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Introducing a Science Interest Network Model to Reveal Country Differences

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In this article, a science interest network model (SINM) is introduced and a first empirical test of the model is presented. The SINM models interest as a dynamic relational construct, in which different interest components, that is, affective, behavioral, and cognitive components and related motivational components mutually reinforce one another within the development of interest. The dynamical relational perspective hypothesizes that the mutual interactions between interest components underlie the development of interest. Applying the SINM to the PISA 2015 data of 2 countries, that is, the Netherlands and Colombia, we were able to not only illuminate the structure of interactions between the different variables (i.e., indicators) in the networks of different groups of adolescents but we could also make predictions about which variables are of structural importance within the interest construct and as such worthwhile to test as potential candidates for intervention. Additionally, we were able to replicate earlier findings of the literature, namely that (a) enjoyment is central within the interest network and that (b) important structural differences exist in the interest network across countries, which, for instance, point to differences in domain specificity of interest between countries. While the network approach is sensitive to structural differences in science interest across countries, the network structure is stable across subgroups within countries. Future studies are proposed to test theoretically important assumptions of a dynamical perspective on interest, such as the causal role of different interest components in the development of interest.

Educational Impact and Implications Statement

Students with a genuine interest in science are generally more inclined to engage with sciences – for example, by keeping up with news about science or going to a science center. They will learn as a result of this engagement, and are more likely to take up a career related to sciences. In this paper, we introduce the science interest network model, which reveals how mutual interactions of specific behaviors, enjoyments, knowledge components, values, and motivational components such as self-efficacy, constitute the science interest construct. We compare the science interest networks of 15-year-olds from two different countries (the Netherlands and Colombia), using the data of a large-scale assessment, PISA 2015. Important structural differences exist in the science interest network across countries. We found that in the Netherlands science interest is domain-specific (e.g., interest in climate change, but not motion and forces), whereas in the Colombia science interest is more domain-general. Moreover, different indicators are central in the national science interest constructs, suggesting to focus interventions in different countries on different aspects: Enjoyment is central in science interest for adolescents in the Netherlands, whereas having opportunities for learning appears to be more central in Colombia.

Keywords: adolescents, network models, PISA 2015, science interest, self-efficacy

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Imagine you were going to a science center that had a special exhibition on the causes of climate change and its effects on the area you live in. There may be different reasons for you to go to the science center in the first place—perhaps you are interested in the topic of climate change or in the sciences already—or your friends dragged you along because they read a great article on the exhibition in a local newspaper, which sparked their interest. While visiting the exhibition, you enjoy learning new things you did not know before, but you also notice that there is still much more to learn about the topic. Once you are back home, you visit a couple of websites on the topic and are thinking of watching a recent film on the matter, to acquire more knowledge about the topic. As you learn more about climate change you begin to value the topic more: You see its importance for your own life as well as the lives of the people surrounding you. This episode shows how interest is thought to develop: from an event sparking interest (i.e., *situational interest*) to the subsequent reengagement with the topic, which leads to knowledge gain, valuing the object of interest, and an enjoyment of the topic. The mutual interaction of these aspects may enable the formation of a more stable *individual interest* (Hidi & Renninger, 2006; Krapp, 2002).

Because science is relevant for decisions about all domains of our modern world, and with the fast-changing nature of the sciences, youths' development of a science interest has become an important educational outcome (OECD, 2006). Science interest is a driving force of lifelong learning in the sciences, influencing current participation with sciences, such as reading about sciences or going to a science center, as well as intentions of (science) career choices (Ainley & Ainley, 2011; Nugent et al., 2015). Importantly, science interest should not be regarded as an independent construct, but “as part of a network of related processes” (Ainley & Ainley, 2011, p. 69). This view of science interest highlights the importance of relations between components of science interest (i.e., affect, behavior, and cognition) as well as related motivational components (i.e., self-efficacy), which may be mutually affecting each other.

Most theories of interest development take a dynamical perspective on interest development, meaning that the development of interest takes place through mutual, reinforcing interactions between components of interest and related motivational components (e.g., Hidi & Renninger, 2006; Krapp, 2002). We introduce a science interest network model (SINM) to provide a formal account of these mutual interactions. The SINM models relations between indicators of these science interest components and related motivational components as mutual interactions. SINM is adapted from the Causal Attitude Network (CAN; Dalege et al., 2016) model, which models attitudes as mutual interactions between components of attitude: affect, behavior, and cognition. As a first test of the model, we applied it to the 2015 PISA science interest data (OECD, 2016). In doing so, we were not only able to illuminate the structure of interactions between the different variables (i.e., indicators) in the SINM for different groups of adolescents, but we could also make predictions about which indicators are of structural importance within the interest network and as such worthwhile to test as potential candidates for intervention.

Theoretical Background

Although there is still “a lack of a consistent or adequate theory of interest” (Allport, 1946, p. 341) some 70 years after Allport declared this being “one of the biggest defects” within learning research, five characteristics of interest as a motivational variable are commonly agreed upon (Renninger & Hidi, 2011). Three of these characteristics are of relevance in the context of our paper: First, interest is content-specific, meaning that interest is always directed toward something, such as an object, an activity, or a knowledge field, such as climate change, or more broadly, the sciences (e.g., Chen, Darst, & Pangrazi, 1999; Gardner, 1996; Holland, 1985/1997; Silvia, 2006). Second, common definitions of interest describe interest as emerging through the *interaction* of an individual with his or her environment (Hidi & Renninger, 2006; Krapp, 2002; Silvia, 2006), highlighting its dynamic nature, as well as the importance of engagement (or behavior) within interest. Third, interest is a multidimensional construct, including affective and cognitive components (e.g., Hidi, Renninger, & Krapp, 2004; Schiefele, 2009), with the relative amount of the two components possibly differing depending on the interest phase (e.g., Ainley, Hidi, & Berndorff, 2002; Harp & Mayer, 1997; Renninger & Wozniak, 1985).

In addition to describing five core characteristics of interest, Renninger and Hidi (2011) reviewed conceptualizations of interest based on their foci, namely, the development of interest (e.g., Hidi & Renninger, 2006; Krapp, 2002, 2007), interest as an emotion (e.g., Ainley, 2007; Ainley & Ainley, 2011; Silvia, 2006), task features and the experience of interest (Mayer, 2005, 2008; Sansone, 2009), the importance of value (e.g., Schiefele, 2001, 2009; Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2007), or vocational interest (e.g., Alexander, Johnson, Leibham, & Kelley, 2008; Holland, 1997; Lent, Brown, & Hackett, 1994). The focus of this paper lies in the structure of interest as a multidimensional construct that emerges through mutual interactions between individual and environment, which is the core focus of theories of interest development.

Interest is not per se seen as a stable personality trait; it may be of short or long duration as it is partly characterized by an individual's values and feelings toward the object of interest, which may be subject to change (Hidi et al., 2004; Schiefele, 2009). Broadly speaking, a difference can be made between a trait-like form of interest, commonly referred to as *individual interest* (e.g., Hidi & Renninger, 2006; Krapp, 2002), which may, under optimal circumstances, develop from the externally triggered state interest (i.e., *situational interest*). Hidi and Renninger's (2006) four phase model of interest development and Krapp's (2002) person-object theory of interest agree that interest develops following stages from *emerging situational interest* over *stabilized situational interest*, which lasts during a certain learning phase, thus still being temporary, to *individual interest*. The four-phase model additionally differentiates between intraindividual steps of individual interest, resulting in an *emerging individual interest* and a *well-developed individual interest* (Hidi & Renninger, 2006). Both theories agree, however, that individual interest is a relatively stable tendency to reengage with the object of interest (Hidi et al., 2004; Renninger, 1989, 1990; Renninger & Hidi, 2002; Renninger & Leckrone, 1991), whereas situational interest describes a psy-

chological state of focused attention, increased cognitive functioning, persistence and affective involvement during a task. The stages of individual interest are hypothesized to be accompanied by enjoyment, (personal) value, reengaging with the object of interest (behavior), as well as accumulated knowledge (Hidi & Renninger, 2006; Renninger, 1989, 1990; Renninger & Hidi, 2002; Renninger & Wozniak, 1985). That is, it is hypothesized that the structure of relations between these components changes over the development from *situational interest* to *individual interest*.

Interest as Dynamic Construct

The importance of mutually reinforcing relations between the interest components in the development of a more stable individual interest indicates the dynamic character of interest. Ainley (2017) recently described interest as being a dynamic relational construct, highlighting the importance of the person-object relation required when defining interest as well as the changing balance among interest components and its increasing complexity. She based the discussion of interest being dynamic, on dynamic systems theory (e.g., Lewis & Granic, 2000; Thelen & Smith, 2006), in which every individual is seen as a self-organizing system. When defining interest in terms of dynamic systems theory, the content and structure of (individual) interest is seen as having accumulated from an individual's prior engagement with the object of interest, such that the relative importance of the interest components depends on the amount of past interactions with the object of interest as well as expectations of future engagement opportunities (Ainley, 2010; Ainley & Hidi, 2014). Interest has previously been modeled as a latent variable, which is typically derived from several indicators (e.g., items asking for an interest evaluation, such as "I am interested in climate change"). Science interest-related components such as science enjoyment, engagement with science, and value of science are also seen as latent variables (e.g., Ainley & Ainley, 2011; Nugent et al., 2015). Ainley and Ainley (2011), for instance, used the SEM approach on the PISA 2006 data to investigate the relation between science interest-related components across different countries, with the goal being to define a model that predicts engagement with science as well as future-oriented motivation to work on science.

Defining interest as a dynamic relational construct, in which the mutual interactions between components are central, aligns well with the theoretical assumptions of the psychometric network perspective. Psychometric network models were introduced as an alternative to the common cause approach, which underlies latent variable models (e.g., Borsboom & Cramer, 2013; Kendler, Zachar, & Craver, 2011; van der Maas et al., 2006). General intelligence, for instance, was no longer conceptualized as being caused by an underlying latent factor (the *g* factor; Thorndike, 1994), but as a complex system in which reciprocal causation plays a central role in explaining the positive manifold of correlations on intelligence tests (van der Maas et al., 2006). Recently other psychological constructs, such as attitudes, have been described using a network framework (Dalege et al., 2016). The Causal Attitude Network (CAN) model conceptualizes attitudes as networks of causally interacting evaluative reactions, that is, emotions, behaviors and cognitions (e.g., Bagozzi, Tybout, Craig, & Sternthal, 1979; Breckler, 1984; Eagly & Chaiken, 1993), toward the attitude object (Dalege et al., 2016). In the model, evaluative

reactions are represented by so-called *nodes*, causal relations between the evaluative reactions are represented by connections between nodes (i.e., *edges*).

Introducing the SINM

Based on the CAN model (Dalege et al., 2016), we introduce the science interest network model (SINM). In the SINM, the interest construct is seen as a network of indicators, which are connected through dependent developmental pathways—when one indicator changes (e.g., "I enjoy learning about science"), so does the other, connected, indicator (e.g., "knowledge about earth and science"). That is, indicators are part of the construct instead of being measures of it. In the interest literature, interest components (i.e., affect, behavior, cognition), interest evaluations, as well as related (cognitive) motivational components, such as self-efficacy, are of importance for the interest construct (e.g., Ainley, 2017; Hidi & Renninger, 2006; Renninger & Hidi, 2002). The *science interest* construct is thus constituted of indicators of science interest components and their mutual interactions, with affect, behavior, and cognition being central. Moreover, important related motivational components, which have reciprocal relations with science interest, such as self-efficacy (Nieswandt, 2007), goals (Harackiewicz, Durik, Barron, Linnenbrink-Garcia, & Tauer, 2008; Renninger, Jessica, & Posey, 2008), and self-regulation (Sansone, 2009; Sansone, Weir, Harpster, & Morgan, 1992), can be included in the network to give a more complete account of the structure of science interest. It is of importance to note that in contrast to other (traditional) conceptualizations of interest, achieving a high internal consistency is not central in a psychometric network approach; the aim is to include indicators that may play an important, reciprocal role in the construct. The assessment of all *relevant* indicators is thus the focus, meaning that including closely related components such as self-efficacy may indeed give a more complete account of the science interest structure (Dalege et al., 2016). Other factors important for interest, such as country, gender, or the socioeconomic background of individuals, are not included in the network because they do not have a reciprocal relation with interest indicators. Networks based on these factors can be compared to reveal the importance of these factors for the structure (and not the average scores) of science interest.

Conceptualizing science interest as a network model would then mean that interacting indicators of interest components, that is, indicators of affective, behavioral, and cognitive (including value and knowledge) components, as well as closely related motivational components (e.g., self-efficacy) *constitute* science interest. In a network, indicators are represented by nodes, such as the enjoyment item "I enjoy reading about science," which may be connected through edges, given that two indicators are related while controlling for all other indicators included in the network. Following the example in the beginning of the introduction, a typical network might look as shown in Figure 1: Going to the science center, you learn about effects and consequences of climate change and enjoy this learning experience. Because you feel more able to reason about climate change, you enjoy to read up on climate change and to visit websites at home. Consequently, you value the subject of climate change more, which increases your likelihood to go to the science center again. Looking at the network

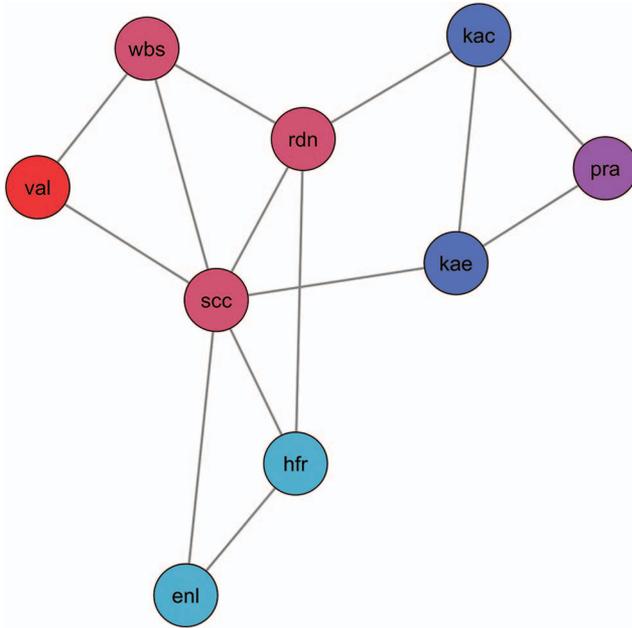


Figure 1. Hypothetical climate change interest network. Nodes represent indicators of science interest components and edges represent the mutual interactions between the nodes. The nodes represent the following indicators: val = valuing the subject; wbs = visiting websites about climate change; scc = visiting science center; rdn = reading about climate change; enl = enjoying learning about climate change; hfr = having fun reading about climate change; kae = knowledge about the effects of climate change; kac = knowledge about the causes of climate change; pra = perceived ability to reason about climate change. The colors of the nodes correspond to the science interest components that the nodes belong to. For simplification, all edges have the same strength (width) and represent excitatory influence. See the online article for the color version of this figure.

structure and the network dynamics allows us to study the function of the indicators.

It is likely that indicators of the same component, for example, items of a subscale enjoyment, will form clusters of highly connected nodes. Clusters of highly connected nodes give rise to a so-called small-world structure (e.g., Watts & Strogatz, 1998). A small-world property implies that, through short cuts connecting the clusters of the network, change spreads rapidly through the network. This means that, if a node changes, for instance because of a targeted intervention, the other nodes will change (i.e., become more positive) as well.

Nodes (i.e., indicators) differ in the extent that they can affect the network, depending on their position within the network and the number and strength of edges they have with the other nodes of the network (Freeman, 1978; Opsahl, Agneessens, & Skvoretz, 2010). If the indicator “enjoyment of reading about science” is central, for instance, it is predicted that interventions that increase the enjoyment of reading about science have a positive effect on science interest. Hence, knowing the structure of the science interest network of a specific group of individuals, that is, the relative strength of different indicators, provides the prediction of possibly effective interventions.

Recently, various statistical tests have been developed to study the characteristics of psychometric networks, such as a small-world structure and the identification of clusters (i.e., communities) of nodes (e.g., Humphries & Gurney, 2008; Pons & Latapy, 2005). For example, using the network comparison test (NCT; van Borkulo, Epskamp, & Millner, 2016), networks of different groups can be compared; we can thus test, for example, whether enjoyment of reading about science is of similar importance in the science interest network of different groups.

A First Empirical Test

To have a first indication of whether science interest can be represented using a network approach, we applied the SINM to the PISA 2015 data of two countries, that is, the Netherlands and Colombia (OECD, 2017a). This available large data set is cross-sectional, meaning that no causal inferences can be made based on the results of this study. However, this cross-sectional data does give a first indication of the structure of relations between science interest components and related motivational components.

To successfully represent science interest as a network, however, it is of importance to include as many as available relevant science interest components and related motivational components. PISA 2015 data include the following components related to science interest: *science enjoyment*, *science-related activities*, *science knowledge*, *science interest evaluations*, and *science self-efficacy*. In contrast to the PISA 2006 data, the PISA 2015 data do not include personal and general value measures and future intentions to engage with science (OECD, 2006, 2016). The PISA 2015 data do include indicators of *future-oriented motivation to learn science*, which we included as an indication of (personal) value. Moreover, of the motivational constructs that have been shown to have reciprocal relationships with interest, only self-efficacy was included in the PISA 2015 data, which was included to give a more complete representation of the science interest structure.

Importantly, structural differences in science interest across different countries have previously been found using the PISA 2006 data (Ainley & Ainley, 2011). Ainley and Ainley (2011) compared countries based on their macrocultural dimensions of traditional versus secular-rational orientations, and survival versus self-expression values, which are thought to be underlying the developmental course of modern nations (Inglehart & Baker, 2000; Inglehart & Welzel, 2005). Countries such as the Netherlands, which is included in the current study, and Sweden, are placed within the secular-rational & self-expression quadrant. In countries placed within that quadrant, obedience to religious authority is not a priority and family and social values are not seen as absolute. Scoring high on the self-expression value means that individual autonomy, subjective well-being, as well as concerns of one’s quality of life are seen as important. Inglehart and Welzel (2005) show that this dimension is also related to economic conditions, such that higher scores are related to higher economic security. Countries in the traditional & survival quadrant are under-represented in the PISA measures (Ainley & Ainley, 2011), Colombia, however, scored close to the mean on the survival/self-expression axis and was one of the more traditional countries, being more than a standard deviation lower than the mean on that scale; Colombia was therefore chosen to be included in their study, as well as the current study. One main difference between the included countries was the role knowledge played: science knowledge was largely unrelated to

interest ratings in Colombia, although it did play an important role in the interest of Swedish students (Ainley & Ainley, 2011). This finding may be attributed to the lower economic security in Columbia and the lower average score for knowledge suggest worse accessibility of good education and less opportunities for participation in science activities, compared with opportunities for teenagers in the Netherlands or Sweden. An expected difference between the Netherlands and Columbia is therefore that Dutch students developed domain-specific knowledge corresponding to their interest. Consequently, the relation between domain-specific knowledge and domain-related interest questions might be relatively strong in the Netherlands. Relations between domain-related interest questions of different domains, on the other hand, might be relatively weak for Dutch students (see also Tucker-Drob & Briley, 2012).

Following previous research in science interest, we also compared the SINM of boys with that of girls, in each country. Although girls and boys have similar levels of interest for biology and life sciences, boys are typically more interested in hard sciences—a difference that manifests itself over the course of their schooling (e.g., Häussler & Hoffmann, 2000; Jones, Howe, & Rua, 2000; Labudde, Herzog, Neuenschwander, Violi, & Gerber, 2000). Also, self-efficacy concerning science is often found to differ between boys and girls. In the Netherlands, for instance, boys have reported higher level of self-efficacy in science than girls in the PISA 2006 science assessment (OECD, 2006). We thus expected that boys score higher on the science interest measure as well as the science self-efficacy measure in the Netherlands, which not necessarily indicates structural differences in relations between components. As structural differences in the relations between components across this group have, to our knowledge, not been studied, we had no expectation on possible differences in the gender-based networks.

Third, we compared socioeconomically advantaged students with students who are socioeconomically disadvantaged, in each country. The differences in interest structure that we expected between the Netherlands and Columbia based on macrocultural differences are also expected between groups with different SES within countries. Tucker-Drob and Briley (2012) show for a U.S. population of students (adolescents of comparable age to the PISA participants) that the relation between domain-specific interest and knowledge of the same domain is moderated by SES, with the relation being stronger in individuals from a high SES background. Therefore, we expected that in the SINM of the high SES group, edges connecting nodes of the knowledge and the other interest components that are related to the same domains are stronger than in the low SES groups. A second expected consequence of the development of domain-specific interest by high-SES groups were weaker connections within the interest evaluation nodes of the network representing their interest structure.

Summarizing, network theory enabled us to look at science interest as a dynamic construct (Dalege et al., 2016). Formulating the SINM model, we first compared the networks of the Dutch and the Colombian sample using the network comparison test (NCT; van Borkulo et al., 2016). Then, we investigated the global structure of the two networks by inspecting their small-world-ness and the clusters in the networks. Next, we examined the centrality of the different indicators within the two networks, which enabled us to generate hypotheses on the most promising targets in an intervention. Furthermore, we compared the SINMs of girls and boys, and of individuals from advan-

taged and disadvantaged socioeconomic backgrounds for the Netherlands and Columbia separately.

Method

Participants

The Netherlands. We included the PISA 2015 data of Dutch HAVO/VWO students, resulting in a sample size of 2492 (1316 girls, 1176 boys). Within the Dutch context, the PISA data makes a difference between the prevocational track (VMBO) and the two forms of selective secondary education (HAVO/VWO). The difference of schooling between VMBO and HAVO/VWO in the Netherlands is quite large, as the focus within VMBO is mainly on preparing students for vocational training and HAVO/VWO is usually leading to higher education. To make sure that the sample would be as homogeneous as possible, we only included the HAVO/VWO¹ subsample. The final sample, after casewise deletion of missing data, included 1441 students from the VWO level and 688 students from the HAVO level, thus 2129 (1149 girls, 980 boys) students in total, with a mean age of 15.73 years ($SD = 0.29$).

Colombia. We included the PISA 2015 data of Colombian upper secondary academica level and upper secondary tecnica level, resulting in a sample size of 7299 (4110 girls, 3189 boys). Within the Colombian context, the PISA data makes a difference between lower secondary education and two forms of upper secondary education (tecnica/academica). To make the Colombian sample comparable with that of the Dutch students, we only included students of the upper secondary education, that is, academica and tecnica,² resulting, after casewise deletion of missing data, in a sample size of 5,557 (3,151 girls, 2,406 boys) in total. Of this sample, 3,775 students were from the upper secondary academica level and 1,782 of the upper secondary tecnica level; the mean age was 15.88 years ($SD = 0.28$).

PISA Measures

The focus of PISA 2015 was on scientific literacy (OECD, 2006, 2016). Scientific literacy was defined as “the ability to engage with science-related issues, and with the ideas of science, as a reflective citizen” (OECD, 2016, p. 13). To measure scientific literacy, adolescents had to answer knowledge questions as well as questionnaires assessing affective components related to scientific literacy (e.g., enjoyment of science). In the following, we will introduce the measures we included in the current analysis. Table 1 gives an overview of all included items. Although we report the reliabilities of the included PISA measures (OECD, 2017b), note that we do not need to assume that the indicators are locally

¹ We compared the network of the VWO students with that of the HAVO students using the NCT (van Borkulo et al., 2016) and did not find a significant difference between the networks of the two school levels. The results of the NCT are in the supplemental materials.

² We compared the network of the academica with that of the students of the tecnica level using the NCT (van Borkulo et al., 2016) and did not find a significant difference between the networks of the two school levels. The results of the NCT are in the supplemental materials.

Table 1

List of Items Used in the Network, Their Item Labels, the Interest-Related Construct They Belong to, as Well as Their Assigned Color

Item label	Construct	Color	Item description
Ibi	Interest	Yellow	Biosphere (e.g. ecosystem services, sustainability)
Imf	Interest	Yellow	Motion and forces (e.g. velocity, friction, magnetic and gravitational forces)
Iet	Interest	Yellow	Energy and its transformation (e.g. conservation, chemical reactions)
Iun	Interest	Yellow	The Universe and its history
Ipd	Interest	Yellow	How science can help us prevent disease
Efu	Enjoyment	Light blue	Fun learning broad science
Elr	Enjoyment	Light blue	Like reading broad science
Ehw	Enjoyment	Light blue	Happy working on broad science
Eac	Enjoyment	Light blue	Enjoy acquiring knowledge on broad science
Eil	Enjoyment	Light blue	Interested learning about broad science
Btv	Behavior	Maroon	I watch TV programs about <broad science>
Bbo	Behavior	Maroon	I borrow or buy books on <broad science> topics
Bws	Behavior	Maroon	I visit web sites about <broad science> topics
Bre	Behavior	Maroon	I read <broad science> magazines or science articles in newspapers
Bsc	Behavior	Maroon	I attend a <science club>
Bsn	Behavior	Maroon	I simulate natural phenomena in computer programs\virtual labs
Bst	Behavior	Maroon	I simulate technical processes in computer programs\virtual labs
Bwe	Behavior	Maroon	I visit web sites of ecology organizations
Bnb	Behavior	Maroon	I follow news via blogs and microblogging
Vwl	Value	Red	Effort in science class worth it, helping for later work
Vdo	Value	Red	Learning school science subject important for later work
Vcp	Value	Red	Studying school science subject worthwhile for improving career prospects
Vhp	Value	Red	Learning things in school science subject helps get a job
Kce	Knowledge	Dark blue	Competency - Explain Phenomena Scientifically
Kcd	Knowledge	Dark blue	Competency - Evaluate and Design Scientific Enquiry
Kci	Knowledge	Dark blue	Competency - Interpret Data and Evidence Scientifically
Kkc	Knowledge	Dark blue	Knowledge - Content
Kkp	Knowledge	Dark blue	Knowledge - Procedural & Epistemic
Ksp	Knowledge	Dark blue	System - Physical
Ksl	Knowledge	Dark blue	System - Living
Kse	Knowledge	Dark blue	System - Earth & Science
Sne	Self-efficacy	Purple	Recognize the science question that underlies a newspaper report on a health issue
Sea	Self-efficacy	Purple	Explain why frequency earthquakes differ for different areas
Sad	Self-efficacy	Purple	Describe the role of antibiotics in the treatment of disease
Sdg	Self-efficacy	Purple	Identify the science question associated with the disposal of garbage
Scs	Self-efficacy	Purple	Predict how changes to an environment will affect the survival of certain species
Slf	Self-efficacy	Purple	Interpret the scientific information provided on the labelling of food items
Slm	Self-efficacy	Purple	Discuss how new evidence can lead you to change your understanding about the possibility of life on Mars
Sfr	Self-efficacy	Purple	Identify the better of two explanations for the formation of acid rain

independent and exchangeable, an assumption that is made in latent-variable models, but not in psychometric network models.

Science interest evaluations (named science interest in PISA 2015). Broad interest in science topics was measured by asking students how interested they were in the following five topics: biosphere, motion and forces, energy and its transformation, the Universe and its history, and how science can help us to prevent disease. Students answered on a 5-point Likert scale ranging from 1 (*not interested*) to 4 (*highly interested*), with 5 (*I don't know what that is*) recoded as a missing value for all analyses. The reliability (Cronbach's alpha) of the science interest scale was 0.82 for the Dutch sample and 0.83 for the Colombian sample (OECD, 2017b).

Science enjoyment. Enjoyment of science was assessed through five items such as "I generally have fun when I am learning broad science." It was measured using a 4-point Likert scale ranging from 1 (*strongly disagree*) to 4 (*strongly agree*). The reliability (Cronbach's alpha) of the science enjoyment scale was 0.95 for the Dutch sample and 0.90 for the Colombian sample (OECD, 2017b).

Behavior: Engagement with science. To assess how much students participated in different science-related activities, they were asked how often they engaged with nine different activities, such as watching TV programs about broad science. They answered these items on a 4-point Likert scale ranging from 1 (*very often*) to 4 (*never or hardly ever*). To derive a coherent picture of the relations between all included indicators, we reversed the coding of all behavior items. Higher scores thus indicated more frequent engagement with the sciences. The reliability (Cronbach's alpha) of the behavior scale was 0.91 for both the Dutch and the Colombian sample (OECD, 2017b).

(Personal) value. Four items were used to measure value of learning science (instrumental motivation); it should be noted that instrumental motivation to learn science is not an ideal indicator of (personal) value as it focuses on science as relevant for a future career. In contrast, most conceptualizations of interest refer to value of an object of interest as having everyday relevance or being (personally) meaningful. Such a measure was not included in the PISA 2015 data set, however. On a 4-point Likert scale ranging from 1 (*strongly agree*) to 4

(*strongly disagree*), students rated how much they agreed with statements such as “Making an effort in my <school science> subject(s) is worth it because this will help me in the work I want to do later on.” To derive a coherent picture of the relations between all included indicators, we reversed the coding of all value items. Higher scores thus indicated higher levels of valuing of the sciences. The reliability (Cronbach’s alpha) of the instrumental motivation scale was 0.95 for the Dutch sample and 0.89 for the Colombian sample (OECD, 2017b).

Science knowledge. Participants had to answer different science knowledge items. Each knowledge item had three labels. First, each knowledge item was assessing one competency of scientific literacy, that is, either the ability to *explain phenomena scientifically*, to *evaluate and design scientific enquiry*, or to *interpret data and evidence scientifically* (OECD, 2016). Second, each knowledge item was assessing one subcategory of scientific knowledge, either *content knowledge* (i.e., knowledge of facts, concepts, ideas and theories that have been established by science) or *procedural/epistemic knowledge* (i.e., knowledge of the bases of empirical enquiry and knowledge about those constructs and features essential to the process of knowledge-building in science). Lastly, every knowledge question was classified as belonging to one of three systems (i.e., physical, living, earth and space; OECD, 2016). As each student only answered a subset of all science knowledge items and subsets differed across students, the PISA database included plausible values (PVs) as an index of science competency. PVs are draws from the estimated distribution of each student’s proficiency, based on the responses to the subset of items. In total, the PISA 2015 database included 10 PVs per science knowledge scale and subscale (OECD, 2017a). As done in the study of Ainley and Ainley (2011), we only used one PV³ per science knowledge indicator as our index of science knowledge; more specifically, we used PV 10 in all analyses.

Science self-efficacy. To assess science self-efficacy, students were asked how they would perform in different science tasks, such as recognizing the science questions underlying a newspaper report on a health issue. They answered the set of eight questions on a 4-point Likert scale ranging from 1 (*I could do this easily*) to 4 (*I couldn’t do this*). To derive a coherent picture of the relations between all included indicators, we reversed the coding of all science self-efficacy items. Higher scores thus indicated higher self-efficacy. The reliability (Cronbach’s alpha) of the science self-efficacy scale was 0.90 for the Dutch sample and 0.88 for the Colombian sample (OECD, 2017b).

Socioeconomic status (SES). One of the network comparisons within country was based on SES. Based on different indicators related to student’s family background, that is, parents’ education, parents’ occupations, number of home possessions indicating material wealth, and the number of books as well as other educational resources that are available at home, the PISA index of economic, social and cultural status (ESCS) of students was estimated via principal component analysis (PCA). The ESCS values were estimated by PISA and standardized per country, with the standardized scale reliabilities (Cronbach’s alpha) being 0.67 for the Dutch sample and 0.70 for the Colombian sample (OECD, 2016, 2017b).

Network Estimation

We visualized the structure of the different networks using the R-package *qgraph* (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). All indicators of the previously discussed interest components were included in the estimation and were represented as “nodes.” Partial correlations between two indicators, controlling for all other indicators included in the network, were represented by “edges” connecting the indicators. Positive partial correlations were represented by green edges and negative correlations by red edges, with the width and saturation of the edges showing the strength of the correlation (Epskamp et al., 2012). The darker and thicker the edge, the stronger the partial correlation between two nodes.

As proposed in the CAN model, we estimated the networks using the R-package *IsingFit* (van Borkulo et al., 2016), which requires all data to be binary. The data were binarized as follows: Low scores (i.e., 1, 2) of the Likert-scale items were transformed into a score of 0, thus, for instance, indicating low levels of interest; and high scores (i.e., 3, 4) were transformed into a score of 1, thus indicating high levels of science interest. As the behavior items were largely skewed to the right, we transformed the scores differently; here, a transformed score of 0 indicated that an individual did not engage in the activity, whereas a score of 1 indicated that an individual (at least) sometimes engaged in the activities (scores 2–4). Concerning the knowledge scores, we binarized the data using the median per indicator.

To estimate the network, we used the eLasso-procedure (van Borkulo et al., 2015), in which every indicator is regressed on each other indicator, with each regression being subjected to regularization. The regularization is done to control for the problem of multicollinearity, which is present in data sets with many indicators (Friedman, Hastie, & Tibshirani, 2008; Tibshirani, 1996) and to make the model sparser, therefore better interpretable. The regression function with the best fit was then selected using the extended Bayesian information criterion (eBIC; as in Foygel & Drton, 2010). In the figures, closely connected nodes were placed near each other and nodes with weaker connections were placed closer to the periphery of the network, whereas nodes with stronger connections were placed in the center of the network, which matches the layout used by Fruchterman and Reingold (1991).

In total, we constructed 10 different networks: Per country, we estimated an overall science interest network, two networks based on the gender of the students, and two networks based on the students’ socioeconomic status.

Network Analysis

Network comparison. The Network Comparison Test (NCT; van Borkulo et al., 2016) was used to compare the interest networks of groups (the Netherlands versus Colombia; boys versus girls; advantaged versus disadvantaged socioeconomic background), using permutations, that is, repeated rearrangements of the samples. First, the NCT tested whether the network structure of

³ To test whether using one PV was a feasible representation of the knowledge indicators, we ran the analyses with PV1 and PV10 and compared the two networks applying an NCT (van Borkulo et al., 2016). As the two networks did not significantly differ, we decided to use only PV10.

the two networks was invariant, that is, whether they were completely identical. Second, if the network structure was invariant, we used the NCT to investigate whether specific edges were equally strong across the two networks. Lastly, the invariance in global strength (or overall connectivity) was investigated, which was conceptualized as the weighted sum of absolute connections (Barrat, Barthélemy, Pastor-Satorras, & Vespignani, 2004). Please note that we only performed the additional analyses described below when the NCT showed significant differences between the two networks.

Importantly, the NCT is sensitive to differences in sample sizes between groups. In case the two groups we wanted to compare differed importantly in size, we created a subsample of the bigger group having the same size as the smaller group using a random sampling method. With the Colombian sample being much larger than the Dutch sample, for instance, we randomly sampled 2129 individuals from the Colombian group to create a Colombian subsample with the same size as the Dutch group. Please see the [supplemental materials](#) for the resulting sample sizes and results of all NCTs.

Community detection. We were interested in detecting communities (or clusters) in the networks as this is a way to make sure that the items we included in the network belong to the components that they were intended to belong to. To this end, we used the walktrap algorithm (Pons & Latapy, 2005), which has been shown to perform well on psychological networks (Gates, Henry, Steiny, & Fair, 2016; Golino & Epskamp, 2017). Moreover, the walktrap algorithm can, in contrast to factor analysis, detect dimensions of a variable very well even when the different dimensions are highly correlated (Golino & Epskamp, 2017). In the figures of the estimated networks, nodes belonging to the same community have the same color.

Small-world-ness. To test whether the networks had a small world structure (Albert & Barabási, 2002; Watts & Strogatz, 1998), we determined the small world index of each network. Networks with a small world structure have a high clustering and high global connectivity, meaning that all nodes are, on average, closely connected (Watts & Strogatz, 1998). To have a small-world structure, a network should have a higher clustering than a random graph and about the same connectivity as a random graph. The small-world index is therefore based on the clustering index (C) of both the given graph and a random

graph as well as the average path length (L) of both graphs, which is an indicator for connectivity. A small-world index higher than one is an indication of the small-world-ness of a network (Humphries & Gurney, 2008). To test whether the small-world index of the constructed networks was significantly higher than one, we calculated confidence intervals using 1,000 Monte-Carlo simulations of random graphs (Humphries & Gurney, 2008), as done in Dalege and colleagues' (2016) paper, but using the "global" transitivity type.

Node centrality. To investigate the structural importance of the different nodes, we tested their centrality, which can be used to infer which indicators should be targeted for intervention. The most commonly used centrality measures are strength, betweenness, and closeness (Barrat et al., 2004; Freeman, 1978; Opsahl et al., 2010). Based on the analysis of the accuracy of the three centrality measures implemented in the R package *bootnet* (Epskamp & Fried, 2017), we decided to focus on node strength, as its correlation stability coefficient (CS-coefficient) surpassed the proposed threshold of 0.5 in all estimated networks. Node *strength* in weighted networks is the sum of all edge values connected to a given node; it therefore is an index of the direct influence of that node on the network.

Additional analyses. We performed stability and accuracy checks to investigate the stability of the generated networks and of the centrality indices (Epskamp, Borsboom, & Fried, 2018). Moreover, we ran additional NCTs to compare the networks of different subgroups of individuals per country. More specifically, in the Dutch sample, we ran NCTs comparing the HAVO with the VWO students. In the Colombian sample, we first compared the students of the upper academica and upper tecnica tracks. Lastly, we ran simulations on the two country networks to test the effect of external pressure on the dynamics of the networks. Please see the [supplemental materials](#) for the stability checks as well as the results of the additional NCTs and the simulation results.

Results

Descriptive Statistics

The descriptive statistics per country and subgroup can be found in [Table 2](#). The two countries differ significantly on the sum score

Table 2
Means and Standard Deviations of the Science Interest Components per Country and Subgroup

Country/Group	<i>N</i>	Interest	Enjoyment	Behavior	Value	Knowledge	Self-efficacy
The Netherlands	2,129	2.53 (.96)**	2.36 (.89)**	1.38 (.61)**	2.53 (.99)**	588.15 (71.28)**	2.79 (.86)
Boys	980	2.62 (.95)**	2.50 (.90)**	1.50 (.69)**	2.63 (.97)**	598.42 (74.48)**	2.86 (.83)
Girls	1,149	2.44 (.93)**	2.25 (.86)**	1.28 (.50)**	2.45 (1.01)**	579.40 (67.08)**	2.72 (.86)
Low SES	533	2.47 (.97)**	2.31 (.87)**	1.33 (.57)**	2.52 (.98)**	573.58 (70.16)**	2.70 (.86)
High SES	533	2.67 (.94)**	2.46 (.89)**	1.45 (.67)**	2.63 (.99)**	605.42 (72.19)**	2.92 (.82)
Colombia	5,557	2.87 (.88)**	2.82 (.77)**	1.83 (.88)**	2.93 (.80)**	454.99 (76.24)**	2.66 (.86)
Boys	2,406	2.90 (.88)**	2.81 (.79)**	1.91 (.91)**	2.92 (.80)**	469.14 (76.39)**	2.67 (.85)
Girls	3,151	2.85 (.87)**	2.83 (.75)**	1.76 (.85)**	2.94 (.79)**	444.18 (74.30)**	2.66 (.89)
Low SES	1,390	2.83 (.87)**	2.80 (.76)**	1.81 (.88)**	3.01 (.75)**	419.71 (67.04)**	2.61 (.88)**
High SES	1,390	2.90 (.89)**	2.83 (.80)**	1.85 (.88)**	2.90 (.82)**	493.40 (72.82)**	2.75 (.86)**

Note. The subgroups per country (i.e., boys vs. girls; high SES vs. low SES) and the overall scores of the countries were compared.
* $p < .05$. ** $p < .001$.

of all science interest components apart from the self-efficacy component, with the Dutch students scoring higher on knowledge and the Colombian students indicating higher rates of science interest, enjoyment, behavior, and value. Moreover, clear country differences regarding the mean scores per subgroup became apparent: Although there were gender differences in all science interest components but in the related motivational component self-efficacy in the Netherlands, with boys scoring higher on all science interest components, boys only scored higher on the knowledge and behavior components in the Colombian sample. In both countries, students from a high SES background had a higher knowledge score and indicated a higher science interest than students from a low SES background. In the Dutch sample, students from a high SES background additionally had higher scores on the enjoyment and behavior components and Colombian students from a high SES background indicated higher levels of self-efficacy than those from a low SES background, whereas Colombian students from a low SES background valued sciences more than Colombian students from a high SES background.

Network Analysis

The Netherlands versus Colombia. Visually, the networks of the Dutch (Figure 2, left) and the Colombian (Figure 2, right) differed considerably: First, interest nodes were more central in the Dutch network but did not form a tight cluster, whereas interest nodes formed a tight cluster in the Colombian network like the other science components. Second, the nodes of the Dutch network were connected through a number of edges that were not present in the Colombian network; the Dutch network thus seemed to have an overall higher connectivity than the Colombian network.

Network comparison tests (NCT). With the Dutch SINM being based on a smaller sample (2129) than the Colombian SINM (5557), we randomly sampled 2129 individuals from the Colombian sample,⁴ to make the sizes of the two samples comparable. Apparent differences between networks were supported by the NCT, which showed that the two networks differed in their network structure ($M = 1.06, p < .01$), as well as on 18 specific edges. Edges connecting the self-efficacy cluster with nodes of the other clusters were stronger in the Dutch interest network, connecting self-efficacy nodes with nodes from the knowledge (SIm-Ksp, Sfr-Ksp), interest evaluations (Sne-Ipd, Sea-Ibi, Sea-Iun, Sad-Ibi, Sfr-Ibi), and behavior (Sea-Btv) cluster. There were a number of stronger edges within the knowledge, interest evaluation, and behavior clusters of the Colombian network (Kkc-Kse, Ibi-Imf, Iet-Ipd, Iun-Ipd, Bst-Bnb) as well as within the enjoyment, behavior, and value cluster of the Dutch network (Efu-Eil, Bbo-Bws, Bsc-Bwe, Vwl-Vdo, Vcp-Vhp). Moreover, self-efficacy seemed to play a more central role in the Dutch network, with self-efficacy being more strongly connected to knowledge, interest evaluation, enjoyment and behavior nodes.

The test on invariance of global strength was also significant ($S = 9.37; p < .01$), with the Dutch SINM having a higher global strength ($S = 98.02$) than the Colombian SINM ($S = 88.64$). The Dutch and Colombian science interest networks thus not only differed significantly in their structure, on specific edges but also in their global strength. With the two networks being significantly different, we will discuss all further analyses per country.

The Netherlands. The first network we constructed illustrates the relation between all included indicators for the whole Dutch sample (Figure 2, left). All nodes were connected through a number of positive edges, but, strikingly, the interest evaluation items did not seem to form an interest evaluation cluster, which was confirmed by the community detection analysis (Figure 3, left). Three interest evaluation items, Ibi (“Biosphere”), Iun (“Universe”), and Ipd (“Preventing disease”) were included in the self-efficacy cluster, whereas the other two interest evaluation items, that is, Iet (“Energy and its transformations”) and Imf (“Motion and forces”) were included in the enjoyment cluster (light blue). Lastly, the knowledge and value clusters were the most peripheral clusters, not having as many intercluster relations as the other interest components, meaning that their roles seemed to be less central in the SINM than the roles of interest evaluation and enjoyment, for instance.

Small-world-ness. The Dutch SINM had a higher clustering (0.45) compared with a random graph of the same dimensions (0.26), while having a comparable average shortest path length (1.96 to 1.79), leading to a small-world index of 1.58. The upper limit of the 99.9% confidence interval of the small-world index for the random graphs is 1.19. We can thus conclude that the Dutch SINM has a small-world structure.

Centrality. To investigate which nodes had the strongest relations to the rest of the network, we looked at the strength of each node, which is displayed in Figure 4. The strongest related nodes were all from the enjoyment component, that is, being interested to learn about science topics (Eil), followed by enjoyment to acquire science-related knowledge (Eac) and like to read about sciences (Elr). The high strength of the enjoyment nodes may be partly due to the strong clustering within the enjoyment cluster, but as nodes of this cluster were connected to nodes from the other clusters, the enjoyment cluster seemed to play an important structural role within the network. The Eil node, for instance, had direct connections with Imf (0.31) from the interest evaluation component, Vwl (0.44) from the value component, Bws (0.59) from the behavior component, Sne (0.15) from the self-efficacy component, and Ksl (0.27) from the knowledge component.

NCT: Boys versus girls. The NCT indicated that the network structure of Dutch boys did not differ significantly from that of Dutch girls ($M = 1.09, p = 0.35$), hence we did not test whether specific edges differed. Moreover, the global strength of their networks did not significantly differ ($S = 2.42; p = .65$), hence we can conclude that the two networks were not meaningfully different from each other.

NCT: Low versus high SES. The NCT indicated that the network structure of the Dutch high versus low socioeconomic populations did not differ significantly ($M = 1.77; p = .08$), hence we did not test whether specific edges differed. Moreover, the two networks did not differ significantly in their global strength ($S = 3.33; p = .48$), hence we can conclude that the two networks were not meaningfully different from each other.

⁴ We compared the network of the large Colombian sample with that of the small Colombian subsample using the NCT (van Borkulo et al., 2016) and did not find a significant difference between the networks of the two school levels. The results of the NCT are in the supplemental materials.

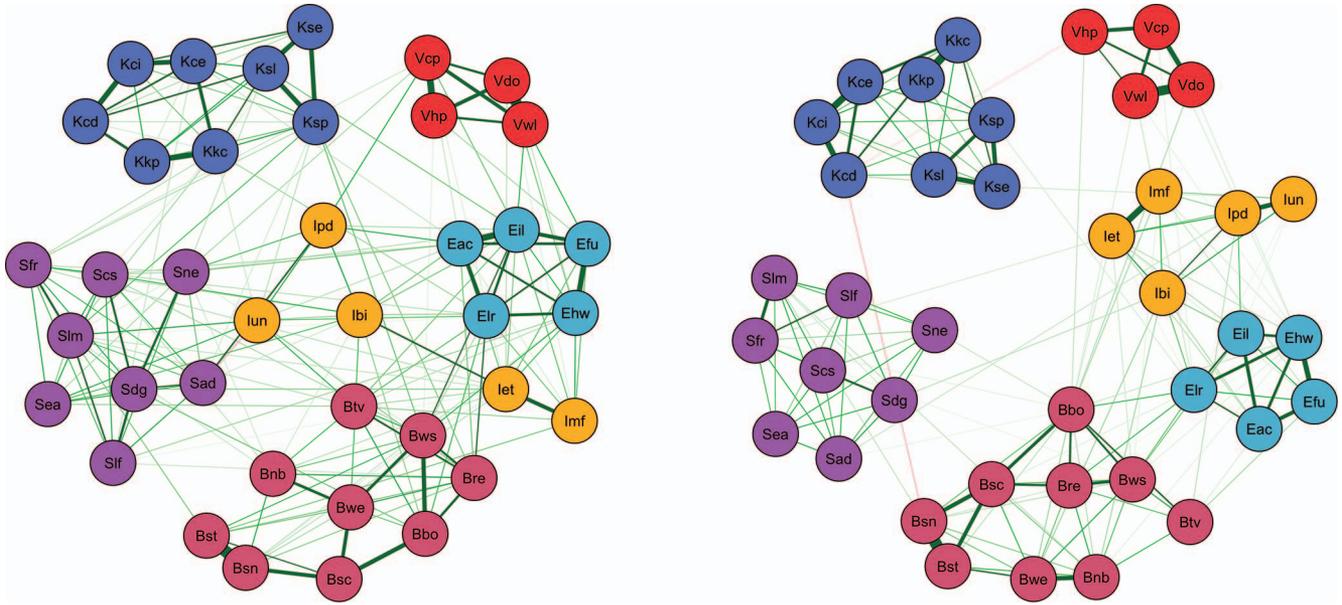


Figure 2. Network depicting the relation between the nodes of interest, enjoyment, personal value, behavior, knowledge, and self-efficacy in Dutch Havo/Vwo students (left) and Colombian upper secondary students (right). Each node represents an indicator, with the colors of the nodes being based on the included science-interest related variables (e.g., enjoyment, knowledge) as defined by PISA. Each edge corresponds to a partial correlation between two nodes. The thicker an edge, the stronger the correlation between two items, with green edges indicating positive correlations and red edges indicating negative correlations. See [Table 1](#) for the item labels of the nodes. One striking difference between the networks is the presence of more edges between clusters in the Dutch network. See the online article for the color version of this figure.

Colombia. In the Colombian network, all included indicators formed clusters confirming to the (PISA) components they were measuring ([Figure 2](#), right). Here, the interest evaluation indicators formed a separate cluster, as confirmed by the community detection analysis ([Figure 3](#), right). Interest evaluation therefore seemed to be less domain-specific, with individuals evaluating one science-related topic to be interesting also being interested in other science-related topics. Overall, the Colombian SINM network had a quite sparse connectivity, with knowledge, value, and self-efficacy being the most peripheral components and no nodes being placed in the center of the network. The interest evaluation variables were most closely related with the enjoyment nodes and not with the topic-related self-efficacy nodes.

Small-world-ness. The Colombian network had a higher clustering (0.59) compared with a random graph of the same dimensions (0.22), while having a comparable average shortest path length (2.26 versus 1.90), leading to a small-world index of 2.25. The upper limit of the 99.9% confidence interval for the random graphs is 1.24. We can thus conclude that the Colombian SINM had a small-world structure.

Centrality. To investigate which nodes had the strongest direct relations to the rest of the network, we looked at the strength of each node, which is displayed in [Figure 4](#). The strongest nodes are from the behavior component, that is, borrowing or buying books on science topics (Bbo), attending a science club (Bsc) and simulating natural phenomena on the computer (Bsn). The high strength of the behavior nodes Bsc and Bsn was likely attributable to the strong relations within the behavior cluster, specifically the

strong relation between Bst, Bsn, and Bsc. The node Bbo, however, also had direct connections with nodes from the enjoyment component (Elr; 0.51), the interest-evaluation component (Imf; 0.23), the value component (Vdo; 0.21), and the self-efficacy component (Sne; 0.14), highlighting its structural importance.

NCT: Boys versus girls. We ran the NCT on data of all boys ($N = 2460$) and a random subsample of the Colombian girls ($N = 2406$). The network structure of Colombian boys did not differ significantly from that of Colombian girls ($M = .72$, $p = .16$). Moreover, the global strength of their networks did not significantly differ ($S = 0.52$; $p = .79$), hence we can conclude that the two networks were not meaningfully different from each other.

NCT: Low versus high SES. The NCT indicated that the network structure of the Colombian high versus low socioeconomic populations did not differ significantly ($M = .84$; $p = .30$). The two networks did, however, differ significantly in their global strength ($S = 5.94$; $p = .01$), with the low SES network having a higher global connectivity ($S = 90.06$) than the high SES network ($S = 84.11$). As the two networks differed significantly, we further investigated the two networks by looking at the clusters they formed, their small-world-ness as well as the strength of the nodes of both networks.

SINM for low versus high SES. We constructed and illustrated the networks of the students from a low ([Figure 5](#), left) versus high SES ([Figure 5](#), right) background. Overall, the low SES network seemed to have more (weak) edges, especially connecting nodes from the enjoyment, behavior and interest-evaluation clusters. The community detection produced the same networks as the ones depicted in [Figure 5](#), indicating that, in both

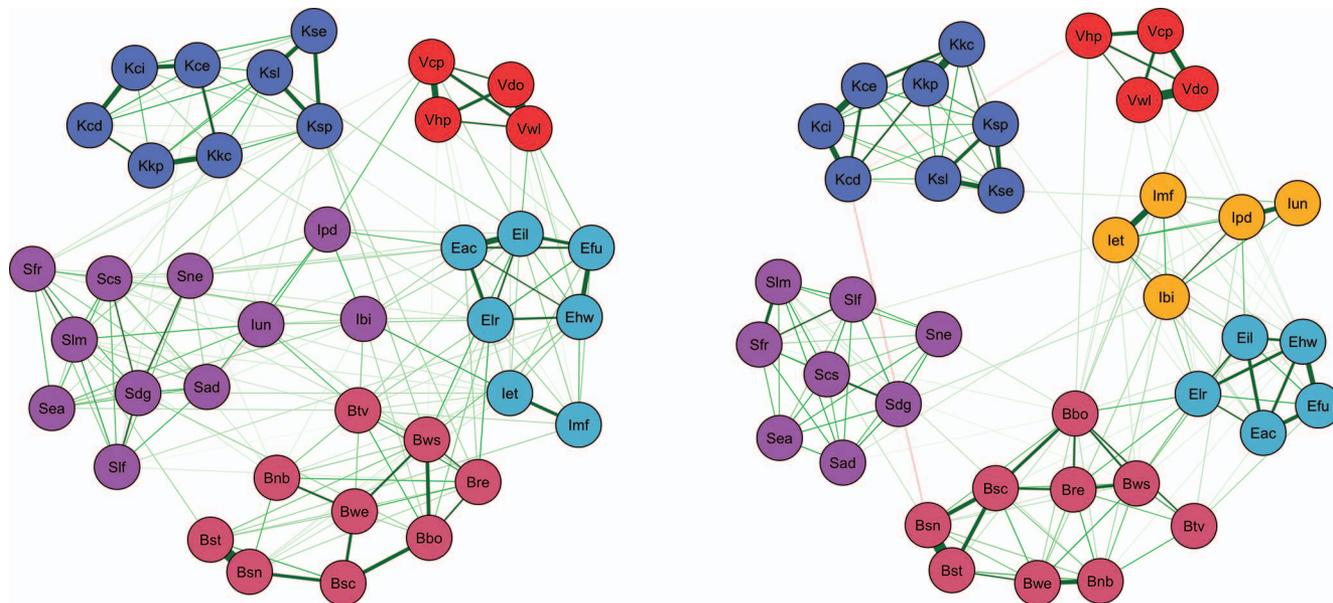


Figure 3. Networks depicting the *detected* communities of the nodes representing the science-interest-related variables in Dutch Havo/Vwo students (left) and Colombian upper secondary students (right). The detected communities are based on the walktrap algorithm and can be differentiated by their colors, which are for convenience based on the colors of the constructs in the network depicted in Figure 2. See Table 1 for the item labels of the nodes. One striking difference between the networks is the presence of an interest-evaluation community in the Colombian network, which is not present in the Dutch network. See the online article for the color version of this figure.

networks, the detected communities corresponded to the components as intended by the PISA measures.

Small-world-ness low versus high SES. The low SES network had a higher clustering (0.61) compared with a random graph of the same dimensions (0.18), while having a comparable average shortest path length (2.72 versus 2.06), leading to a small-world index of 2.59. The upper limit of the 99.9% confidence interval for the random graphs was 1.37, so that we can conclude that the low SES network had a small-world structure. This was also true for the high SES network, having a higher clustering compared with a random graph (0.65 versus 0.16) and a comparable average shortest path length (2.88 versus 2.15), leading to a small-world index of 2.98, which is higher than the 99.9% confidence interval for the random graph (1.44).

Centrality low versus high SES. The strength of each node of the low SES and the high SES network are displayed in Figure 6 (right side). For both groups, the strongest node was from the behavior component, that is simulating technical phenomena on the computer (Bst). For the low SES network, the second strongest node was knowledge of living systems (Ksl) and for the high SES network it was the knowledge node competence of interpreting data and evidence scientifically (Kci). Overall, the strength of the nodes of the two networks were comparable, with interest-evaluation nodes having comparably low strength and nodes from the behavior and knowledge component having comparably high strength.

Summary. The Dutch and Colombian science interest network models differ on the aspects tested by the NCT, that is on their structure and specific edges, as well as their global strength. In more detail, concerning the detected communities and the

strength of specific nodes (centrality), we found differences between the structure of the Dutch and Colombian networks. The characteristics of the Dutch network support the notion of domain-specificity of science interest, as the interest-evaluation nodes do not form a separate cluster but cluster with topic-related self-efficacy nodes, or, as is the case with interest-evaluation nodes measuring interest-evaluations in hard science topics (Iet, Imf), with enjoyment nodes. In the Colombian network, the interest-evaluation nodes do form a separate cluster, which is connected to the other clusters through only a few edges, indicating a domain-general science interest. Concerning the difference in global strength between the two networks, the Dutch SINM is more highly connected than the Colombian SINM, which may indicate that there are more mutual interactions (i.e., self-reinforcing loops) within the Dutch than the Colombian network. Lastly, although the sum scores on most interest components of girls versus boys and low versus high SES differ significantly, the networks comparing the groups per country are not meaningfully different from each other, showing that the structure of science interest is relatively stable across subgroups. Although the global connectivity of the Colombian SES networks differed significantly from each other, the follow-up analyses did not reveal any interesting structural differences between these networks.

Discussion

The current paper is the first to apply a psychological network approach to science interest to provide a formal account of the dynamic structure of the multidimensional construct. More specif-

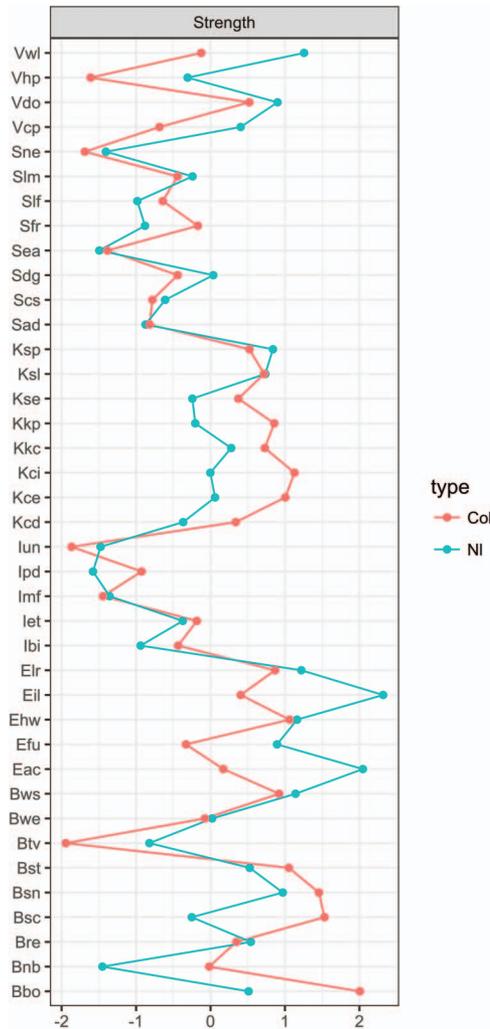


Figure 4. Centrality plot of the overall science interest network of Dutch Havo/Vwo students (blue) and Colombian upper secondary students (orange). See Table 1 for the item labels of the nodes. From the plot, it becomes apparent that the enjoyment nodes “Eil” and “Eac” are strongest in the Dutch network, whereas the behavior nodes “Bbo” and “Bsc” are strongest in the Colombian network. See the online article for the color version of this figure.

ically, we introduced a SINM by extending the CAN model, which has been developed to represent attitudes as networks of evaluative reactions (Dalege et al., 2016), with several affective, cognitive, and related components that are believed to be part of the multi-dimensional construct of interest. As a first empirical test of the model, we successfully applied the SINM to the PISA 2015 data of two different countries, the Netherlands and Colombia, which differ importantly on Inglehart and Baker’s (2000) macrocultural dimensions, traditional versus secular-rational orientations, and survival versus self-expression values. Our results replicated earlier findings highlighting the important role of enjoyment in science interest as well as important between-country differences in the structure of science interest (Ainley & Ainley, 2011). In the following, we will first discuss the theoretical relevance of our

findings, that is, how network analysis in general and our findings in particular fit in the theoretical framework of interest (development). Second, we will discuss the practical implications of our results, with a focus on how network analysis can be used to inform researchers and policymakers on possible intervention targets aimed at increasing science interest. Lastly, we will discuss the limitations of the current study and future directions to further test the SINM.

Theoretical Relevance

The SINM is a formal account of the dynamic relation perspective on science interest development (Ainley, 2017). The focus of the SINM is the structure of relations between variables that have reciprocal relations. Although the mutual interactions and dynamical interplay between (science) interest components, such as interest-evaluations and knowledge, and related motivational components, such as self-efficacy, are a central part of theories of interest development (e.g., Ainley, 2017; Hidi & Renninger, 2006; Krapp, 2002), they are not accounted for in the SEM models typically used to analyze science interest (e.g., Ainley & Ainley, 2011; Nugent et al., 2015). In a first application of the SINM to (cross-sectional) PISA 2015 data, we tested the assumption of interest theories concerning mutual interactions between interest related components. The importance of mutual interactions within the science interest network becomes apparent, first, in the finding that both the Dutch and the Colombian SINM possessed a small world structure. In the SINMs, items within interest components generally formed tight clusters, which were connected with the other clusters through a number of shortcuts. Importantly, having a small-world-structure implies that information can carry change through the whole network quickly (Watts & Strogatz, 1998). Moreover, as the interest components in the Dutch network are more closely related than those in the Colombian network, as indicated by a higher global connectivity, they may more strongly reinforce each other, which may be explained through stronger synergistic interactions^{5,6} (or enhancing interaction; Cohen, Cohen, West, & Aiken, 2003) within the Dutch SINM. Synergistic interactions have been found to play an important role in the relation of interest and other motivational components, such as competence beliefs, in predicting academic outcomes such as achievement or engagement (Nagengast et al., 2011; Trautwein et al., 2012). Moreover, Jack, Lin, and Yore (2014) found synergistic interactions of students’ science-related affective and self-related cognitive components (self-concept, self-efficacy) in deeper understanding and commitment for environmental issues, highlight-

⁵ In networks, synergistic effects have previously been referred to as emergence. In intelligence, for instance, the positive manifold of cognitive processes emerges through mutually beneficial interactions between these processes (van der Maas et al., 2006). In interest, then, the components may start to interact as children or teenagers have opportunities to engage with sciences, as they will then form judgments about their ability of solving science-related questions (self-efficacy), about their valuing science, their affective experiences when interacting with sciences (enjoyment) and so forth. This is in accordance with findings from our simulation study of network dynamics of strongly versus weakly connected networks (see the supplemental materials).

⁶ We would like to thank the anonymous reviewer for proposing that higher global connectivity might be a result of stronger synergistic interactions.

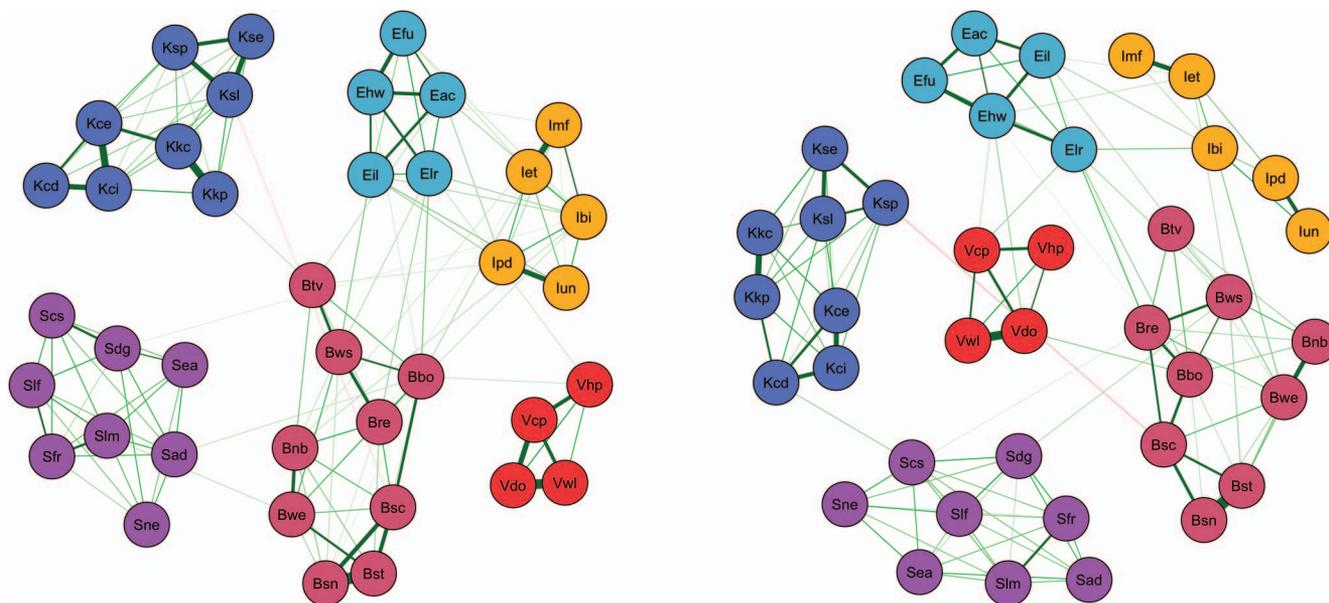


Figure 5. Networks depicting the *detected* communities of the nodes representing the science-interest-related variables in Colombian students of a low socioeconomic status (SES) background (left) and of a high SES background (right). The detected communities are based on the walktrap algorithm and can be differentiated by their colors, which are for convenience based on the colors of the constructs described in Table 1 along with the item labels of the nodes. The two networks seem to be quite similar, with the low SES network (left) having more (weak) connections between clusters. See the online article for the color version of this figure.

ing the importance of the interplay of both cognitive and affective components in determining student outcomes.

In addition to the importance of mutual interactions in the development of interest, definitions of interest highlight that interest is content-specific (Gardner, 1996). How to describe the content structure of science interest, however, seems to be problematic (Krapp & Prenzel, 2011), with the conceptualization being either more general or more concrete. On a more general level, science interest includes all science-related subjects and topics, whereas the more concrete conceptualization takes into account that an individual may only be interested in a particular school subject or specific topics and activities. Strikingly, analyzing the PISA 2015 data in a SINM framework, we found both levels of conceptualization: In the Dutch science interest network, interest seemed to be more domain-specific, with interest-evaluation items not forming a separate cluster, but clustering with either the self-efficacy cluster or the enjoyment cluster. Tellingly, the interest-evaluation items included in the self-efficacy cluster were measuring interest evaluations that were related to the topics assessed by the self-efficacy items; being interested in biosphere, for instance, was closely related with the self-efficacy variable of being able to explain how environmental change affects the survival of species. The two interest-evaluation items included in the enjoyment cluster in the Dutch network were both related to hard sciences. Dutch adolescents who generally enjoy science thus seem more likely to be interested in hard science topics. In the Colombian network, on the other hand, the interest-evaluation items did form a tight cluster, indicating that science interest is more general in Colombia. This difference in domain-specificity across coun-

tries has been hypothesized to underlie earlier findings based on large scale assessments, where students in less wealthy countries have been found to have higher overall interest scores, which may thus have been driven by less specificity in science interest in these students (e.g., Mullis, Martin, & Foy, 2008; Osborne & Dillon, 2008; Sjøberg & Schreiner, 2005). Whereas such differences in domain-specificity may not be so easily revealed when using SEM models, as all interest-evaluation items are combined to form the latent variable interest (-evaluation), using the network approach enabled us to show a between-country difference in domain-specificity.

Practical Relevance

An important goal of research in science interest is to find ways to increase youths' interest in science, as it is an important predictor of lifelong learning and study choices (Ainley & Ainley, 2011; Lin, Lawrenz, Lin, & Hong, 2013; Nugent et al., 2015). When viewing science interest as a network of causally connected indicators of components, we predict that the most central components are the most influential ones when it comes to positively affecting the network. According to a psychometric network approach (in contrast to a latent variable approach) a causal intervention on a single node within the network is hypothesized to change the other, connected, nodes in the network. If we were to increase the node "enjoying learning about science," a change in "finding science interesting" should ensue (Epskamp, Maris, Waldorp, & Borsboom, 2016). Importantly, this is a testable implication, as experimental interventions could be designed to target a single node (or a group of

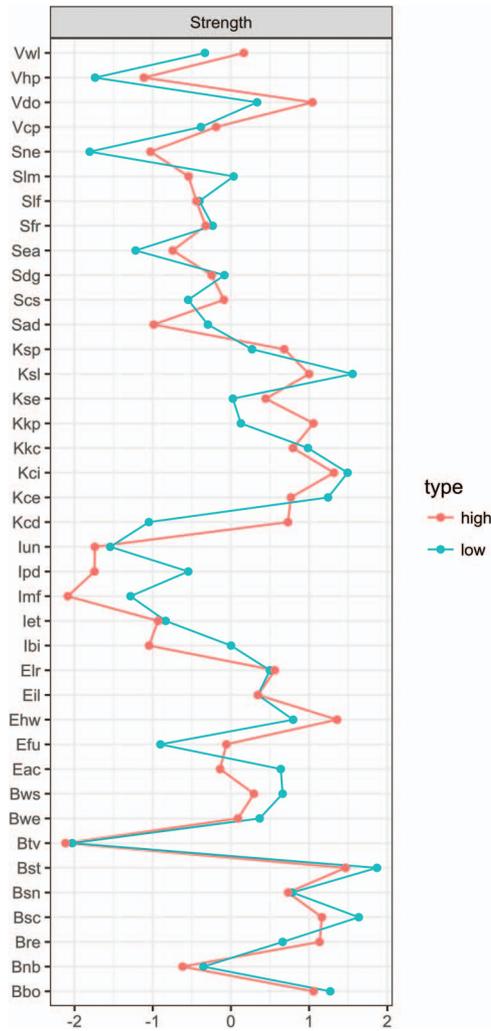


Figure 6. Centrality plot of the Colombian students from a low SES background (blue) and from a high SES background (orange). The node strength distribution of the two networks has a similar pattern, with behavior nodes (“Bst,” “Bsc”) and knowledge nodes (“Ksl,” “Kci”) being the strongest across both networks. See Table 1 for the item labels of the node. See the online article for the color version of this figure.

nodes) in the network. At the same time, the network shows that other indicators of components play a substantive role as well in the network, but the centrality of indicators provides important evidence for making a choice when it comes to designing and testing interventions. In the context of science interest, this conceptualization is of relevance for policymakers as well as educators as interventions could be tested that target specific parts of the network. Note that large-scale interventions aimed at closing the gender gap, for instance, often focus on only one specific variable (such as gender stereotypes; as the “Science—it’s a girl thing!” EU campaign from 2012). Comparable with the finding of Ainley and Ainley (2011), highlighting the important role of enjoyment in science interest in Sweden, nodes from the enjoyment cluster are the most central ones in the Dutch SINM. In Colombia, on the other hand, behavior nodes

are most central, which points to the importance of providing adolescents in Colombia with possibilities to engage with sciences. Notably, behavior is often *predicted* by the other interest components in models using cross-sectional data, such as the PISA 2006 data (e.g., Ainley & Ainley, 2011; Lin et al., 2013), which may not do justice to the importance of behavior within the interest structure.

Moreover, as indicated in the study by Ainley and Ainley (2011), knowledge seems to play a different role within science interest across countries, a finding we replicated in our country comparison. Knowledge was only sparsely connected to the other interest-related variables in the Colombian SINM, with edges connecting knowledge nodes to self-efficacy nodes being stronger in the Dutch than the Colombian SINM. Interest in higher income countries, such as Sweden, or, in our case, the Netherlands, is grounded on a solid knowledge base; this does not seem to be the case in lower income countries, such as Colombia (Ainley & Ainley, 2011). Fewer opportunities for participating in science activities and less access to good education in Colombia may be the reason for this difference.

Limitations and Future Research

With the current article, we have introduced a theoretical model of science interest that provides a formal account of science interest as a dynamic relational construct, and we present a first test of the SINM. Our results should be interpreted with care, considering the following limitations. First and foremost, as the current study served as a first test of the SINM, it relied on cross-sectional data. All results should thus be seen as a first indication of the dynamical structure of interest development. We can therefore not make any reliable conclusions about the direction of relations between indicators of components (in SINM modeled as mutual interactions) and principles of interest development in individual cases (Krapp, 2002). The network approach does, however, provide us with tools that allow for the analysis of time-series data, enabling us to model intraindividual dynamical structures as well as between-subjects differences, if the time-series data include several individuals (Epskamp, Waldorp, Möttus, & Borsboom, 2018). Showing that the network approach is suitable for the representation and analysis of interest as networks, the current paper paves the way for future studies using the psychometric network approach to further investigate the dynamics of interest development. Especially the possibility to model the development of interest within and between individuals may be beneficial, as it may allow us to identify critical transitions between phases of interest, as earlier done in the context of clinical psychology, in which critical slowing was shown to be a personalized early warning signal of depression (van de Leemput et al., 2014). This may provide a fruitful avenue for future research as a major challenge for psychological interest research lies in the identification of combinations of interest components indicative for the different levels of interest development (e.g., Ainley, 2017; Renninger & Hidi, 2011).

Second, we relied on the data of a large-scale project (OECD, 2016), meaning that we had to use the measures included within that project. While the PISA 2015 measures are constructed to fit a latent variable perspective, however, other indicators may

be more appropriate from a network perspective. In contrast to the empirically driven approach used to construct questionnaires in the latent variable perspective, a theory-driven approach to questionnaire construction should be adopted (see Borsboom, Mellenbergh, & van Heerden, 2004). As in attitude networks, it is of importance to assess all relevant indicators of the interest network instead of focusing on internal consistency (Dalege et al., 2016). On this note, especially the lack of a good measure of (personal) value has to be mentioned, which may explain why the indicators of value did not play an important role within the networks. Perceived value or importance plays an important role in many interest theories as value is thought to be one of the core components of interest (Ainley, 2010, 2017; Ainley & Hidi, 2014). Other motivational components might also play a crucial role in science interest, Lin and colleagues (2013), for instance, showed that in Taiwanese students who took part in the PISA 2006 assessment, self-concept was positively related not only with self-efficacy, but also with enjoyment and interest evaluations, all of which were significant predictors of engagement with the sciences; including self-concept items may thus be relevant.

Third, to be able to investigate the two science interest networks, we had to dichotomize the variables we used, which leads to a significant loss of information. Techniques need to be developed to handle continuous variables in important statistical tests. An extended discussion of the issue using binary variables can be found in (Dalege et al., 2016).

Additionally, as discussed by Krapp and Prenzel (2011), it is important to consider the difference in level of specificity of interest. Someone might be interested in one topic within physics (i.e., content), but not in physics, or the sciences, overall; as well as the context of learning. Although this was considered in the PISA 2006 data (OECD, 2006), where interest in learning science topics was measured using an embedded approach—interest-evaluation items were presented within the knowledge assessment—it was not in the PISA 2015 assessment (OECD, 2016). The items included in our analysis differed in their domain-specificity; the enjoyment, value and behavior items were assessing global interest in the sciences (e.g., “I enjoy acquiring new knowledge in science”), whereas the interest-evaluation and self-efficacy items were content-specific (e.g., “I am interested in: Biosphere”). For the knowledge items domain-specificity was not given because ability estimates were based on a collection of items on different topics. To obtain a more accurate representation of a science interest network, it would thus be important to take into account the level of specificity of interest.

Conclusion

Introducing the SINM in the current paper, we established that a psychometric network approach provides a formal account of science interest that agrees with a dynamic-relational perspective on interest development. Moreover, a psychometric network approach provides new statistical tools to analyze the structure and dynamics of science interest. In doing so, we were not only able to illuminate the structure of interactions between the different indicators in the science network for different groups of adolescents but could also make predictions about which indicators are of structural importance and as such worthwhile to test as potential candidates for intervention. The net-

work approach is thus sensitive to structural differences in the network structure across countries, but it is mostly stable across subgroups within countries. Structural differences not only have important theoretical implications but also practical ones, as they can indicate which indicators should be targeted in an intervention aimed at increasing science interest. Using a psychometric network approach is a promising way to study the dynamics of science interest development, especially as it can be applied to not only cross-sectional but also time-series data, thus allowing for the study of the development of interest.

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