. The clustering algorithm

The Louvain clustering algorithm and the Leiden clustering algorithm are both implemented and compared. The Louvain algorithm is a bottom-up hierarchical community detection algorithm introduced by Blondel et al. [3][1]. The Leiden algorithm, introduced by Traag et al. [4][2] is based on the Louvain algorithm, but instead of continuously checking all nodes in the network whether they can be moved to a different cluster, it only checks so-called unstable nodes. The heatmap in Figure shows the overlapping publications per community for the clustering algorithms. We see a clear diagonal line in the figure, which means that the publications in the communities are nearly equal for both clustering algorithms. For our analysis the Louvain algorithm showed to be faster. Moreover, the Louvain algorithm is a more broadly used and well-known algorithm. Because of the little difference between both clustering algorithms, we use the Louvain clustering algorithm. The Louvain algorithm results 229 clusters in the network, with a modularity of 0.98.

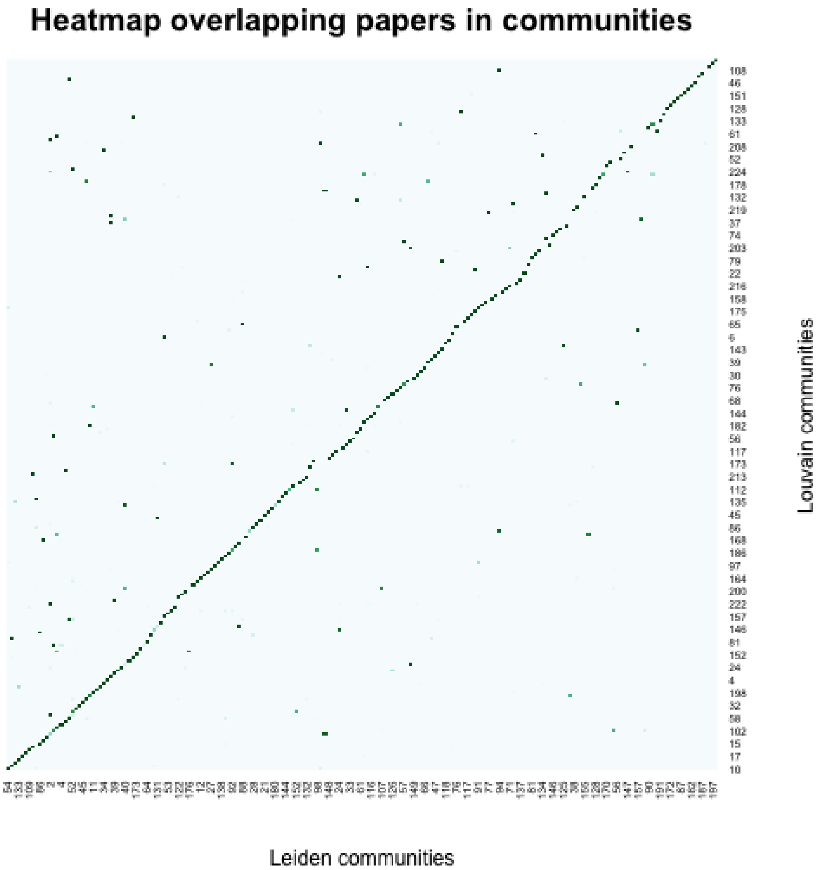



Figure S4: Heatmap with the overlapping publications in the communities by the Leiden and Louvain algorithm

[1] https://arxiv.org/abs/0803.0476
[2] https://arxiv.org/abs/1810.08473

### 1.3. The co-bibliography network

The co-bibliography network is created, where the nodes are the bibliometric data sources from Web of Science and the ties are the shared bibliography. To find well defined communities with strong cognitive relationships we set a threshold for a link between two publications to be meaningful (cut-off point). Different thresholds and the corresponding modularity, nodes and communities in the network are evaluated. Figure shows the values for the different thresholds. Based on this figure the threshold for a link to be meaningful is set to be 17, which gives a large set of documents in the network, but also a high modularity of the communities in the network as recommended by Romero et al., [1]. All non-meaningful links and nodes are removed from the network, resulting in a network with 48,994 nodes and 159,903 links.

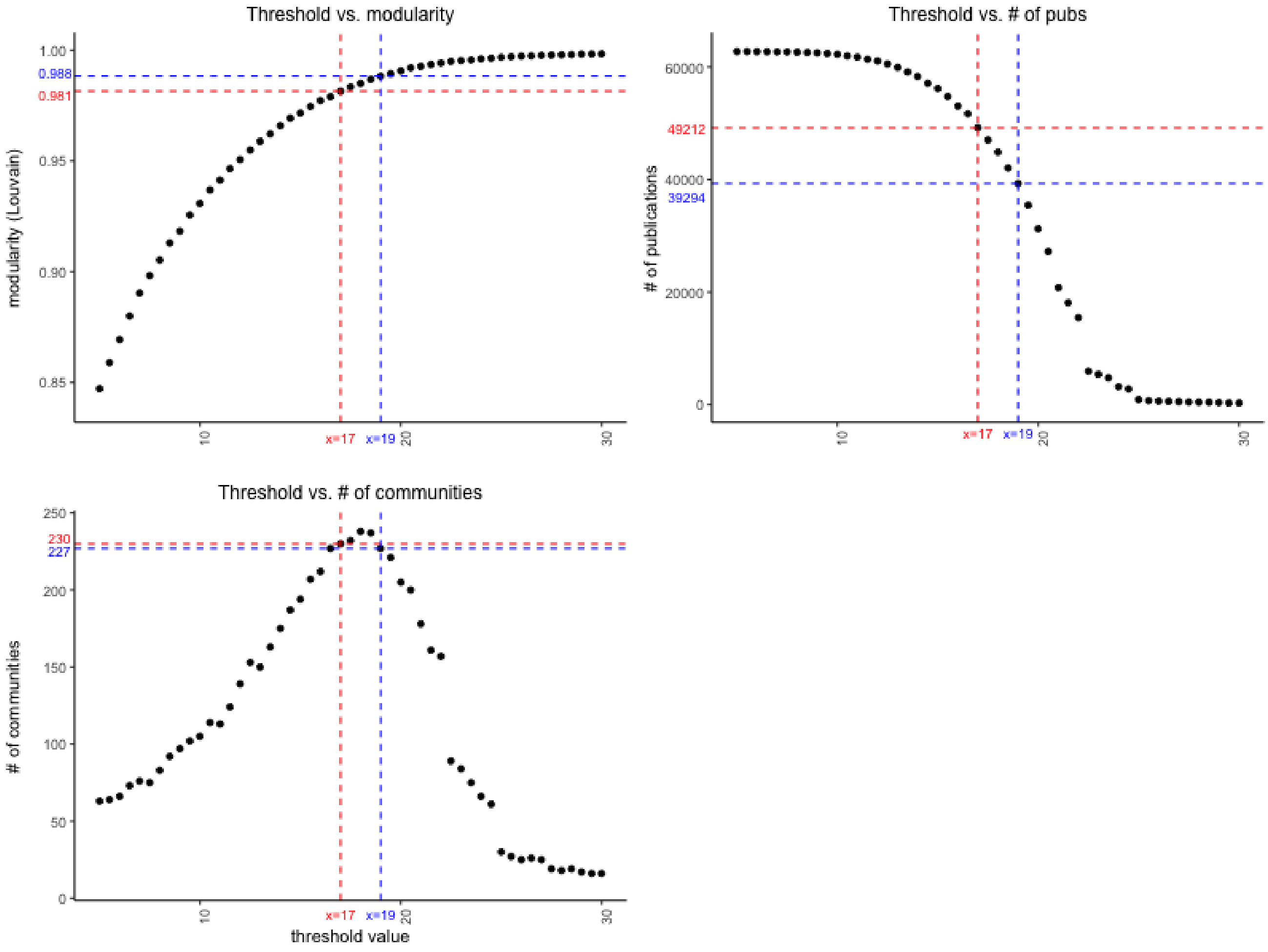



Figure S5: Graphs of the modularity, number of publications and communities for different threshold values

### Section 1.4. SDG knowledge communities

Based on the previous criteria, a community is defined as an SDG community if it satisfies *at least* one of the following conditions:

- The SDG share of the community is higher in T4 than the SDG share in T3 *and* the SDG share in T4 is higher than 0.39
- The slope of the trendline of a community is larger than zero *and* the total SDG share is higher than 0.30

The first condition is based on the idea that the SDGs were introduced in 2015. If the SDG publication share of a community did not increase since the introduction of the SDGs, compared to the five years before (T3), it is not regarded as an SDG community. Additionally, the SDG publication share of a community should be at least 0.39 in T4. This is based on the turning point in the left graph in Figure. The second condition is based on whether a community shows a promising trajectory towards the SDGs. If the slope of the trendline is larger than zero it means that the SDG publication share in the community shows an increasing trend of the past 20 years. Additionally, the community should have an SDG publication share of at least 0.30, based on the turning point in the right graph in Figure.

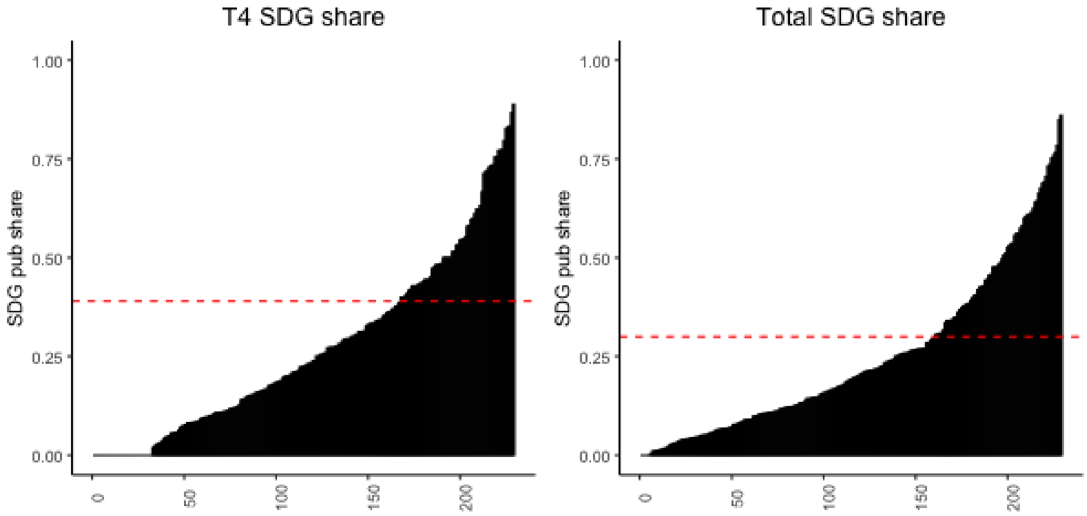



Figure S6: SDG share in T4 (2015-2020) (left), total SDG share (right)

These conditions are defined for this research and allow us to make a distinction between communities focussing on SDG research and communities *less focussed* on SDG research. By analysing the entire network of Utrecht University, the interactions between SDG and non-SDG communities are taken into account. Some 'non-SDG communities' are facilitating knowledge circulation for the SDG communities, or execute the research underlying research on the SDGs. These communities are not marked as 'SDG community' but are nonetheless of importance. The distinction between SDG and non-SDG communities is made for analysing the differences in communities and comparing the communities with a high SDG research focus and communities with a lower SDG research focus, their interactions and research topics.

## 1.5. Details temporal analysis

Because we are interested in where selected communities emerged and how they developed, we do not need to relabel over the timeframes. We create the similarity matrix between communities for each timeframe, and communities in graph $G_{T-1}$ get a similarity score with the communities in the current graph ($G_T$). The similarity *s* is defined follows:

$$s_{ij} = \frac{P_i \cap P_j}{P_i}$$

Where $P_j$ is the set of publications in community *i* in $G_{T-1}$ and $P_i$ the set of publications in community *j* in $G_T$. This similarity measure is adapted from the Jaccard similarity, but because we want to know in which community in $G_T$ the publications from community *j* in $G_{T-1}$ are, we only need to know what the share of $P_i$ in some community in $G_T$ is. The similarity matrix $M_s$ is created where the rows correspond with the communities in $G_T$ and the columns with the communities in $G_{T-1}$. If the similarity score between community $i$ and $j$ is equal to 1, it means that all publications from community $i$ in $G_{T-1}$ are in community $j$ in $G_T$. However, over the years new knowledge communities are formed, whereby communities split into new communities, or communities merge together. This is represented in the similarity matrix $M_s$. If community $i$ from $G_{T-1}$ has a similarity score of 0.5 with community $j$ in $G_T$ and a similarity score of 0.5 with community $k$ in $G_T$, community $i$ split into two new communities, $j$ and $k$. On the other hand, if both community $i$ and community $l$ in $G_{T-1}$ have a similarity score of 1 with community $j$ in $G_T$, community $i$ and $l$ merged together into community $j$. It is very well possible that communities from $G_{T-1}$ that split, one part of them also merged with another community into a new community in $G_T$. Due to the nature of the clustering algorithm, it is possible that unstable publications are assigned to a different cluster. Therefore, a threshold of $s_{ij} >= 0.1$ is implemented for the split and merge of communities.

## References

[1] O. Y. Romero, M. Ramirez, F. Arroyave, and J. Schot, "Mobilizing the transformative power of research for achieving the Sustainable Development Goals," *Res Policy*, vol. (in press), 2022.

[2] SPRU, "STRINGS – Science technology research and innovations for the global goals," 2019. http://strings.org.uk/ (accessed Aug. 31, 2021).

[3] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre, "Fast unfolding of communities in large networks," *Journal of Statistical Mechanics: Theory and Experiment*, vol. 2008, no. 10, p. P10008, 2008, doi: 10.1088/1742-5468/2008/10/P10008.

[4] V. Traag, L. Waltman, and N. J. van Eck, "From Louvain to Leiden: guaranteeing well-connected communities," *Sci Rep*, vol. 9, no. 1, Oct. 2018, doi: 10.1038/s41598-019-41695-z.