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Article

Attitudes Towards Science During the Covid-19 Pandemic

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A Psychological Network Approach

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Abstract

A better understanding of the public attitude towards science could be crucial to tackle the spread of mis- and disinformation related to the Covid-19 pandemic and beyond. We here contribute to this understanding by conceptualising and analysing the attitude toward science as a psychological network. For this analysis, we utilised cross-sectional data from a German probability sample (N = 1,009), the "Science Barometer", collected during the first wave of the Covid-19 pandemic. Overall, our network analysis revealed that especially the perceived value of science for curbing the pandemic is central to the attitude towards science. Beliefs about this value are related to trust in science and trust in scientific information and to positive and negative evaluations of scientific controversy and complexity. Further, valuing common sense over science was related to seeking less scientific information on official websites, suggesting that this belief, in particular, may drive mis- and disinformation and could be a promising target for interventions. Finally, we found no evidence that seeking scientific information on social media had detrimental consequences for the attitude towards science. Implications for health communication and science communication, limitations, and future directions are discussed.

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Keywords
Covid-19, psychological networks, attitudes towards science, trust in science, science communication.

The Covid-19 pandemic is one of the worst global crises since the Second World War (United Nations, 2020). By February 2022, the Coronavirus had infected at least 500 million people worldwide, resulting in over 5 million deaths (Worldometer, 2022). Despite the immense effort of scientists, who early on provided information and recommendations on how to prevent infections, societies around the globe were unable to stop this fatal spread of the virus.

One reason for the limited effectiveness of these recommendations could be that some people hold negative attitudes towards science and scientific recommendations. Whilst a large share of the (German) population initially adopted the recommended protective behaviours (Dohle et al., 2020), there were notable exceptions, such as Corona-parties (Lipsky, 2021) and other super spreader events (Krueger, 2020), and anti-scientific conspiracy theories strived early on in the pandemic (Imhoff & Lamberty, 2020). A variety of research projects found that a low adoption of recommended protective behaviours is related to negative attitudes towards science, indicated by perceiving science and scientists as untrustworthy (Algan et al., 2021; Dohle et al., 2020; Plohl & Musil, 2021) or by ignoring scientific information (Fridman et al., 2020; Qazi et al., 2020).

Thus, a better understanding of attitudes towards science could be crucial to tackle mis- and disinformation related to Covid-19 and beyond. Deepening our understanding of the attitude towards science, with a particular focus on the Covid-19 pandemic, is thus the central goal of this article. We contribute to this goal by applying a psychological network perspective to people's attitudes towards science during the Covid-19 pandemic, following the *Causal Attitude Network (CAN)* model (Dalege et al., 2016).

The recently proposed CAN model conceptualises attitudes as a network of different nodes (i.e., evaluative reactions towards the attitude object) and edges (relations) between these various attitude elements (Dalege et al., 2016). The model assumes that edges represent relations between different elements of an attitude, reflecting causal interactions between these elements. These causal links can result from direct causal influences (e.g., beliefs that a person is friendly may cause liking of that person). Further, causal links can also result from cognitive mechanisms that support evaluative consistency between related contents of evaluative reactions, such as the need for consistency (Festinger, 1957).

In contrast to the classic *tripartite model of attitudes* (Rosenberg & Hovland, 1960), attitudes are not seen as latent factors but as an emergent structure resulting from relations between evaluations of the attitude object (Carter et al., 2020; Dalege et al., 2016). In line with the tripartite model, however, the CAN model also assumes that attitudes consist of affective, cognitive, and behavioural components. Due to its conceptualisation of attitudes as networks, the CAN model allows the visualisation and interpretation of even highly complex relationships between evaluative reactions towards an attitude object. Importantly, this approach is not primarily theoretical: Due to recent advancements in statistical network models and accessible tutorials (e.g., Dalege, Borsboom, van Harreveld, & van der Maas, 2017; Epskamp & Fried, 2018), attitude networks can now be computed and visualised.

A network analysis can, for example, identify evaluative reactions that are central to an attitude, relevant relations between these reactions, and clusters of evaluative reactions. Indeed, the CAN model assumes that attitude networks do show a structure with high clustering (Dalege et al., 2016). Clusters are thereby defined as groups of similar evaluative reactions that exert a stronger influence on each other compared to dissimilar evaluative reactions (Dalege, Borsboom, van Harreveld, & van der Maas, 2017). For example, in an attitude network concerning a specific person, beliefs about whether the person is competent, intelligent, and qualified may be strongly related to each other and would thus form a cluster in the attitude network. Identifying clusters allows direct insights into the structure of a specific attitude, which can differ from theoretical predictions. For example, even though theories on attitudes, in general, assume three major components of attitudes (affect, cognition, and behaviour), the observed attitude structure for a specific attitude may reveal entirely different (and more) clusters.

The areas that have already been studied with a psychological network approach are manifold and not limited to attitude research. This includes research on mental disorders (Duek et al., 2021), job satisfaction (Carter et al., 2020), mindfulness (Lecuona et al., 2021), emotions (Lange & Zickfeld, 2021), and health behaviours in general (Nudelman et al., 2019). Network models have also already been applied to model Covid-19 related behaviours and their predictors, such as goals (Costantini et al., 2021), mental health (Fried et al., 2021), risk perception and social norms (Chambon et al., 2021), and group membership (Maher et al., 2020), but importantly not with a direct focus on attitudes towards science.

In the field of attitudes, investigations have, for example, focused on political attitudes (Dalege, Borsboom, van Harreveld, & van der Maas, 2017; Dalege, Borsboom, van Harreveld, Waldorp, et al., 2017), pro-environmental behaviour (Zwicker et al., 2020), or implicit attitudes (Dalege & van der Maas, 2020). Psychological networks on the perception of science, however, have thus far only focused on very specific scientific issues, such as childhood vaccines and genetically modified food (Dalege & van der Does, 2021), and on educational aspects, that is science interest during adolescence (Sachisthal et al., 2019, 2020). However, to our best knowledge, no work so far has directly investigated the public's attitudes towards science more broadly, either in light of the Covid-19 pandemic or in general, using a psychological network approach.

However, conceptualising public attitudes towards science as a psychological network may be especially promising because psychological networks allow the visualisation and interpretation of even very complex attitude structures (Dalege et al., 2016). Due to the inherent complexity of science, it seems indeed likely that the attitude towards science is highly complex and consists of various evaluative reactions, including aspects such as scientific knowledge, scientific methodology, and the scientific community itself (e.g., Altenmüller et al., 2021; Bromme et al., 2010; Wingen et al., 2020). For example, regarding the *affective component*, the attitude towards science may include ratings of scientists' warmth (Fiske & Dupree, 2014) or specific emotions felt towards science or scientists (Furman, 2020). Moreover, trust in science is likely an especially important affective evaluation because people often have to rely on trust when engaging with science, as science is inherently complex and often inaccessible for non-scientists (Bromme & Goldman, 2014; Hendriks et al., 2016). It is, however, important to note that trust in science is probably not purely affective and relates also to cognitive beliefs about scientists' competence (Altenmüller et al., 2021; Hendriks et al., 2015). The *cognitive component* of attitudes towards science may further include beliefs about the value of science for solving problems (Broomell & Kane, 2017; Hilgard & Jamieson, 2017), evaluations of scientific uncertainty and complexity (Rabinovich & Morton, 2012; van der Bles et al., 2019), or even views about rather specific scientific methods and controversies, such as replicability or publication modes (Hendriks et al., 2020; Mede et al., 2020; Wingen et al., 2022). Finally, the *behavioural component* of attitudes towards science may include seeking information about new developments in science and research (Scharrer et al., 2014, 2017; Sweeny et al., 2010). It may further involve following scientific recommendations (Dohle et al., 2020; Plohl & Musil, 2021), but this still requires people first to seek information on these recommendations. Thus, in our view, information seeking is likely an especially central part of the attitude towards science.

Conceptualising seeking scientific information as a behavioural and hence a key component of the attitude towards science implies that this attitude has direct relevance for understanding and tackling mis- and disinformation about Covid-19. Seeking sound scientific information may provide people with relevant knowledge and entails various beneficial behaviours, such as social distancing during a pandemic (El-Far Cardo et al., 2021; Fridman et al., 2020). If people do not seek scientific advice from official sources, they have to rely on other, less informative sources, such as their social environment (Chambon et al., 2021), conspiracy theories (Imhoff & Lamberty, 2020), or even fake news on social media, which can lead to negative consequences such as reduced vaccination uptake (Loomba et al., 2021). Of course, the beneficial effects of seeking scientific information require that scientific information is typically more valid than other information sources (cf. O'Brien et al., 2021). This, however, seems likely because scientific information is provided by experts and typically peer-reviewed (Scharrer et al., 2014; Schroter et al., 2004; Wingen et al., 2022).

Thus, changing public attitudes towards science, and especially its behavioural component, could be a promising approach to tackle mis- and disinformation. However, to achieve this goal, a deeper understanding of public attitudes towards science is needed. It would be crucial to understand which components are central to this attitude and which components are especially closely linked to information seeking-behaviour. Conceptualising the attitude towards science as a psychological network can directly answer these questions, thereby informing future theorising and interventions. Providing a descriptive account of this attitude network, including central attitude elements and their relations and clusters, is thus the central aim of this article. Given the lack of prior work on this topic, our approach was exploratory, and we had no explicit hypotheses regarding the network structure of the attitude towards science.

Methods

Design and Participants

To examine public attitudes towards science during the Covid-19 pandemic, we ran secondary analyses of survey data from the German Science Barometer (Wissenschaftsbarometer). The Science Barometer annually investigates public attitudes toward science and research in Germany. Importantly, during the first wave of the Covid-19 pandemic, a special issue, the Science Barometer Special Edition on Corona (Wissenschaftsbarometer Corona-Spezial April 2020) was published, which contains data on public attitudes towards science in light of the Covid-19 pandemic (Wissenschaft im Dialog, 2020). Data were collected on 15 and 16 April 2020, three weeks after the German government imposed heavy restrictions to stem the spread of Covid-19, including banning gatherings of more than two people (Dohle et al., 2020).

On the day the survey started, 127,584 cases and 3,254 deaths due to Covid-19 had been reported in Germany (Robert Koch Institute, 2020).

This Science Barometer Special Edition includes data from a German probability sample (N = 1,009, 56.5 % female; age: M = 55.9, SD = 17.5) collected using computer-assisted telephone interviewing. This sample size should be sufficient to estimate a moderately-sized network (maximum of 30 nodes) for which already a sample size of 500 participants would be likely to result in accurate network estimation (Chambon et al., 2021). As the utilised network analysis methods cannot handle missing data, we imputed missing responses using the multiple imputation method available in the R package *mice* (Van Buuren & Groothuis-Oudshoorn, 2011). Descriptive statistics for all variables before and after imputation are presented in the supplemental materials (see Table S1). As only a very small percentage of responses (between 0.3 and 4.2% per item) was missing, and no meaningful differences regarding means and standard deviations occurred (see Table S1), it is unlikely that this imputation had an impact on the results and should rather be considered as a technical necessity. However, to reduce the risk of false-positive findings (i.e., identifying relations in the network that are not there), we relied on a very conservative imputation method (called *sample*), which replaced missing values with a random sample from the observed values, thereby ignoring any potentially existing relations among nodes.

Survey

The Science Barometer Special Edition on Corona primarily focused on public attitudes towards science (see Table 1). Questions were asked with a special focus on Covid-19 related science, as participants were informed at the beginning of the survey that "The following questions are about the current Corona pandemic – from here on referred to as Corona". Only the question assessing general trust in science was asked before this specification, but it can be assumed that this context was nevertheless highly accessible, as the media routinely reported on the Covid-19 pandemic and its consequences (Dörnemann et al., 2021; Zimmermann et al., 2021). Beyond assessing people's attitudes towards science, the questionnaire also included a few questions on trust in several non-scientific institutions (e.g., politics) and on how well-informed participants felt about the Coronavirus, which are, however, not analysed in this article. Moreover, the dataset contained various demographic variables, including gender, age, education, occupation, household size, income, and political views, which, however, also fall beyond the scope of this article. After registration and in compliance with the terms of use, the data is publicly available for academic research (including publication of the results) and teaching on https://doi.org/10.4232/1.13574.

Attitude Measures

For our main network analysis, we selected the items assessing participants' attitudes towards science to include them as nodes in our network (see Table 1 for all nodes/items). All items were originally coded on five-point rating scales, with 5 (counterintuitively) indicating disagreement and 1 indicating agreement with the item. We thus reverse-coded all items to ease interpretations. The items can be grouped according to the three main components of attitudes; affect, cognition, and behaviour, indicating that the theoretically most relevant attitude components were included in the survey. To provide an initial and more traditional overview of the relationship among nodes, we present zero-order Pearson correlations in the supplemental materials (see Figure S1).

Table 1. Overview of the Different Nodes (Items) Used for the Network Analysis

Node	Corresponding Item
Cognitive nodes	
Solution soon	"In the foreseeable future, science and research will provide vaccines or medication that will allow us to successfully deal with Corona."
Knowledge important	"The knowledge of scientists is important to slow the spreading of the coronavirus in Germany."
Common sense	"We should rely more on common sense when dealing with Corona and we do not need any scientific studies for this."
Policy	"Political decisions on handling Corona should be based on scientific evidence."
No involvement	"It is not up to scientists to get involved in politics."
Controversy helpful	"Controversies between scientists regarding Corona are helpful because they help to ensure that the right results research prevail."
Uncertainty communicated	"Most scientists currently speaking up differentiate clearly between what they know for sure and what are open questions on Corona."
Too complicated	"Science and research on Corona are so complicated that I do not understand much of it."
Disagreement difficult	"When scientists disagree regarding Corona, it is difficult for me to judge which information is correct."
No understanding	"Science and research do not properly understand the coronavirus yet."
(Partly) affective nodes	
Trust science	"How much do you trust science and research?"
Trust statements	"How much do you trust statements on Corona made by scientists?"
Behavioural nodes	
	"How often do you inform yourself about new developments regarding Corona in science and research:"
TV	"on television?" (including media library)
Radio	"on the radio?" (including audio library)
Newspaper	"in newspapers and magazines?" (including online issues)
Official websites	"on official websites of public authorities and research institutions on the internet?"
Social media	"online on social media?"

Note. Translations from German into English were provided by the authors of the original survey (Wissenschaft Im Dialog, 2020).

The cognitive component of attitudes included diverse items related to various beliefs about science. After reverse-coding, all items were measured on a 1 *Disagree strongly* to 5 *Agree strongly* rating scale. First, three items related to whether or not science provides valuable knowledge for tackling the Covid-19 pandemic (Nodes: “Solution soon”, “Knowledge important”, and “Common sense”). Second, two items indicated whether science should influence policy or not (Nodes: “Policy” and “No involvement”). Finally, five nodes related to scientific controversy and complexity, either positively (Nodes: “Controversy helpful” and “Uncertainty communicated”) or negatively (Nodes: “Too complicated”, “Disagreement difficult”, and “No understanding”).

Two nodes were identified as (partly) relating to affect and, more specifically, affective trust, measured on a 1 *Distrust completely* to 5 *Trust completely* rating scale. These items measured trust in science and trust in scientific statements (Nodes: “Trust science” and “Trust statements”).

The behavioural component of attitudes contained five nodes indicating the frequency of seeking scientific information about Covid-19. More specifically, participants indicated for five different information sources how often they use them to learn about scientific news regarding Covid-19 (1 = *Never*, 5 = *Very often*), corresponding to five nodes in the network (Nodes: “TV”, “Radio”, “Newspaper”, “Official websites”, and “Social media”).

Statistical Analysis

We applied *regularized partial correlation networks* (*RPCNs*) to perform the network analysis (Epskamp & Fried, 2018). Essentially, RPCNs estimate a partial correlation matrix between variables (edges), thereby forcing small correlations to zero using regularization techniques (for details, see Epskamp & Fried, 2018). Since our data was ordinal, we chose polychoric correlations with the standard estimation method for RPCNs (*EBIC-gLASSO; Expected Bayesian inference criteria with graphical least absolute shrinkage optimization).* All analyses were computed using the R environment (R Development Core Team, 2021). The network analyses were computed using the R packages *bootnet* (Epskamp et al., 2018), *mgm* (Haslbeck & Waldorp, 2020), and *networktools* (Jones, 2021).

To assess clusters (also called communities) of nodes, we performed an *exploratory graph analysis* (EGA; Golino & Epskamp, 2017). This network analysis technique has shown comparable performance to traditional latent variable extraction methods, such as Parallel Analysis (Golino, Shi, et al., 2020). To ensure the stability of results, we compared the default EGA algorithms (i.e., *walktrap* and *Louvain*) with alternatives, like *spinglass* and *multilevel*, along with bootstrapping all EGAs with node- and cluster stability indices. To assess model fit, we assessed entropy indices for models, where lower values indicate better fit (Golino, Moulder, et al., 2020). The EGAs were computed using *EGAnet* (Golino & Christensen, 2020). For transparency, we share our analyses scripts at https://osf.io/nge84.

Results

Network Analysis

Figure 1 shows the attitude towards science visualised as a psychological network. Each node represents a specific survey item. The edges represent the mutual relation between nodes, which are calculated after controlling for every other node in the network. These edges are weighted (i.e., an edge strength reflects a regression weight) and undirected. Central edge weights are presented in the text.

As a robustness check, we repeated our network analysis after excluding behavioural nodes. We report the results for this analysis in the supplemental materials, but excluding these nodes overall did not meaningfully impact the network structure of the remaining nodes (see supplemental Figures S4 and S5).

Cluster Detection

Our cluster detection algorithm (Golino & Christensen, 2020; Golino & Epskamp, 2017) revealed four clusters (i.e., groups of nodes that are more connected to each other than to the remaining nodes; Dalege, Borsboom, van Harreveld, & van der Maas, 2017). We interpret these clusters as (1) a pro-science cluster (red), including feelings that science is trustworthy, beliefs that science provides valuable knowledge, that science should influence policy, and that scientific controversies advance science, (2) an anti-science cluster (orange) including beliefs that people should rely on common sense instead of science, that science should not get involved into politics, and negative views about scientific complexity, (3) a cluster containing nodes related to seeking scientific information in old media, namely “TV”, ”Radio”, and ”Newspaper” (yellow) and (4) a cluster of two nodes related to seeking scientific information in new media (light blue), namely “Official websites” and “Social media”.

Relations in the Network

Overall, most affective and cognitive nodes had no or only a very small direct relation with behavioural nodes. There was, however, a notable exception, as we observed a negative relation between “Common Sense” and “Official Websites”. This relationship indicates that an increase in the belief that people should rely on common sense instead of science is associated with a reduced frequency of seeking scientific information about Covid-19 on official websites (-.14).

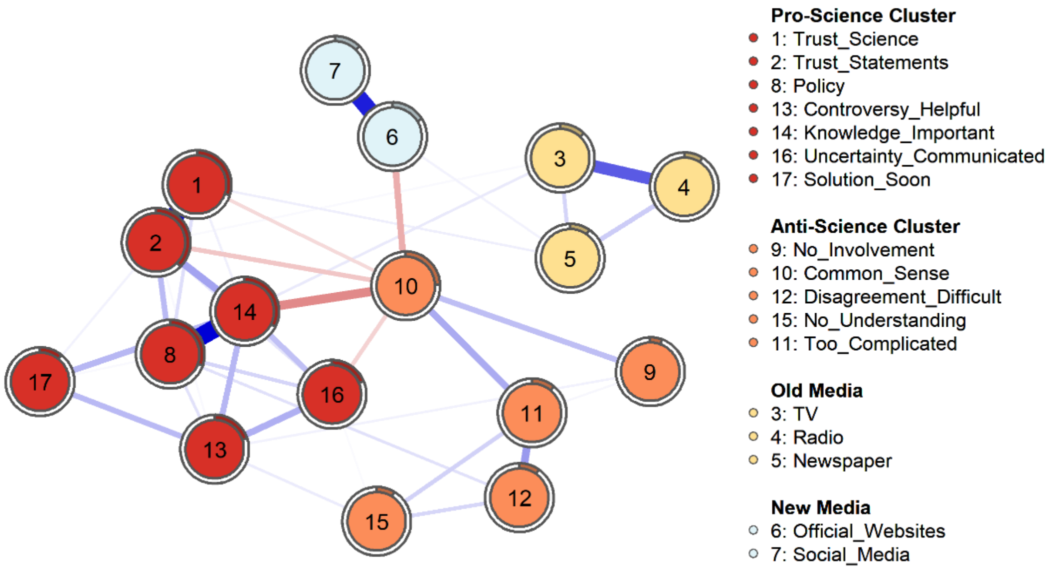

Figure 1. Network of the Attitude Towards Science in Light of Covid-19

Note. Nodes represent survey items, reflecting evaluations of science. Edges indicate the relation between these nodes (blue = positive and red = negative). Stronger relations are indicated by brighter colours and wider edges. A cluster detection algorithm revealed four clusters, highlighted in the legend. Rings indicate for each node the proportion of explained variance (R^2) by the network.

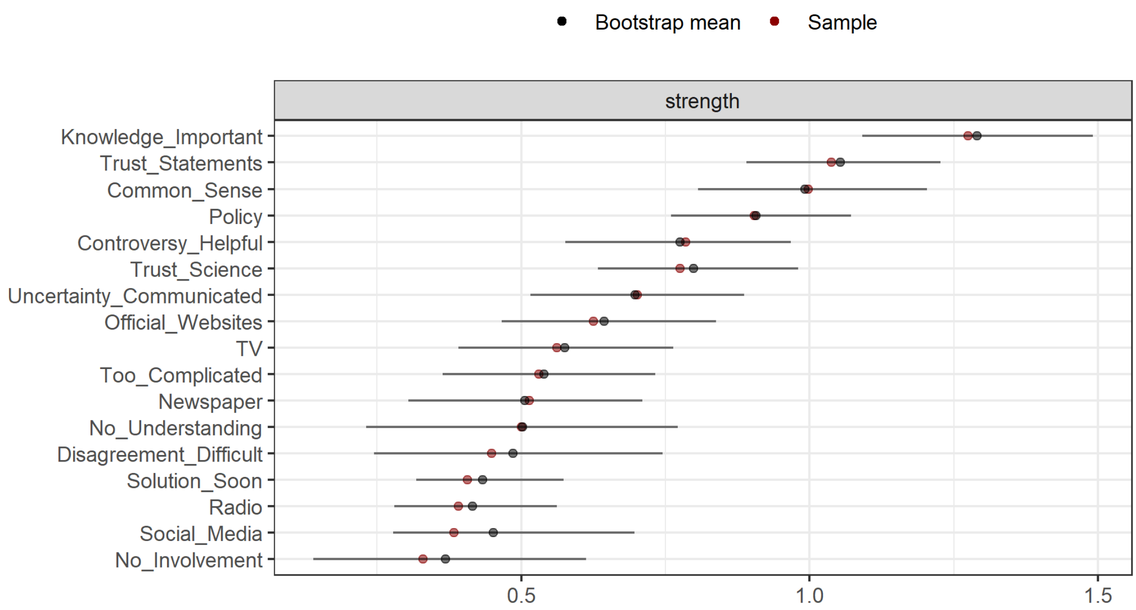

Figure 2. Centrality Plot of the Attitude Towards Science During the First Wave of the Covid-19 Pandemic in Germany

Note. Strength refers to how strongly a given node is directly connected to other nodes in the attitude network. Bootstrap mean refers to the mean strength across all collected bootstrap samples. The lines represent 95% confidence intervals around this mean.

Moreover, it is noteworthy that nodes regarding the usage of old and new media were not connected with each other, indicating that an increase in using old media for seeking scientific information is not directly associated with an increased (or reduced) use of new media. Regarding the new media, it is interesting that “Official websites” and “Social media” were strongly tied together (.31), suggesting that an increase in using social media for seeking scientific information is related to also using official websites.

Further, there were several negative connections between nodes from the anti- and pro-science clusters. “Common sense” was negatively related to “Knowledge important” (-.19), “Trust statements” (-.12), and “Uncertainty communicated” (-.10). Interestingly, there were also a couple of (small) positive links between edges from the anti- and pro-science clusters (see Fig. 1), in particular connections between “Controversy helpful” and “No understanding” (.07) and between “Controversy helpful” and “No involvement” (.07).

Centrality of the Nodes

Centrality refers to how important a particular node is relative to other nodes in the attitude network. There are different centrality measures, but we here focus on strength, which represents the sum of the edge weights of the relations a specific node has with connected nodes. Strength thereby indicates the direct influence of a specific node on the attitude network (Dalege, Borsboom, van Harreveld, & van der Maas, 2017) and is often recommended as the most straightforward and suitable centrality measure for psychological networks (Bringmann et al., 2019; Chambon et al., 2021). The strength of all nodes with corresponding Confidence Intervals (CIs) is presented in Figure 2. Results regarding further centrality measures (closeness, betweenness, bridge strength, bridge closeness, bridge betweenness) are presented in the supplemental materials (see Figures S2 and S3).

As can be seen in Figure 2, three of the four most central nodes were related to whether science produces valuable knowledge to tackle the Covid-19 pandemic ("Policy", "Knowledge important"), or whether people should rather use common sense instead of relying on science ("Common sense"). Changing these nodes likely has a strong impact on the overall attitude network (Dalege et al., 2016). Further, the two trust-related nodes, in particular "Trust Statement", also had a relatively high centrality. In contrast, the behavioural nodes mostly had a relatively low centrality, suggesting that changes on these nodes would likely have little impact on the full attitude network.

Discussion

The present work aims to deepen our understanding of the attitude towards science in light of the Covid-19 pandemic. To achieve this aim, we built on the CAN model (Dalege et al., 2016), which challenges established attitude models and conceptualises attitudes as networks of evaluative reactions. We followed this novel idea and conceptualised the attitude towards science as such a psychological network. We provided a description of this attitude network, highlighting clusters, central nodes, and relevant connections. In contrast to comparable studies (Anderson et al., 2019; Sassenberg & Ditrich, 2019), we analysed responses from a highly diverse probability sample, which thus may be particularly suitable for providing an unbiased view of the public attitudes towards science (Mede et al., 2020). This network analysis provided a variety of novel insights, which are relevant for theorising on the attitude towards science, but also have practical importance for tackling mis- and disinformation.

First, it is noteworthy that many highly central nodes of the attitude network relate to the perceived value of science, such as beliefs about whether science has important knowledge for the fight against the pandemic or whether people should rather rely on common sense. The CAN model predicts that nodes with high centrality are most relevant for the overall attitude and have the highest impact on decisions and behaviour (Dalege et al., 2016). Thus, interventions addressing the perceived value of science may have a particularly strong effect on the attitude network. Many studies investigated the public's evaluation of science by focusing on trust in science (Hendriks et al., 2015, 2016; Wingen et al., 2020), on scientific uncertainty and controversy (Koehler, 2016; van der Bles et al., 2019, 2020), or by highlighting the role of science-related behaviour and engagement (Stilgoe et al., 2014; Wynne, 2006). However, it seems that beliefs about the value of science are even more central to this attitude. Perhaps, this reflects that non-scientists primarily evaluate science by whether it fulfils its societal function by providing valuable knowledge for an increasingly complex world (Hendriks et al., 2016).

Second, it is interesting that cognitive beliefs fell into two different clusters, which can be described as a pro- and an anti-science cluster. The pro-science cluster includes beliefs that scientific knowledge is valuable for fighting the pandemic, that scientific controversies are beneficial for scientific progress, and that scientists transparently communicate the boundaries of their knowledge. Finally, this cluster also includes the perceived trustworthiness of science and scientific statements. As nodes within a cluster are strongly connected, changing any of these nodes will likely impact the other nodes within the cluster (Dalege, Borsboom, van Harreveld, & van der Maas, 2017; Dalege et al., 2016). For example, changing beliefs about whether science produces valuable knowledge should influence the perceived trustworthiness of science. In line with this idea, recent research observed that damaging the perceived value of a scientific field also reduced its perceived trustworthiness (Wingen et al., 2020), and other work showed that after science made a valuable contribution (i.e., developing a Zika vaccine), trust in science was increased (Hilgard & Jamieson, 2017). This provides initial evidence that (some) observed edges in the network indeed reflect causal relations, as assumed by the CAN model. Given widespread concerns about the replicability of published research findings (Open Science Collaboration, 2015), it is reassuring that our network analysis is in line with these earlier findings, suggesting robustness across highly different analytical strategies.

The anti-science cluster consists of beliefs that scientific knowledge is too complex to be understood, and that people and politicians should rely on common sense instead of science. This opens an interesting perspective on recent research, which suggests that when science is made too easy, people rely less on experts (Scharrer et al., 2014, 2017). However, our network analysis suggests that it is likewise not a good idea to describe science as highly complex, as this belief is also related to a reduced preference for experts' opinions, suggesting a potential inverted U-shaped relation between perceived complexity and reliance on experts. This idea could be further explored by future (experimental) work, which could also test whether this observed link reflects a causal relationship.

Scientific knowledge is, by definition, uncertain and tentative (Bromme & Goldman, 2014), which seems to be reflected in both the pro- and the anti-science clusters. In the pro-science cluster, this uncertainty is reflected in the beliefs that scientists transparently communicate the boundaries of their knowledge and that scientific controversy contributes to scientific progress. In the anti-science cluster, however, this uncertainty is reflected in beliefs that science is highly complex and difficult to understand, which in turn are related to beliefs that one should not rely on science. This would predict that framing scientific uncertainty in terms of high complexity could have detrimental effects, whereas framing uncertainty as part of a productive scientific controversy could have positive effects on the attitude toward science. In line with this reasoning, prior research found that when researchers reacted to uncertainty and controversy with productive self-correction, the public evaluated this positively (Altenmüller et al., 2021; Ebersole et al., 2016). The reflection of scientific uncertainty in both clusters may also explain some of the observed positive relations between nodes from the pro- and the anti-science cluster. For example, even positive views on scientific controversy may (through increased perceptions of uncertainty) add to beliefs that scientists do not truly understand a topic and should not influence policy.

We further investigated the behavioural component of the attitude towards science, namely how often people seek scientific information, which could be crucial for tackling mis-and disinformation (Fridman et al., 2020). Importantly, the behavioural nodes had only a few connections to the affective and cognitive nodes, which suggests that changing feelings and beliefs about science may have little impact on behaviour, or even that the measured behaviours are not part of the attitude towards science. However, such gaps between cognitive and behavioural aspects of attitudes are well known in the attitude literature (Ajzen, 1991; Glasman & Albarracín, 2006; Siegel et al., 2014). For example, even though a vast majority of people report positive beliefs about organ donations, this is not reflected in the number of registered donors (Siegel et al., 2014).

However, by conceptualising the attitude toward science as a network, we could nevertheless identify one specific belief that was related relatively strongly to behaviour, which could thus be a promising target for interventions. More specifically, we found that the belief that people should rely on common sense instead of science was negatively related to the frequency of seeking scientific information on websites by official sources. Thus, reducing the belief that people can simply rely on common sense instead of science would likely lead people to seek more official information, potentially decreasing mis-and disinformation. Perhaps, this could be achieved by providing people with examples of how scientific knowledge contributed to decision-making (Ruggeri et al., 2021), by highlighting counterintuitive scientific findings, or by finding the sweet spot between describing science as too easy or as too complex (Scharrer et al., 2014, 2017). Interestingly, recent work suggests that anti-scientific populism often aims at replacing scientific knowledge with people's common sense (Mede & Schäfer, 2020), suggesting that (some) populist movements intuitively target this central node in the network, which may be a particularly effective strategy.

Finally, the network analysis also provided interesting insights regarding the role of social media. A variety of researchers have recently argued that social media may contribute to the spread of fake news and disinformation (Allington et al., 2021; Koch et al., 2021; Loomba et al., 2021; Pennycook et al., 2020). When it comes to seeking scientific information, however, the present network analysis points to the contrary: Seeking scientific information on social media is not central for the attitude towards science and thus likely has no detrimental impact on this attitude, in contrast to recent concerns about this issue (Weingart & Guenther, 2016). Moreover, seeking scientific information on social media was positively related to seeking information on official websites. It should, however, be noted that our findings cannot speak to the effects of social media when used for other purposes than seeking scientific information, in which cases social media still could contribute to mis- and disinformation (e.g., when encountering fake news while using social media for leisure). Future research could investigate this idea and test whether people encounter different information sources when they actively search for Covid-19-related information compared to when they coincidentally encounter this information.

Further, future research could address some of the limitations of this study. The probably most important limitation is that the utilised data is cross-sectional, which makes causal claims (e.g., changing beliefs will change people's behaviour) difficult. Our investigation builds on the CAN model, which assumes that nodes in an attitude network are causally and bidirectionally related (Dalege et al., 2016), reflecting direct causal influences and consistency pressures. Yet, whether these nodes indeed represent causal relations is ultimately an empirical question, as unmeasured third variables may also cause the observed links. Nevertheless, throughout this article, we have provided a couple of examples of recent work suggesting that (some) edges do reflect causal relations. The present network analysis may provide valuable directions for future experimental and longitudinal studies testing additional causal effects.

Another way to clarify the question of causality would be to test strong theories that posit clear directional links between variables (Rohrer, 2018). Perhaps, our observed relations in the attitude network could be a fruitful inspiration for such theorising. However, if testing such models provides evidence that certain attitude elements are not, or only unidirectionally related, this would constitute a major challenge for the CAN model (Dalege et al., 2016) in the context of attitudes towards science. Proposing and testing alternative models of the structure of attitudes towards science is thus a highly promising endeavour for future work.

Another important limitation is that the frequency of seeking scientific information in various media (i.e., the behavioural component of the attitude towards science) was measured using a self-report scale. Recent work focusing on social media and smartphone usage suggests that self-report scales do not necessarily correlate well with the actual frequency of behaviour (Andrews et al., 2015; Ernala et al., 2020). Furthermore, these frequencies may just reflect broader information seeking-habits (e.g., people who frequently watch TV are also more likely to learn about science on the TV). Thus, future research could benefit from using different measures of behaviour, for example, by combining survey responses with behavioural smartphone data on media usage (Andrews et al., 2015; Silber et al., 2021), which would allow obtaining more detailed data on information seeking behaviour. Future research may also investigate different types of science-related behaviour, such as the adherence to scientifically recommended measures (Dohle et al., 2020).

Another potential limitation is that we may not have included all relevant science-related evaluations into the attitude network, which could have changed the network structure (Clifton & Webster, 2017). In particular, nodes regarding the affective component of the attitude towards science may be missing, as this component was measured with only two trust-related nodes. Moreover, trust is not necessarily solely an affective reaction, as many scholars argue that trust has both affective and cognitive components (Altenmüller et al., 2021; Hendriks et al., 2015; Johnson & Grayson, 2005). Thus, future research should add additional affective nodes into the network, such as perceptions of scientists' warmth (Fiske & Dupree, 2014) or specific emotions felt toward science and scientists (Furman, 2020), to ensure that the attitude network is estimated correctly.

It remains an interesting question whether the observed attitude structure also generalises to later stages of the pandemic, to other scientific issues (e.g., climate change), or to science in general. For example, it seems possible that the high network centrality of the perceived value of science is Covid-19 specific. People experienced the Covid-19 pandemic on a daily basis, for example, through governmental restrictions (Dohle et al., 2020) or media reports (Dörnemann et al., 2021). Perhaps, when thinking about such a pressing and directly relevant problem, it is crucial for the overall attitude whether science provides valuable knowledge for curbing the pandemic. In contrast, for other scientific fields, the trustworthiness of scientists (Hendriks et al., 2015, 2016), scientific controversies (Anvari & Lakens, 2018; Koehler, 2016), or simply whether the research topics seem interesting (Sachisthal et al., 2020) may be more central for public attitudes.

Finally, it would be a promising direction for future research to compare the attitude towards science with other attitudes that may guide the public's behaviour during the Covid-19 crises and beyond. For example, behaviour during the Covid-19 pandemic is also related to attitudes towards politics (Dohle et al., 2020). Certain attitude elements are likely part of both the attitude towards science and the attitude towards politics. Future work could, for example, investigate whether these attitudes have similar structures (e.g., whether trust in politics is also closely related to positive views on political controversies) and similar central elements (e.g., whether the value of politics is central for the attitude towards politics). Such comparisons may help to identify general patterns of attitudes towards institutions.

To sum up, conceptualising the attitude towards science as a psychological network provided a variety of novel insights, highlighting the value of this approach and the CAN model (Dalege et al., 2016). First, we found that the perceived value of science is central to the attitude towards science and would thus be an important target for potential interventions. Second, cognitive beliefs about science were split into two different clusters, namely a pro- and an anti-science cluster. Importantly, our network analysis revealed central components of these distinct clusters (e.g., complexity and controversy), which show interesting theoretical connections to previous experimental findings and have applied relevance. Third, cognitive and affective components of the attitude toward science were relatively independent of behaviour, suggesting that changing these components may overall have little impact on information seeking. However, the belief that people should rather rely on common sense than on science was negatively related to seeking official information, suggesting that changing this specific belief could be crucial to tackle mis- and disinformation. Finally, our network analysis suggests that seeking scientific information on social media likely has no detrimental consequences, as it was not central to the attitude towards science and positively related to seeking official information. Overall, these insights provide valuable directions for future research and could inform interventions for changing public attitudes toward science as well as for tackling mis- and disinformation.

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Conflict of Interest

The authors declare no conflict of interest.

Supplementary Material

The supplementary material including additional figures and tables can be found here: https://doi.org/10.47368/ejhc.2022.105.

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Author Contributions

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