Supplementary Material

Accuracy and stability estimation

To assess the accuracy and stability of the SINMs, we used two main analyses of the R- package *bootnet* (Epskamp & Fried, 2017). First, to estimate the accuracy of the edge weights of the SINMs, we bootstrapped the 95% confidence intervals of the edge weights of the networks. Secondly, to examine the stability of the centrality indices, we used a method called subsetting bootstrap, in which the network is re-estimated multiple times after dropping a number of participants. The order of the centrality indices is then correlated to that of the original network, so that the centrality indices can be considered stable if the correlation is large. We therefore estimated the centrality stability coefficient (CS-coefficient), which should be at least 0.25 for a centrality index to be seen as stable, but preferably above 0.5. We applied the edge weight bootstrap as well as the subsetting bootstrap on the Dutch as well as the Colombian SINMs. For more information on these methods, please see Epskamp's and colleagues tutorial on the accuracy and stability of psychological networks and the use of the R-package *bootnet* (2017).

Dutch SINM. The results of the accuracy and stability estimations of the Dutch SINM are displayed in Figure S1a for the accuracy of edge weights and Figure S1b for the stability of the centrality indices. The edge weight bootstrap revealed that the Dutch SINM is moderately accurately estimated, as that there is considerable overlap among the 95% CIs of the edge weights. Especially the 95% CIs of the strongest edges do not have much overlap with the other CIs, so that they can be considered to be indeed stronger than the other edges. The subset bootstrap (Figure S1b) showed that the order of node strength is most stable, followed by closeness, with betweenness being considerably unstable. This is supported by the CS-coefficient, which was 0.75 for strength, 0.36 for closeness and 0 for betweenness. As the CS-coefficient should preferably be above 0.5, we only considered strength when looking at the centrality indices of the Dutch SINM.

Colombian SINM. The results of the accuracy and stability estimations of the Colombian SINM are displayed in Figure S2a for the accuracy of edge weights and Figure S2b for the stability of the centrality indices. The edge weight bootstrap revealed that the Colombian SINM is moderately accurately estimated, as that there is considerable overlap among the 95% CIs of the edge weights. Especially the 95% CIs of the strongest edges do not have much overlap with the other CIs, so that they can be considered to be indeed stronger than the other edges. The subset bootstrap (Figure S2b) showed that the order of node strength is most stable, followed by closeness, with betweenness being considerably unstable. This is supported by the CS-coefficient, which was 0.75 for strength, 0.21 for closeness and 0 for betweenness. As the CS-coefficient should preferably be above 0.5, we only considered strength when looking at the centrality indices of the Colombian SINM.

A **B**

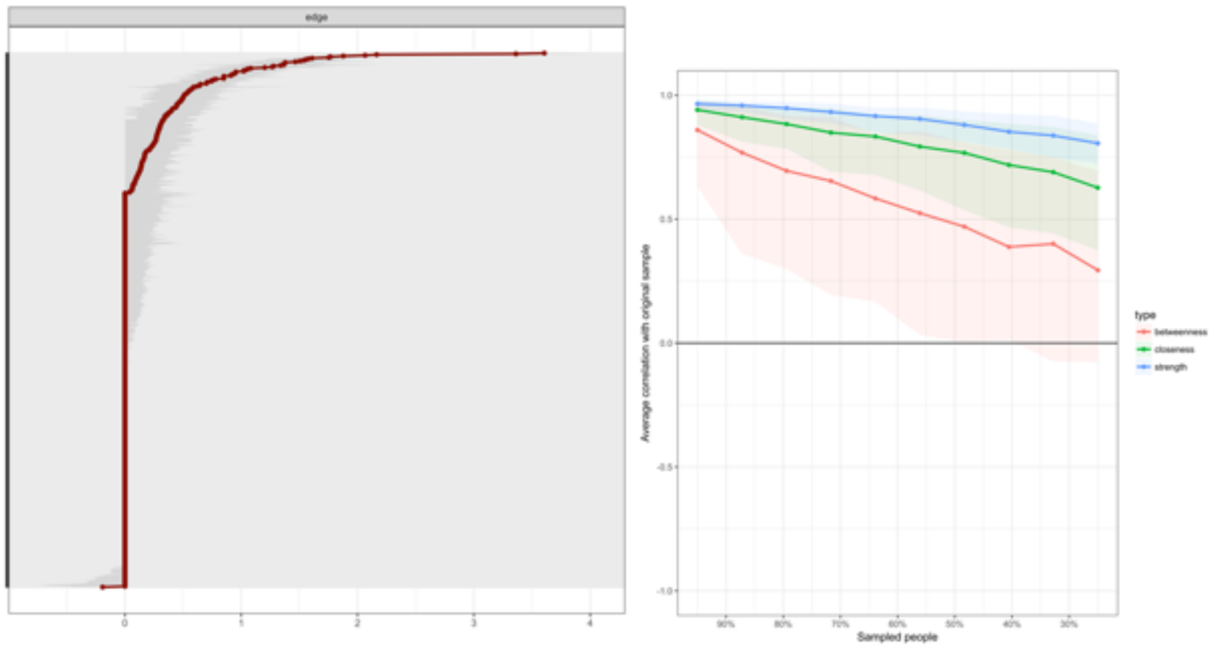

Figure S1. Panel A: Bootstrapped 95% CIs of all edges of the Dutch SINM. The red line indicates the estimated edge weights in the Dutch SINM, with the grey area surrounding it indicating the bootstrapped CIs per edge. The x-axis represents the strength of the edge weights, whereas all possible edges between two nodes are listed on the y-axis, ordered from highest edge weight (top) to lowest edge weight (bottom). Panel B: Subsetting bootstrap for the Dutch SINM, showing the average correlation between the three centrality indices of the original network (full data set) with networks estimated on smaller subsamples of the data set.

A **B**

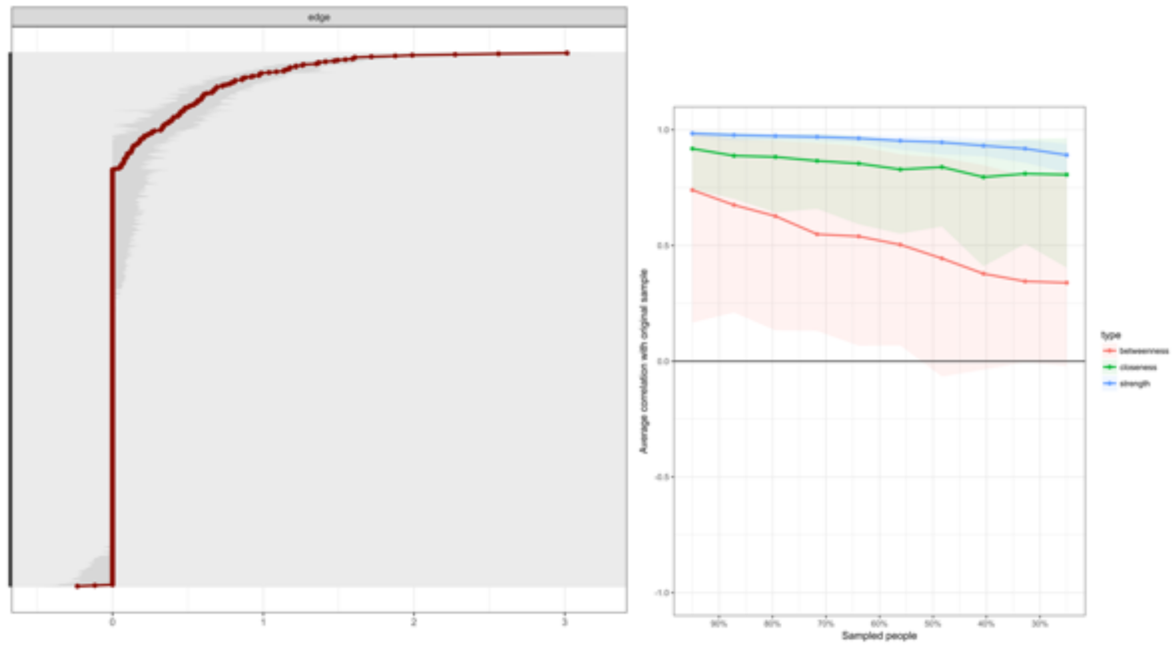

Figure S2. Panel A: Bootstrapped 95% CIs of all edges of the Colombian SINM. The red line indicates the estimated edge weights in the Colombian SINM, with the grey area surrounding it indicating the bootstrapped CIs per edge. The x-axis represents the strength of the edge weights, whereas all possible edges between two nodes are listed on the y-axis, ordered from highest edge weight (top) to lowest edge weight (bottom). Panel B: Subsetting bootstrap for the Colombian SINM, showing the average correlation between the three centrality indices of the original network (full data set) with networks estimated on smaller subsamples of the data set.

Table S1.

Results of the network comparison test (NCT) of subgroups of the Dutch and Colombian sample.

Subgroups	N	Structure		Specific Edges	Global Strength	
		M	*p-value*		*S*	*p-value*
Netherlands						
HAVO vs.	688	1.42	0.17		1.30	0.77
VWO	688					
HAVO/VWO vs. MBO	2129	1.21	0.05	Ibi-Imf; Vwl-Vdo;	0.45	0.89
	2012			Ipd-Vcp; Bbo-Bsn;		
				Sne-Sea; Slm-Sfr;		
				Sea-Kce; Eil-Ksl		
Colombia						
Total sample vs. small	5557	0.35	1.00		7.88	0.66
sample	2129					
Academica vs.	1782	0.16	0.81		0.02	0.99
tecnica	1782					
Upper secondary vs.	2728	0.68	0.17		0.45	0.81
lower secondary	2728					

Note. The subgroups per country (i.e., HAVO vs. VWO school level of the Netherlands, Academica vs. tecnica school level of Colombia) were compared. If the sample sizes were substantially different, group sizes were made equal through random subsampling, as the NCT is sensitive to differences in group size. This was not done for the comparison of the total Colombian sample with the Colombian subsample, as we wanted to make sure that comparing the small Colombian sample with the Dutch SINM would be feasible.

Connectivity simulation

To gain a first indication of possible differences of the dynamics of the two country networks we performed a simulation study. A difference in dynamics may be due to stronger synergistical influences (or emergence) between indicators in the Dutch network than in the Colombian network. To gain a first indication of the dynamics of the Dutch and Colombian network, we simulated the effect on external pressures on the two networks. External pressures could be forcing students to choose either a science or a humanities study program (Dalege, Borsboom, van Harreveld, Waldorp, & van der Maas, 2017; Epskamp, Maris, Waldorp & Borsboom, 2016; Wainwright & Jordan, 2008). Importantly, this so-called consistency pressure can be linked to the connectivity of a network, as connectivity grows with higher consistency pressure (i.e., higher external pressure on the network) (Dalege, Borsboom, van Harreveld, Waldorp, & van der Maas, 2017). Connectivity, in turn, is interesting to investigate, as networks may behave differently with different levels of connectivity: In a more highly connected network, nodes have stronger effects on other nodes, so that strong edges may keep nodes in check - change may be harder to bring by.

More specifically, we investigated the dynamics of the overall science interest networks by testing the influence of external consistency pressure on the network (Dalege, Borsboom, van Harreveld, & van der Maas, 2017), using the Ising-model (Ising, 1925) and changing its degree of connectivity (Epskamp, Maris, Waldorp, & Borsboom, 2016; Wainwright & Jordan, 2008). While low connectivity makes the network behave in a more random manner by decreasing the influence of edge weights and thresholds, the opposite is true for high connectivity. We used the IsingSampler function, available in the R-package *IsingSampler* (Epskamp, 2015), to simulate the dynamics of the estimated SINM with three degrees of connectivity, that is, a low (.60), mid (1.20) and high (1.80) connectivity, while the thresholds of the nodes were set to 0.

Dutch SINM. The three networks with low, mid- and high degree of connectivity and their associated distributions of sum scores are displayed in Figure S3 (left). As can be seen in Figure S3, with increasing connectivity, the distribution of the sum scores changes from a normal distribution to a bimodal distribution, showing the importance of network connectivity in determining the sum score distribution. In a weakly connected network, the sum score distribution is normal, indicating that such interest networks behave as dimensions (i.e., interest can range from low to high), whereas highly connected networks behave as categories (i.e., interest is either low or high). Interestingly, in the low connectivity network, three of the interest evaluation nodes are not connected to any other nodes, whereas the other two interest evaluation nodes are closely connected to the enjoyment cluster. Moreover, only with increasing connectivity, the different clusters start to be connected through shortcuts. Again, it becomes apparent that the knowledge and the value clusters are not as closely connected to the other clusters.

Colombian SINM. The three networks with low, mid- and high degree of connectivity and their associated distributions of sum scores are displayed in Figure S3 (right). As can be seen in Figure S3, with increasing connectivity, the distribution of the sum scores gradually changes from a normal distribution to a bimodal distribution; indicating that the sum score distribution of interest networks can be interpreted as the level of interest in a population. In the weakly connected network, the sum score distribution is normal, indicating that such interest networks behave as dimensions (i.e., interest can range from low to high), whereas the highly connected networks behave as categories (i.e., interest is either low or high), but in a less polarized manner than the Dutch network. Interestingly, in the low connectivity network, there are only three shortcuts between clusters. Moreover, even in the high connectivity network, the knowledge cluster is not connected to any other clusters and self-efficacy as well as value are only connected with the other clusters through one shortcut. It becomes apparent that the knowledge and the value clusters are not as closely connected to the other clusters. The interest-evaluation, behavior and enjoyment cluster, on the other hand, are more closely connected.

Summarizing. The two networks show some difference in their dynamic behavior with different levels of connectivity, as shown by the connectivity simulation. While the sum scores of all included indicators of weakly connected networks are normally distributed, the sum scores of the highly connected networks form a bimodal distribution. The sum score distribution of interest networks may be an indication of the level of interest in a population (cf. Dalege, Borsboom, van Harreveld, & van der Maas, 2017; Dalege, Borsboom, van Harreveld, Waldorp, & van der Maas, 2017). The results of the connectivity simulation study on the networks of the two countries indicate that science interest may develop differently across countries. More specifically, the importance of mutual interactions became apparent in the connectivity simulation of the Dutch interest network: In the low connectivity SINM, the sum scores of the network were normally distributed, meaning that science interest could be at any level – from low interest to high interest; whereas in the highly connected SINM, the sum scores were distributed bimodally, indicating that science interest was generally either low or high. The global connectivity in the network represents the level of the science interest and influences the way science is dealt with (Dalege et al., 2016). With growing connectivity, the different variables reinforce each other to a larger extent, that is, if one enjoys learning about sciences more, one will seek to read more about sciences, which will, in turn, lead to gaining more knowledge in the interest domain. But also, the other way around, with a negative science interest (i.e., a science dislike) science is avoided as much as possible. In the connectivity simulation on the Colombian SINM, in contrast, higher connectivity did not lead to a strong bimodal distribution of the network's sum score. The reinforcing relations between the variables in the Colombian SINM thus seem to be weaker, which may be due to the lower number of connections between clusters. That is, under external pressure (for example to make choices about future involvement) the Dutch interest network behaved as categories (low vs. high interest), whereas the Colombian network behaved in a more dimensional way (interest can range from low to high).

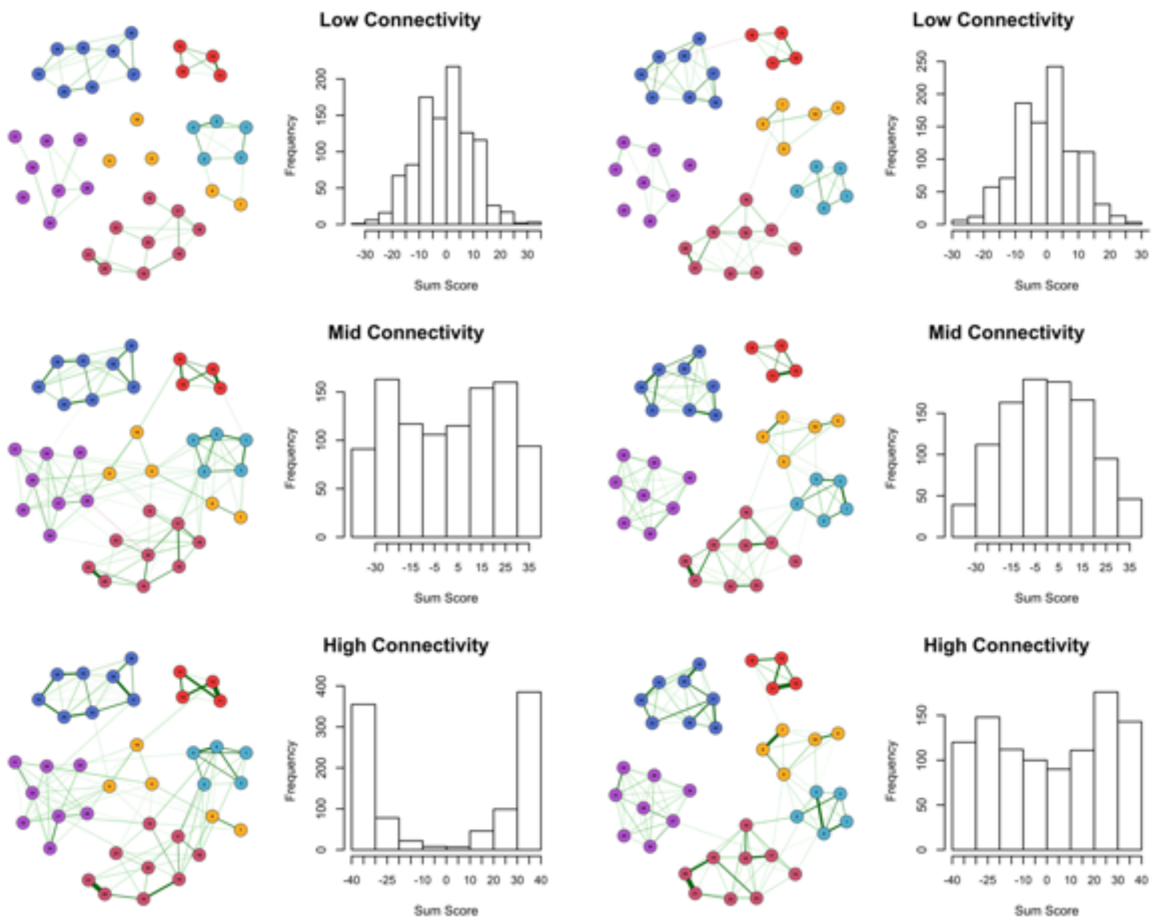

Figure S3. Simulation of different levels of connectivity of the Dutch (left) and Colombian (right) interest networks and their associated distributions of sum scores. Strikingly, the sum score distribution in the Dutch network (left) becomes bimodal with increasing connectivity, a trend which seems to be weaker in the sum score distribution of the Colombian network (right). For a color version, please see this figure online.

References

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