Robust Relationships between Science Knowledge and Favorable Attitudes Towards Science and Scientists in the United States

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Abstract

People who know more about science are more interested in science and related fields and show more positive attitudes towards science and scientists. This covariation may be important for advocating the beneficial effects of continued science education in the American public. This covariance, however, may be confounded by methodological artifacts or share a common cause through general Cognitive Ability. Furthermore, the measurement properties of science knowledge have not been fully tested. We use data from the General Social Survey, a nationally-representative sample of American adults ($N = 1,543$) to tease these apart. We build a series of structural equation models, starting with a simple covariance structure and then adding in the effect of general Cognitive Ability on both science knowledge and attitudes and interests, moving to one that concurrently accounts for methodological problems like acquiescence bias. Here we show general Cognitive Ability has a strong predictive relationship with science knowledge ($\beta = .65-.79$), and a number of items are affected with acquiescence bias. We also show the science literacy items as a whole are not an ideal scale, but can become one by removing three items. Taking these issues into account, however, does not eliminate the positive relationship between science knowledge and interests in science, technology, space exploration, foreign policy, environmental issues, and having positive attitudes towards science and scientists (all β s $> .13$; all p s $< .03$). Eliminating possible methodological and common-cause confounds from the relationship is an important step towards warranting experimental tests.

Keywords: Intelligence; Science Literacy; Science Opinions; Scientists; National Representativeness

It is of the utmost importance to get people to believe in science—to accept vaccines, to understand biology, to understand climate changes. We need people to believe in and have a basic understanding of these problems. Although we don't know causal direction, we know that people with more scientific knowledge have more positive attitudes about science. People who know more scientific facts tend to show more interest in and have more favorable views towards science (e.g. Allum et al., 2008; Onel & Mukherjee, 2016; National Science Foundation, 2018; see also Rolfhus & Ackerman, 1996). Such connections could be used to argue in favor of expanding science education in American schools, as such an effort could make youths more interested in scientific careers and make the electorate more favorable towards funding and supporting scientific discovery (Miller & Pardo, 2000; Smith, 2003; Lee et al., 2005; Maher & Rabbani, 2014; Bainbridge, 2015; Besley, 2015; Johnson et al., 2015; Takahashi & Tandoc Jr, 2016).

One possibility, therefore, is boosting science literacy through a public education campaign could promote better attitudes towards science. Such a connection, however, requires scientific knowledge to have a causal effect on attitudes and interests. The evidence for such covariation claims, however, come from correlational studies. As such, methodological confounds and omitted variables could change the strength of evidence for making the leap from correlational evidence to causal claim.

There are, however, a couple of methodological problems to these connections. The common test of science knowledge has not been investigated strictly from a measurement perspective. The assessment of both science knowledge and science attitudes and interests rely on surveys. As such, they share a common format of questions and answers (e.g. word-based questions with common responses formats) that can cause a spurious covariance due to similarity

of format (Van Vaerenbergh & Thomas, 2012). Another cause for concern is acquiescence bias (Spector, 1987; see also He & Van de Vijver, 2013), the tendency for people to agree with statements regardless of their content. Such a person may ‘agree’ with the statement ‘I support NASA’ but, if asked, would agree with the statement ‘I do not support NASA’. As many science interest and attitude questions are given with agree/disagree responses and science knowledge questions with true/false responses, a covariance may occur simply through the tendency to acquiesce.

Another concern are the measurement properties of the science knowledge test itself. The test of science knowledge often used and explored here involves 11 questions that were not selected through any formal test designs procedure but instead were questions made up to understand whether someone could read a newspaper article about science. As we will see, not all of the items are adequate for anything close to this purpose.

Research has also not sufficiently investigated the possibility that the covariance of science knowledge and interest/attitudes towards science may be due to a common cause. The covariation may also be confounded by sharing a common cause, in this case general Cognitive Ability. Among the many reflections of general Cognitive Ability, the ability to retain and report stored information has a long history of being a central component (e.g. Binet & Vaschide, 1897; Binet & Simon, 1908). Any knowledge based questions requiring previous exposure, adequate storage, and retrieval on demand, will have in its process a covariance with the general Cognitive Ability of the individual (e.g. McGrew, 2009). Thus, science knowledge questions, asking about factual scientific statements involving the recall of previously exposed and stored information, will covary with general Cognitive Ability. Therefore, if more intelligent people also have more interest in science and show more positive attitudes towards science and scientists, the

covariation between knowledge and interests/attitudes may be entirely be due to a common cause.

To strengthen the case that future educational effort at increasing science knowledge is beneficial to addressing the world's problems, we need to shore up these methodological limitations. In this short report, we pre-register and target two such serious concerns in the predictive ability of science knowledge to interests and attitudes; acquiescence bias and confounded general Cognitive Ability. We use the 2018 data from the nationally-representative General Social Survey (GSS) of American adults to investigate the robustness of this covariance between science knowledge and interests and attitudes from acquiescence bias and general Cognitive Ability.

Methods

Data

Data were drawn from the GSS, a nationally-representative survey of American adults conducted biennially since 1972. For this short report, we only use the 2018 dataset, but in an exploratory analysis validate our procedure in previous years. This dataset contains 2,348 American adults. Only a subset of the participants were randomly assigned to receive the science knowledge items, only a subset received the general Cognitive Ability measure, and only a subset received the science interests and attitudes scales. Participants with missing data on all scales were excluded from this analysis ($N = 808$). Missing data within participants was modelled using Full-Information maximum Likelihood (Muthen & Muthen, 2019). Before the data was downloaded, the analysis plan and procedure was pre-registered at <https://osf.io/ubtyz>.

Measures

Science Knowledge

Science knowledge was measured by eleven items covering a range of science-based facts from physics, chemistry, evolution, geology, to astronomy. Participants who answered the question correctly were coded as 1, those answering incorrectly, saying they did not know, or giving no answer coded as 0. For the distribution of scores, see Figure 1.

Figure 1: Distribution of scores of the number of science knowledge questions gotten correct by a representative-sample of American adults in 2018 ($M = 5.95$, $SD = 2.39$).

Acquiescence bias.

Ten of the science knowledge questions are given with true/false responses, lending themselves to acquiescence bias. To account for this possible bias, we imposed a latent factor on just those ten items to represent a methods factor accounting for acquiescence bias. The other two items had open responses for the respondent and were not a part of the method factor.

Interests in Science

Interests in Science and related disciplines was measured by nine questions about participants' interests in different topics. All questions started by naming the topic, and asking: "...Are you very interested, moderately interested, or not at all interested?". Among the nine topics, four were included that follow the same format but are unrelated to science (international issues, farm issues, economic issues, and military policy). The distribution of the interests across the three response options (very interested, moderately interested, or not at all interested) can be seen in **Figure 2**.

Figure 2: Distributions of Americans' (N = 1,173) interest in different topics. Topics ordered by average strength of interest from least interested on top (agricultural & farm issues) to most interested on bottom (new medical discoveries).

Attitudes towards Science and Scientists

Attitudes towards science was measured with eight items. A confirmatory factor analysis showed the items held together adequately as stemming from a common factor (CFI = .92, RMSEA = .065; see Hu & Bentler, 1999); so subsequent analyses used this science attitudes factor as a dependent variable.² The items and their factor loadings can be seen in Table 1.

Table 1: Questions assessing attitudes towards science and scientists. 4-point Likert responses were 1 = Strongly Disagree, 2 = Disagree, 3 = Agree, 4 = Strongly Agree. Response options for the benefits/harm question were coded as 1 = Harm Greater, 2 = About equal, 3 = Benefits Greater).

Question	Responses	Factor loading
Scientific researchers are dedicated people who work for the good of humanity.	4-pt Likert	.827
Most scientists want to work on things that will make life better for the average person	4-pt Likert	.708
Even if it brings no immediate benefits, scientific research that advances the frontiers of knowledge is necessary and should be supported by the federal government	4-pt Likert	.597
Because of science and technology, there will be more opportunities for the next generation	4-pt Likert	.521
As far as the people running these institutions are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?	3 options	.479
Supporting scientific research, are we spending too much, too little, or about the right amount on supporting scientific research?	3 options	.402
People have frequently noted that scientific research has produced benefits and harmful results. Would you say that, on balance, the benefits of scientific research have outweighed the harmful results, or have the harmful results of scientific research been greater than its benefits?	See caption	.327
Science makes our way of life change too fast.	4-pt Likert	-.104

General Cognitive Ability

General Cognitive Ability was measured using the wordsum test. This test involves 10-items taken from a full 40-item vocabulary test (see Thorndike et al., 1927; Thorndike & Gallup,

² This was not part of the original pre-registration. This decision, however, does not alter the results of the analyses that follow.

1944). As vocabulary is among the highest loaded subtests from numerous batteries of intelligence subtests (Johnson et al., 2004), we use it as a proxy for general Cognitive Ability. The distribution of the manifest scores can be seen in Figure 3. As the items correlate highly with one another and fit well in a single-factor model (CFI = .994, RMSEA = .089), we use the latent factor as our measure of general Cognitive Ability in all subsequent analyses.

Figure 3: Distribution of scores of the number of vocabulary questions gotten correct by a representative-sample of American adults in 2018 ($M = 5.91$, $SD = 2.02$).

Analysis Plan

Our primary analyses proceeded in three stages. In the first stage, we created a latent variable for the science knowledge items, a latent variable for the science attitudes questions, a latent variable for the intelligence items, and the individual items of interest in science and other

fields. With this, we investigated the predictive validity of science knowledge on both interests and attitudes, conditioning general Cognitive Ability on interests and attitudes.

In the second stage, we regress the general Cognitive Ability factor onto not just the science attitudes/interests but also onto the science knowledge factor itself. This alters the interpretation of the science knowledge to attitudes/interests effect substantially. This analysis answers the question: what is the relationship of science knowledge specifically to science interests and attitudes, after removing variance attributable to general Cognitive Ability to recall and use facts?

In the third stage, we introduce the methods factor onto the true/false science knowledge items and build paths from that acquiescence factor onto the science attitudes and interests variables. This controls for the possible covariance that can be accounted for between items simply as a function of acquiesce.

Overall, this three-step analytic approach seeks to take a targeted look at the relationship between science knowledge and attitudes and interests in science, conditioning on both a methodological factor and general Cognitive Ability. We then engage in an exploratory analysis of improving the measurement of science knowledge both psychometrically and theoretically using only the available data in the GSS.

Results

Overall, we confirmed there is a significant relationship between science knowledge and both positive attitudes towards science and scientists and an interest in science (but not in discriminant fields), conditioning on general Cognitive Ability.

The first model showed the significant covariance between science literacy and positive attitudes towards science and scientists ($\beta = .486, p < .001$, 95%CI = .675 to .298), and interest in science ($\beta = .407, p < .001$, 95%CI = .541 to .274), interest in technology ($\beta = .412, p < .001$, 95%CI = .548 to .276), interest in space exploration ($\beta = .468, p < .001$, 95%CI = .608 to .329), and interest in international and foreign policy ($\beta = .25, p < .001$, 95%CI = .372 to .128) but not interest in any of the other discriminant fields (all other β s $< .13$; all other p s $> .06$). Furthermore, latent general Cognitive Ability also predicted positive attitudes towards international and foreign relations ($\beta = .229, p = .001$, 95%CI = .362 to .096) but not interest in any of the other discriminant fields (all other β s $< |.14|$, all other p s $> .07$). In addition, after conditioning on science knowledge, greater intelligence *negatively* predicted interest in attitudes towards science ($\beta = -.268, p = .002$, 95%CI = -.441 to -.096). This suggests a very specific role for science knowledge covarying with positive attitudes towards science. This analysis, however, does not test the crucial path of intelligence on science knowledge.

The second model, which now conditions general Cognitive Ability not just on the science interests and attitudes but also concurrently on science knowledge largely shows the same results. Importantly and as predicted, general Cognitive Ability is strongly related to science knowledge ($\beta = .787, p < .001$, 95%CI = .843 to .732). Thus, more intelligent people are better able to recall science-based information. Science knowledge, now after removing the variance attributable to general Cognitive Ability, still predicts positive attitudes towards science and scientists ($\beta = .486, p < .001$, 95%CI = .675 to .297), interest in science ($\beta = .408, p < .001$, 95%CI = .541 to .274), interest in technology ($\beta = .412, p < .001$, 95%CI = .548 to .275), interest in space exploration ($\beta = .468, p < .001$, 95%CI = .608 to .329), and interest in

international and foreign policy ($\beta = .25, p < .001, 95\%CI = .372 \text{ to } .128$), but not interest in any of the other discriminant fields (all other β s $< .13$, all other p s $> .06$).

Our third model adds in the methodological factor best described as acquiescence bias. This methods factor for acquiescence bias significantly predicted affirmative responses on two science knowledge items (both β s $> .37$, both p s $< .001$), significantly predicted *negative* responses on three science knowledge items (β s $< -.36, p$ s $< .003$), and was non-significant on four other science knowledge items (all p s $> .22$). Furthermore, this acquiescence methods factor did not itself predict positive attitudes towards science and scientists ($\beta = -.014, p = .916$), nor interest in science or any specific domain except for negatively predicting interest in space exploration ($\beta = -.219, p = .014, 95\%CI = -.393 \text{ to } -.045$; all other β s $< |.098|$, all other p s $> .34$). Despite this, science literacy, again absent general Cognitive Ability, still holds the same covariation with science attitudes and interests, also significantly predicting interest in environmental issues ($\beta = .139, p = .034, 95\%CI = .267 \text{ to } .01$; see Figure 4).

Figure 4: Structural model of science knowledge predicting interest in science, technology, space, international affairs, environmental issues, and having positive attitudes towards science and scientists, after conditioning on cognitive ability and acquiescence bias. Structural paths are weighted by their β coefficient. Dashed lines are negative in sign. Measurement paths are not weighted in the diagram.

Extending the Science Knowledge Scale

Latent variables are a standard psychometric approach to understanding covariance among items. Latent variables are predicated, however, on a number of crucial assumptions. Two relevant here are a) the latent variable represents a real underlying trait; and b) the latent variable causes the reflected manifest scores, so that a manipulation to the latent variable would lead to a change in the manifest outcomes (see Borsboom et al., 2003). When it comes to these assumptions for science literacy, both are dubious.

There is little chance there exists an underlying ‘science knowledge’ construct. The theoretical rationale behind science literacy is that it is something that can be increased through learning. Its measurement is not meant to tap an underlying ability to learn and remember (as in general Cognitive Ability), but is specifically about the *content* of the knowledge. Thus, teaching the manifest items increases the underlying ability, unlike something like general Cognitive Ability where teaching the content area would not increase the underlying ability (see Protzko, 2017).

That theoretical rationale is not represented in a latent variable approach—where there is no causal relationship from the manifest items to the underlying trait (see in Figure 4 the lack of causal path arrows from the manifest items upwards to the latent variable). To make this clear, teaching people about science increases their scientific literacy, but teaching them the answers to an intelligence test does not increase their underlying ability. Therefore, a typical reflective latent variable approach is inappropriate for modeling or conceptualizing science literacy.

One solution would be to use a standard summary score. Summary scores are the default approach used in most previous investigations. Two large assumptions underlie using summary

scores: 1) the items are unidimensional, 2) the items are equally good at informing the underlying construct. The first assumption can be tested with a Confirmatory Factor Analysis, the second can be tested by imposing a Rasch model on the items (note that both of these are still latent variable approaches).

The first assumption, that the items are unidimensional (represent only one underlying reason for their covariance) is only weakly tenable. Model fit shows a single factor to provide borderline adequate fit ($CFI = .883$, $RMSEA = .053$). The second assumption can be tested by imposing the Rasch requirement on the IRT parameters (equal loadings). Imposing this requirement resulted in significantly worse model fit ($\chi^2_{\text{difference}}(9) = 33.387$, $p < .001$), suggesting not all items are equal. Thus, a base summary score approach should not be used when assessing science literacy with these items as they are likely not unidimensional nor conforming to an equal informativeness assumption. It is possible to remove some misfitting items to improve this model and get the scale to one where a simply summary score would be more appropriate.

To improve the Rasch-informed model, we explored the modification indices. This showed three items to be particularly problematic (modification indices all above 12). Two items showed particularly low factor loadings in the 2-parameter model (boyorgirl = .371, solarrev = .35) while the third item showed a factor loading relatively high (condrift = .621). Furthermore, the two items with the poorest discrimination (provide the least amount of information) were the two items with poor factor loadings (boyorgirl = .412, solarrev = .375; all other item discriminations .52 - .802). Thus, a fruitful first step may be to drop these two particularly poor items.

Dropping the solarrev and boyorgirl items improved model fit to more acceptable levels (CFI = .934, RMSEA = .046), but imposing the Rasch model still showed a significant decrease in fit ($\chi^2_{\text{difference}} (7) = 17.092, p = .017$). Thus, if we wish to use an equally weighted summary score for science literacy, we should identify other misfitting items. By examining infit and outfit statistics (measures of the residuals), all items except one showed acceptable residuals in the Rasch model. The misfitting item was ‘hotcore’ (outfit = .674, infit = .83; below the recommended values of Wright & Linacre, 1994). Dropping this item meant that imposing the Rasch model onto the remaining items did not cause a significant reduction in model fit ($\chi^2_{\text{difference}} (5) = 9.586, p = 0.088$) and thus could be said to conform to a unidimensional, equally weighted model. Therefore, future investigations using simple sum totals of the science literacy items should consider only using the following items in the ‘refined science literacy’ scale (see Table 2).

Table 2: Rasch parameters form a shortened science literacy scale from the GSS. Note three items were dropped from the full set of items in order to create a scale that can metrically be used as a simple summary score.

Item	Difficulty	Outfit	Infit	Discriminations	Person-item Map
Condrift	-1.6	.79	.87	.32	
Earthsun	-1.13	.82	.90	.35	
Radioact	-.97	.89	.91	.33	
Viruses	-.08	1.02	1	.27	
Electron	.14	1.01	.98	.29	
Lasers	.23	.95	.95	.33	
Evolved	1.25	1.07	1	.25	
Bigbang	2.17	.78	.82	.27	

One possible concern over the creation of a refined science literacy scale used here is the problems with measurement fit were idiosyncratic and the decisions made would be ‘overfitting’ to the data. To examine this, we ran the analysis again, this time using the data from the 2016 administration of the GSS, instead of the 2018. This is likewise a nationally-representative sample using different participants. First, imposing the same Rasch model onto the full 2016 science knowledge items showed a significant reduction in model fit ($\chi^2_{\text{difference}}(9) = 75.704, p < .001$). Dropping the same items as in the 2018 data and imposing the Rasch model onto the data returned a model with good fit (CFI = .94, RMSEA = .04) conforming to the Rasch criteria

($\chi^2_{\text{difference}}(5) = 4.591, p = .468$). Thus, the refined science knowledge scale from the 2018 data was not overfitting and can be replicated in independent samples.

Re-running our previous model now using the refined science literacy scale allows for a more psychometrically sound investigation of the role of science knowledge, now captured as an unweighted sum of a Rasch-derived scale, has for predictive ability on interest and attitudes towards science—after accounting for general Cognitive Ability on attitudes/interests and on science knowledge.

This analysis shows what was largely seen before. There is a strong relationship between general Cognitive Ability and science knowledge, such that smarter people are more knowledgeable ($\beta = .648, p < .001, 95\% \text{CI} = .673 \text{ to } .623$). Furthermore, general Cognitive Ability still predicted interest in science ($\beta = .162, p = .003, 95\% \text{CI} = .268 \text{ to } .057$).

Science literacy, now using our refined scale and conditioned on general Cognitive Ability, still shows its incremental predictive effects on interest in science ($\beta = .254, p < .001, 95\% \text{CI} = .339 \text{ to } .169$), technology ($\beta = .243, p < .001, 95\% \text{CI} = .33 \text{ to } .156$), space exploration ($\beta = .281, p < .001, 95\% \text{CI} = .365 \text{ to } .198$), and international relations ($\beta = .155, p < .001, 95\% \text{CI} = .235 \text{ to } .076$). Furthermore, people with more science knowledge, conditioned on their level of general Cognitive Ability, also hold more favorable views towards science and scientists ($\beta = .157, p = .001, 95\% \text{CI} = .252 \text{ to } .063$; see Figure 5). Thus, there may be something to increasing science knowledge for increasing the interests Americans have in science.

Figure 5: Structural model of science knowledge predicting interest in science, technology, space, international affairs, environmental issues, and having positive attitudes towards science and scientists, after conditioning on cognitive abilities. Structural paths are weighted in this display by their β coefficient. Measurement paths are not weighted in the diagram.

Discussion

Summary

In this brief report, we investigated the potential confounded relationship between science literacy and holding positive attitudes towards science and scientists, as well as being interested in scientific and science-related fields. Our two main confounds were general Cognitive Ability and a methodological complication of acquiescence bias. We also worked to investigate and improve the methodological quality of the science knowledge questions commonly used.

We found a strong relationship between general Cognitive Ability and science knowledge, with the strongest structural path being latent Cognitive Ability predicting science literacy. This is unsurprising, given general Cognitive Ability is theorized to be content neutral and simply manifests wherever (among other things) the recall of previously learned material is necessary (e.g. Cattell, 1944). That science knowledge continues to predict science attitudes and interests over the effect of general Cognitive Ability helps lead credence to the view that there is something important about science literacy alone.

Past studies with similar findings

Few studies have looked at the relationships between science literacy, general Cognitive Ability, and science attitudes and interests as we have here. One study found the connection with general Cognitive Ability and science literacy, but did not connect it with science attitudes and interests (Wallick, 2012). Other studies have found science literacy positively predicts interests and funding decisions towards NASA and spaceflight, but without taking into account general Cognitive Ability (Smith, 2003; see also Bainbridge, 2015). Furthermore, previous work has shown a relationship between science literacy and science interests, but again without the

necessary controls of general Cognitive Ability on both knowledge, attitudes, and interests (Miller & Pardo, 2000; Lee et al., 2005; Maher & Rabbani, 2014; Besley, 2015; Johnson et al., 2015; Takahashi & Tandoc Jr, 2016). Thus, as general Cognitive Ability is important to scientific literacy as well as interests and attitudes, our work helps clarify the specific role of science knowledge on its own has with these desirable outcomes.

Furthermore, investigations of science literacy normally uses a summary score of all the items. We showed such endeavors to be flawed by the poor psychometric and theoretical properties of the science knowledge items. The refined science literacy scale presented here, simply the same items dropping the three psychometrically poorest ones, has the desirably theoretical and psychometric properties, covaries largely with general Cognitive Ability (as predicted), and still shows incremental predictive effects on science interests and attitudes. Thus, future investigations into science literacy should use this sub-set of items identified here in a summary score approach.

Science Knowledge

Here we also investigated the 11 science knowledge items for the quality of their measurement properties. Although some of the assumptions of true reflective measurement are untenable, we found that the test could be treated as an adequate formative measurement model if three items were dropped. The resulting 8-item refined science literacy scale can be used with all of the current available data and future GSS data collection can also rely on the refined scale. We suggest all future investigations into science literacy use this refined scale.

Limitations, Implications for theory and real-world applications

We can now see that a scale with better measurement properties can be made from the existing data, and that covariance between science knowledge and positive interests and attitudes towards science is not confounded by either methodological factors nor a plausible common cause. This can strengthen the case that science knowledge is an important aspect to an educated populace and there can be societal benefits from policy initiatives aimed at increasing science knowledge. A number of limitations, however, still remain.

From a measurement perspective, we were able to investigate and improve the measurement of science knowledge through an investigation of the conformity of the science knowledge items to a Rasch model. A Rasch model, however, is still an extension of a latent variable model, which is grounded in the assumption that there is a latent ‘science knowledge’ being measured. As this is not a tenable assumption by the arguments above, an even more theoretically sound method forward could use this refined science literacy scale with a measurement model reflecting the theoretical position that directly teaching someone the content *should* increase the underlying construct of interest. This is the assumption of causal formative indicators (Bollen & Diamantopoulos, 2017).

The problem with analyzing this data using the most theoretically-consistent formative model would be the inability to aggregate the evidence across cohorts. An aspect of causal-formative indicators is that when weights change from study to study (or in the case of the GSS, from cohort to cohort) technically the interpretation of the formative indicator is not consistent. Meaning, if a given item such as ‘antibiotics kill viruses as well as bacteria’ loads onto a formative ‘science knowledge’ factor in 2018 at .7 but in 2020 at 1.2, the formative indicator is not technically measuring the same thing from year to year. This phenomenon is called ‘interpretational confounding’ (Howell, Breivik, & Wilcox, 2007) and, especially across studies

or cohorts as in the GSS, should be reason enough not to use such approaches (see also Edwards, 2011; Markus & Borsboom, 2013). Thus, as the modeling is less accessible and the use of our refined scale here is psychometrically and theoretically sound, we propose future research use the simpler refined science knowledge scale here.

Finally, future work should investigate the tenability of a formative model through interventions aimed at increasing science knowledge through teaching the content of these items to see if any change in science interest/attitudes emerges. Furthermore, general interventions aimed at increasing all science knowledge can also be informative to the direction of causality.

Conclusion

While an easy interpretation of the results here could be science knowledge *causes* interests in and positive attitudes towards science, the reverse may be equally true. It may be that being more interested in science and having more positive attitudes towards science and scientists causes one to have more science knowledge. This could be through a selective exposure effect where people who are more favorably interested in science go to science museums, talks, read books, engage with information increasing their exposure to scientific knowledge (e.g. gene by environment interactions: Scarr & McCCartney, 1983; see also Tucker_Drob et al., 2014; Tucker-Drob, 2017). Additionally, people who are more interested in a topic are better able to remember newly-learned information relevant to that topic (e.g. O'Connell & Greene, 2017), which could also explain the covariance. What is needed is establishing exogenous effects on science knowledge or science interests and attitudes to see which direction causality may be operating. The work here represents a strong next step forward

towards building a knowledge of the role of science literacy, general Cognitive ability, and interests and attitudes towards science.

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