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Causal or spurious? The relationship between knowledge, attitudes, and trust in science and technology.

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1. Introduction:

According to Giddens (1990), trust in systems (e.g., economic, legal, political and scientific systems) implies faith “in the correctness of abstract principles” such as technical knowledge. Both Giddens (1990) and Luhmann (1988) have argued that trust has transformed as a consequence of modernity. In pre-modernity, trust predominantly involved face-to-face communication between two well-acquainted individuals. In modernity, people trust abstract expert systems (Giddens, 1990; Luhmann, 1988), wherein “Trust . . . takes the form of *faceless commitments*, in which faith is sustained in the workings of knowledge of which a lay person is largely ignorant” (Giddens, 1990, p. 88). According to Luhmann (1988), trust is required in order for these expert systems to function and “stimulate supportive activities in situations of uncertainty and risk” (p.103).

Science is an expert system that traditionally has sustained high levels of public trust. By "trust", in this context, we mean the public's willingness to be vulnerable to the actions of the designers, creators, and operators of science on the expectation that they will behave in a way beneficial to the public. We also include the public’s willingness to be vulnerable to scientific methods, findings, recommendations and technologies because the public anticipates that the outcome will be positive. Due to the public’s high levels of scientific trust, science has had a large impact on society through the adoption of new technologies, which ideally minimise uncertainty and risk (Giddens, 1990). In 2000, however, the U.K. House of Lords Select Committee on Science and Technology raised concerns about a crisis of scientific trust. In light of this anxiety about declining scientific trust, it has become increasingly important to understand the factors that shape trust in science. The study reported here used data collected in the Western Canadian province of Alberta and structural equation modeling to help infer the causal relationships between trust in science and technology, a set of mediating variables dealing with scientific knowledge and attitudes toward science, and background demographic variables that lead to their development.

2. Background

2.1 The knowledge agenda

In 1985, the U.K. Royal Society released an influential report called *The Public Understanding of Science* (Bodmer, 1985). The report declared that the public's interest and support for science were dwindling, and it identified the public's deficit in scientific knowledge as the root of the declining interest and support. The author of the report, Sir Walter Bodmer, therefore advocated for improvements in the public's scientific knowledge, which he believed would directly lead to improvements in public attitudes towards science. In response to this agenda, a large body of research emerged examining the public's levels of scientific knowledge as well as their scientific attitudes.

Scientific knowledge – The majority of research on scientific knowledge dealt with objectively measured knowledge which relies on test items that are marked right or wrong (e.g., True/False items). These test items are typically based on content taught in primary and secondary school. In line with 1985 Royal Society Report, a number of studies raised concern about the low level of science knowledge the public holds (e.g., Bauer, Durant, & Evans 1994; Bauer, 1996; Bauer, Petkova, & Boyadjieva, 2000; Durant, Evans, & Thomas, 1989; Hayes, 2001; Miller, 1987, 2004; European Commission, 2005). Several factors have been shown to have a small but significant effect on the amount of knowledge adults hold, including formal education, age, gender, socio-economic status (SES), and community of habitation (Bauer, 1996; Bauer et al., 2000; Durant et al., 1989; Einsiedel, 1994).

While objectively measured knowledge shows what participants actually know, perceived knowledge is participants' perceptions of what they know. Research examining the correlation between perceived and objectively measured knowledge can be found mainly within the field of consumer research. The correlation between perceived knowledge and objectively measured knowledge falls between .30 and .60 (Cole, Gaeth, Chakraborty, & Levine, 1992; Feick, Park, & Mothersbaugh, 1992). Members of the public often overestimate what they know (Alba & Hutchinson, 2000; Ellen, 1994; Feick et al., 1992). Given the weak to moderate correlations between these constructs it is reasonable to view them as related but somewhat different from each other (Klerck & Sweeney, 2007).

Attitudes toward science – Whereas trust implies a willingness to be vulnerable, we take attitudes to be judgments of worthiness or favourableness. Research suggests that the public tends to hold positive attitudes towards science and technology in general (e.g., European Commission, 2005; Miller, 2004; Office of Science and Technology and The Wellcome Trust, 2001). Public attitudes toward science and technology vary according to demographic variables such as gender, education, income, and age. Individuals with positive attitudes toward science tend to be more educated, from a higher SES, and male (Einsiedel, 1994; Hayes, 2001; Hayes & Tariq, 2000; Office of Science and Technology and The Wellcome Trust, 2001).

2.2 The trust agenda

In light of the large amount of research dedicated to scientific knowledge and attitudes, it is not surprising that studies emerged that challenged the premise of the knowledge agenda. For example, Evans and Durant (1995) used survey research in Britain to demonstrate that high levels of scientific knowledge did not always translate into support for science. They found that, although knowledgeable individuals might be more likely to support basic science (r=0.31), they were less likely to support morally contentious scientific research (r=0.07), such as human embryology. Wynne's (1996) qualitative study on Cumbrian sheep farmers in the aftermath of the Chernobyl radioactive disaster, also was used to question the proposition that low levels of scientific literacy result in negative attitudes toward science. Wynne showed that the Cumbrian farmers were unwilling to support the expert advice of experts, not because they had low levels of scientific literacy, but rather because they did not trust the scientists.

Wynne's research championed earlier theoretical concerns about a crisis of trust in science. For instance, Beck (1992) argued that as we enter late modernity (or what he called "risk society") technological "hazards and potential threats have been released to an extent previously unknown" (p.19). In light of the overwhelming nature of risks in late modernity, society becomes a reflexive modernization – people reflect on and begin to question their trust in science because they recognize its fallibility. Similarly Habermas (1989) also raised theoretical concerns over a crisis in trust, which he referred to as a "legitimacy crisis." However, Habermas's legitimacy crisis was not caused by people's recognition that science is fallible, but rather by the way that institutions like science monopolize knowledge production.

In response to academic concerns about diminished trust in science, the U.K. government released a report in 2000 that officially declared a crisis of trust in science. The report (House of Lords Select Committee on Science and Technology, 2000) delegitimized the knowledge agenda by suggesting that trust, as opposed to low levels of scientific literacy, was at the heart of the public's low level of support for science. Consequently, "trust in science has become a major policy concern internationally" (Bates, Faulkner, Parry, & Cunningham-Burley, 2010, p. 703) and trust studies have emerged as the new academic agenda.

Consistent with our definition of trust as a willingness to be vulnerable, Earle (2010) defined trust as the willingness to take a social risk and accept on faith that an individual or institution has the intention of acting in your best interest. He differentiated trust from the closely related concept of confidence. Earle (2010) argued that trust is about evaluating another's intentions, whereas confidence involves evaluating another's past behaviour and abilities. This experience-based evaluation allows for much more certainty than is possible with trust, because trust is grounded in a reliance on the intentions of another party. According to Midden and Huijts (2009), "trust becomes the basis of decisions at the point when other assurances are not available and (experience-based) confidence is lacking" (p. 744).

Scientific social trust –The literature on scientific trust primarily focuses on trust in experts (e.g., scientists, environmentalists or business leaders), organizations and institutions. This type of trust is referred to as social trust. Siegrist, Cvetkovich and Roth (2000) define social trust as "the willingness to rely on those who have a responsibility for making decisions and taking actions related to the management of technology, the environment, medicine or other realms of public health and safety" (p.354). The literature on scientific social trust is structured around three key questions: 1) Is there a crisis of trust in scientific experts, organizations or institutions? 2) Does increased social trust lead to increased willingness to accept scientific technologies? and, 3) What are the factors that influence people's trust in scientific experts, organizations and institutions?

A review of existing survey data suggests that whether or not there is a crisis of social trust depends on the definition of trust, object of trust, type of survey conducted, questions asked and the country studied (e.g., Allum 2007; Barnett, Cooper, & Senior, 2007; Cobb & Macoubrie, 2004; Gaskell et al., 2006). As for whether or not trust plays a role in the acceptance of a technology, several studies posit an indirect relationship between social trust and public acceptance for technology (e.g., Flynn, Burns, Mertz, and Slovic, 1992). Siegrist (2000) used structural equation modeling on survey data to show that people's trust in gene technology institutions or people doing genetic modification moderately affected people's perceived risk (β=-.46) and benefit (β=.44) of the technology, which subsequently determined people's uptake of the technology (-.23 and .60 respectively). Other studies, however, identified a direct relationship between social trust and public acceptance for technology (e.g., Critchley, 2008; Gaskell et al., 2001; Gutteling, Hanssen, van de Veer, & Seydel, 2006; Hornig Priest, 2001).

The third question that the literature explores is the variables that determine scientific social trust. Luhmann (1988) criticised the literature on trust for failing to specify "the social mechanisms which generate trust…" (p. 95). Since Luhmann's critique, social scientists have begun to elucidate not only the social, but also the cognitive and demographic factors that affect trust in a number of areas, including scientific social trust. Several research studies suggest that social trust is dependent upon multiple factors (e.g., Frewer, Howard, Hedderley & Shepherd, 1996), and Wynne (1996) argues that the multiple factors are likely to vary from one situation to another. For example, Peters, Covello and McCallum (1997) used survey data to explore the general public's perception of trust for the experts involved in environmental science – the chemical industry, the U.S. Environmental Protection Agency, and environmental groups. They found that trust and credibility are based on three factors: 1) perception of knowledge and expertise; 2) perception of openness and honesty; and 3) perception of concern and care. The salience of the factors varied according to the group of experts involved. For example, a perception of increased concern and care is most likely to improve people's trust in industry; a perception of increased knowledge and expertise is most likely to increase trust associated with environmental groups. Critchley (2008) conducted telephone interviews with Australians and used covariance structure analysis to map variables that affect trust in stem cell scientists. She found two factors impacted trust: 1) belief that the scientists were motivated by benevolence (β=.30), and 2) belief that the benefits of the research would be accessible to the general public (β=.26).

Trust in generalized science and technology, and trust in specific technologies – Although most literature on scientific trust addresses social trust, our study diverges from these studies by examining two other forms of scientific trust – trust in generalized science and technology, and trust in specific technologies. The distinction between these two forms of trust is important because Michael (1992) found that lay discourse about science is structured around discussions of science-in-general and science-in-particular.

Our definition of trust in generalized science and technology (or what we referred to as "trust in science and technology" for this study) includes making oneself vulnerable to the uncertain outcome that science and technology will lead to the positive outcomes one expects. Trust is placed not only in scientific actors and organizations, but also in scientific methods, findings, recommendations and technologies. An example of a study that examines trust in generalized science and technology is Einsiedel's (1994) research. She applied structural equation modeling to survey data on Canadian adults and concluded that "scientific literacy was positively correlated with attitudes of trust" in science (p.35). Organization of the variables in her model was based on theoretical work in psychology suggesting that the cognitive structures or schemas people have about a subject can influence their affect towards that subject. Einsiedel explored the knowledge-affect link by modeling knowledge as the antecedent variable that influences the development of attitudes and trust. Her study showed that the higher a person's scientific literacy, the more likely the person is to place trust in science (β=.60).

Our definition of trust in specific technologies involves a willingness to makes oneself vulnerable to specific products of science, such as genetically modified food and nuclear power. Studies that deal with specific technologies tend to investigate acceptance and support for these technologies (e.g., Critchley, 2008; Gutteling et al., 2006), rather than looking at whether people trust them in the sense we have defined.

2.3 Our agenda

Our study brings together both the knowledge agenda and trust agenda of the last 25 years, by exploring the relationship between knowledge, attitudes, and trust. The goal of our study was to understand how knowledge and attitudes work together to shape trust in science and technology. In particular, our research answers the following four questions:

1. Do educational level, age, gender, income, and size of community play a role in developing perceived knowledge of and attitudes towards science?
2. Does perceived knowledge of science affect trust in science and technology?
3. Does an attitude that science improves quality of life and an attitude about personal attachment to science affect trust in science and technology?
4. Does a trust in generalized science and technology affect trust in specific technologies; does trust in specific technologies affect trust in generalized science and technology?

Although previous studies have explored factors that affect trust in science, our study is unique in that it relates both people's attitudes and what they think they know about science to their trust in science and technology. Furthermore, although the literature does contain reports that, for example, there are gender or educational differences in scientific attitude, no study has taken into account as many mediating variables between demographic factors and trust as we have here. The significance of adding additional variables is that it allows a test of whether scientific knowledge is truly causal of trust in generalized science and technology, as Einsiedel's (1994) evidence appears to show, or merely spurious – that is, related to trust in science only insofar as it is related to other variables that are causally related to trust.

3. Method

3.1 Sample

The data were collected in an internet-based survey conducted by Ipsos Reid Public Affairs[1] in 2006 and commissioned by the Science Alberta Foundation to investigate awareness of, and support for, science in Alberta, Canada. Potential participants first were contacted by telephone based upon a stratified random sampling protocol developed by the research agency. When contacts agreed to participate they were directed to the internet site housing the questionnaire. The data had been cleaned by Ipsos Reid and most of the demographic data categorized prior to our obtaining them.

A total of 1217 participants (615 females; 602 males) were recruited to complete the online survey. Seven age ranges were defined from 12-17 to 65+ years and coded from 1 to 7. The mean age of the participants was in the age range of 25-34 years (M=3.66, SD=1.69). Almost one-fifth of participants were younger than 18 years old (17.6%), with 8.1% in the 18-24 range, 18.3% in the 25-34 range, 19.1% in the 35-44 range, 21.1% in the 45-54 range, 15.1% in the 55-64 range, and less than 1% were over 65 years of age.

Education was coded on a scale from 1 to 8, from primary school or less to university graduate degree, respectively. The average education level of the participants was some community college or trade school (M=4.74, SD=1.65). A little more than one-quarter of the sample had a high school education or less (26.7%), 24.7% had at least some community college

[1] Ipsos Reid is one of the world's leading organizations specializing in survey research. The authors obtained the data for this study directly from Science Alberta Foundation. Detailed information about Ipsos Reid's sampling design including stratification variables and potential attrition of the sample between the phone and internet stages were not made available with the data set. It is reasonable to assume that Ipsos Reid's sampling procedure was completed in line with the intent to generalize the results across Alberta only.

or trade school education, 14.3% completed community college or trade school, 15.4% had some university education, 14.0% completed an undergraduate degree, and 5.0% possessed a graduate degree.

The average income of participants was in the range of $55,000-$59,999 per year (*M*=10.62, *SD*=3.93), with salaries of under $10,000 to $150,000 or more per year coded from 1 to 16. Approximately one-quarter of the sample earned $44,999 or less per year (25.6%), a third earned between $45,000 and $80,000 per year (33.6%), 26.5% earned between $80,000 and $120,000 per year, and approximately 15% of the participants earned over $120,000 per year.

Community size was coded from 1 to 6 with participants living in communities that have fewer than 1,499 people to living in large urban centers with populations near 1,000,000. The average community size was in the range of 100,000-499,999 (*M*=3.90, *SD*=1.35). One-fifth of the participants resided in communities with a population fewer than 10,000 (20.4%), 22.4% lived in areas with populations between 10,000 and 99,999, and a little over half of the participants (57.2%) lived in a community with a population between 500,000 and 999,999.

3.2 Questionnaire

The questionnaire was composed of eight subsections: Science and Technology Interest and Knowledge, Science and Technology in Alberta, Science Education in Alberta, Science Careers, Communication and Information Needs, Science Alberta Foundation, Attitudes Towards Science and Technology, and Demographics. The total number of lead items on the questionnaire was 47, and the majority of these contained multiple sub-questions designed to further explore the reasons behind a participant’s response to the lead questions. Not all items and subsections were used in our analysis. Items from five of the eight subsections were extracted from the survey data for analysis: Science and Technology Interest and Knowledge, Science and Technology in Alberta, Science and Education in Alberta, Attitudes Towards Science and Technology, and Demographics. A copy of the original survey instrument can be made available by contacting the fourth author.

Science and technology interest and knowledge – From this subsection, seven items were selected that were designed to measure participants' perceived level of knowledge of both science and technology topics. Unlike items designed to objectively measure science knowledge, these questions were worded in such a way that participants evaluated what they believed to be their levels of knowledge on science topics (see Table 2). Participants were asked to rate their levels of perceived knowledge on seven scientific topics using a 4-point Likert scale from 1 (very informed) to 4 (not at all informed).

Science and technology in Alberta – Seven items were selected from this subsection, which asked participants to rate the importance of science and technology in seven key areas of Albertan life using a 4-point Likert scale from 1 (a great extent) to 4 (not at all).

Science and education in Alberta – Six items were selected that were designed to assess participants' attitudes towards science classes taken either currently or in the past. These items asked participants to respond to six statements regarding attitudes toward science classes. For example, participants were asked to rate the statement, "I think everybody should learn science at school," on a scale of 1 (strongly agree) to 4 (strongly disagree).

Attitudes towards science and technology – Twelve items were selected from this subsection for analysis. This subsection comprised two sets of items designed to assess participants' agreement with a series of statements about science and technology. One set of statements assessed participants' agreement with general science matters and the other set of statements assessed agreements with contemporary science matters and science applications. Participants were asked to rate their level of agreement with each statement on a scale of 1 (strongly agree) to 4 (strongly disagree). We note that although the survey labeled the subsection from which these items were chosen as "attitudes towards science and technology," the items fit better with our category of trust, a judgment we shall defend in the section on the factor analyses we conducted.

Demographics – The following participant information was collected: year of birth, gender, age, marital status, number of children under the age of 18 living in the household, level of education, employment status, income, region of Alberta, and community size. Five items were selected from the Demographics subsection: gender, age, level of education, level of income, and community size of current residence.

3.3. Procedure

Exploratory factor analysis of selected items – Ipsos Reid used a conceptual procedure to name the subsections of its questionnaire and to group items under them. We employed exploratory factor analyses (EFA) in order to gain a clearer understanding of the data set, to test Ipsos Reid's conceptual structure against the empirical data, and to eliminate any items that resisted interpretation as empirically coherent parts of the larger body of items. The EFA were completed using SPSS 16.0 (SPSS Inc., 2008a). The potential range of number of factors using Principal Components extraction, Scree test, and Image Analysis was used as input for specifying the number of factors for EFA using MINRES extraction with Varimax rotation. Oblique transformations were not considered because the primary purpose for conducting the EFA was to ascertain an estimate of the factor structure for use in subsequent structural equation analyses. The criterion of simple structure, in which most variables load onto only one factor, was used to select the final factor solution. Items that loaded onto more than two factors or demonstrated inconsistent behavior with factor loadings from one analysis to another were judged to have too complex a nature for interpretation and thus were removed from subsequent analyses.

Construction and analysis of the structural model – After determining the factor structure, the factors and their respective items were organized into a structural equation model to investigate the causal relations among the variables of interest. Structural equation modeling enables the test of effects of variables within a theoretical model against data. The causal arrangement of variables within a model implies a pattern of correlations among the variables in the data set when the model fits the data. Although, structural equation modeling is not the same as conducting experiments, the accepted terminology to communicate findings includes the use of words such as “cause” and “effect”.

Structural equation modeling analysis was completed using AMOS 16.0 (SPSS Inc., 2008b) with maximum likelihood estimation to test both measurement and structural models. The data input for the structural equation analysis was a variance-covariance matrix created with pairwise deletion from the original data set (N=1217) using SPSS 16.0. A sample size of n=698 was specified for the pairwise variance-covariance matrix, which corresponds to the N obtained with a listwise deletion of missing cases from the original data set (resulting in complete data on those 698 participants). This approach kept the maximum amount of usable data and an appropriate sample size for statistical testing. The smaller sample size resulted in a less conservative test because it made it less likely to reject the null hypotheses of perfect fit between the hypothesized structural model and the data.

Assessing model-to-data fit – Several indices were available to assess the adequacy of model-to-data fit for both measurement and structural models. Hu and Bentler (1999) have stated there are two sources of information for assessing model-to-data fit: *structurally* using component statistics and *overall* using global indices. Structurally, path coefficients are tested for statistical significance using a *t*-test statistic and the estimated standard error. The *t* statistic is used to test the null hypothesis that the population parameter for the path coefficient is equal to zero. Globally, the null hypothesis tested is that the specified model provides an exact fit to the observed data (the variance-covariance matrix). There are several test statistics available to assess global model-to-data fit. The *chi-square* is the most widely known test statistic. However, its value is sensitive to sample size, because a fit no matter how close can be rejected with a sufficiently large sample, and a poor fit can be accepted with the choice of a small enough sample. Other goodness-of-fit indices have been proposed to address the dependency of the *chi-square* test on sample size. Byrne (2001) has suggested using the ratio of the *chi-square* value to the degrees of freedom as a better indicator of model-to-data fit, with values less than 3 indicating good fit (Kline, 1998). Four other goodness-of-fit indices most frequently used are the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), the root mean square error of approximation (RMSEA), and the root mean square residual (RMR). Values between .90 and 1 are desirable for the GFI and AGFI (Byrne, 2001). The RMSEA is a measure of fit that estimates the error in how well the model accounts for variances and covariances in the *population* using sample data. Values ≤ .05 indicate close fit, values up to .08 indicate reasonable fit, and values > .10 indicate misfit (Browne & Cudeck, 1993). RMR takes the mean of the residuals between the model-implied and observed covariances. RMR values ≤ 0.05 indicate good model-to-data fit.

The availability of numerous model-to-data fit indices and suggested cut-off values for goodness of model fit suggest that the six global indices be considered together. Ideally, the model should minimize the *chi-square* to degrees of freedom ratio, RMSEA, and RMR, while maximizing GFI and AGFI values.

4. Results

4.1 Exploratory factor analysis

Simple structure was achieved with five, six, and seven factor solutions. The six and seven factor solutions allowed the item sets to emerge as separate factors. Items associated with each of the seven factors were inspected and assessed for meaning. Five of these factors corresponded to our variables of interest and were partitioned from the original data set and a new data set created for further analysis. The final five factors included in the analysis were labeled perceived science knowledge, attitudes–quality of life, attitudes–personal attachment to science, trust in science and technology, and trust in specific technologies. The factors and their respective reliabilities are provided in Table 1. Given the small number of items measuring each factor, the reliabilities are respectably high except for the case of trust in specific technologies. The items corresponding to each factor are contained in Table 2. The two additudinal factors include items that ask participants to make judgments of the worthiness and favourableness of science and science learning. Naming the factors as additudinal is consistent with our conception of attitudes towards science supplied previously. The two trust factors also are named consistently with our conception of trust. Both factors contain items that assess participants' willingness to make themselves vulnerable either to science and technology in general or to specific outcomes of science and technology.

4.2 Measurement model

All latent variables were correlated with each other to assess whether the measurement model was an acceptable fit to the data. The fit for the measurement model was acceptable, with the following global fit indices: $\chi^2(598, N=698)=1235.81$, $\chi^2/df = 2.10$, GFI = 0.90, AGFI = 0.88, RMSEA = 0.04 (90% confidence interval [CI] = 0.037, 0.043), and RMR = 0.04.

Examination of the path coefficients revealed that all measured variables loaded onto their respective latent variables ($p < .001$) and their standard errors were appropriately small (see Table 3). All correlations among the five latent variables were statistically significant at $p < .001$, except for the correlation between attitudes–quality of life and trust in specific technologies, which was statistically significant at $p < .05$. Given the acceptable fit of the measurement model to the data, no changes were made to the model to improve fit prior to the structural model analysis.

Figure 2 illustrates the measurement models with standardized path coefficients. Path coefficients of the seven measured variables from the latent variable perceived knowledge were moderate to large in magnitude ranging from 0.52 to 0.70 with squared multiple correlations from 0.27 to 0.48. Path coefficient values of the measured variables from the latent variable attitudes–quality of life and the latent variable attitudes–personal attachment to science were, again, moderate to large in magnitude ranging from 0.47 to 0.76 and 0.44 to 0.73, respectively, with squared multiple correlations from 0.22 to 0.58 and 0.19 to 0.54.

Stronger indicators for the latent variable trust in science and technology compared to those with the variable trust in specific technologies were evident by more consistently large path coefficients. Path coefficient values for trust in science and technology were moderate at 0.40 to 0.64, with squared multiple correlations ranging from 0.16 to 0.41. In comparison, path coefficient values for two indicators of trust in specific technologies were low at 0.22 with the strongest indicator having a coefficient of 0.71. Squared multiple correlations ranged from 0.05 to 0.51.

4.3 Structural model

Figure 1 presents the structural model tested. Demographic variables were considered to be exogenous (i.e., to exert but not to receive effects and believed to pre-exist and to influence the development of attitudes and knowledge). The demographic variables selected for inclusion in the model (i.e., gender, age, level of education, income, and community size) are consistent with those used in previous studies investigating the relationships among knowledge, attitudes, and trust (e.g., Bauer, 1996; Durant et al., 1989; Einsiedel, 1994). It was assumed that each of the demographic variables would be correlated with each other but would not be related casually. Mediating endogenous variables (i.e., those that both receive and exert effects) were selected using the rationale that attitudes towards science and science knowledge likely form prior to trust (Einsiedel, 1994; Osborne, Simon, & Collins, 2003). Using this logic, the terminal endogenous variables were trust variables. In our model, each exogenous variable was hypothesized to exert direct effects on the three mediating variables. Trust in science and technology was hypothesized to receive direct effects from the mediating variables and indirect effects from the exogenous demographic variables. Trust in science and technology and trust in specific technologies were hypothesized to have causal effects on each other.

The reasons for hypothesizing this particular model are several. As we have previously shown, models providing evidence that scientific knowledge directly influences trust in science (e.g., Einsiedel, 1994) have been called into question by subsequent research on trust in scientific actors (e.g., Critchley, 2008; Wynne, 1996). Moreover, it can be inferred from other research that we have reviewed (e.g., Peters et al., 1997) that if knowledge has a role in creating trust in scientific actors it is not so much the knowledge of the one trusting that counts as it is the perceptions of the knowledge of the one trusted from the perspective of the one trusting. The question therefore arises: What sort of structure would allow knowledge of those trusting to appear to have an effect on their trust when it does not? The structure is one in which knowledge is related to another variable that itself causes trust. If this latter one is the proper structure, then placing that other variable in a model as a co-variate of knowledge should eliminate the perceived effect of knowledge. We have created such a structure in Figure 1 by using attitude variables as co-variates with knowledge.

The structural model was tested and the path coefficients among the latent variables in the model were estimated. The specified model provided an acceptable global fit to the data. The global fit indices obtained were: χ^2(604, N=698)=1476.14, χ^2/df = 2.44, GFI = 0.89, AGFI = 0.87, RMSEA = 0.05 (90% confidence interval [CI] = 0.043, 0.048), and RMR = 0.06. Eight structural paths among the latent variables were significant as indicated in Figure 1. Structural component indices revealed all measured variables retained statistically significant path coefficients from their respective latent variable.

The correlations among the following demographic variables were statistically significant at $p < 0.001$: education and income, education and gender, and age and gender. Education and community size, and gender and community size yielded correlations that were statistically significant at $p < 0.05$. The correlations among the remaining demographic variables were not significant.

We tested a reduced structural model that also showed an acceptable global fit to the data. In this reduced model, both attitude variables and the trust in specific technologies variable were removed from the analysis. The result was a model closely comparable to the one tested by Einsiedel (1994), the major difference being her use of objectively measured knowledge versus our use of perceived knowledge. The results are similar in interesting ways. Most notably, in the reduced model, we found a significant standardized path coefficient between perceived knowledge and trust in science and technology of .25, compared to a coefficient of .60 between objectively measured knowledge and trust in science found by Einsiedel and a coefficient of zero found by us in the non-reduced model (Figure 1). The comparisons show that, when attitudes are not considered, perceived knowledge behaves similarly to objectively measured knowledge and appears to cause trust in science and technology. When attitudes are in play, perceived knowledge has no effect on trust in science and technology, suggesting that the causal link between knowledge and trust found by Einsiedel (1994) is spurious – that is, that the proper analysis of the link between knowledge and trust is that knowledge is related to attitudes, which themselves are the direct causal link to trust. The basis for this interpretation is strengthened further because, in our dataset, the zero-order correlations between composite variables comprised of the items measuring perceived knowledge, and attitudes–quality of life and attitudes–personal attachment to science were: between perceived knowledge and attitudes–quality of life, r=.24, $p < .01$; between perceived knowledge and attitudes–personal attachment, r=.40, $p < .01$. Whether knowledge or perceived knowledge are causally related to attitudes was not tested by our model.

5. Conclusions

Prior to discussing our results, we identify two key limitations of our study that should be addressed in future research. First, this study embarked on a secondary analysis of data taken from a survey created by Ipsos Reid and commissioned by the Science Alberta Foundation. One could argue that a limitation of any secondary data analysis is the quality of the measurement instrument, such as reliability of certain scales and the subsequent validity of the interpretations. This limitation could be addressed in subsequent research studies if researchers create a measurement instrument specifically for testing the variables in the model. Researchers would then have greater control over the psychometric properties of the instrument through the wording of items and the designation of a certain number of items to measure each variable in the model.

Second, the data used for analysis were based upon a sample drawn from the province of Alberta, Canada. Generalization from our findings should therefore be made only to populations that share similar characteristics to Alberta (i.e., a society with higher than average incomes based upon strong industries in petroleum, manufacturing, farming, and tourism). Subsequent studies are needed to determine the extent to which our model and findings can be generalized across other geographic regions and populations. This could be accomplished by testing the model with random and representative samples from other regions of interest.

In spite of these limitations, our results show trust in generalized science and technology affects trust in specific technologies, but not vice versa. Therefore, it is entirely consistent to be distrustful of particular technologies and, at the same time, to be trusting of science as a whole. Our research also suggests that if scientists and policy makers want to improve the public's trust in a specific technology, they might first increase the public's overall trust in science and technology. In line with Frewer et al.'s (1996) belief that multiple factors affect the formation of trust, our research demonstrated two attitudinal variables that shape a person's overall trust in science and technology. While Einsiedel (1994) provided evidence of a causal connection between the development of knowledge and the fostering of trust, our study shows that this finding might rest on a failure to consider multiple variables that affect trust in science and technology. Based upon our results, what adults believe they know about science does not influence trust in science and technology once their attitudes are taken into account. However, as noted at several points in the paper, the knowledge variable used in our study was not objectively-measured knowledge, but rather participants' perceptions of their own knowledge.

Each variable has its own uses, and we have not strayed beyond the interpretations sanctioned by the variable we employed. The question of whether objectively-measured knowledge would behave the same way, however, is not definitively answered by our study, but could be answered by use of a similar model in subsequent studies.

Our model suggests that it is attitudes, rather than perceived knowledge, that lead directly to an increase in trust in science and technology, and the subsequent link to trust in specific technologies is also very strong. A hypothetical link between attitudes and trust is not difficult to draw. Attitudes as measured by the instruments in this study are expressed judgments of the worthiness and favourableness of science and technology. Trust is expressed in a willingness to allow oneself to be vulnerable to the actions of science and technology. If one judges science and technology more favourably, then it should not be surprising to also be more inclined to open oneself to the outcomes of science and technology.

The attitudes we have identified as important relate to a personal attachment to science, and also to the role of science in producing a higher quality of life. By examining the individual items that measured these attitudes, we see that individuals who believe that science has changed the way they view the world and the type of persons they are tend to trust science more. These are people who credit to science their curiosity and their ability to think critically. They are also people who see clear consequences flowing from science to improvements in quality of life and who are prepared at least to a degree to defer to the experts on matters of science policy. Indeed, it might be seen as a somewhat ironic, but nevertheless hopeful sign that part of what develops trust in science and technology are the very capacities that enable individuals to be more critical and sceptical of it. Perhaps this should not be surprising – people often rightly are suspicious of that which they cannot comprehend. Comprehension brings with it two capacities that might seem opposed but are not necessarily so, the one to critique and the one to appreciate.

While previous research has shown that gender, education, income, and age are determinants of public attitudes toward science (Einsiedel 1994; Hayes 2001; Hayes & Tariq, 2000), our research found that demographic determinants varied according to the type of attitude studied. For example, education and gender were the greatest predictors of attitudes of personal attachment. Highly educated people and males typically held positive attitudes of personal attachment to science. Gender and age, on the other hand, influenced attitudes about quality of life. Women and elderly people often displayed loftier attitudes about science's ability to improve quality of life. Demographic variables such as participants' income levels and community size made no difference to their scientific attitudes, which perhaps speaks to an equitable education system across SES.

If our results are to be accepted, they have profound implications for the way science is communicated. Although the direct relationship between perceived knowledge and attitudes was not tested by our model, our research supports a move away from the knowledge agenda in communications (e.g., Bodmer, 1995) that advocates scientific literacy as the key to increasing the general public's interest and support for science. In line with research showing that increased scientific literacy does not always result in increased interest and support for science (e.g., Bauer et al., 2000), our study shows that increases in perceived scientific literacy also do not lead to increases in scientific trust. The House of Lords Select Committee on Science and Technology (2000) suggested that trust, as opposed to scientific literacy, is needed to increase public support for science. The authors of the report suggested that two-way dialogue between the general public and scientists would help to increase trust. Our research suggests, in addition, that fostering positive attitudes towards science plays an important role in developing trust in science and technology. The development of positive attitudes also might be achieved through such a two-way dialogue where the general public has an opportunity to engage with experts in order to foster their personal attachment to science and recognize some of the positive implications that science has on the quality of their lives.

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